PH.D THESIS

The Search for Performance Related Factors in Biomechanics

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Declaration

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy is entirely my own work, that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Abstract

Introduction: The identification of performance related factors (PRFs) is a major goal in sports biomechanics. However, PRFs identified across studies are inconsistent and this might be explained by the limitations of discrete point analysis, which is commonly used. New data analysis techniques involving continuous waveform analysis (e.g. functional principal component analysis, fPCA) have been suggested, but their use in biomechanics is not widespread, and they also have limitations. Another problem in current studies is the general use of a single group analysis design. The primary aim of this work was to develop and test a novel, enhanced method of continuous waveform analysis. A secondary aim was to examine the benefits of a subgroup analysis design, when identifying performance related factors.

Methods: A self-developed data analysis technique (Analysis of Continuous Phase; ACP) was compared to fPCA and discrete point analysis in their ability to identify PRFs in the countermovement jump (CMJ). In addition, the generally used single group design was compared to a subgroup analysis design.

Results: The ability to explain jump height was: ACP (99 %), fPCA (79 %) and discrete point analysis (23 %). ACP identified previously hidden PRFs in CMJs and was able to explain inconsistencies in previous studies that used discrete point analysis. The subgroup analysis demonstrated a better ability to describe jump height than the single group analysis (+10 %) and indicated that different subgroups / individuals have different PRFs.

Conclusion: The findings of this work demonstrate large advantages of continuous data analysis, especially the novel ACP method, and in employing a subgroup analysis. Furthermore, findings indicate that discrete point analysis and single group analysis are sources of inconsistencies in previous experiments on the CMJ.

List of Publications

Journal articles

Roemer K., Hortobagyi T., Richter C., Munoz-Maldonado Y. and S. Hamilton (2013). Effect of BMI on Knee Joint Torques in Ergometer Rowing. Journal of Applied Biomechanics: In Press

Richter C., Marshal B., O'Connor N.E. and K. Moran (2013), Analysis of Characterizing Phases on Waveforms An Application to Vertical Jumps. Journal of Applied Biomechanics: In Press

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Submitted journal articles

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Wundersitz D.W.T., Gastin P.B., Richter C. and K.J Netto (2013), Validity of an accelerometer to assess peak impact during three movement tasks. Submitted to: Journal of Medicine and Science in Sports and Exercise

Conference proceedings

Poster presentations

Ò Catháin C., Richter C., O'Connor N.E. and K. Moran (2013), The Effect of Compliant Running on Kinetics and Joint Kinematics, Symposium of the International Society of Biomechanics in Sports. Taiwan, Taipei.

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Petushek, E.P., Richter C., Donovan D., Ebben W.P. and R.L. Jensen (2011), Comparison of Tibial Impact Accelerations: Video Vs. Accelerometer. Symposium of the International Society of Biomechanics in Sports. Porto, Portugal. 2011.

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Oral presentations

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Whyte, E, Richter C, Gibson G, O'Connor N and K. Moran (2013), An investigation into the effects of a high intensity, intermittent exercise protocol on knee kinetics and kinematics in a stop jump manoeuvre. 10th Annual Scientific Conference of the Faculty of Sports and Exercise Medicine, RCSI.

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Abbreviations and Acronyms

PCA principal component analysis

fPCA functional principal component analysis

ACP Analysis of Characterising Phases

CoM Centre of Mass

CMJ Countermovment Jump

vs. versus

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Chapter 1

Introduction

The success of a movement task such as a vertical jump, a tennis serve or a soccer kick is dependent on various external and internal factors acting on an athlete. Athletes and coaches endeavour to alter the internal factors (e.g. technique, neuromuscular capacity, coordination) through training interventions in order to enhance performance outcome. To design and optimise a training intervention it is necessary to identify the biomechanics based performance related factors. Performance related factors are features that have been found to (a) discriminate between poor and good performances or (b) correlate to the performance outcome of a movement task. However, examination of the studies that have searched for these factors reveals an inconsistency in results, generating an unsatisfactory situation for athletes and coaches, since it is not clear what an optimal training intervention needs to address.

Inconsistencies in performance related factors found across studies may be caused by an inappropriate data analysis technique and / or a lack of consideration of inter-subject variability. Discrete point analysis is by far the most utilized data analysis technique in biomechanical experiments and involves the analysis of individual data points that are preselected (e.g. peak knee power, knee power at peak force). It is a common believe that these variables hold important information and collectively describe the movement task. Functional principal component analysis (fPCA) appears to be a promising and most commonly used continuous waveform analysis procedure. In addition, fPCA is part of the functional data analysis family, and treats a signal as a single function rather than as a series of individual data points. As such, fPCA does not require a linear time normalization, which can alter the data (Donoghue et al., 2008), allowing examination of the underlying structure while maintaining all of the information in the signal (Ramsay and Silverman, 2002). To examine data functional data analysis incorporates the representation of the data in smooth functions and allows the application of landmark registration or other tools such as fPCA. However, it may be limited by three factors. However, discrete point analysis holds three significant limitations that might play a major role in the inconsistencies observed across studies. Firstly, the pre-selection of measures is strongly dependent on previous knowledge and has the potential to discard extremely important information (Donoghue et al., 2008; Dona et al., 2009). Secondly, discrete point analysis does not necessarily take into account the position of pre-selected variables (i.e. the timing of the peak force). Finally, discrete point analysis cannot examine performance related features that exist as phases, which cannot be captured in a single time point.

An alternative to discrete point analysis is a continuous waveform analysis which has grown in popularity within many disciplines, including biomechanics, and has been reported to provide a better insight than discrete point analysis (Dona et al., 2009; Donoghue et al., 2008; Newell et al., 2006; Godwin et al., 2010; Ryan et al., 2006; Harrison et al., 2007; Ramsay and Silverman, 2002). Functional principal component analysis (fPCA) appears to be a promising and most commonly used continuous waveform analysis procedure. However, it may be limited by three factors. Firstly, while it can be done, fPCA is generally performed over the whole movement cycle, where the influence of non-key phases has the potential to mask performance related features. Secondly, the location and length of a phase over which a performance related feature exists tend to be estimated based on subjective inspection of a visual tool (Donoghue et al., 2008; Dona et al., 2009; Godwin et al., 2010; Harrison et al., 2007; Newell et al., 2006; Ramsay, 2006; Ryan et al., 2006). Finally, fPCA generally does not examine the combined magnitude-time domain[1]. It would therefore, be useful to develop a continuous waveform technique to address these limitations.

Limitations in the performed data analysis technique may not be the only reason for the inconsistencies in performance related factors across previous studies. Inter-subject variability within a group level analysis (single group analysis) may also contribute. While, various movement strategies within a movement task can lead to the same movement outcome, performance related factors might differ across movement strategies and mask each other in a group level analysis (Stergiou, 2004; Stergiou and Scott, 2005). A possible solution to avoid the masking of performance related factors during an analysis is to employ a subgroup level analysis; where similar patterns (curve shapes or movement strategy) are classified into separate groups (clusters).

The countermovement jump (CMJ) is an important task in a number of sports (e.g. volleyball, basketball) and its biomechanics have been frequently studied (Klavora, 2000). However, features that relate to the performance outcome (jump height) are often inconsistent. For example, maximum vertical ground reaction force is reported in some studies as a performance related factor (Cormie et al., 2009; Dowling and Vamos, 1993; Sheppard et al., 2009), while it is not in others (Morrissey et al., 1998; Newton et al., 1999; Petushek et al., 2010).

The primary motivation of the present work was to examine the influence of discrete point analysis and inter-subject variability to inconsistencies across previous studies and to develop a combination of data analysis approaches (Analysis

[1]The combined magnitude-time domain merges information from the time and magnitude domain and can reflect important information for example the impulse-momentum relationship in vertical jumps.

of Charactering Phases) which could more effectively identify real performance related factors. A secondary motivation was the application of Analysis of Charactering Phases to identify performance related factors in kinematic and kinetic waveforms for the CMJ.

Chapter 2

The State of the Discipline: Data Analysis in Biomechanics

Research studies in the field of biomechanics aim to identify performance related factors, by comparing differences between groups of individuals (e.g. pre- vs. post-training) or by examining the relationship (e.g. correlation) between a factor (e.g. kinematic or kinetic measure) and the performance outcome. The present work uses the term performance related rather than performance determining factor because it, like the vast majority of studies, solely examines the relationship of a parameter's magnitude to performance. Hence, the present and most previous study design's do not demonstrate a cause-effect relationship which would be required for a parameter to be considered as a performance determining factor.

Over the last few decades, the ability of data recording has improved significantly. As such, the recorded data is temporal dependent, and high in dimensionality and variability and data analysis has become challenging. In contrast to the technological developments, the data analysis techniques commonly employed have not changed significantly and the vast majority of biomechanical studies continue to use discrete point analysis to examine the observed data. While discrete point analysis does provide some level of insight it has significant limitations and may be a possible source for the inconsistencies across previous studies. Due to these limitations, a variety of new approaches have been applied to examine biomechanical data.

This chapter will give an overview of the research model used to compare different data analysis techniques, and the limitations and possibilities of common and novel data analysis techniques applied in biomechanical research studies.

2.1 Research Model: Countermovement Jump

The countermovement jump (CMJ) was chosen as research model due to its clearly defined and easily measurable performance outcome. The performance outcome, jump height, is directly and fully determined (theoretically) by the impulse-momentum relationship. This property allows the comparison of the effectiveness across analysis techniques in their ability to identify performance related factors in the vertical ground reaction force data (force). In addition, the CMJ is an important task in a number of sports (e.g. volleyball, basketball) and its biomechanics have been frequently studied (Klavora, 2000). However, the understanding of neuromuscular factors that determine it performance is challenging since performance related factors are inconsistent across studies.

2.1.1 Basic Mechanics

The CMJ can be separated into three phases; the unloading, the loading and the propulsion phase (Figure 2.1). In maximal effort CMJ's the aim is to jump as high as possible. The CMJ is initiated by an unloading phase where the height of the body's centre of mass (CoM) reduces as the hip, knee and ankle joints flex. This results in the force time curve falling below body weight (Meylan et al., 2010). The loading phase starts with an eccentric contraction of muscles to decelerate the downwards velocity of the body's CoM. The propulsion phase starts with the extension of the hip, and knee and the plantar flexion of the ankle joint, caused by a concentric contraction of the hip and knee extensor muscles and the ankle plantar flexors, respectively and propulsion phase propels the CoM vertically from the ground (Bobbert et al., 1986). The sum of the rotation moments in each of the extending joints defines the net vertical ground reaction forces (forces) generated during the propulsion phase and fully determines jump height (Figure 2.1). The eccentric loading phase enhances the subsequent concentric propulsion phase impulse, which is associated by the stretch-shortening cycle, and enhances the performance of the jump (Bobbert et al., 1996; Bosco et al., 1981; Moran and Wallace, 2007; Laffaye and Wagner, 2013). Enhancements associated with the stretch-shortening cycle are greater with higher magnitudes of eccentric loading (Cavagna et al., 1968), higher speeds of eccentric loading (Bosco et al., 1981), smaller amplitudes of stretch (Marshall, 2010) and shorter durations between the eccentric loading phase and the concentric propulsion phase Moran and Wallace (2007). While not examined within the present work, performance related factors identified during the concentric propulsion phase may be the results of the loading strategy during the eccentric loading phase.

The use of an unloading and loading before the propulsion phase enables athletes to enhance the performance of the jump, which is associated with enhancements of the stretch-shortening cycle (Bobbert et al., 1996; Bosco et al., 1981; Moran and Wallace, 2007; Laffaye and Wagner, 2013). The stretch-shortening cycle is influenced by the pre-activation of the muscles in the unloading phase, the stretch (eccentric contraction) of the muscles in the loading phase, and the shortening (concentric contraction) in the propulsion phase. While not examined within the present work, performance related factors identified may be the results of the stretch-shortening cycle.

The rotation moments (flexion or extension) in hip, knee and ankle joint during a CMJ are caused by forces generated from skeletal muscles. Magnitude and tim-

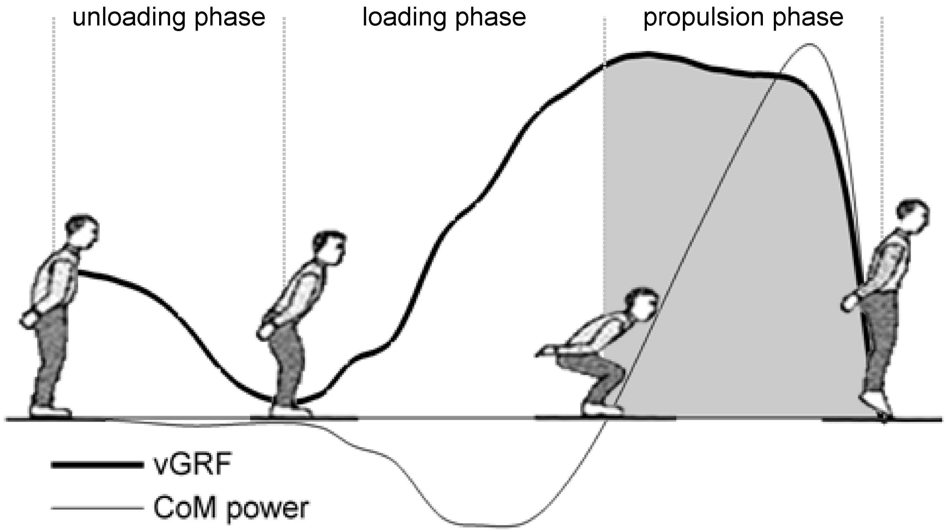


Figure 2.1: Graphical representation of the CMJ; the impulse generated during the propulsion phase is shaded grey and was determined using the Centre of Mass (CoM) power

ing properties of the muscular force development is determined by the number, frequency and synchronisation of electrochemical messages (motor unit action potential) sent form the nervous system to the muscles (Tortora and Derrickson, 2008). Appropriate neuromuscular training can induce adaptations to the muscular force development by altering the number or frequency of motor unit action potentials, a better synchronisation of action potentials or by muscle hypertrophy. Such changes may lead to a greater impulse during the propulsion phase and thus may increase maximal CMJ jump height.

The impulse generated during the propulsion phase is a key determinant of CMJ jump height and hence is the only phase considered in the present work. However, it is recognised that the loading phase of a CMJ influences the propulsion phase and is an important factor in for CMJ jump height (Bobbert et al., 1996; Bosco et al., 1981; Moran and Wallace, 2007; Laffaye and Wagner, 2013). Due to the importance of the propulsion phase in CMJ, the relationship of various parameters within the propulsion phase to jump height has been examined. This includes the forces produced during the CMJ generated by the body as a whole and each joint. In addition, many studies have examined parameters describing jumping technique and coordination as they may give a greater insight into the performance of CMJ jump height (AragonVargas and Gross, 1997b; Bobbert and Van Soest, 1994; Lees, 2002; Vanezis and Lees, 2005).

2.1.2 Previously Identified Performance Related Factors

Kinematic Waveforms The CMJ is often simplified by considering the body's centre of mass (CoM) as a projectile and its performance can be enhanced by increasing the vertical CoM height at takeoff and / or the vertical CoM velocity at takeoff.

The vertical CoM height at takeoff has been shown to be higher in skilled compared to non-skilled jumpers (Cormie et al., 2009). The vertical height of the CoM is determined by the joint angle of the hip, knee and ankle joint and examining these might identify a specific joint extension pattern that is beneficial towards CMJ jump height. However, to the author's knowledge only one study exists, which has examined the relationship between joint angles at takeoff and jump height (AragonVargas and Gross, 1997b). However, in the study of AragonVargas and Gross (1997b) joint angles at takeoff of the ankle, knee and hip joint were not included in good jump height predictor models. The second principle to enhance the performance of a CMJ is to increase the vertical CoM velocity at takeoff (Equation 2.1), which is dependent on the generated net impulse.

$$jump\ height = (v_{takeoff}^2/2g) \tag{2.1}$$

Where the vertical CoM velocity at takeoff is $v_{takeoff}$ and g is gravity. Consequently, vertical CoM velocity at takeoff has been described as a very strong predictor (r^2 = 0.95) for jump height (AragonVargas and Gross, 1997b). A parameter that has been found to increase the vertical impulse is the CoM amplitude. The CoM amplitude is the difference between the minimum and maximum CoM position and has been reported to be a significant predictor of jump height (AragonVargas and Gross, 1997b). However, while large CoM amplitudes hold the potential to increase the impulse, large CoM amplitude can also be counter-productive towards generating high forces at the start of the propulsion phase (Marshall, 2010). The ability to generate high forces at the start of the propulsion phase depends on the amount of flexion within a joint at the end of the loading phase. If the flexion angle is too large it can decrease the ability to generate high extension moments at the start of the propulsion phase due to the force-length relationships within a muscle (Hill, 1939). While, numerous studies have examined joint angles at the start of the propulsion phase, no study examined the relationship initial joint angles and jump height in CMJ (Marshall, 2010).

Kinetic Waveforms The most important waveform in CMJ is the vertical ground reaction force (force) curve because its magnitude (f) and temporal (t) information completely determine the amount of the generated impulse (Equation 2.2).

$$\int_{start}^{takeoff} f(t)dt = mass * \Delta velocity \tag{2.2}$$

Hence, the performance of a CMJ depends on a combination of the duration of the propulsion phase (phase duration) and forces generated during the propulsion phase. The phase duration however was not found to be a significant predictor of jump height in the study of AragonVargas and Gross (1997b). This might be explained by the fact that an increase of the phase duration requires a proportional increase of the CoM amplitude to not affect jump height. Hence, increasing phase duration may lead to CoM amplitudes that are counter-productive towards generating high forces at the start of the propulsion and can have no, or a reducing effect to the performance outcome.

In contrast to increasing phase duration, increasing forces during the CMJ has a non-controversial positive impact on jump height (Zajac, 1993). Consequently previous research has mainly focused on forces generated during the CMJ.

A frequently studied discrete parameter is peak force, which implicitly or explicitly appears to be viewed as a criterion to generate high forces throughout the propulsion phase. While it would be assumed that peak force should be identified consistently as a performance related factor, it is reported in some studies as a performance related factor (Cormie et al., 2009; Dowling and Vamos, 1993; Sheppard et al., 2009; Harman et al., 1990) but not in others (Morrissey et al., 1998; Newton et al., 1999; Petushek et al., 2010; Floría and Harrison, 2013). Dowling and Vamos (1993) and Harman et al. (1990) found a significant relationship of peak force to jump height (r = 0.53 and r = 0.52, respectively). Sheppard et al. (2009) found that the change in peak force is related to the change in jump height (r = 0.55). Cormie et al. (2009) found peak force to be greater in skilled jumpers (23.4 N/kg = 100 %) compared to non-skilled jumpers (21.0 N/kg = 90 %). In contrast, Morrissey et al. (1998) examined two training interventions and found no significant increase in peak force within group A which increased significantly jump height, while group B showed a significant increase in peak force but not in jump height. Newton et al. (1999) and Petushek et al. (2010) examined the effect of a training intervention. Both reported non significant changes in peak force but significantly enhanced jump heights. Two exceptional studies that examined force curves are Cormie et al. (2009) and Floría and Harrison (2013). Both studies used a point-by-point analysis to examine every point in time for its relationship to jump height. While Cormie et al. (2009) identified the end (95-98 %) of the movement cycle to be related to jump height, Floría and Harrison (2013) identified the start (1-15 %) of the movement cycle as a performance related factor. However, these studies should not be compared directly. Cormie et al. (2009) examined thirty male subjects (20.2 $\pm$ 2.9 years), while Floría and Harrison (2013) examined twenty-four girls (6.5 $\pm$ 0.8 years). In addition, a point-by-point analysis results in an underestimation of variability (Lenhoff et al., 1999; Duhamel et al., 2004; Schwartz et al., 2004). This limitation might be overcome by using a bootstrap approach to estimate the variability in the data (Dixon et al., 2013). An explanation for the contrasting findings of peak force might be that it solely captures magnitude information of the force curve. Hence, some studies have examined parameters that combine temporal and magnitude information. A parameter that combines both temporal and magnitude information is the rate of force development, which is often calculated using initial and maximum force (Equation 2.3).

$$RoDF = \frac{(force_{maximum} - force_{initial})}{(\Delta time)} \tag{2.3}$$

However, while Newton et al. (1999) and Morrissey et al. (1998) reported that an improvement in rate of force development is associated with a change in jump height, Cormie et al. (2009) found higher but not significant rate of force development in non-skilled (25.0 N/kg/s = 100 %) compared to skilled jumpers (24.0 N/kg/s = 96 %).

In contrast to peak force and initial-to-maximum rate of force development, peak CoM power (Equation 2.4 and Equation 2.5) is found by many studies to have a strong relationship (r $>$ 0.72) to jump height (Cormie et al., 2009; Dowling and Vamos, 1993; Harman et al., 1990; AragonVargas and Gross, 1997b).

$$CoM\ power(t) = force(t) * vertical\ CoM\ velocity(t) \tag{2.4}$$

$$vertical\ CoM\ velocity(t) = (\int_{n=1}^{t} (force(n) - body\ weight)dt)/body\ mass \tag{2.5}$$

Table 2.1: Previously reported kinematic parameters generated during a CMJ (peak moment, peak power and work done)

Study	Subjects	Peak moment ($Nm*kg^{-1}$)		Peak power ($W*kg^{-1}$)		Work done ($J*kg^{-1}$)		Percentage contribution	
Aragon-Vargas and Gross (1997)	52 male	Hip	4.0	Hip	16.3		-		-
	Physically	Knee	3.0	Knee	20.1		-		-
	active	Ankle	3.3	Ankle	25.9		-		-
Bobbert et al. (1986)	13 male Handball	Hip	4.7	Hip	19.5	Hip	2.8	Hip	38
		Knee	3.7	Knee	20.6	Knee	2.3	Knee	32
		Ankle	3.4	Ankle	24.4	Ankle	2.2	Ankle	20
Bobbert et al. (1987)	10 male Volleyball	Hip	5.0	Hip	18.0	-	-		
		Knee	4.3	Knee	30.1	-	-		
		Ankle	3.1	Ankle	28.9	-	-		
Vanezis and Lees (2005)	9 male	Hip	3.5	Hip	15.9	Hip	3.2	Hip	43
	Soccer (high	Knee	3.4	Knee	18.5	Knee	2.3	Knee	29
	group)	Ankle	3.1	Ankle	21.6	Ankle	2.2	Ankle	28
	9 male	Hip	3.1	Hip	12.6	Hip	2.5	Hip	41
	Soccer (low	Knee	3.1	Knee	15.6	Knee	2.1	Knee	31
	group)	Ankle	2.8	Ankle	17.1	Ankle	1.8	Ankle	28
Vanrenterghem et al. (2008)	20 male	Hip	3.7	Hip	15.9		-		-
	Physically	Knee	2.8	Knee	15.3		-		-
	active	Ankle	3.2	Ankle	19.4		-		-
Hubley and Wells (1983)	6 male		-		-	Hip	2.5	Hip	41
	Physically		-		-	Knee	2.1	Knee	31
	active		-		-	Ankle	1.8	Ankle	28

To understand how a greater CoM peak power can be achieved, it is necessary to investigate properties of the forces generated in the extending joints, that can be described by joint moment, joint power and joint work-done (Table 2.1).

Joint moments represent a summed measure for the amount of the force generated by the extending muscles within a joint. The analysis of joint moments might therefore give an indication if the relative strength across joint extensor muscles should follow a specific pattern to achieve a maximal CMJ jump height. Peak moments have been reported to be highest in the hip joint (Vanezis and Lees, 2005; Bobbert et al., 1987; Vanrenterghem et al., 2008). Peak moments in knee and ankle joint however are not ranked consistently, some studies found peak moments in the knee joint to the greater than the ankle joint (Bobbert et al., 1987; Vanrenterghem et al., 2008), while others found the opposite (Vanezis and Lees, 2005; AragonVargas and Gross, 1997b). In terms of the relation of joint moments to jump height, AragonVargas and Gross (1997b) identified the peak hip moment (r = 0.53) and hip moment at the start of the concentric phase (r = 0.48) to be significantly related to jump height.

Joint power represent a measure for the explosiveness of muscles that extend a joint and might give an indication if a specific pattern in joint power is necessary to enhance jump height. The majority of studies that examined peak power reported it is greatest in the ankle joint (AragonVargas and Gross, 1997b; Bobbert et al., 1986; Vanezis and Lees, 2005; Vanrenterghem et al., 2008), while Bobbert et al. (1987) found the knee joint to generate the greatest power. Although the hip joint is often reported to generate the smallest peak power (AragonVargas and Gross, 1997b; Bobbert et al., 1986; Vanezis and Lees, 2005; Bobbert et al., 1987), Vanrenterghem et al. (2008) identified the knee joint to have the smallest peak power. While Vanezis and Lees (2005) identified ankle peak power to differ significantly between a group of good (21.6W/kg = 100 %) and poor (17.1W/kg = 79 %) jumpers, Vanrenterghem et al. (2008) found no significant relationship (r = 0.18) between ankle peak power and jump height. In addition, AragonVargas and Gross (1997b) reported knee peak power as an important predictor of jump height[1], while Vanrenterghem et al. (2008) reported no significant correlation to jump height (r = 0.12).

The last parameter discussed in this work is joint work-done. Work-done[2] has been used by a number of researcher to identify which joint is dominant during the CMJ (Bobbert et al., 1986; Vanezis and Lees, 2005; Hubley and Wells, 1983; Vanezis and Lees, 2005). The majority of the findings indicate that the order across the joints is (descending): hip, knee and ankle joint (Bobbert et al., 1986; Vanezis and Lees, 2005). However, Hubley and Wells (1983) found that the knee joint was dominant, followed by the hip and ankle. Vanezis and Lees (2005) found

[1]Knee peak power was included in several best predictor models of jump height ($0.48 < r^2 < 0.61$)

[2]The reader should note, that work-done is not in an directly related to jump height on either a joint and whole body level

significant higher work done in the ankle joint in good jumpers (2.2J/kg = 100 %) compared to poor jumpers (1.8J/kg = 81 %).

In summary, eight parameters (beyond the impulse-momentum relationship, vertical CoM velocity and CoM displacements) were found to be a performance related factor; peak force, rate of force development, peak hip moment, hip moment at the start of the propulsion phase, CoM peak power, ankle peak power, knee peak power knee and ankle work-done. However, only the CoM peak power appears to have been consistently identified across studies. Consequently, no clear indication exists of what an optimal training intervention has to address to enhance performance, beyond the CoM peak power.

2.2 Discrete Point Analysis

A factor that can restrict the identification of performance related factors is the data analysis technique performed. The vast majority of studies that examined the CMJ in biomechanics almost exclusively use discrete point analysis; of all the reviewed studies only Cormie et al. (2009) and Floría and Harrison (2013) did not. In discrete point analysis, a continuous waveform is reduced to pre-selected summary variables (e.g. mean) or key events (e.g. peak or time to peak) assuming that the pre-selected discrete measures collectively describe the observed waveform. These variables are subsequently analyzed for differences between groups (e.g. skilled athletes vs. non-skilled athletes) or for a relation to a dependent variable using a univariate approach such as a t-test or a correlation analysis. This 'self-selected' data reduction, however, holds four significant limitations.

Firstly, the pre-selection of measures is strongly dependent on previous knowledge and the experience of a researcher, and hence has the potential to discard extremely important information (Dona et al., 2009; Donoghue et al., 2008). This can be highlighted by the variance and inconsistency in the number of analyzed measures across previous studies, which differs drastically across studies. For example, AragonVargas and Gross (1997b) examined thirty-two variables using the whole body and joint kinematics and kinetics. Vanezis and Lees (2005) examined nine variables using only joint kinetics (ankle, knee and hip peak power, moment and work done); while Vanrenterghem et al. (2004) examined twelve variables spread over whole body and joint kinematics and kinetics. Despite the difference and variety in considered variables, most of the reviewed studies do not report or examine the timing of key events or the modality / shape of curves. How strongly previous knowledge and experience influences the pre-selection of discrete measures can be shown by comparing directly the number of examined variables just within force curves. Within a selection of 15 studies that searched for performance related factors within the forces generated during vertical jumps, a total of fourteen 'key' measures were examined, while the number of analyzed measures varied from one to six across these studies (Cormie et al., 2009; Dowling and Vamos, 1993; Feltner and MacRae, 2011; Harman et al., 1990; Kollias et al., 2004; Laffaye and Choukou, 2010; McBride et al., 2002; Meylan et al., 2010; Morrissey et al., 1998; Newton et al., 1999; Pappas et al., 2007; Petushek et al., 2010; Sheppard et al., 2008; Smith et al., 2011; Walsh et al., 2007).

Secondly, discrete point analysis does not consider the vast majority of a signal. For example, AragonVargas and Gross (1997b) examined thirty-two variables within 16 waveforms that described whole body and joint kinematics and kinetics. Assuming that every waveform consisted of 101 data points, AragonVargas and Gross (1997b) examined only 1.4 % of their data. The reader should note that AragonVargas and Gross (1997b) examined two times more information within the waveforms compared to Vanezis and Lees (2005) and Vanrenterghem et al. (2004), which examined only 0.5 % and 0.7 % of their data.

Thirdly, the analysis of a discrete point might not be appropriate to identify performance related factors because a discrete point represents only a 'snapshot' of a variable. A 'snapshot' of a moment-time curve might not be able to capture performance related factors as they may occur over phases and are not necessarily captured in a single data point. Hence, it might be important to consider specific phases of a movement which cannot be done using a discrete point analysis.

Finally, discrete point analysis does not necessarily take into account the position of 'key' measures. For example, when examining the peak in a bi-modal waveform, where the peak could occur at the first or second maximum, discrete point analysis has the potential to compare measures that represent non-related neuromuscular capacities. This may partly explain the contrasting results in previous studies that used discrete point analysis.

2.3 Continuous Waveform Analysis

One possible solution to overcome limitations in discrete point analysis is to analyze kinematic and kinetic waveforms as a whole. Over the last decade much work has been dedicated to this idea and has introduced analysis techniques originating from a variety of fields including computer science, psychology, cognitive science, physics and engineering (Chau, 2001a,b; Kelso, 1995; Ramsay, 2006). Chau reviewed, in two texts, data analysis techniques that have been used in gait studies to overcome limitations of discrete point analysis such as: multivariate statistics (e.g. principal component analysis, factor analysis and multiple correspondence analysis), fractal dynamics (e.g. de-trended fluctuation analysis), neuronal networks (multilayer forward network) or time frequency analysis (wavelet transformation; Chau 2001a,b). Additionally, new data analysis theories have been introduced to analyze coordination or pattern of variation within data such as: dynamical system theory (Kelso, 1995) or functional data analysis (Ramsay and Silverman, 2002). In contrast to discrete point analysis, continuous waveform analysis considers every possible variable within a waveform, can detect patterns within data and is not inappropriately influenced by any previous knowledge or the experience of the user. Consequently, the use of continuous waveform analysis over discrete point analysis has been recommended in multiple studies (Dixon et al., 2013; Ullah and Finch, 2013; Crane et al., 2010; Dona et al., 2009; Preatoni et al., 2009; Epifanio et al., 2008; Donoghue et al., 2008; Newell et al., 2006; Ryan et al., 2006; Ramsay, 2006; Harrison et al., 2007).

The theory of functional data analysis received great attention in a variety of fields, which is highlighted by 363 citations of the book 'Functional data analysis' solely in 2013 (assessed on Goggle scholar at November 6th 2013). The basic idea of functional data analysis is to transform a series of independent data points into a series of dependent data coefficients, called functional data (Ryan et al., 2006). The main goals of functional data analysis are listed below, while mathematical principals are described in Appendix A and B:

- To represent data in ways that allow further analysis
- To display data and highlight various characteristics
- To study important sources of patterns and variation
- To explain variation in the outcome or dependent variables by using input or independent variable information
- To compare two or more sets of data with respect to a certain type of variation, where two sets of data can contain different sets of replications of the same function or different functions for common sets of replicates (Ramsay and Silverman, 2002)

Functional data analysis is generally performed in four steps: a) derivation of functions, b) landmark registration, c) data analysis, and d) visualising findings.

Derivation of functions: Data is typically captured in discrete time points over regular intervals and contains noise. A number of techniques can be applied to reduce the noise in the raw data (e.g. digital filtering as described in Winter 2009). In functional data analysis, the application of basis function expansions is used to reduce the noise in a waveform and to generate smooth functions. Hence, functional data analysis provides an effective smoothing approach (Ramsay, 2006). How functional data is created is described in detail in Appendix A.

Landmark registration: A procedure which is often applied before examining the generated functional data is landmark registration. Biomechanical waveforms follow often similar pattern, with distinct visible features (e.g. peak values). Landmark registration aligns these features to allow a comparison of curves and provides a more meaningful average curve. However, landmark registration cannot be applied in some cases because some waveforms do not hold visible features or when the timing of landmarks is not comparable across curves. Hence, the application of landmark registration depends on the data examined and is therefore not always performed. More information about landmark registration can be found in Ramsay and Silverman 2002.

Data analysis: Functional data analysis uses existing data analysis techniques to examine the generated functions.

Visualising findings: Following data analysis, findings in functional data analysis are often represented visually to allow insightful interpretation.

The full process of performing a functional data analysis is described in Appendix A and B, using functional principal component analysis as an example.

Despite the increase in awareness of functional data analysis, only 84 actual research studies in the public health and biomedical field have used it (Ullah and Finch, 2013).

2.3.1 Functional Principal Component Analysis

One of the more promising and applied techniques for extracting information from functional data is functional principal component analysis (fPCA); 51 of the 84 studies (60.7 %) in the public health and biomedical field used fPCA (Ullah and Finch, 2013). Specifically in biomechanics studies, the number of researchers that recommend the use of fPCA over discrete point analysis is growing (Dixon et al., 2013; Ullah and Finch, 2013; Crane et al., 2010; Dona et al., 2009; Preatoni et al., 2009; Epifanio et al., 2008; Donoghue et al., 2008; Newell et al., 2006; Ryan et al., 2006; Ramsay, 2006; Harrison et al., 2007).

Functional principal component analysis transforms the collected waveforms into functions and detects patterns of variance within the functions, which are used to analyse the data by performing a principal component analysis. The key benefit of fPCA is the ability to reduce the dimensionality of a set of signals, while preserving the information needed to describe a data set (Jolliffe, 2005). In addition, fPCA is part of the functional data analysis family, and presents a signal as a single function rather than as a series of individual data points. As such, fPCA does not require linear time normalization, which can alter the data (Dona et al., 2009), and uncovers the underlying structure while maintaining all of the information in the signal (Ramsay, 2006).

To date the only research study that has used fPCA to examine the CMJ is Harrison et al. (2007), which analyzed lower limb kinematic data from children with different developmental stages, performing a vertical jump. Their study aimed to identify factors that can distinguish between different developmental stages in children using inter-segment coordination pattern of the hip-ankle, hip-knee and knee-ankle joint angle. The results of the analysis indicate that the coordination pattern between the knee and hip are most effective at discriminating between developmental stages and support the application of fPCA for the analysis of joint coordination or time series data.

Like Harrison et al. (2007) other studies have recommended the use of fPCA for biomechanical analysis. Donoghue et al. (2008) examined the mechanisms of chronic achilles tendon injury and reported that fPCA was able to provide additional information about movement patterns compared to traditional approaches. Dona et al. (2009) identified and evaluated performance related factors in race walking using fPCA. They reported that fPCA was able to provide evidence of athletes technical differences and asymmetries even when traditional discrete point analysis failed to do so. Furthermore, generated principal components provided features for race walkers classification and identified potentially important technical differences between higher and lower skilled athletes. Epifanio et al. (2008) examined the sit-to-stand of individuals with and without an osteoarthritic condition. They analyzed analogous knee flexion angle and flexor moment waveforms using a bivariate fPCA and reported that fPCA presents better discriminatory power compared with the classical multivariate approach PCA.

Factors That Can Influence Findings of Functional Principal Component Analysis

While previous studies highlight strongly the benefits of fPCA, there are factors that can influence the ability of fPCA to identify performance related factors: the chosen number of basis, the chosen order and the chosen number of examined principal components.

The Use of Functional Data The ability to detect performance related factors using functional data can be influenced by the chosen number of basis (n basis) and the chosen order (h order; degree of freedom - 1) within a basis system. Both

Table 2.2: The amount of variance examined in previous studies

Study	Examined % of variance
(Carriero et al. 2009)	61.0
(Mantovani et al. 2011)	85.0
(Harrison, Ryan, and Hayes 2007)	<90.0
(Daffertshofer et al. 2004)	90.0
(Deluzio and Astephen 2007)	90.0
(Newell et al. 2006)	94.3
(Dona, Preatoni, and Cobelli 2009)	95.0
(Wrigley et al. 2006)	97.0
(Coffey et al. 2011)	97.5
(Epifanio et al. 2008)	97.8
(Donoghue et al. 2008)	<98.0

factors determine the fit of the function to the discrete data and, to the author's knowledge, their impact towards the performance of fPCA has not been examined. The reader who has not worked previously with functional data is referred to Appendix A or to the text of Ramsay and Silverman (2002) for information about functional data.

The Chosen Number of Examined Principal Components Another factor that can influence the ability of fPCA to detect performance related factors is the number of principal components examined. The reader who has not worked previously with fPCA/PCA is referred to the Appendix B or the text of Jolliffe (2005) for detailed information about fPCA.

When applying fPCA a threshold (x % of the total variance in the data) is chosen by the user, which defines the amount of information in the original signal preserved and determines the number of retained principal components. While a variety of thresholds are used, a 95 % threshold appears to be the most frequently used in recent biomechanical studies (Table 2.2; Carriero et al. 2009; Mantovani et al. 2011; Harrison et al. 2007; Daffertshofer et al. 2004; Deluzio and Astephen 2007; Newell et al. 2006; Dona et al. 2009; Wrigley et al. 2006; Coffey et al. 2011; Epifanio et al. 2008; Donoghue et al. 2008).

Principal components beyond the threshold of 95 % are often discarded as they account for little of the variation in the data (Donoghue et al., 2008; Daffertshofer et al., 2004), while the examined variance can be as low as 61 % (Carriero et al., 2009). This is based on the assumption that only principal components with large effect sizes, called Eigen values, describe important patterns of variation. However, the Eigen value of a principal component is based on its influence to the variance within the data set and may have no relation to the examined dependent variable. Hence, the Eigen value does not necessarily describe the pattern of variation that is sensitive to changes in the dependent variable (von Tscharner et al., 2013). This is supported by findings of Harrison et al. (2007) and von Tscharner et al. (2013). The study of von Tscharner et al. (2013) found a principal component (generated from discrete data) which explained only 1.8 % of the variances in the data to have the highest accuracy in discriminating between running pattern in two different shoe conditions. Harrison et al. (2007), considered only three principal components in their analysis ($<$ 90 % of the total variance in the data), found a principal component that explained only 7 % of the variances in the data to be the best discriminator between different development stages in vertical jumps performed by children.

Limitations of Functional Principal Component Analysis

Despite the fact that fPCA has many advantages for data analysis in biomechanics it also presents two possible limitations: (a) the score generation, and (b) it generally does not examine the combined magnitude-time domain

The Generation of Principal Component Scores An advantage of fPCA is that it examines the whole continuous curve when screening a sample of curves for pattern of variation. However, computing subject scores (principal component scores) by utilizing the whole movement cycle[3] might hamper the ability of fPCA to identify performance related factors. The aim of principal component scores is to describe how strong an individual is affected by a pattern of variance. When calculating principal component scores it is assumed that phases that hold high variation (key phases) have an overwhelming effect on the generated principal component score. However, non-key phases also contribute to the final score. Biomechanical data often contain small differences between populations and it is necessary to capture accurately the behaviour of a subject to a pattern of variance. Oscillations in the principal components score outside of the key phases do not belong to the specific pattern of variance defined by a principal component and might inappropriately alter the final principal component score. This effect can be visualized by demonstrating the growth of a principal component score over time to its final value (Figure 2.2). It is clearly visible in figure 2.2 that non-key phases before and after the key phase (e.g. 56-68 %) artificially alter the final principal component score.

The Examination of the Combined Magnitude-Time Domain A limitation in fPCA is that previous studies did not examine the combined magnitude-time domain, which can hold important information. The author believes it is important to consider the combination of absolute timing and magnitude during an analysis. As an example, a data capture of multiple jumps performed by an athlete may result in very similar force-time curves. Even when differences in jump height do exist, neither the time history nor the force history data alone may differ significantly across the jumps. However, given that the impulse-momentum relationship completely determines jump height, analyzing the combined magnitude-time domain might enable the detection of such differences. Consequently, analyzing

[3] Crane et al. 2010; Dona et al. 2009; Preatoni et al. 2009; Epifanio et al. 2008; Donoghue et al. 2008; Newell et al. 2006; Ryan et al. 2006; Ramsay 2006 and Harrison et al. 2007

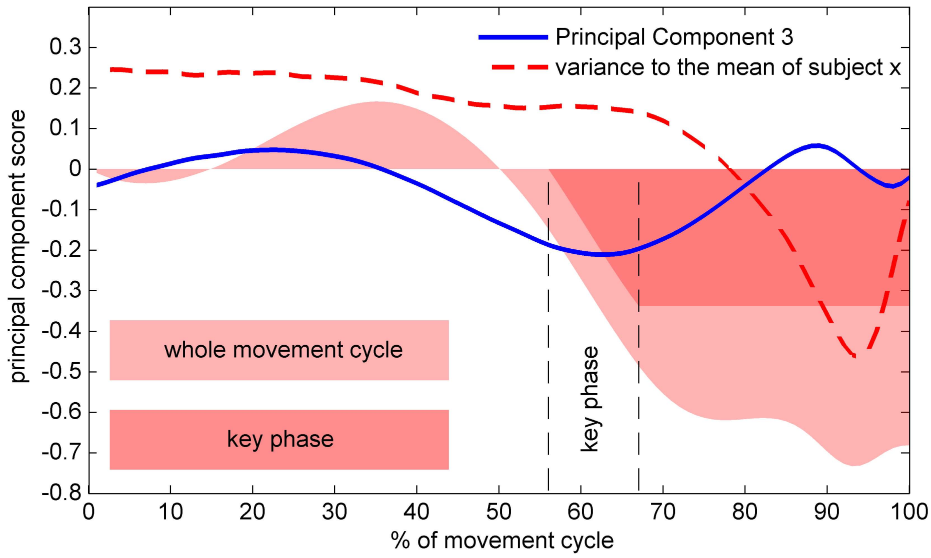


Figure 2.2: Demonstrates the differences in principal component scores calculated over the whole cycle vs. modified principal component scores (calculated over the key phase)

the combined force-time domain has a significant importance and can provide important information.

To date, no data analysis technique appears to fully address the above mentioned limitations.

2.4 Single Group and Subgroup Design

Another reason for the contrasting findings in previous CMJ studies that aimed to identify performance related factors may be inter-subject variability (different groups of subjects utilising different movement strategies). It has been suggested in previous research that jumping strategies differ across individuals (Vanezis and Lees, 2005), which may in turn imply that performance related factors differ across individuals. If performance related factors differ across individuals, the generally used study design (single group design) is likely to have, at least in part, contributed to the inconsistency in the findings of the reviewed studies.

The statistical analysis in biomechanical research studies is generally performed using a single group design (Bates, 1996). In a single group design it is assumed that performance related factors within a group (e.g. male athletes in volleyball) are equal across the entire population. However, movement strategies may differ significantly across athletes and may have different performance related factors that could mask each other in a single group analysis (Stergiou, 2004; Stergiou and Scott, 2005; Bates, 1996; Vanezis and Lees, 2005). For example, Vanezis and Lees (2005) found in their study that some individuals were knee dominant, while others were hip dominant (as determined by the mechanical work-done). In light of this finding, the performance of a CMJ might relate more to knee joint kinematics and kinetics for some individuals, while it relates more to the hip joint kinematics and kinetics for others (as indicated by AragonVargas and Gross 1997a). Consequently, utilizing a single group analysis for a sample of individuals where the performance of a CMJ is related to either the knee or the hip joint kinematics or kinetics will mask performance related factors; the knee dominant subgroup masks the performance related factors of the hip dominant subgroup, vice versa[4].

An alternative design is the analysis of subgroups, which accounts for different movement strategies across individuals. A subgroup analysis classifies individuals into subgroups (clusters), based on their movement strategies, and aims to maximize the ability to predict dependent variables (e.g. performance) of a data set by classification (Han et al., 2006). Hence, a subgroup analysis should not mask

[4]Another design is the analysis of a single subject, which assumes that every individual has a unique movement strategy and consequently unique performance related factors (Bates, 1996). However, findings are dependent on the studied athlete itself and its current mental and physical condition during the data capture (Backman and Harris, 1999). Consequently, findings are limited because the number of observations might affect findings (due to practice or fatigue effects), the generalization of findings is problematic and the comparison of interventions is difficult (as the ordering of interventions might affect results (Morgan and Morgan, 2008; Backman and Harris, 1999).

performance related factors, or at least reduce the risk of masked performance related factors.

While the subgroup design is frequently used in experiments that examine human gait (Carriero et al., 2009; O'Byrne et al., 1998; Kienast et al., 1999; Toro et al., 2007; O'Malley et al., 1997; Stout et al., 1995), no study that examined the CMJ appears to have used a subgroup analysis.

Kienast et al. (1999) classified joint kinematics of 24 children with cerebral palsy and 15 healthy children, using a k-nearest neighbour algorithm with three clusters. The subgroup analysis classified 95.3 % of the healthy and 6.7 % of children with cerebral palsy into cluster1, 37.3 % of children with cerebral palsy into cluster 2 and 4.7 % of the healthy and 56.0 % of children with cerebral palsy into cluster3. This indicates that the subgroup analysis was a feasible design to differentiate between normal and pathological walking patterns. Similar results were found by Carriero et al. (2009), who examined gait pattern between normal and children with spastic diplegic cerebral palsy using a fuzzy c-mean cluster analysis. The findings of both studies help to recognize pathological gait pattern and can lead to an earlier start of rehabilitation interventions and hence have a huge importance for clinical implications. Toro et al. (2007) used a hierarchical cluster analysis to increase the understanding of walking patterns in children with cerebral palsy. In their study, they examined joint kinematics of 56 children with cerebral palsy (boys and girls, 5-16 years). Findings show that 82 % of the examined gait cycles hold walking pattern associated to cerebral palsy, which were classified into three general walking patterns (crouch, equines and other gait types), while 18 % of the data indicated a normal walking pattern. The classification of gait patterns enabled clinicians without access to analysis equipment to rely on visual or simple video gait assessment, allowing care pathways to be standardized for different gait patterns, with subsequent service delivery and efficiency benefits (Toro et al., 2007). This demonstrates a huge benefit of a subgroup analysis.

However, there is a lack of standardised methods of gait classification (Toro et al., 2007) caused by the variety of classification techniques, which may result in different clusters (Jain et al., 1999; Hastie et al., 2001; Witten and Frank, 2005; Martinez et al., 2004), and the lack of biomechanical studies that have compared the ability of cluster techniques to identify movement strategies

To the knowledge of the author, no biomechanical study has compared the ability of cluster techniques to identify movement strategies. In light of this, the following section describes the basic ideas behind three commonly used data clustering techniques.

2.4.1 Hierarchical Clustering

Hierarchical clustering follows the idea that the similarity of individuals is represented by the distance of the observed measures (features) to each other. A hierarchal cluster algorithm starts with considering each individual as one group (Step1; Figure 2.3). Subsequently, it calculates the distance between every individual and searches for the two individuals with the smallest distance to each other (e.g. the two most similar individuals), which are then merged into one group. In the next iteration the two merged individuals are considered as one group that is located at the mid-point between both individuals (Step2; Figure 2.3). The hierarchical clustering algorithm repeats this process until it has created one single group that contains every individual (Step3-5; Figure 2.3; Segaran 2007).

The results of hierarchical clustering are commonly visualized in a graph called a dendrogram. The dendrogram displays the calculated distances and the connections made by every repetition until the sample of individuals get merged into one group (Figure 2.4; Segaran, 2007).

In the given example, it can be seen that individuals E and D are much closer than individuals A and B (Figure 2.4). Further, it can be seen that individual C was

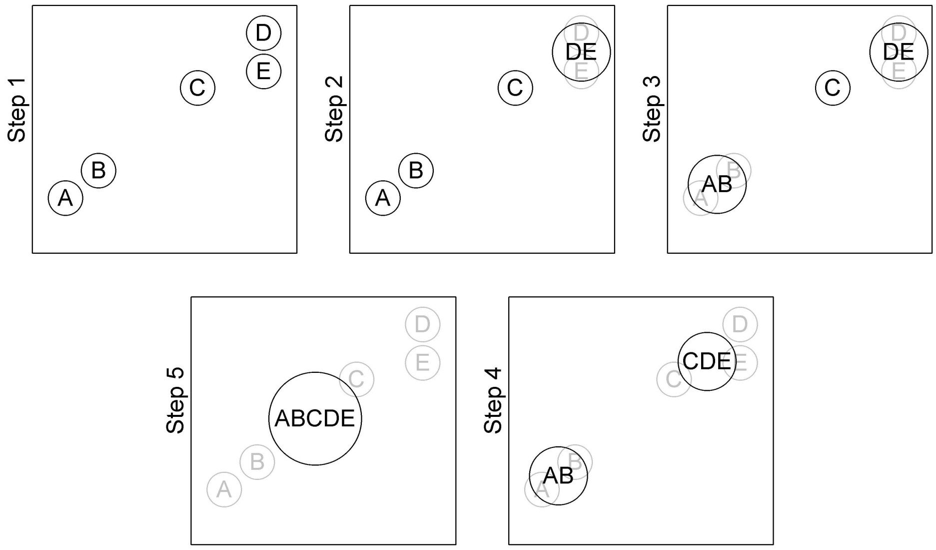


Figure 2.3: Demonstrates the process of hierarchical clustering

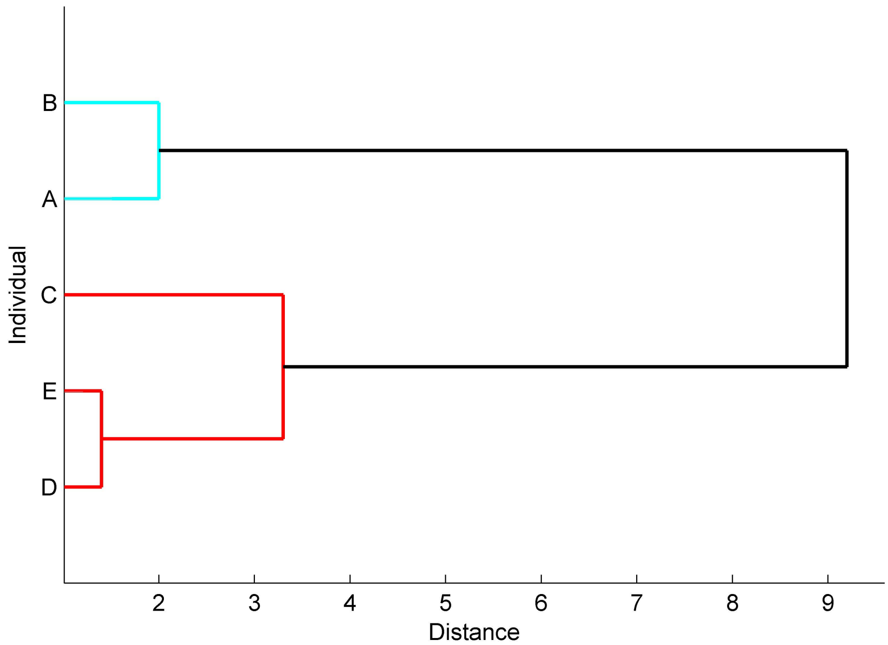


Figure 2.4: Shows the dendogram generated using hierarchical clustering

closer to the centre of E and D than A and B. The simplicity and great visualisation in hierarchical clustering make it an often used tool to explore data. However, disadvantages in hierarchical clustering are: it requires the user to choose the number of groups and it requires the generation of inter-point distances between the individuals, where different inter-point measures can give very different results (Hastie et al., 2001; Martinez et al., 2004; Witten and Frank, 2005).

2.4.2 K-Means Clustering

A very popular alternative method is k-means clustering. In k-means clustering the number of clusters is chosen prior to analysis and individuals are assigned into groups based on the location of their observations (features). K-means clustering starts with k randomly placed centroids (Step1; Figure 2.5). The factor k represents the number of clusters chosen. Centroids represent a group's or cluster's location in space. Once the centroids have been placed, each individual is assigned to the nearest centroid (Step2; Figure 2.5). Subsequently, every centroid's location is moved to the average location of its members (the individuals that have been assigned to a centroid; Step3; Figure 2.5). This process it repeated until the members of a centroid stop changing (Segaran, 2007) and is visualized below (Figure 2.5). K-means clustering can be performed without calculating inter-point distances and is usually more suitable for large data sets than hierarchical clustering (Martinez et al., 2004). However, the construction of a dendrogram is computationally prohibitive and the number of clusters needs to be chosen prior to analysis (Jain et al., 1999; Witten and Frank, 2005; Martinez et al., 2004; Hastie et al., 2001).

2.4.3 Model-Based Clustering

Both hierarchical and k-means classification techniques follow a deterministic process where the generated clusters and their members are somewhat dependent on the ordering of samples (Witten and Frank, 2005). Consequently, a third method, model-based clustering techniques might be more appropriate for classifying

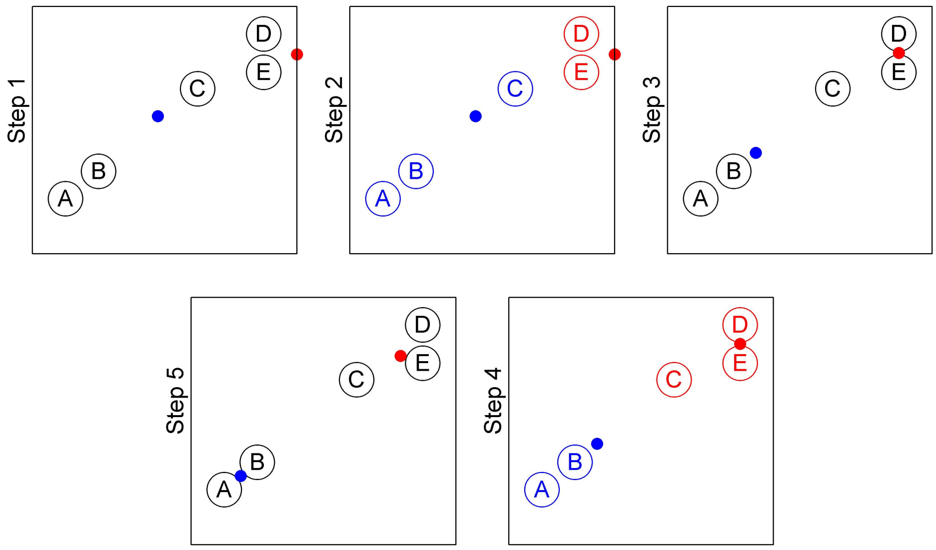


Figure 2.5: Demonstrates the process of k-means clustering using a sample of individuals, with k = 2 clusters. Black dots represent centroid's

biomechanical data. Model-based clustering techniques assign individuals to clusters based on their fit to a given mathematical model. One often used model is the Gaussian mixture model. The Gaussian clustering model is based on the assumption that the distribution from the examined individuals is generated by multiple probability distributions (Han et al., 2006) and clustering approaches aim to detect these underlying distributions. To do so, a popular and well established method is the maximum likelihood estimation which can be estimated using the Expectation-Maximization algorithm (Dempster et al., 1977; Han et al., 2006). The theory of model-based clustering will be explained using the example data visualized below (Figure 2.6).

The idea of Gaussian mixture model clustering (in a biomechanical understanding) is that every movement strategy can be represented by a specific probability distribution, among the overall probability distribution. Hence, every movement strategy can be presented as a cluster with its own distribution (mean and

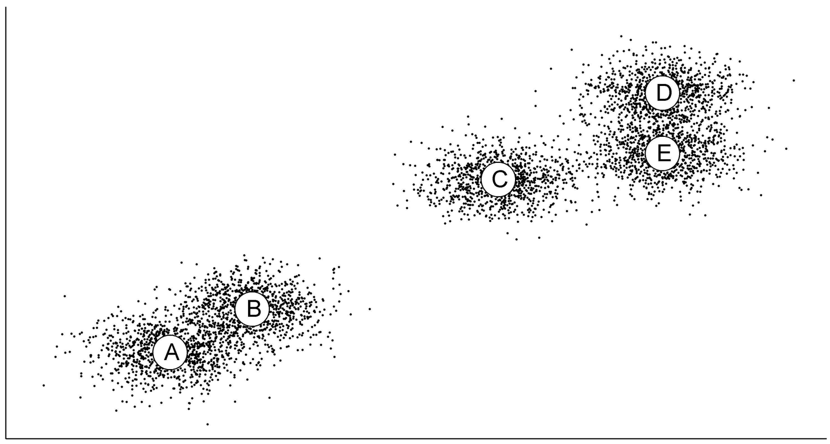


Figure 2.6: Example of a sample of features of individuals

standard deviation). The Expectation-Maximization algorithm can be used to identify underlying distribution within the probability distribution and can be seen as an extension of the k-means algorithm (Han et al., 2006). As in k-means, the Expectation-Maximization algorithm starts with a guess by generating k random probability distributions. Subsequently, it calculates for each individual the probability of a membership to one of the k estimated probability distributions (Expectation). The calculated probability of membership is then used to update or re-estimate the mean and standard deviation of the generated k probability distributions (Maximization). This process is repeated until the mean and standard deviation of the k probability distributions converge (Figure 2.7; Han et al. 2006; Martinez et al. 2004). The interested reader is referred for further reading to the text of McLachlan and Peel D. (2000).

2.4.4 Factors that Influence the Performance of a Cluster Analysis

Input Features The success of a subgroup analysis is not just dependent on the choice of the right clustering technique; it is also dependent on the input

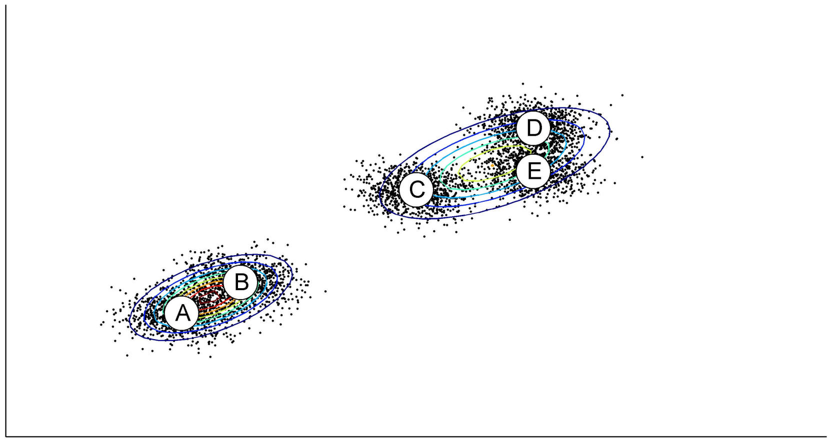


Figure 2.7: Result of Gaussian mixture model clustering using a sample of individuals

features (observations of individuals) used (Jain et al., 1999). Jain et al. reported that no critical analysis of clustering algorithms has examined the important questions: "Should the input features be normalized?" and "Which normalization approach is appropriate for a given situation?". Normalisation refers to the change of the features domain into another domain which could expose important information. Consequently, normalizing the input features can be really helpful in identifying the 'true' clusters of the data. To date, numerous normalization techniques exist; e.g. Chebyshev, Mahalanobis, City-block (Manhattan) Metric, Minkowski to name just a few. It appears that current research has aimed to create specific measures to optimize the accuracy for a given situation. However, the effect of normalizing input features when identifying movement strategies from biomechanical data has not been examined previously.

Normalization techniques are based on two basic ideas. The first theory is to use the distance between features as a indicator of similarity. A simple normalization technique to increase the strength of the distance is to use the squared Euclidean distance, which could increase the ability to identify movement strategies of a clustering technique. The second theory is to use the relationship between individuals as a indicator of similarity. A simple normalization technique to expose the relationship between individuals is to transform into their input features their correlation.

A aim of data clustering in biomechanics is to classify different movement patterns into separate clusters. Movement patterns that are similar are, theoretically, likely to be correlated, and might 'overlap' in space with other movement patterns due to a wide range of feature magnitudes. Therefore, using the distance as a indicator of similarity might not be sufficient, while using the relationship may be sufficient. The reviewed gait studies that used a subgroup analysis used exclusively the Euclidean distance (original distance domain), which might have hampered their ability to separate movement patterns accurately. To the author's knowledge, no biomechanical study has examined the influence of normalising input features on the ability of a clustering technique to identify movement pattern. The present work is focused on only one distance measure (Euclidean Distance) and similarity measure (correlation). The reader who wants more information on normalization techniques is advised to research 'proximity measures' or to read the following texts Jain et al. (1999), Everitt et al. (2011) or Carugo and Eisenhaber (2010).

The Number of Clusters Of equal importance to choosing the appropriate distance measure is the choice of the number of clusters. To examine how many clusters should be used during a cluster analysis a variety of ideas exist and four approaches will be briefly explained using the example data (Figure 2.6).

The first approach uses 'fusion levels' and the 'elbow rule' to estimate the best number of clusters. Both were introduced by Mojena (1977) and can only be used when performing hierarchical clustering. The 'fusion level' is described by the distance between the groupings, which is plotted against the number of clusters. To decide how many clusters should be used, the user has to search the 'elbow' in the generated curve (Figure 2.8). The 'elbow' is indicated by a distinctive break in the decreasing slope of the 'fusion level'. Using the example data (Figure 2.6), the 'fusion levels' and the 'elbow rule' suggest to use two clusters (Figure 2.8). The advantage of this approach is its simplicity, but with more complex data set multiple 'elbows' can occur which suggests multiple 'best' numbers of clusters.

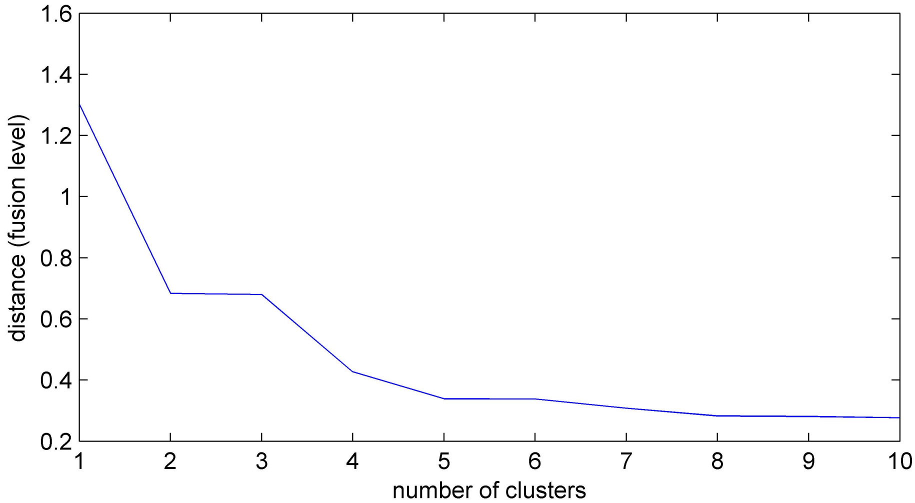


Figure 2.8: Fusion levels of the sample of individuals. It can be seen that the 'elbow' in occurs at k = 2 clusters

The second approach to estimate how many clusters should be chosen is the silhouette statistic. The silhouette statistic can be used for any clustering technique and visualizes the similarity between every individual within a cluster (Figure 2.9). Individuals with a large silhouette value (width which can range from 0 to 1) are well classified, while individuals with small silhouette values are classified poorly (Kaufman and Rousseeuw, 1990; Martinez et al., 2004).

For the example data, it can be seen that almost all individuals, for k = 2 in clusters 1 and 2, have high silhouette values, while for k = 3 most silhouette values in clusters 1 and 2 are low. In addition, Kaufman and Rousseeuw (1990) suggested using the average silhouette width to estimate the number of clusters. The overall mean silhouette values are 0.92 and 0.82 for k = 2 and k = 3, respectfully. Based

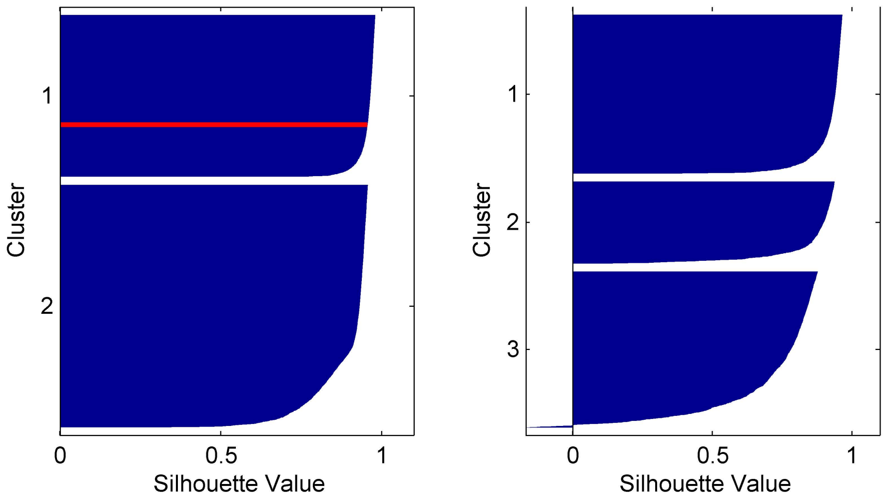


Figure 2.9: Silhouette statistic of the sample of individuals. The red line in cluster 1 in the left graph represents one random individual

on the author's interpretation of both the silhouette plot's overall mean silhouette values, two clusters (k = 2) is the better choice for the example data.

The third approach is called gap statistic (Tibshirani et al., 2001). Gap statistic can be used for any clustering technique and seems to be successful at estimating the number of clusters (Hastie et al., 2001; Martinez et al., 2004). In gap statistic, the within-cluster dispersion of a data set [$log(W_k)$] is compared with the average within-cluster dispersion [$log(\bar{W_k})$] computed from B reference data sets (uniform copy's of the real data) that hold a null distribution (no clusters). The difference between the within-cluster dispersions ($W^*_{k,b}$) represents the gap statistic (Equation 2.6 and 2.7).

$$gap(k) = \bar{W_k} - log(W_k) \tag{2.6}$$

where

$$\bar{W_k} = \frac{1}{B}\sum_b log(W^*_{k,b}) \tag{2.7}$$

Tibshirani et al. (2001) suggest that the optimal number of clusters is when the k gap statistic is greater or equal to the k-1 cluster minus its standard deviation of the within-cluster dispersion of the computed B reference data sets (Equation 2.8, 2.9 and 2.10).

$$sd_k = \sqrt{\frac{1}{B}\sum_b log(W^*_{k,b} - \bar{W})} \tag{2.8}$$

$$s_k = sd_k\sqrt{1 + 1/B} \tag{2.9}$$

$$gap(k) \geq gap(k = 1) - s_{k+1} \tag{2.10}$$

The interested reader is referred to the text of Tibshirani et al. (2001) or Martinez et al. (2004) for further information. For the given example, the optimal number of clusters is k = 2 (Figure 2.10).

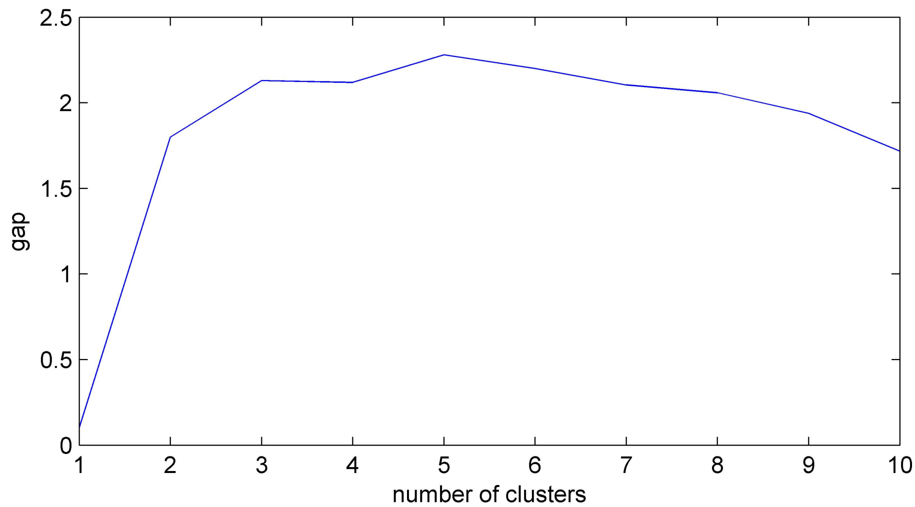


Figure 2.10: Gap statistic of the sample of individuals

The reader should note the local maxima in the plotted gap statistic at k = 3 and k = 5. These local maxima show an increase in the gap between the within-cluster dispersion of a data set to the within-cluster dispersion for the reference data sets and indicate that choosing 3 or 5 clusters might also give a beneficial insight to the data.

The above presented approaches are somewhat dependent on visual inspection and the experience of the user to read those graphs. Another approach, which measures the predictive power for different solutions (i.e. the different number of clusters) and that does not depend on visual inspection is cross-validation. Cross-validation is often used to estimate the value of smoothing factors (Martinez et al., 2004; Ramsay, 2006) and can be used to evaluate the accuracy of a cluster solution (Han et al., 2006). However, cross-validation can only be performed if a dependent variable exists within the data. Fortunately, this is sometimes the case in biomechanical data. To perform a cross-validation to determine the optimum number of clusters, a regression analysis can be used to assess the predictive power for the number of clusters, where the k (number of clusters) with the highest ability to predict the dependent variable is the optimal solution. This is in accordance with the aim of performing a cluster analysis to find an optimal classification that maximizes the ability to predict dependent variables of a data set (Han et al., 2006).

2.5 Aims of This Work

The current process of identifying performance related factors in biomechanical studies appears to have two major limitations: the use of the commonly performed discrete point analysis, and the generally performed group analysis design. As a consequence, previously found performance related factors are inconsistent across CMJ studies which can hamper the ability to identify effective movement techniques and neuromuscular intervention programmes.

Due to limitations in discrete point analysis, novel data analysis techniques have been purposed for biomechanical analysis. One of the most promising techniques is functional principal component analysis (fPCA), which has been shown to be much more powerful than discrete point analysis. However, it is unclear if factors that have to be chosen during an fPCA influence the ability of fPCA to identify performance related factors (Chapter 3 and 4). In addition, fPCA holds two potential limitations for biomechanical experiments. Consequently, **the primary aim of the present work is to develop a novel technique which can address the limitations of previously employed data analysis techniques in biomechanics** (Chapter 5).

In respect to the generally performed group analysis design, the review of previous research supports the assumption that different movement strategies exist across individuals. A group analysis does not account for this and hence may significantly hamper the ability to identify performance related factors. The use of a subgroup analysis has been shown to be successful in identifying different movement strategies and might therefore be more appropriate than a group analysis. However, a limitation in subgroup analysis is that it is unclear what clustering methods should be used and if the data should be normalized. Consequently, **the secondary aim of this work is to examine which of the most commonly used methods of clustering should be used and whether data normalization (Euclidan Distance vs. Correlation) is useful** (Chapter 6).

The knowledge created by examining both aims will create a data analysis framework which might be able to increase our knowledge in respect to what factors are related to performance. Hence, **a tertiary aim is to apply the created data analysis framework to determine the performance related factors for the CMJ** (Chapter 7).

Summary of aims for each chapter

Chapter 3 to examine if the chosen number of basis and order influence the ability to detect performance related factors in fPCA.

Chapter 4 to identify the optimal variance threshold in fPCA for jump height prediction.

Chapter 5 to present a self developed data analysis technique, which addresses the limitations of discrete point analysis and fPCA.

Chapter 6 to assess and compare the performance of commonly used classification techniques to appropriately identify movement patterns within kinematic and kinetic waveforms and to examine if there are benefits to performing a subgroup analysis compared to the commonly used single group analysis.

Chapter 7 to identify performance related factors in CMJ using the previously identified most appropriate data analysis techniques.

Chapter 3

The Influence of Number of Basis and Order in Functional Data

3.1 Introduction

Despite the fact that fPCA has many advantages for data analysis in biomechanics, the user needs to chose a number of basis (n basis) and order (h order; degree of freedom - 1) when transforming the discrete into functional data. It is unclear if these factors can influence the ability of fPCA to identify performance related factors. A common suggestion is to use the smallest n basis and h order that generate a good fit to the observed data (Ramsay, 2006; Ferraty, 2011). The fit to the observed data can be assessed by various approaches such as visual examination or a root mean square error (RMSE) measure (Ramsay, 2006; Ferraty, 2011). However, suggested values might differ across approaches and it is not clear if and how strong such differences affect the ability to describe a dependent variable (e.g. jump height).

The aim of this section is to examine if the suggested values of n basis and h order differ between the methods of 'visual examination' and RMSE, and if differences effect the ability to detect performance related factors in fPCA.

3.2 Method

For the visual examination, the smallest n basis and h order that resulted in a good fit, judged by the author, were used as suggested n basis and h order.

For the RMSE approach, the RMSE was generated for multiple n basis and h order. To estimate the optimal n basis, the RMSE was calculated for a range of n basis (n = 5, ... ,49)[1], with h order set at h = 5[2]. To estimate the optimal k order, the RMSE was calculated for a range of h order (h = 1, ... ,25), with n basis set at n = 25.

The RMSE (Equation 3.1) was generated by calculating the root square of the difference between the solved function and the observed data (discrete curve). The RMSE was averaged across each curve (i).

$$RMSE = N^{-1} \sum \sqrt{(function_i - discrete\ curve_i)^2} \tag{3.1}$$

The n basis and h order were considered as optimal when no significant decrease in the RMSE occurred (Equation 3.2).

$$RMSE_{n-1,h-1} \ll RMSE_{n,h} \approx RMSE_{n+1,h+1} \tag{3.2}$$

To assess the ability of the suggested n basis and h order to describe a dependent variable, a stepwise multiple regression model was performed for each of the given n basis and h order. The r^2-value generated by the stepwise multiple regression model was used as the ability measure. The jump height of a CMJ was chosen as the dependent variable because it is fully captured by force generated during the propulsion phase. A sample of 42 force curves (from 42 separate people), captured using two force platforms (1000 Hz; BP-600900, AMTI, MA, USA),

[1]The minimum number of examined basis is equal to the chosen degrees of freedom used during the transformation. The maximum number of examined basis is one less than the minimal number of discrete points within a curve across the examined curves

[2]H order was set at 5 to allow a flexible adaptation of the function to the discrete data

was used for the analysis. All curves were normalized to body mass (N/BM) and only the propulsion phases were used for analysis. Functional principal component scores were generated using VARIMAX rotated functional principal components and used as input variables (Appendix B). The VARIMAX rotated functional principal components accounted for 99 % of the variance in the data set.

3.3 Results

The visual examination demonstrated a good fit between the functional and discrete data at n = 20 and h = 3. Basis and order below these values resulted in an under fitting of the function to the discrete data (shifted peak values and differences in magnitude; Figure 3.1). The suggested n basis and h order explained 81 % of the variances in jump height (r^2 = 0.81).

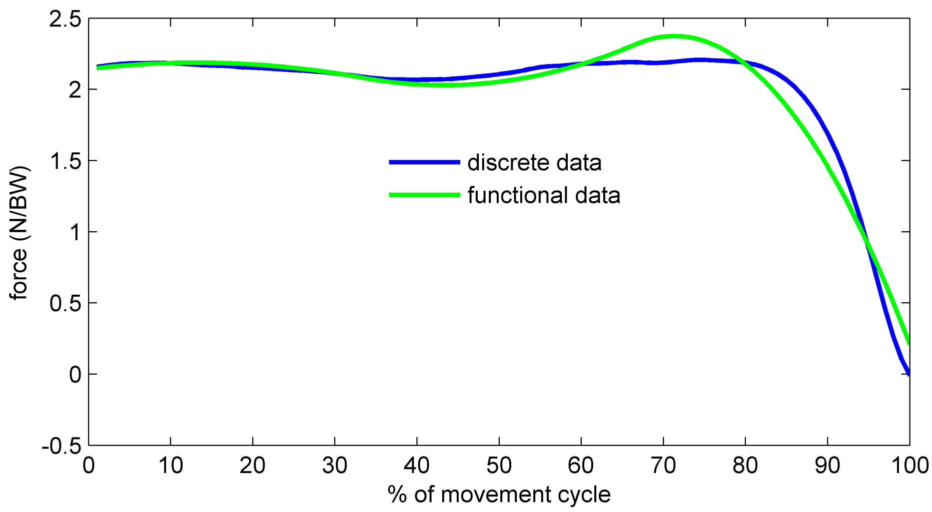


Figure 3.1: Example of under fitting caused by choosing a too little basis (n = 5, h = 3)

For the RMSE approach, no significant decrease in the RMSE occurred at n = 25 and h = 3 (Figure 3.2 and Figure 3.3). The suggested n basis and h order explained 81 % of the variances in jump height (r^2 = 0.81).

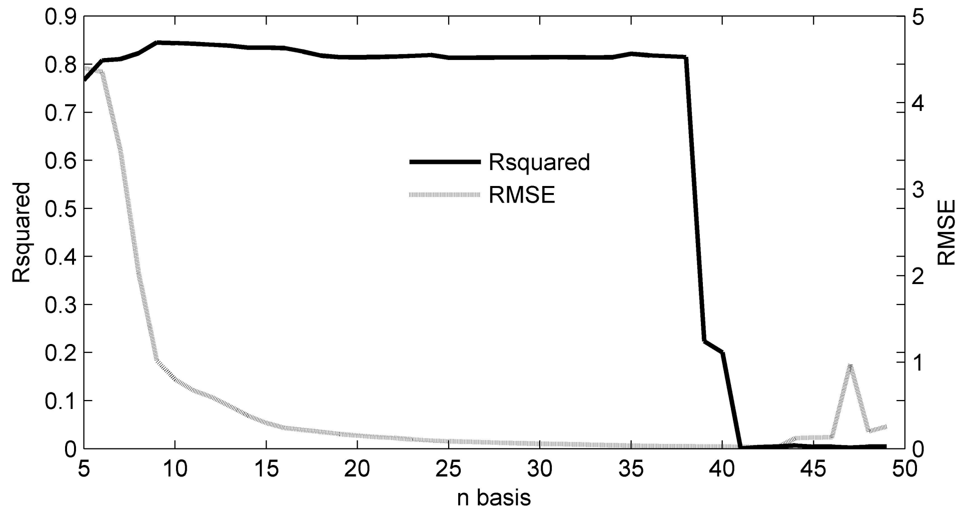


Figure 3.2: RMSE and r^2-values for a given numbers of basis

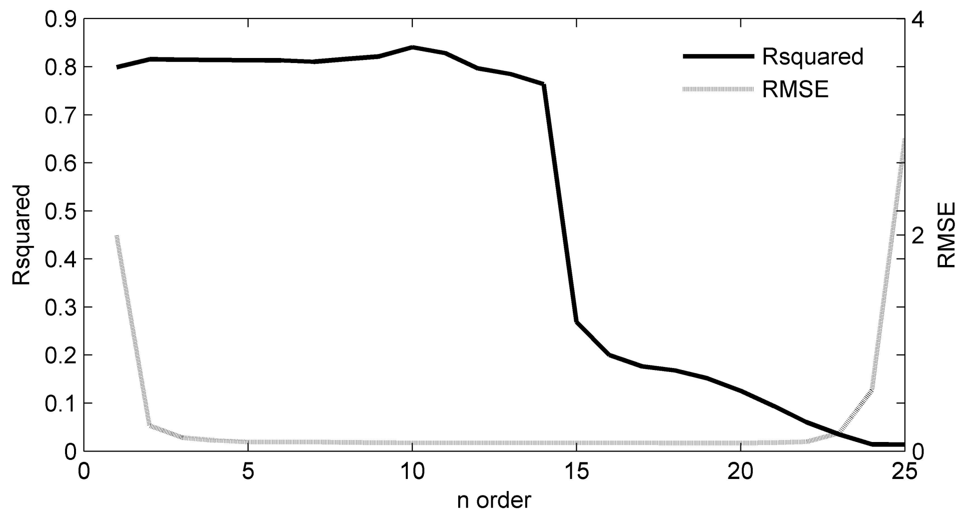


Figure 3.3: RMSE and r^2-values for a given order

3.4 Discussion

While visual examination (n = 20 and h = 3) and RMSE (n = 25 and h = 3) differed in their suggestion how many basis should be used, no difference exist between them in terms of their ability to describe the dependent variable. Both approaches were able to describe 81 % of the variances in jump height ($r^2 = 0.81$). Hence the use of either visual examination or RMSE is a valid suggestion for how many basis and order should be used when transforming discrete into functional data.

Further, the assumption that the chosen n basis and h order can limit the ability of fPCA to describe a dependent variable is not supported. The influence of n basis and h order to describe variances in jump height is minor for functions that result in a good fit to the observed data. This is demonstrated by the consistency of r^2-values around the suggested n basis and h order (Figure 3.2 and 3.3).

3.5 Conclusion

The choice of n basis and h order has a minor effect on ability of functional data to describe a dependent variable, for functions which show a good fit to the discrete observations. Hence, the need to choose n basis and h order does not represent a limitation in functional data analysis. However, the choice of n basis needs to result in a good fit to the discrete data, which can be judged by visual examination or the RMSE. The chosen h order should be between 3 and 5 as suggested in Ramsay (2006).

Chapter 4

Identification of an Optimal Number of Principal Components

4.1 Introduction

Another important factor in fPCA is the chosen amount of preserved information. The amount of information preserved in a principal component is described by its Eigen value and the sum of all Eigen values fully describes the examined data. When applying fPCA, a threshold (x % of the total variance in the data) is chosen by the user, which defines the amount of information preserved and determines the number of retained principal components. While a variety of thresholds have been used across previous studies, a threshold of 95 % or less appears to be the most common in recent biomechanical studies (Table 4.1; Carriero et al. 2009; Mantovani et al. 2011; Harrison et al. 2007; Daffertshofer et al. 2004; Deluzio and Astephen 2007; Newell et al. 2006; Dona et al. 2009; Wrigley et al. 2006; Coffey et al. 2011; Epifanio et al. 2008; Donoghue et al. 2008).

This 95 % threshold is chosen based on the fact that a small number of principal components usually describe essential features of the data (Daffertshofer et al., 2004; Donoghue et al., 2008). Consequently, principal components beyond the

Table 4.1: Summary of previous used examined percentage of within the analyzed data

Study	Examined % of variance
(Carriero et al. 2009)	61.0
(Mantovani et al. 2011)	85.0
(Harrison, Ryan, and Hayes 2007)	<90.0
(Daffertshofer et al. 2004)	90.0
(Deluzio and Astephen 2007)	90.0
(Newell et al. 2006)	94.3
(Dona, Preatoni, and Cobelli 2009)	95.0
(Wrigley et al. 2006)	97.0
(Coffey et al. 2011)	97.5
(Epifanio et al. 2008)	97.8
(Donoghue et al. 2008)	<98.0

threshold of 95 % are often discarded as they are thought to have very little influence (Donoghue et al., 2008). A tool that can be used to determine beyond what number of principal components there will be little influence on the data is the scree plot. A scree plot is a line that shows how much variance within a data set is preserved by a number of principal component (red line in figure 4.1). However, the captured influence of principal components in this context is assessed only in relation to the data's variance rather than the variance in the dependent variable, the latter of which is extremely important in biomechanical analyses. It is important to realise that the effect size of a principal component describes its influence to the data and not its influence to the dependent variable (von Tscharner et al., 2013).To date, no biomechanical studies appear to have examined if there is an optimal threshold that retains sufficient information to best describe a dependent variable.

The aim of this chapter is to identify the optimal threshold for jump height prediction and test if a principal component beyond the 95 % threshold can have significant influence on explaining the dependent variable.

4.2 Method

A feed-forward back-propagation network (network) with a single hidden layer containing 20 hidden units was used to identify the optimal threshold for inferring a dependent variable (jump height) from an input matrix (principal component scores). The jump height of a CMJ was chosen as the dependent variable because it is fully captured by the force generated during the propulsion phase of the jump. A sample of 42 force curves (from 42 separate people), captured using two force platforms (1000 Hz; BP-600900, AMTI, MA, USA), was used for the analysis. All curves were normalized to body mass (N/BM) and only the propulsion phases were used for analysis.

Functional principal component analysis was performed to generate principal components for a given threshold using the captured force curves. The generated principal components were VARIMAX rotated to optimize their interpretability (Ramsay, 2006; Harrison et al., 2007). Principal component scores were calculated to reflect the degree to which a subject is affected by a principal component over the whole function (Ramsay, 2006).

The fPCA threshold can be seen as a parameter of the jump height's prediction model. In machine learning the optimal value for such parameters is typically chosen using a leave-one-out cross-validation, which uses one sample as the test data and retains the other samples as training data (Hastie et al., 2001; Han et al., 2006). This process was repeated until each sample was used once as test data. The network was trained using the principal component scores as input data and jump heights as target data. After training, the principal component scores of the test sample were input into the network to predict jump height. The absolute difference between predicted and actual jump height (absolute error) was calculated to measure the accuracy of the network, and averaged over each round of cross-validation. Cross-validation was performed for fPCA thresholds from 75-100 % by increasing the number of retained principal components. The entire process was repeated 25 times using different random initial weights in the network to achieve a repeatable measure of the expected accuracy.

A repeated measurement ANOVA (Bonferroni adjustment for multiple comparisons) was performed to examine the effect of the threshold on the magnitude and spread of the absolute error of the network. The significance level was set at α = 0.05. Data processing and statistical analysis were performed using MatLab (R2012a, MathWorks Inc., USA).

4.3 Results

The statistical analysis and visual inspection show clear differences across the generated absolute errors (Figure 4.1). Thresholds smaller than 90 % (up to 2 principal components) show the largest magnitude and spread in absolute errors when predicting jump height, thresholds smaller than 99 % (up to 5 principal components) and greater than 99.9 % (more than 11 principal components) show moderate absolute errors and a wide spread of the absolute errors, while thresholds between 99 % (from 6 principal components) to 99.9 % (to 10 principal components) show the smallest magnitude and spread in absolute errors. The statistical analysis found significantly lower ($p < 0.001$) absolute errors for the thresholds between 99 % and 99.9 % compared to other thresholds. The spread in absolute error values was significantly greater in thresholds for principal component 1-4 compared to thresholds for principal component 2-25 ($p < 0.05$).

4.4 Discussion

Findings show that fPCA thresholds between 99-99.5 % (optimal threshold) are most effective in describing jump height, generating significantly lower absolute

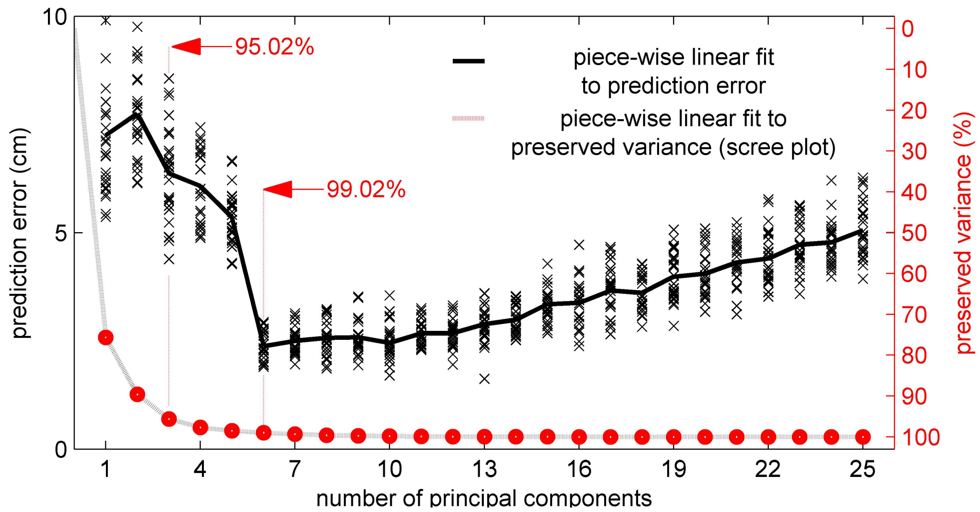


Figure 4.1: Absolute error (cross-validated) of the used network in predicting jump height from principal component scores. Each point is the average accuracy from a complete run of cross-validation

error than other thresholds. Thresholds below the optimal threshold (< 99 %) generated significantly higher absolute errors, indicating that the performed fPCA did not preserve enough information for the neural network to find the relationship between input data and target (dependent) data accurately. Thresholds above the optimal threshold (> 99.5 %) generated significantly higher absolute errors than the optimal threshold, because they preserved unnecessary information (such as noise) that decreased the power of the input data to explain the target data. Further, statistical analysis and visual inspection of the generated absolute error shows higher variation in absolute error below or above the optimal threshold, highlighting again either a lack of information or too much information retained.

The findings indicate that principal components beyond the threshold of 95 % can hold very important information, demonstrating that the effect size of principal components represents its relation to the variances in the data, not the variances in the dependent variable. Consequently, principal components beyond the threshold of 95 % had a large influence on the dependent variable (jump height) and decreased significantly absolute error values. For example, principal

Table 4.2: The percentage of the data's variance explained by a principal component (PC), the absolute error and the change in absolute error

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
% PC	75.6	13.9	6.1	2.1	0.8	0.5	0.3	0.3
absolute error	7.3	7.8	6.4	6.1	5.4	2.4	2.5	2.6
change in absolute error	---	0.5	-1.4	-0.3	-0.7	-3.0	0.1	0.1

component 6 accounted for 0.5 % of the variances in the data and decreased the absolute error of the jump height prediction by 3 cm, while principal component 2 accounting for 13.9 % of the variances in the data actually increased the absolute error of the jump height prediction by 0.5 cm (Table 4.2).

This has also been demonstrated in previous research. von Tscharner et al. (2013) reports that principal components (generated using discrete waveforms) accounting for as little as 3.3 % and 1.8 % allowed for a significant classification rate of 72.7 % and 81.8 %, respectively. Harrison et al. (2007), who considered only three principal components ($<$ 90 % of the total variance in the data), found a principal component accounting only 7 % of the variances in the data to be the best discriminator between different development stages in vertical jumps performed by children. This indicates that fPCA as employed in most previous studies may have been limited in its ability to identify factors; eight of the twelve studies listed in table 4.1 have not examined variances beyond 95 % and hence ignored possible important information. Further, principal components beyond a threshold of 99.9 % significantly increase absolute error in this experiment. This indicates that principal components beyond a threshold of 99.9 % can be discarded without the lost of important information.

Finally, the number of principal components suggested by the scree plot (4 principal components) differs from the optimal number identified by the network.

The scree plot underestimates the number of principal component needed to describe jump height because it assesses the influence of a principal component to the data's variance, not the variances in the dependent variable. It should be noted however that this comment specifically relates to the number of principal components needed to describe the dependent variable. The use of the scree plot may be appropriate when selecting the number of principal components to describe variances in the data.

4.5 Conclusion

An optimal fPCA threshold to describe a dependent variable (jump height) accurately utilizing force data is within 99-99.9 %. A scree plot should not be used to choose the number of principal components when the research aim is to describe a dependent variable (although it can possibly be used when the research question relates to describing the variances in the data set itself). Further, the findings demonstrate it is extremely important to select the correct number of principal components because even principal components that account for only a small amount of variance in the whole data set can account for large variances in a dependent variable.

Chapter 5

Analysis of Characterising Phases

5.1 Introduction

The identification of performance related factors is a major goal in sports biomechanics, providing useful information to athletes, coaches and sport scientists for developing and improving training programs to optimise performance. The most commonly used technique to identify such features is discrete point analysis, which reduces the dimensionality of a waveform by examining pre-selected 'key' measures (e.g. maximum or minimum). However, this approach may present three significant limitations. Firstly, the pre-selection of measures is strongly dependent on previous knowledge and has the potential to discard extremely important information (Donoghue et al., 2008; Dona et al., 2009). Secondly, discrete point analysis does not necessarily take into account the position of 'key' measures. For example, when examining the peak in a bi-modal waveform, the peak could occur at the first or second maximum. Consequently, discrete point analysis has the potential to compare measures that represent non-related neuromuscular capacities. Finally, discrete point analysis cannot examine performance related features that exist as phases.

One possible solution to overcome these limitations is to analyze kinematic and kinetic waveforms as a whole, by performing for example a functional principal component analysis (fPCA; section 2.3.1), which has been recommended over discrete point analysis by a number of researchers (Donoghue et al., 2008; Dona et al., 2009; Godwin et al., 2010; Harrison et al., 2007; Newell et al., 2006; Ramsay, 2006; Ryan et al., 2006). The key benefit of fPCA is the ability to reduce the dimensionality of a set of signals, while preserving the information needed to describe a data set (Jolliffe, 2005). In addition, fPCA is part of the functional data analysis family, and treats a signal as a single function rather than as a series of individual data points. As such, fPCA does not require a linear time normalization, which can alter the data (Dona et al., 2009), allowing examination of the underlying structure while maintaining all of the information in the signal (Ramsay, 2006). Despite the fact that fPCA has many advantages for data analysis in biomechanics it also presents three possible limitations (section 2.3.1).

To date, no data analysis technique appears to fully address the above mentioned limitations. The aim of this section is to present a self developed data analysis technique named 'Analysis of Characterising Phase', which aims to address the limitations within discrete point analysis and fPCA.

5.2 The Idea of Analysis of Characterising Phases

The main idea behind Analysis of Characterising Phases (ACP) is to detect phases of variance (pattern characterising phases) within a data set, which are separated into segments (based on their influence on the pattern characterising phases). The segments with the strongest effect are considered as key phases and are utilized to calculate subject scores (similarity scores). Similarity scores aim to capture how similar two waveforms are over a key phase and can be calculated utilizing the time, magnitude and the combined magnitude-time domain; allowing for a statistical analysis for differences across groups, or a key phase's relation to a dependent variable in each domain of the waveform. If a key phase demonstrates significant differences across groups, or a significant relation to a dependent variable, the process of computing and analyzing similarity scores is re-iterated for the segment with the next highest effect on the pattern characterising phase to identify the exact phase over which performance related factor exist (see section 5.3).

Examining similarity scores differs significantly from examining discrete measures (e.g. peak force). A discrete measure solely represents a 'snapshot' of the movement at a specific point in time and might not be capable of describing fully a specific movement pattern that determines the success of movement. In contrast, similarity scores represent a summary of multiple 'snapshots' and may have a greater ability to describe a movement pattern that relates to the performance outcome of a movement.

Examining similarity scores also differs from examining principal component scores because similarity scores are not influenced by non-key phases. As described in section 2.3.1, it is assumed that 'key phases' have an overwhelming effect on the magnitude of principal component scores. However, non-key phases contribute to a principal component scores' magnitude, which could hamper the ability of fPCA to describe a movement pattern that does relate to the performance outcome of a movement. In contrast to principal component scores, the magnitude of a similarity score is determined exclusively by key phases. In addition, due to the generation of principal component scores, fPCA requires the user to subjectively identify the phases of the movement cycle which influence the movement outcome (i.e. jump height); because principal component scores are generated over the whole movement cycle. In contrast, ACP identifies these phases objectively, which is important to identify the exact phase that has to be overloaded during a training intervention to enhance performance.

Another advantage of identifying key phases is the possibility to examine the time, magnitude and combined magnitude-time domain, by extracting the information within the identified key phases. Examining every domain of a waveform might give a better insight into the performance of a movement; examining the combined magnitude-time domain might hold important information (e.g. impulse-momentum relationship) and has not been examined before.

5.3 The Process of Analysis of Characterising Phases

The following section explains ACP (Figure 5.1) and is separated in three sections: a) normalization, b) identification of characterising phases and, c) examining pattern characterizing phases. Initial steps of ACP (data normalization and Eigen analysis) are covered in Appendix A and B.

Normalization Biomechanical data is often a collection of waveforms differing in length (duration), which has to be normalized before applying ACP using both the magnitude and time domain. A basis b-spline system can be used as an approach for normalization to avoid linear time normalization. General properties of basis b-spline system are outlined elsewhere (Ramsay, 2006; Eilers and Marx, 1996; Daffertshofer et al., 2004).

Identification of Pattern - Characterizing Phases To identify key phases, ACP uses the magnitude domain to calculate a variance-covariance matrix, which describes the variance in the data and can be seen as a 'Model of Variance'. To detect and separate patterns of variation contained in the variance-covariance matrix, ACP performs an Eigen analysis. An Eigen analysis 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. Prin-

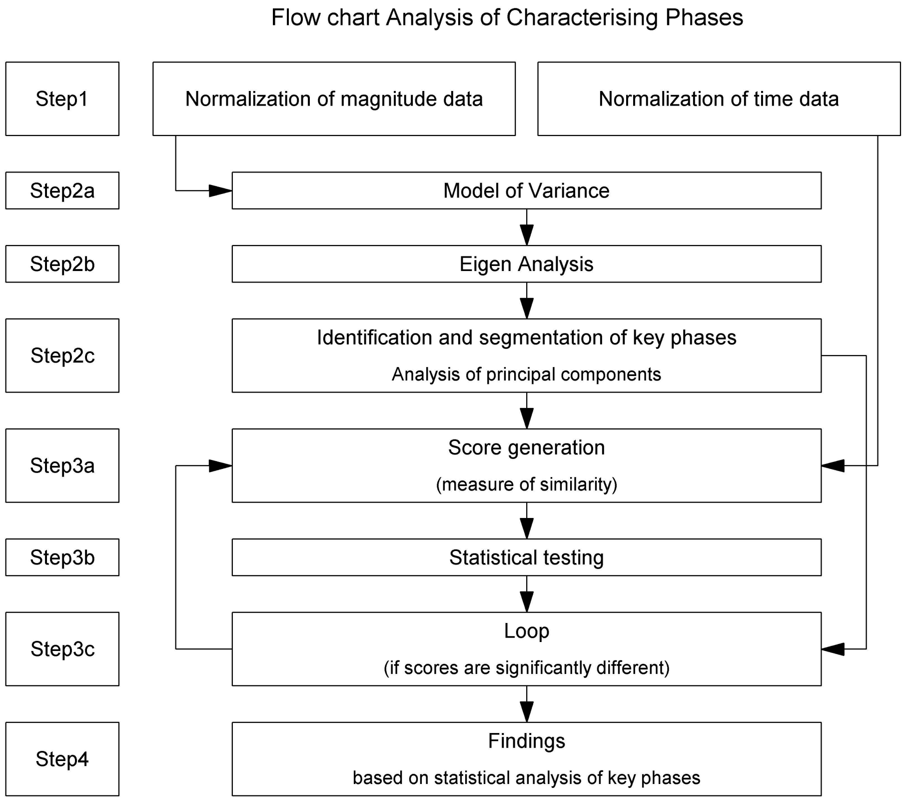


Figure 5.1: Flow chart describing the process of ACP

cipal 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 of a principal component 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 (Appendix B). To increase the interpretability of the retained principal component, ACP performs a VARIMAX rotation (Ramsay, 2006; Harrison et al., 2007; Ryan et al., 2006). Subsequently, the rotated principal components are used to identify pattern-characterizing phases, called key phases. Analysis of Characterizing Phases identifies the position and sign of the principal component's absolute maximum to establish a start and an end point of a key phase. The last value differing in sign before the absolute maximum is defined as the start of the key phase, while the first value differing in sign after the absolute maximum is defined as the end of the key phase (Figure 5.2a). After a key phase is identified ACP separates the key phase 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 5.2b). 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 To examine the identified key phases, participant scores (similarity scores) have to be calculated as a measure of behaviour across participants. Analysis of Characterizing Phases uses the information gained in the previous step (Identification of Pattern - Characterizing Phases) to calculate a similarity score which reflects the difference within the segment holding the highest pattern-characterizing potential, between the curves of a participant and a reference curve (e.g. mean curve). Similarity scores can measure the relationship between curves with respect to time, magnitude or the combined magnitude-time domain, and are used for statistical analysis. Similarity score (SS) can be generated by calculating the area between a participant's curve (p) and the mean curve across the data set (q) for every point (i) within a key phase (Equation 5.1 for the time or magnitude domain; Equation 5.2 for the combined magnitude-time domain).

$$score = \int q_i - p_i \tag{5.1}$$

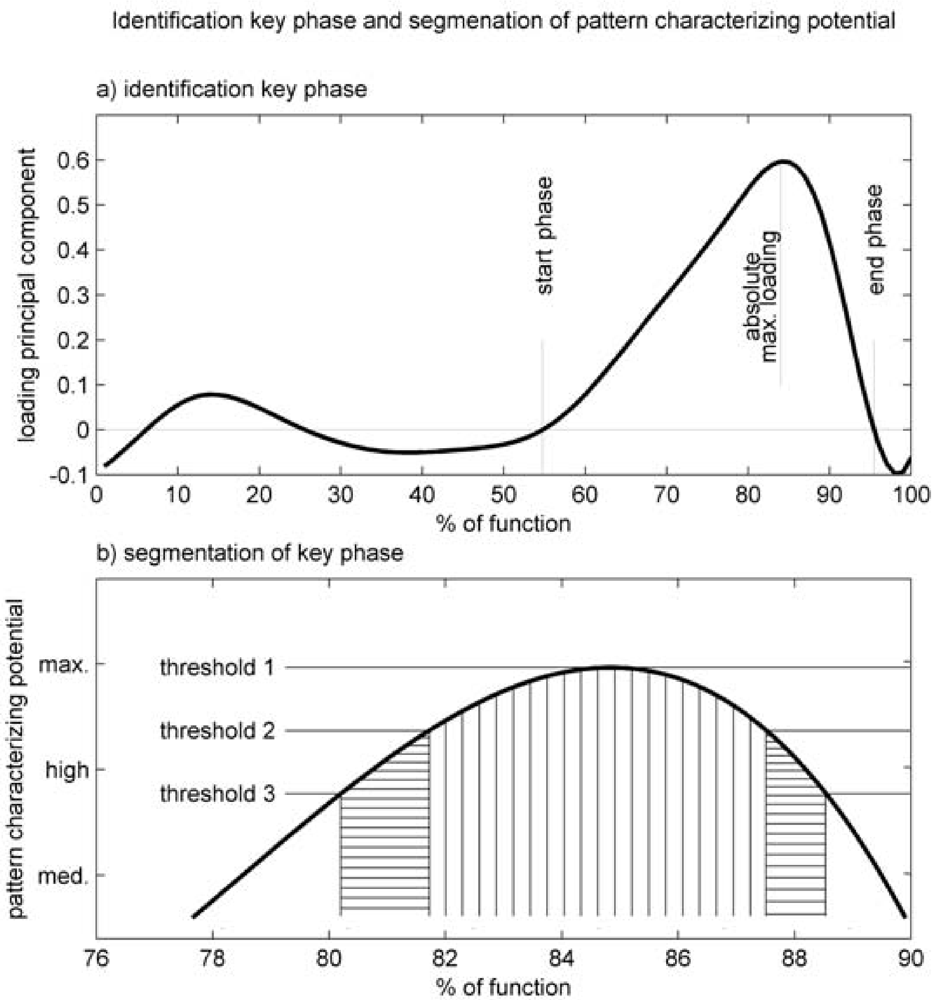


Figure 5.2: Visualisation of a) the detection of the start and the end point of a key phase over the whole function and, b) the separation of a key phase into segments with different pattern-characterizing potential)

$$score = \int 0.5(\Delta_{time} q_{i,i+1} + \Delta_{time} p_{i,i+1}) \Delta_{magnitude} q_i p_i \tag{5.2}$$

A low similarity score indicates high similarity between the signals, and vice versa. Where a significant difference between the similarity scores is evident, ACP re-calculates the similarity score within the segments of the next lowest pattern-characterizing potential phase (to explore the exact phase over which the difference exists). If, for example, the scores of the phase with the highest potential (Figure 5.2b: 81.8-87.7 %), defined between thresholds 1 and 2, were able to describe the movement outcome, ACP iterates the analysis from the scores generated with the segments within the second highest potential (Figure 5.2b: 80.1-81.8 % and 87.7-88.5 %), identified between thresholds 2 and 3, separately. This process is terminated when (i) a non-significant stage, (ii) the start point, or (iii) the end point of the key phase is reached, and explores the total phase over which a difference exists. In the illustrated example given (Figure 5.2), it should be noted that for the second iteration the score 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 %). This allows ACP to individually explore phases with different pattern-characterizing potential, thereby avoiding a possible overwhelming effect of a highly significant phase erroneously causing a non-significant phase to appear significant.

5.4 Comparison to Other Data Analysis Techniques

To compare the ability of analysis techniques in identifying performance related features, it is necessary to examine a movement where the performance outcome is clearly defined and fully captured by the examined waveform. In CMJ, the performance outcome (jump height) is fully determined by the force-time history as evident from the impulse-momentum relationship for the propulsion phase.

The aim of this section is to compare and assess the ability of discrete point analysis, fPCA and ACP in identifying performance related features captured by the force generated during the propulsive phase of the CMJ.

5.4.1 Methods

Subjects One hundred-and twenty five male athletes (age = 22.4±4.2 years; mass = 71.1±9.4 kg; height = 1.82±0.1 m), who were physically active, experienced in performing the CMJ (based on the sports they played: Gaelic football, Gaelic hurling and basketball), and free from lower limb injury participated in this study. The University Ethics Committee approved the study and all participants were informed of any risk and signed an informed consent form before participation.

Data collection Prior to data collection, every participant performed a standard warm-up routine consisting of low intensity jogging, stretching and ten sub-maximal and five maximal CMJ. Data collection comprised of participants performing 15 maximum effort CMJs without an arm swing, standing with each foot on a separate force platform (1000 Hz; BP-600900, AMTI, MA, USA). Participants rested for 30 seconds between trials. 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 takeoff, with takeoff determined when the force fell below 5 N. Only the vertical force-time curve during the propulsion phase was analysed because it holds the information needed to fully describe jump height. The start of the propulsion phase was identified from the power-time curve of the body's centre of mass, when the power became positive (Figure 5.3).

Discrete Point Analysis Based on previous literature (Cormie et al., 2009; Dowling and Vamos, 1993; Morrissey et al., 1998; Newton et al., 1999; Petushek et al., 2010; Sheppard et al., 2008) the following measures were identified and used for statistical analysis in the discrete point analysis: a) initial force, b) maximum force, c) initial-to-maximum rate of force development, d) time from initial-to-maximum force, e) percentage initial-to-maximum force, f) time from maximum force to take-off, and g) propulsion phase duration (Figure 5.4). Mean force and the impulse were not included in the examined measures, since these variables cannot give an insight into how movement technique or neuromuscular capacities

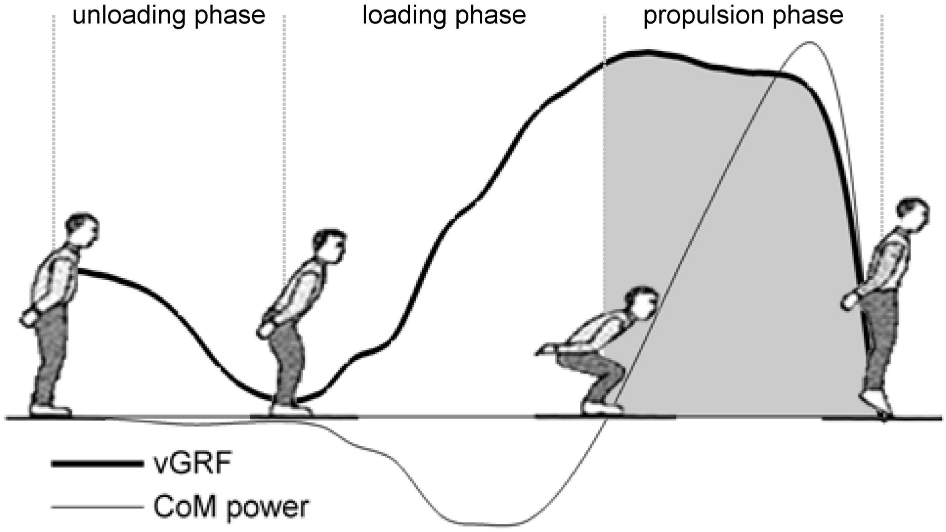


Figure 5.3: Identification of the propulsion phase

should to be altered during a training intervention to enhance performance. The initial-to-maximum rate of force development was calculated from the initial force to the point at which the maximum force occurred (Cormie et al., 2009). All results are reported as mean ± standard deviation.

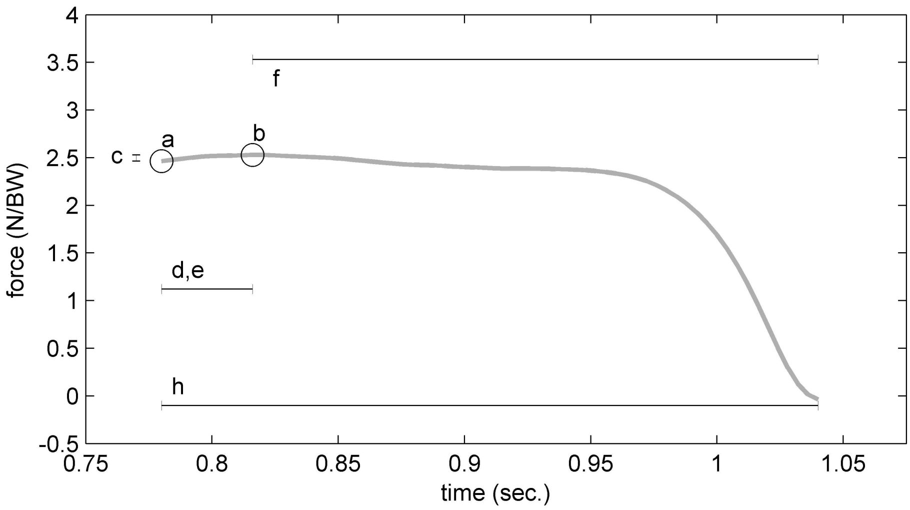


Figure 5.4: Examined variables using the discrete point analysis on an example force curve

Functional Principal Component Analysis Functional principal component analysis was performed to generate principal component scores, which were used for statistical analysis. The principal component scores used retained more than 99 % of the variance of the data (section 4.4), and were VARIMAX rotated to optimize their interpretability (Harrison et al., 2007; Ramsay, 2006; Ryan et al., 2006). To transform the discrete data into functional data a beta-spline (b-spline) basis system was chosen because of its ability to model non-periodic data (Ramsay, 2006), and reproduce natural fluctuations (Ryan et al., 2006). No additional smoothing was applied to the functional data as it resulted in good fit and smooth derivatives. The time domain was not included within the extracted features as it is not in most of the studies which previously used fPCA (Donoghue et al., 2008; Dona et al., 2009; Godwin et al., 2010; Harrison et al., 2007; Ramsay, 2006; Ryan et al., 2006).

Analysis of Characterising Phases Analysis of Characterising Phases was applied to generate similarity scores, which were used for statistical analysis. Key phases were identified using information from VARIMAX rotated functional principal components, which retained more than 99% of the variance within the data's magnitude domain. Key phases were used to calculate similarity scores for the time, magnitude and combined magnitude-time domain by calculating the area between a participant's curve (p) and the mean curve across the data set (q) for every point (i) within a key phase (Equation 5.1 for the time or magnitude domain; Equation 5.2 for the combined magnitude-time domain).

Data Analysis Generated features for each data analysis technique (discrete measures, principal component scores and similarity scores) were input into a separate stepwise multiple regression model to assess the ability of each technique to explain jump height. The ability of a regression model to describe jump height was judged based on its r^2-value, which was classified into weak ($r^2 < .09$), moderate ($.09 < r^2 < .49$) and strong ($r^2 > .49$; Cohen 1988). In a multiple regression model two or more predictor variables can be highly correlated, which is called multicollinearity, which can affect the selection of predictor variables. Multicollinearity can be addressed by a) removing one of the highly correlated features from the data, or b) performing a principal components analysis to generate uncorrelated features. However, the issue of multicollinearity was not addressed because the present work focuses on identifying which technique has the greatest ability to describe jump height not to identify which of factor determines jump height. The normality of the data was assessed by calculating skewness and kurtosis statistics. Features were considered to be normally distributed if the magnitude of the skewness and kurtosis statistics divided by their respective standard errors did not exceed $\pm$ 1.95 (Howell, 2012). If a feature was not normally distributed, it was log transformed. Features were considered as outliers and removed when their value exceeded 1.5 times the interquartile range (Martinez et al., 2004). Residual plots of the generated regression models were used to assess the presence or absence of homogeneity of variance (Gelman and Hill, 2007; Larsen and McCleary, 1972). To compare the accuracy of the three data analysis techniques to explain jump height, the prediction error of each regression model was measured using a leave-one-out cross validation (see section 4.2) and analyzed for differences using a repeated measure ANOVA (Bonferroni adjustment for multiple comparisons). The significance level was set at $p = 0.05$. Data processing and statistical analyses were performed in MATLAB (R2012a, MathWorks Inc., USA).

5.4.2 Results

All examined features (discrete measures, principal component scores and similarity scores) were normally distributed, except for the following discrete measures:

initial-to-maximum rate of force development, time from initial-to-maximum force and percentage initial-to-maximum force. Residual plots of the generated regression models indicated a good fit and homogeneity of variance for the computed residuals. Residuals were normally distributed ($p > 0.195$) with less than 5 % of the standardized residuals extending beyond a value of 2 or -2.

The regression model created using discrete measures ($p < 0.001$, $r^2 = 0.228$, std. error = 6.1) generated a moderate ability to explain the variance in jump height (Table 5.1). Predictor variables were maximum force ($p < 0.001$, std. slope = 0.70, slope = 18.1, 95 % CI = 11.9 to 24.3) and phase duration ($p = 0.002$, std. slope = 0.36, slope = 54.6, 95% CI = 19.1 to 90.1).

Table 5.1: Predictor variables and r^2 values of the generated regression models

Discrete point analysis		Functional principal component analysis			Analysis of Characterizing Phases		
feature	standardized coefficient	feature estimated phase		standardized coefficient	feature domain | phase		standardized coefficient
peak force	0.70	PCscore5	80-88%	0.39	phase 5	comb.| 82-87%	0.40
phase duration	0.36	PCscore1	1-13%	0.18	phase 2	comb.| 28-42%	0.60
		PCscore2	24-46%	0.22	phase 3	time | 91-94%	1.76
		PCscore3	90-95%	0.49	phase 4	comb.| 57-69%	0.65
					phase 1	comb.| 1-9%	1.20
					phase 3	comb.| 91-94%	0.24
$r^2 = 0.228$		$r^2 = 0.787$			$r^2 = 0.989$		

The regression model created using principal component scores ($p < 0.001$, $r^2 = 0.787$, std. error = 3.2) used four scores as predictor variables and showed a strong ability to explain jump height (Table 5.1). Predictor variables were forces at the beginning (approx. 1-13%, $p < 0.001$, std. slope = 0.18, slope = 0.8, 95 % CI = 0.4 to 1.3) the middle (approx. 24-46 %, $p < 0.001$, std. slope = 0.22, slope = 0.7, 95 % CI = 0.3 to 1.1) and the end (approx. 80-88 %, $p < 0.001$, std. slope = 0.39, slope = 3.9, 95 % CI = 2.7 to 4.3 and approx. 90-95 %, $p = 0.002$, std. slope = 0.49, slope = -1.5, 95 % CI = -2.5 to -0.5) of the movement cycle (Figure 5.5).

Similarity scores from the ACP method demonstrated the strongest ability to explain variances in jump height ($p < 0.001$, $r^2 = 0.989$, std. error = 0.7). The

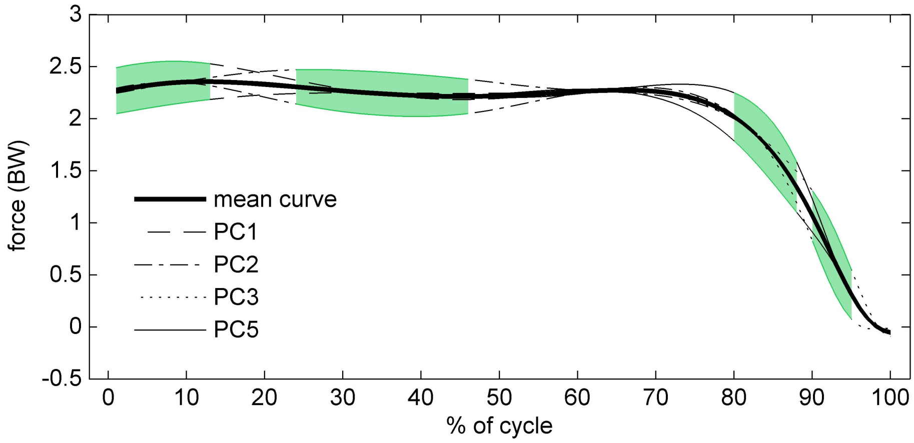


Figure 5.5: Predictor variables identified using fPCA indicating that differences in jump height are described by forces over the movement cycle of approx. 1-13 %, approx. 24-46 %, approx. 80-88 % and approx. 90-95 %

ACP regression model explained 98.9 % of the variance in jump height using five key-phases as predictor variables utilizing information from the time domain and the magnitude-time domain (Table 5.1). Predictor variables used in the ACP regression model were key-phases in the beginning (1-9 %, $p < 0.001$, std. slope = 1.20, slope = 2765.6, 95 % CI = 2610.3 to 2920.8), the middle (28-42 %, $p < 0.001$, std. slope = 0.60, slope = 1412.3, 95 % CI = 1328.3 to 1496.4 and 57-69 %, $p < 0.001$, std. slope = 0.65, slope = 1167.6, 95 % CI = 1068.5 to 1266.6) and the end (82-87 %, $p < 0.001$, std. slope = 0.40, slope = 1408.1, 95 % CI = 1249.8 to 1566.2; 91-94 %, $p < 0.001$, std. slope = 0.24, slope = 1406.1, 95 % CI = 1165.8 to 1646.5) utilizing the combined force-time domain; and the end of the movement cycles utilizing the time domain alone (91-94 %, $p < 0.001$, std. slope = 1.76, slope = 4422.0, 95 % CI = 4233.2 to 4610.8; Figure 5.6).

With respect to the prediction errors computed during the leave-one-out cross validation, the regression model created using the three data analysis techniques differed significantly from each other ($p < 0.01$, Table 5.2): discrete measures (error = 5.03±3.93cm) were greater than principal component scores from fPCA

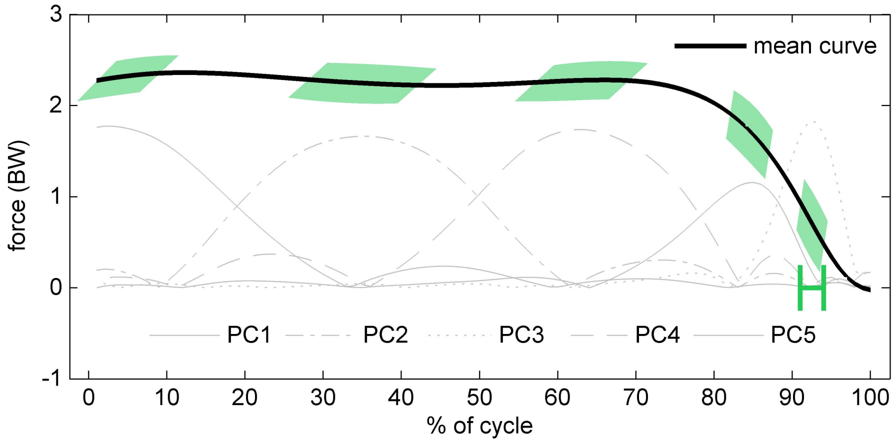


Figure 5.6: Summarising predictor variables of ACP indicating that differences in jump height are described by forces over the movement cycle of 1-9 %, 28-42 % and 57-69 %, in the force-time domain; and 91-94 % in the time, force and force-time domain

(error = 2.49±2.18cm) which was greater than similarity scores from ACP (error = 0.59±0.49cm).

Table 5.2: Prediction errors computed the generated regression models

	DPA	fPCA	ACP
error (mean ± std)	5.03 ± 3.93	2.49 ± 2.18	0.59 ± 0.049
	DPA > fPCA > ACP ($p < 0.01$)		

5.4.3 Discussion

The analysis techniques differ in their ability to describe the dependent variable jump height. Based on their effectiveness (high to low) the techniques are ranked: ACP (99 %), fPCA (79 %) and discrete point analysis (23 %).

Discrete point analysis had the lowest ability because it was not only incapable of generating strong predictors from the force curves, it also generated erroneous variables and hence treats non-related features as related features. For example, visual examination of each force curve indicated that the curves were frequently non-, uni- or bi-modal. The inconsistency in the curve shape resulted in large differences in the position of maximum force; maximum force could occur at the start (non-modal), the middle or the end (uni- or bi-modal) of the movement cycle. Hence, maximum force does not describe a consistent neuromuscular capacity across subjects, making it difficult to identify appropriate training interventions, and should only be examined when the shape of the examined waveforms is considered[1]. The same argument holds for time from initial-to-maximum force, percentage initial-to-maximum force and initial-to-maximum rate of force development, because of their dependency on maximum force. Due to the pre-selection of key measures and the inability to take into account their position, discrete point analysis failed to generate information which would help to improve our knowledge beyond the impulse-momentum relationship itself. These findings (i) provide support for the suggestion that fPCA and ACP are better suited than discrete point analysis for examination of waveforms with multi-modal shapes (as well as novel or little researched data curves in biomechanics), and (ii) may explain the direct contrast in findings between previous studies that used discrete point analysis, where some found maximum force to be a performance related factor (Cormie et al., 2009; Dowling and Vamos, 1993; Sheppard et al., 2008) while others did not (Morrissey et al., 1998; Newton et al., 1999; Petushek et al., 2010).

The comparison between ACP and fPCA indicates that ACP is more effective in describing jump height than fPCA (r^2 = 99 % vs. r^2 = 79 %, respectively)[2]. A

[1] In addition, no significant correlation exists between maximum force and jump height. However, this might be due to the differences in modality (curve shape). To examine the influence of the modality of the curves 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. 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). The relationship between maximum force in the second phase and jump height is similar to results reported by Dowling and Vamos (1993) and Harman et al. (1990) who found a significant relationship of maximum force (unspecified region) to jump height of $r^2 = 0.28$ and $r^2 = 0.27$, respectively.

[2] It might be argued the ACP resulted in a higher ability to describe jump height because it considered a greater range of the captured force curves. However, the reader should note that the ACP regression model using two predictor variables (phase $5_{comb.}$ and phase $1_{mag.}$) had an equal ability (r^2 = 79 %) to the fPCA regression model using four predictor variables to describe jump height.

major reason for the difference between the techniques is that fPCA does not inherently consider the time domain. To treat both techniques equally the variable 'phase duration' was added to the fPCA regression model. This increases its ability to explain variances in jump height by 12 % (r^2 = 91 %) and highlights the need to consider the time domain when performing fPCA. However, while including the time domain enhanced the ability of fPCA to describe jump height, ACP still outperforms fPCA by 8 %. The greater effectiveness of ACP is likely due to a combination of three factors. Firstly, in contrast to fPCA, ACP utilizes the combined magnitude-time domain. The benefit of examining the magnitude-time domain is highlighted by the fact that the ACP regression model frequently included variables from the combined magnitude-time domain rather than features from the magnitude domain. Secondly, unlike fPCA, ACP examined key phases of the waveforms without the influence of non-key phases. Differences between athletes are often small and non key phases can artificially increase or decrease a subject score, which can alter findings and mask performance related features. Finally, while ACP generates subject scores utilizing a key phase, fPCA generates subject scores utilizing generated functional data. Functional data is represented by coefficients that are calculated over pre-defined phases. The duration and location of these phases is chosen prior to analysis and based on the fit of the functional data to the discrete data. This approach can be a limitation as the pre-defined phases do not coincide with key phases of the waveform. Key phases spread across the pre-defined start and end points of the computed coefficients can result in a reduced ability to capture key phases (Figure 5.7). In addition, while not an aim of the present study, it is worth noting that fPCA is further limited because it generally requires the user to subjectively identify the phases of the movement cycle which influence the movement outcome (i.e. jump height), while ACP identifies them objectively. Given that biomechanical studies attempt to identify an appropriate training intervention it is important to accurately identify the phase over which the performance related factor acts to ensure that a training intervention enhances the performance related factor.

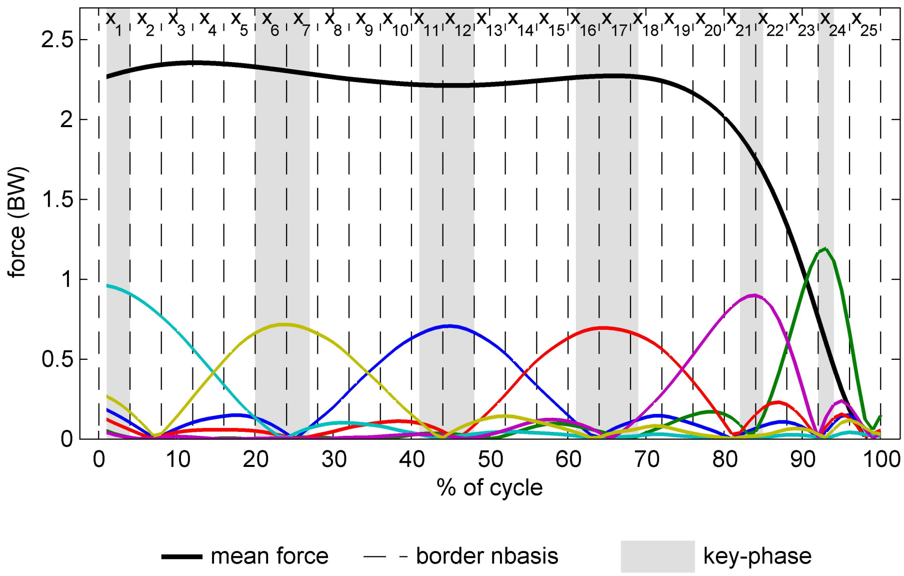


Figure 5.7: Demonstrates the possible disadvantage of using pre-defined boundaries of the basis when transforming discrete data to functional data. Key phases might not be captured well as key phases do not lie within the boundaries of the n basis

In conclusion, the continuous techniques (fPCA and ACP) were more effective at identifying performance related features in the force curves of countermovement jumps than discrete point analysis. Additionally, ACP seems superior to fPCA, since it (i) is able to statistically analyze the time, magnitude and combined magnitude-time domains and, (ii) examines solely key phases without the deleterious interaction of non-key phases. Consequently, ACP may be able to identify previously hidden performance related features, thereby identifying the movement phase over which a training program should aim to alter technique or neuromuscular capacities to enhance performance outcome.

5.5 Conclusion

This chapter introduced a new data analysis technique (Analysis of Characterising Phases), which addresses limitations of discrete point analysis and fPCA. Findings, strongly suggest the use of continuous waveform analysis. Both continuous waveform analysis techniques (fPCA and ACP) were able to describe jump height approximately 70 % better than discrete point analysis, while the use of ACP is suggested over fPCA. The findings of this section can be summarized as the following:

1. Discrete point analysis may not only fail to identify performance related factors, but it can also identify erroneous factors. This may explain, at least in part, the contrasting findings in the literature

2. Continuous data analysis procedures (ACP and fPCA) on the other hand, can identify functionally relevant performance related factors

3. The analysis strongly highlighted the importance of including the time domain when performing a fPCA, including the variable 'phase duration' to the fPCA regression model increases its ability to explain variances in jump height by 12 % (r^2 = 91 %)

4. ACP outperformed fPCA because subjects scores are not influenced by non-key phases, ACP considers the combined magnitude-time domain and does not use functional data to generate similarity scores

Chapter 6

The Influence of Inter-Subject Variability

6.1 Introduction

The countermovement jump (CMJ) is an important task in a number of sports (e.g. volleyball, basketball) and its biomechanics have been frequently studied (Klavora, 2000). However, identified features that relate to the performance outcome (jump height) are often inconsistent (section 2.1.2). This makes it difficult to conclude which neuromuscular capacities or movement techniques should be altered to enhance jump height, the criterion performance outcome in CMJs. The present work has demonstrated that some of the contrasting findings across studies may be due to the use of discrete point analysis (section 5.4.3). An alternative to discrete point analysis is a continuous waveform analysis (e.g. functional principal component analysis or analysis of characterizing phases) which has grown in popularity within many disciplines, including biomechanics, and has been reported to provide a better insight than discrete point analysis (Dona et al., 2009; Donoghue et al., 2008; Newell et al., 2006; Godwin et al., 2010; Ryan et al., 2006; Harrison et al., 2007; Ramsay and Silverman, 2002). This is supported by findings of the present work (section 5.4.3).

An additional reason for the inconsistencies across studies however, may be inter-subject variability. Force curves generated during a CMJ can differ significantly in shape across subjects (e.g. non-modal, uni-modal or bi-modal), which could imply that different movement strategies are being employed, which may in turn have different performance related factors. This might explain some the contrasting findings, since previous studies generally employed a single group analysis which can, if different shapes have different performance related factors, mask performance related factors (Stergiou, 2004; Stergiou and Scott, 2005; Bates, 1996). An alternative to a single group analysis is a subgroup analysis, which classifies similar patterns (curve shapes or movement strategies) into subgroups; so called clusters. An optimal classification maximizes the ability to predict dependent variables (e.g. jump height) of a data set (Han et al., 2006). To the author's knowledge it appears that none of the previous CMJ studies have used a subgroup analysis, while a subgroup analysis has been frequently performed in studies that examine human gait (Carriero et al., 2009; O'Byrne et al., 1998; Kienast et al., 1999; Toro et al., 2007; O'Malley et al., 1997; von Tscharner et al., 2013; Stout et al., 1995) and demonstrate the advantages of doing so.

A challenge in subgroup analysis is that a variety of classification techniques exists that may result in different clusters (Jain et al., 1999; Hastie et al., 2001; Witten and Frank, 2005; Martinez et al., 2004). Additionally, while the number of studies that have used continuous waveform analysis in the area of biomechanics is increasing (section 2.3.1), little is known about the performance of different clustering techniques with continuous waveform analysis in biomechanics. The computed 'continuous' features aim to represent the pattern of a curve over multiple phases of the movement cycle and can be highly collinear, which may influence results of some clustering techniques. Classification approaches differ in their underlying assumptions and can be divided broadly into hierarchical, partitional and probabilistic clustering (Hastie et al. 2001; Martinez et al. 2004; Witten and Frank 2005, section 2.4).

The advantage of hierarchical classification techniques is that they provide a highly interpretable description of the hierarchy within the data (i.e. dendrogram) and do not require the number of clusters to be chosen prior to the analysis. However, the assignment of samples into clusters requires the generation of inter-point distances of the input data (where different approaches can give very different results) and imposes a hierarchical structure within the examined data (Hastie et al., 2001; Martinez et al., 2004; Witten and Frank, 2005). In contrast, partitional classification (e.g. k-means) can be performed without calculating inter-point distances, it is commonly used and is usually more suitable for large data sets (Martinez et al., 2004). However, the construction of a dendrogram is computationally prohibitive and the number of clusters needs to be chosen prior to analysis (Jain et al., 1999; Witten and Frank, 2005; Martinez et al., 2004; Hastie et al., 2001). In addition, both hierarchical and partitional classification techniques follow a deterministic process where the generated clusters and their members are somewhat dependent on the ordering of samples (Witten and Frank, 2005). Consequently, a third method, model-based clustering might be more appropriate for classifying biomechanical data. Model-based clustering techniques assign individuals into clusters based on their fit to a given mathematical model. An often used model is the Gaussian mixture model (Han et al., 2006), which assign subjects into clusters based on the nature of statistical inference might be more appropriate for classifying movement strategies. Due to the variation in clustering approaches, and the relative novelty of classifying continuous biomechanical data, it is important to identify which classification technique has the greatest ability to recognize and separate appropriately patterns within multiple curves. The primary aim of this study is to assess and compare the performance of commonly used hierarchical, partitional and probabilistic classification techniques and the influences of normalizing input data to appropriately identify patterns within a sample of self created curves (manipulated data set) and a sample of force curves captured during countermovement jumps (real data set), using a continuous waveform analysis. A secondary aim is to examine if there are benefits to performing a subgroup analysis compared to the commonly used single group analysis when identifying vertical ground reaction force factors related to jump height.

6.2 Methods

Manipulated Data Set A random force curve from the real data set (Figure 6.1) was selected and used to create a sample of 100 manipulated curves, which contained three clusters to reflect some of the general shapes of the force curve. Curves in the first cluster (n = 33) were manipulated to have a unimodal shape, where the peak value occurred from 25-30 % of the cycle. Curves in the second cluster (n = 33) were manipulated to have a unimodal shape, where the peak value occurred from 70-75 % of the cycle. Curves in the third cluster (n = 34) were manipulated to have a bimodal shape, where the peak value occurred from 75-80 % of the cycle (Figure 6.1). To generate a manipulated data set the randomly selected curve was transformed into a function, using seven coefficients and a b-spline basis system (De Boor 1978; Ramsay 2006; Appendix A). The third (cluster 1 and 3) and fifth (cluster 2 and 3) coefficients were multiplied with a random factor between one and two, while the fourth coefficient (Cluster 3) was multiplied with a random number between minus one and zero. After the coefficients were altered, manipulated curves were generated by solving the altered functions to 101 points. Subsequently, the peak position of each curve was shifted randomly in time, using a dynamical time warping approach (as described in Ramsay 2006), within a random range of -2.5 and 2.5 %.

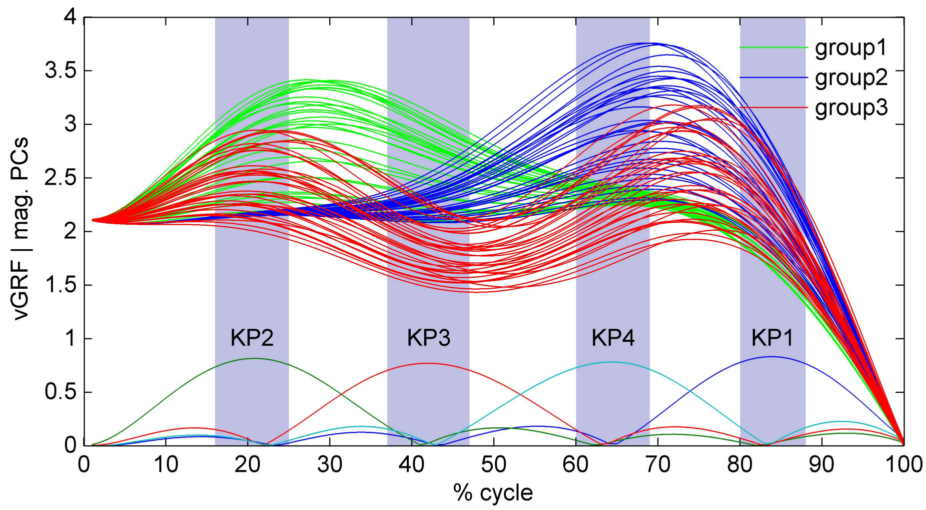


Figure 6.1: Manipulated data set, its pattern of variation (displayed by principal component curves at the bottom of the figure) and its key phases (KP, blue shading)

Real Data Set One hundred-and twenty two male athletes (age = 22.4 ± 4.2 years; mass = 71.1 ± 9.4 kg; height = 1.82 ± 0.1 m), who were physically active, experienced in performing the countermovement jump (based on the sports they played: Gaelic football, hurling and basketball), and free from lower limb injury participated in this study. The University Ethics Committee approved the study and 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 ten sub-maximal and five maximal effort countermovement jumps. Each participant performed 15 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, MA, USA) recorded the vertical ground reaction 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 takeoff, with takeoff determined when the force fell below 5 N. Only the vertical force-time curve during the propulsion phase was analyzed because it holds the information needed to fully describe jump height. The start of the propulsion phase was identified from the power-time curve of the body's centre of mass, when the power became positive.

Data Classification To generate scores that capture the patterns within the continuous waveforms, an Analysis of Characterising Phases (ACP) was performed (see section 5.3). Analysis of Characterising Phases detects phases of variation (key phases) within the sample of curves which are used to generate subjects scores (similarity score). Similarity scores were computed for key phases using the magnitude domain. Similarity scores were determined by calculating the area between a participant's curve (p) and the mean curve across the data set (q) for every point (i) within the key phases (Equation 6.1).

$$similarity\ score = \int p_i - q_i \tag{6.1}$$

Key phases were identified using the information generated by the principal components needed to describe 99.5 % of the variances in the data (see section 4.4). To increase the interpretability of the retained principal components a VARIMAX rotation was performed (Harrison et al., 2007; Ramsay and Silverman, 2002). Given that ACP generates just a few similarity scores to describe a complex waveform, it was necessary to insure that the generated scores preserve the information needed to cluster curves with similar patterns (shapes). The quality of the preserved information was estimated, for only the manipulated data set, by a subjective visual inspection of the generated similarity scores and was judged sufficient since a clear linear relationship exists for curves within each cluster (Figure 6.2).

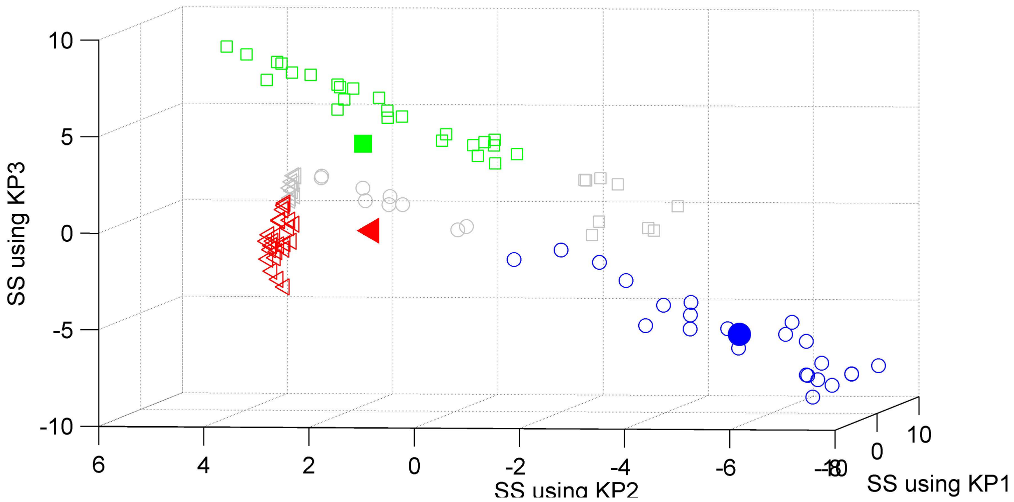


Figure 6.2: Similarity scores of the manipulated data set; x, Δ and $\Box$ symbols represent curves of the first, second and third cluster, respectively; symbols that are filled represent the position of the centroid of a k-means clustering approach and grey colored symbols represent misclassified similarity scores when using a k-means

To classify the manipulated and real data sets the computed similarity scores were input into a hierarchical classification algorithm (hierarchical classification), a k-means approach (partitional classification) and an Expectation-Maximization algorithm (model-based classification). Due to the linear relationship between similarity scores within a cluster, where clusters could 'overlap' in space possibly hampering the ability of the hierarchical and the k-means classification, the hierarchical and the k-means classification were also performed using normalized similarity scores (as suggested in Jain et al. 1999). The normalization was performed by transforming the similarity scores into their correlation matrix (Equation 6.2), to quantify numerically the relationship between the similarity scores, which cannot be described by distances of the generated similarity scores. The correlation matrix (corrMat) between curves was created by calculating the

Pearson's r-value for the similarity scores ($SS1, SS2, \ldots, SSz$) for every curve ($i, j = 1, 2, \ldots$ number of curves).

$$corrMat_{(i,j)} = \frac{\sum_{i=1}^{n}(SS1_i - \overline{SS1_{(i,j)}}) \ldots (SSz_i - \overline{SSz_{(i,j)}})}{\sqrt{\sum_{i=1}^{n}(SS1_i - \overline{SS1_{(i,j)}})^2} \ldots \sqrt{(SSz_i - \overline{SSz_{(i,j)}})^2}} \tag{6.2}$$

The hierarchical algorithm calculated pairwise distances using Euclidean distance, and created a hierarchical cluster tree using the nearest distance (Martinez et al., 2004). The quality of the hierarchical classification was measured by calculating the cophenetic correlation coefficient between the hierarchical cluster tree and the pairwise distances (Sokal and Rohlf, 1962; Martinez et al., 2004). Hierarchical classification properties were changed if the cophenetic correlation coefficient was less than 0.7, which indicates a low or medium correlation between the hierarchical cluster tree and the pairwise distances[1] (Cohen, 1988). The k-means classification technique used the squared Euclidean distance as the distance measure and the Expectation-Maximization algorithm was applied using the Gaussian mixture model (Martinez et al., 2004).

For the *manipulated data*, the performance of each cluster technique was assessed by the percentage of accurately classified curves, accessed by counting how often the assigned membership and the actual membership of a curve matched. To examine the benefits of using a subgroup analysis, key phases were identified using both a single group and a subgroup analysis, and directly compared. The number of clusters in the subgroup analysis was set at three clusters due to the contained number of general shapes (three shapes).

For the *real data set*, the performance of each cluster technique was measured by assessing the ability to explain the variance in jump height (dependent variable) across generated clusters. This approach was based on the assumption that an appropriate grouping of force curve shapes (or similar movement strategies) does

[1]All generated hierarchical cluster trees and the pairwise distances generated a cophenetic correlation coefficient above 0.7

not mask performance related factors and hence enhances the ability to describe variances in jump height. In order to assess the ability to explain variances in jump height for a given number of clusters the average r^2-value of a stepwise regression analysis was computed across these clusters. The classification technique with x clusters that generated the highest ability to explain variance in jump height was considered the most appropriate classification technique for the captured force curves. Input variables for the regression model were similarity scores measured solely over the key phases of a cluster. If the stepwise regression analysis was not able to identify any predictor variables within a cluster, the highest r^2-value computed during the correlation analysis (between the generated similarity scores and jump height) was used. If a cluster technique assigned only one participant to a cluster, the cluster was discarded.

To examine the benefits of the subgroup analysis over a single group analysis both the key phases and the predictor variables were compared when calculated for the whole data set (single group) to the key phases and the predictor variables selected within each of the generated clusters (subgroup analysis). The number of clusters was set to increase from one to ten clusters. All statistical analysis were performed using MatLab (R2012a, MathWorks Inc., USA)

6.3 Results

For the manipulated data set, the accuracy of the classification techniques was (from high to low): Expectation-Maximization algorithm (100 % accuracy), k-means clustering utilizing normalized scores (99 % accuracy), hierarchical clustering utilizing normalized scores (97 % accuracy), k-means clustering utilizing similarity scores (73 % accuracy) and hierarchical clustering utilizing similarity scores (72 % accuracy).

Key phases for the whole group analysis were identified at 20-30 %, 45-57 % and 72-82 % of the movement cycle. The key phases for each cluster, examined using a subgroup analysis were identified at (a) 22-36 % and 82-91 %, (b) 55-67 % and 78-87 % and (c) 60-68 %, and 81-89 % of the movement cycle for cluster 1, 2 and 3, respectively.

For the real data set, predictor variables (similarity scores computed from key phases), identified by the stepwise regression analysis, were able to explain 78 % of the variances in jump height (r^2 = 0.78) using the single group design. Hierarchical clustering (normalized scores) reached its highest ability to describe jump height using four clusters (85 %) and k-means (normalized scores) reached its highest ability using four clusters (83 %). The Expectation-Maximization algorithm, hierarchical clustering (non-normalized scores) and the k-means (non-normalized scores) were not able to increase the ability to describe jump height over that achieved using the single group analysis (Figure 6.3).

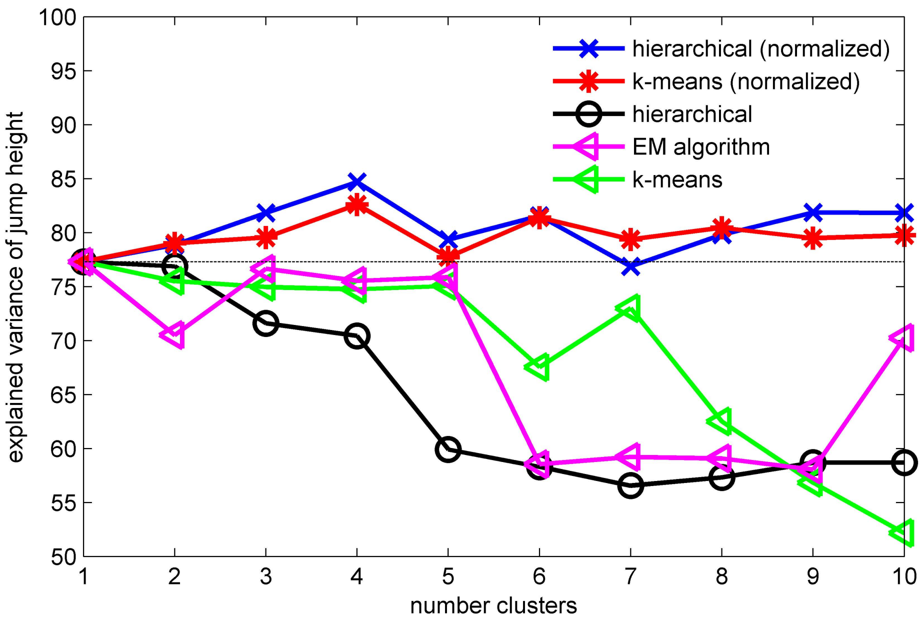


Figure 6.3: Ability to describe jump height for the two hierarchical clustering, the two k-means approaches and the Expectation-Maximization (EM) algorithm, at multiple numbers of clusters

Hierarchical (normalized scores) clustering explained most accurately the variances in jump height but generated two clusters with sample sizes less than ten members (Cluster 1 n = 7; Cluster 3 n = 6). For the clusters with small sample sizes, the regression analysis was not able to identify predictor variables. Hence, k-means (normalized scores) clustering was selected for further analysis, as it had almost the same ability to describe variance in jump height with larger sample sizes and better balanced cluster sizes. Visual inspection of the mean curves of the generated k-means (normalized scores) clusters indicates that members of clusters 1 and 3 tend to follow a unimodal shape where peak force occurred before 15 % or around 70 % of the movement cycle, respectively. Clusters 2 and 4 tend to follow a bimodal shape where peak force occurred either before 15 % or around 80 % of the movement cycle (Table 6.1; Figure 6.4). No significant difference exists in jump height across the clusters.

Table 6.1: Describes mean curve shapes of members within the generated clusters using k-means (four clusters; normalized scores)

Number Cluster	modality	peak	Sample size	r^2
1	unimodal	around 70%	n = 11	0.83
2	bimodal	around 10 or 70%	n = 53	0.88
3	unimodal	around 10%	n = 50	0.72
4	bimodal	before 10%	n = 08	0.88

Key phases and identified predictor variables differed between the single group and subgroup analysis, while the strongest relation to jump height occurred at around 90 % across both subgroup and single group analyses (Figure 6.5). All predictor variables were identified by the stepwise regression analysis. The reader should note that the subgroup analysis was able to increase the ability to describe variances in jump height using less information (less % of the movement cycle).

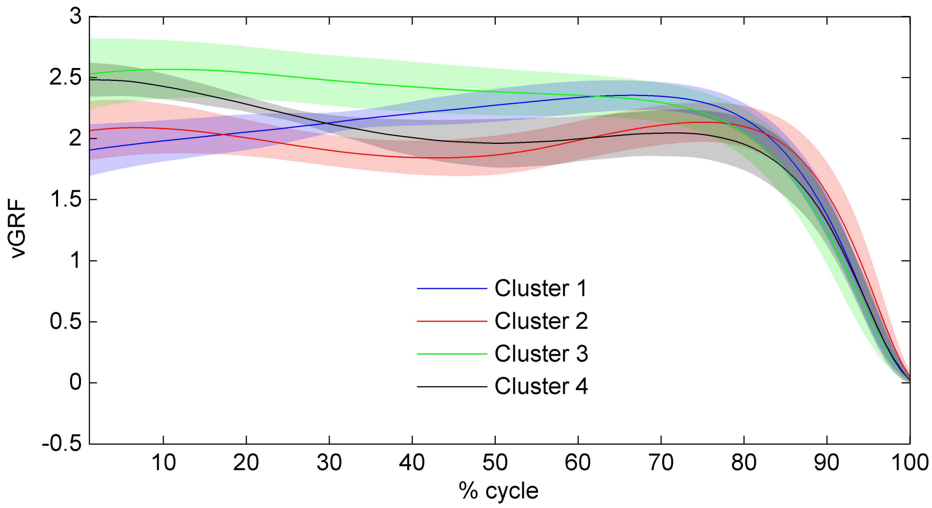


Figure 6.4: Mean curves of clusters generated using k-means clustering with four clusters

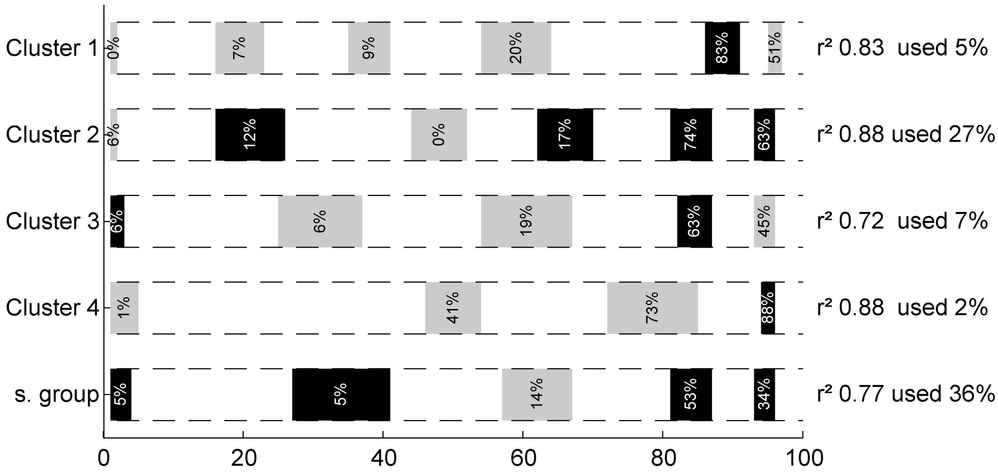


Figure 6.5: Key phases (grey and black shaded) identified using a single group (s. group) and subgroup analysis (Cluster 1-4), the ability to explain variances in jump height and the used % of the movement cycle to predict jump height. Black shaded key phases represent identified jump height predictor variables. The percentage plotted within the identified key phases is the ability to describe jump height of the key phase alone (r^2 value of correlation analysis)

6.4 Discussion

The examined classification techniques differed in their performance in both the manipulated and real data sets. Using the manipulated data, the following accuracy was found (from high to low): Expectation-Maximization algorithm (100 % accuracy), k-means clustering utilizing normalized scores (99 % accuracy), hierarchical clustering utilizing normalized scores (97 % accuracy), k-means clustering utilizing non-normalized scores (73 % accuracy) and hierarchical clustering non-normalized scores (72 % accuracy). Normalizing the input data enabled both the hierarchical and k-means clustering methods to 'recognize' curve patterns with greater accuracy, indicating that the 'overlap' of clusters in space hampered the ability of the hierarchical and the k-means classification.

Using the real data set, only k-means (normalized scores) and hierarchical clustering (normalized scores) extended the ability to describe variances in jump height beyond that achieved using the group analysis (e.g. one cluster). Similar to the manipulated data set, without normalizing the input data the hierarchical and k-means classification techniques had a reduced ability to accurately describe variances in jump height. This highlights the importance of considering the shape of force curves when classifying them. Normalizing similarity scores (transformation of scores into their correlation matrix) had a significantly positive effect on the performance of both hierarchical and partitional classification techniques, indicating that differences in magnitude between similarity scores are not as effective as their quantified numerical relationship at maximising the ability to predict a dependent variable. Although not examined here, the same effect is likely to occur when discrete points are used for classification. To the best of the author's knowledge, previous studies that aimed to identify movement patterns by clustering discrete kinematic and kinetic variables did not normalize their input variables (Marshall 2010; Stout et al. 1995; Carriero et al. 2009; OByrne et al. 1998; Kienast et al. 1999), which may have reduced their ability to recognize movement patterns.

To date, no study has compared classification approaches using biomechanical waveforms, which makes it difficult to compare the present findings relating to the effect of normalizing the input data. For this reason the present work applied k-means clustering to a publically available data set (The Berkeley Growth Data: Tuddenham and Snyder 1954). The Berkeley Growth Data has been used recently to measure the accuracy of k-means (e.g. Jaques and Preda 2013) and, similar to force curves, the shapes of the sample of curves might hold the information needed to classify the data correctly. Applying k-means to the Berkeley Growth Data using non-normalized and normalized similarity scores, k-means attained classification accuracies of 74.2 % and 94.6 %, respectively. In the experiment of Jaques and Preda (2013)[2], the highest accuracy of k-means was 66.7 %. The increase in accuracy of k-means in the present work is due to the effect of normalization (accounting for +20.4 %) and the use of similarity scores (accounting for +7.5 %). The contrasting findings between non-normalized and normalized scores for hierarchical and partitional techniques (for our manipulated and real data, and the Berkeley Growth data) strongly suggest that input variables should be normalized when classifying curves where the curve shape might hold important information.

While the Expectation-Maximization algorithm was effective for classifying the generated data set, it failed to successfully classify the real data;it was not able to generate clusters with a higher ability to describe variances in jump height than that achieved at a single group (i.e. one cluster). A possible reason for this contrasting performance lies in the nature of both data sets. The manipulated data set holds clear distribution patterns where peak force differed across curves within a cluster by only ± 5 %. The real data set, however, has much more variation and the probability distribution does not differ clearly across clusters (Figure 6.6).

In respect to the benefit of performing a subgroup analysis, while some commonalities can be found with the single group analysis regarding the location of

[2]Jaques and Preda (2013), assessed the ability of k-means by utilized non-normalized data (whole discrete curve, 20 spline coefficients and functional principal component scores)

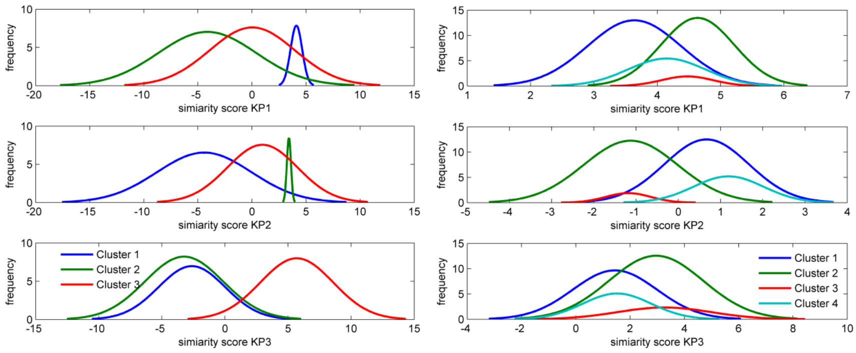


Figure 6.6: Probability distribution for similarity scores computed during three key-phases (KP) for the manipulated (left) and real data set (right)

strongest relation to jump height (around 85 % of the jump cycle), clear differences exist between the findings of the group and subgroup analyses. Alone the subgroup analysis was able to capture key phases which reflect specific characteristics of each cluster, resulting in different locations of key phases and predictor variables across clusters. These differences caused a change in predictor variables (see Figure 6.5) resulting in greater ability of a subgroup analysis to describe variances in jump height over a group level analysis (on average +8.3 %). In addition to this increased ability to describe variances in jump height, the subgroups required less information to predict jump height (on average 17 % less of the movement cycle). This is important as it could be argued that since jump height is directly related to the impulse of the analysed phase, the greater the duration of the phase considered, the more likely it is to explain jump height. While effectiveness of a subgroup analysis has not been examined in previous CMJ studies, gait studies have also concluded that a subgroup analysis is more appropriate than the whole group analysis (Stout et al., 1995; Carriero et al., 2009; O'Byrne et al., 1998; Kienast et al., 1999).

In relation to the use of a subgroup analysis it was possible to identify four distinct force curve shapes: (i) unimodal with high initial forces, where peak force occurs shortly after the start of the concentric phase, (ii) unimodal with low initial force, where peak force occurs around 70 % of the movement cycle, (iii) bimodal with high initial forces, where peak force occurs shortly after the start of the concentric phase, and (iv) bimodal with initial force at both the first and second maxima, where peak force could occur either before 15 % or around 80 % of the movement cycle. The characteristics of these clusters strengthen the idea that different individuals may have different performance related factors (Bates, 1996; Stergiou, 2004; Stergiou and Scott, 2005). The combination of the knowledge of general curve shapes and the location of performance related factors give a further insight into inconsistencies in findings in discrete point analysis studies relating to whether maximum force is a performance related factor (Cormie et al., 2009; Dowling and Vamos, 1993; Sheppard et al., 2009), or is not (Morrissey et al., 1998; Newton et al., 1999; Petushek et al., 2010). In light of the subgroup findings, maximum force does represent different neuromuscular capacities across each cluster. For cluster 1 and 2 (shapes with low initial forces), maximum force represents the ability to generate forces at the end of the movement cycle as the ankle, knee and hip joint extend towards full extension; while it represents the ability to generate forces quickly (1-15 %) after the start of the concentric phase for cluster 3 and 4. Consequently, maximum force should not be compared using a single group analysis because even if an analysis of peak force accounts for different modalities (curve shapes) of a force curve, it can fail to examine comparable neuromuscular capacities. The present work indicates that classifying a sample of individuals into multiple clusters can overcome limitations of a group analysis and hence enhances the understanding of the underlying neuromuscular movement's strategies during a movement task.

6.5 Conclusion

K-means clustering utilizing normalized subject scores appears to be the most suitable technique for clustering force curves, while hierarchical clustering also showed a high level of suitability. Further, when clustering curve shapes, it seems extremely important to normalize subject scores, by transforming them into their correlation matrix, before using a clustering technique. In terms of the benefit of a subgroup analysis, some key phases (phases of variance) differed between clusters which improves the ability to explain variances in a dependent variable (jump height), indicating different movement strategies for which some different performance related factors were evident. Consequently, the findings highlight the benefit of performing a subgroup analysis over a single group analysis and may explain, at least in part, the contrasting findings between previous studies that examined force during vertical jumping at a single group level of analysis.

Chapter 7

The Identification of Performance Related Factors in CMJs

7.1 Introduction

Many studies have aimed to identify features that relate to the performance outcome during a countermovement jump (CMJ; section 2.1). However, identified performance related features are often inconsistent (section 2.1.2), which makes it difficult to conclude how neuromuscular capacities or the movement technique have to be altered to enhance the performance outcome (jump height). The reason for this inconsistency could be explained by both the (commonly) performed data analysis technique and the effect of inter-subject variability (section 2.2 and 2.4). The vast majority of previous studies that aimed to identify performance related factors in CMJs performed a discrete point analysis. Discrete point analysis has significant limitations and has been associated with contrasting finding in previous studies (section 5.4.3). An alternative to discrete point analysis is the analysis of continuous waveforms which has been reported to be much more effective than discrete point analysis (Dona et al., 2009; Donoghue et al., 2008; Godwin et al., 2010; Harrison et al., 2007; Newell et al., 2006; Ramsay and Silverman, 2002; Ryan et al., 2006). This is also supported by findings of the present work (section 5.4.3).

However, limitations in discrete point analysis might not *fully* explain inconsistencies in finding across previous studies. Another source for contrasting findings may be inter-subject variability, because jumping strategies and their performance related factors may differ across individuals (Vanezis and Lees 2005, section 6.4). If performance related factors differ across individuals, they can be masked when examining a single data set that contains different movement strategies (Stergiou and Scott, 2005; Stergiou, 2004). The commonly used single group design therefore may have, at least in part, contributed to the inconsistency in the findings of the reviewed studies (section 6.4).

A possible solution to avoid a masking of performance related factors during an analysis is a subgroup level analysis; where similar patterns, curve shapes or movement strategies are classified into separated groups, so called clusters (section 2.4). The benefit of a subgroup analysis has been demonstrated in section 6.4 and in previous research (Carriero et al., 2009; O'Byrne et al., 1998; Kienast et al., 1999; Toro et al., 2007; O'Malley et al., 1997; von Tscharner et al., 2013; Stout et al., 1995). The combination of a continuous analysis using a subgroup analysis might give a better insight into what factors relate to jump height in the CMJ and might help to understand contradicting findings in previous studies. To date, no biomechanical study has used a continuous waveform analysis and a subgroup analysis in combination to identify performance related factors in the CMJ.

The aim of this study is to examine performance related factors using continuous waveform analysis in combination with a subgroup analysis.

7.2 Methods

Subjects One-hundred-and-twenty-five male athletes (age = 22.4±4.2 years; mass = 71.1±9.4 kg; height = 1.82±0.1 m), who were physically active, experienced in performing the countermovement jump (based on the sports they played: Gaelic football, Gaelic hurling and basketball), and free from lower limb injury participated in this study. The University Ethics Committee approved the study and all participants were informed of any risk and signed an informed consent form before participation.

Data capture Prior to data collection, every participant performed a standard warm-up routine consisting of low intensity jogging, stretching and ten sub-maximal and five 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. A motion analysis (Vicon 512 M, Oxford Metrics Ltd, England) system and two force plates (BP-600900, AMTI, MA, USA) recorded the position of spherical reflective markers[1] (250 Hz) and the vertical ground reaction force (1000 Hz), respectfully. 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 takeoff, with takeoff determined when the force fell below 5 N. Only the vertical force-time curve during the propulsion phase was analyzed because it holds the information needed to fully describe jump height. The start of the propulsion phase was identified from the power-time curve of the body's centre of mass, when the power became positive.

[1]Six spherical reflective markers were placed on the left and right body side on the following anatomical landmarks: fifth metatarsal joint, posterior calcaneus (in line with the fifth metatarsal joint), lateral malleolus, lateral femoral epicondyle, greater trochanter and the glenohumeral joint. These markers were used to reconstruct the position of the ankle, knee, hip and shoulder joint during the CMJ. In addition, the markers were attached to the anatomical landmarks using double-sided tape.

Data processing The raw position and force data were exported and processed using a self-developed MatLab code. The data was filtered using a recursive second-order low pass Butterworth digital filter (Winter, 2009). The force plate data was filtered using a cutoff frequency of 50 Hz and the marker position data was filtered using multiple cutoff frequencies (toe 6.62 Hz, heel 6.62 Hz, ankle 7.52 Hz, knee 9.21 Hz, hip 8.50 Hz and shoulder 6.64 Hz; Moran 1998). The three-dimensional position information of the captured markers was reduced to the sagittal plane and used to create a four-segment model with frictionless hinge joints. Segments of the model were the foot, shank, thigh and head-arms-trunk, which were connected by joints that represent the ankle, knee and hip joint (Figure 7.1). This model has been used in previous studies to examine the CMJ (Petushek et al., 2010; Vanrenterghem et al., 2008).

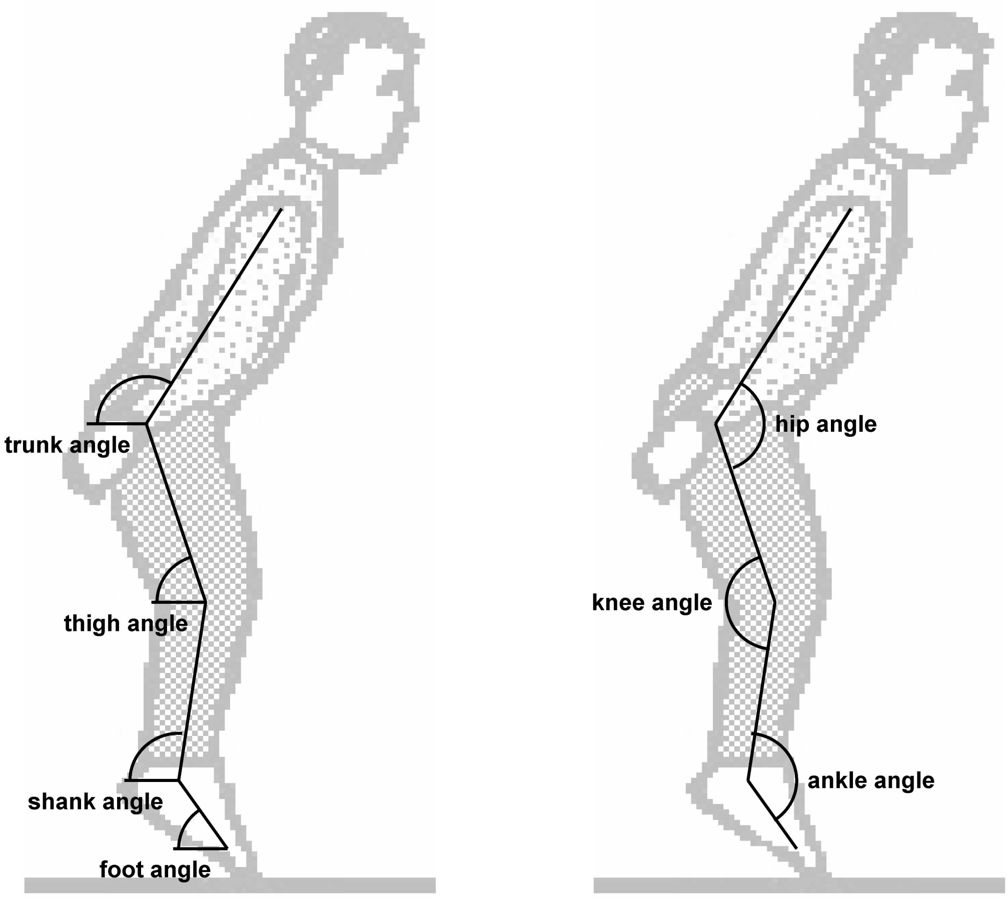
Kinematic and kinetic variables for each joint were computed for the left and right body side. The average of kinematic and kinetic variables of the both body sides was used for data analysis. Segment angles were calculated in an anti-clockwise direction from the right horizontal with the distal end point of the segment as the origin (Figure 7.1). Joint angles (θ) were defined as the angle between the connected segments (Equation 7.1, 7.2 and 7.3).

$$\theta_{ankle} = \theta_{foot} + (pi - \theta_{shank}) \tag{7.1}$$

$$\theta_{knee} = (pi - \theta_{shank}) + \theta_{thigh} \tag{7.2}$$

$$\theta_{hip} = \theta_{thigh} + (pi - \theta_{trunk}) \tag{7.3}$$

Joint kinetics were calculated using standard inverse dynamics, combining kinematic and ground reaction force data with anthropometric data (Winter, 2009). A detailed description of their calculation is given in Appendix C. Joint extensor



(a) definition segment angles (b) definition joint angles

Figure 7.1: Graphical representation of the created four-segment model, joints between the segments represent the ankle, knee and hip joint

moments were defined as positive and flexor moments were defined as negative (AragonVargas and Gross, 1997b).

Data classification To classify the kinematic and kinetic waveforms, subject scores (similarity scores) were computed using Analysis of Characterising Phases (ACP; section 5.3). 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. For detailed information about the clustering process, the reader is referred to Appendix D. Similarity scores were generated using solely kinematic and kinetic variables observed on a joint level to identify movement strategies for the following reasons:

1. CoM velocity, CoM power or vertical ground reaction force (force) have a high relation to jump height (section 2.1, 5.4.3 and 6.4). Including these variables in a classification might result in the generation of clusters based on performance outcome rather than movement strategy.
2. Whole body variables were discarded because the variables observed on a joint level fully determine whole body variables. Hence, the information of whole body variables which are important to describe jump height are hidden within the kinematic and kinetic variables observed on a joint level.
3. In addition, variables on a joint level hold by far the more meaningful information for the identification of a training intervention that overloads neuromuscular capacities to increase the performance outcome. Identifying a training program based on whole body performance related factors has the potential to suggest trainings programs that overload the whole body performance related factors, which may change joint kinematics and kinetics inappropriately and results in a decrease in the performance outcome.

Data analysis Analysis of Characterising Phases was applied to generate similarity scores, which were used for statistical analysis (correlation analysis) to identify performance related factors. Key phases were identified using information from VARIMAX rotated functional principal components, which retained more than 99% of the variance within the data's magnitude domain (section 5.3)[2]. Key phases were used to calculate similarity scores for the time, magnitude and magnitude-time domain by calculating the area between a participant's curve (p) and the mean curve across the data set (q) for every point (i) within a key phase (Equation 7.4 for the time or magnitude domain; Equation 7.5 for the combined magnitude-time domain).

$$score = \int q_i - p_i \tag{7.4}$$

$$score = \int 0.5(\Delta_{time} q_{i,i+1} + \Delta_{time} p_{i,i+1}) \Delta_{magnitude} q_i p_i \tag{7.5}$$

If a key phase correlated significantly with jump height, the key phase was extend to determine the exact phase over which a performance related factor exists (as described in section 5.3). A feature (similarity score or key phase) was considered to be a performance related factor if it correlated significantly with jump height (performance outcome). Performance related factors were classified into weak ($r^2 < .09$), moderate ($.09 < r^2 < .49$) and strong ($r^2 > .49$; Cohen 1988).

To examine if there is a benefit of a subgroup over a single group analysis when identifying performance related factors, ACP was performed on each of the generated clusters (subgroup analysis) and the whole data set (single group analysis). The ability to identify performance related factors was assessed by comparing the r^2-value of a stepwise multiple regression model. In addition, to examine if findings differ between single group and subgroup analysis, performance related factors identified using the single group and each of the subgroups were directly contrasted. Data processing, clustering and analysis were performed in MATLAB (R2012a, MathWorks Inc., USA).

[2] The data's magnitude domain was used to identify pattern of variances because it, unlike the time domain, holds non-linear pattern of variation

7.3 Results

Hierarchical clustering with four clusters utilizing normalized scores was identified as the most appropriate clustering technique for the examined kinematic and kinetic waveforms and generated clusters with distinct movement pattern (Appendix D). The statistical analysis for differences between the clusters found significant differences in jump height (cluster 2 > cluster 4; Table 7.1). It should be noted that findings of the magnitude-time domain are not reported as findings of the combined magnitude-time domain are almost identical to findings of the magnitude domain.

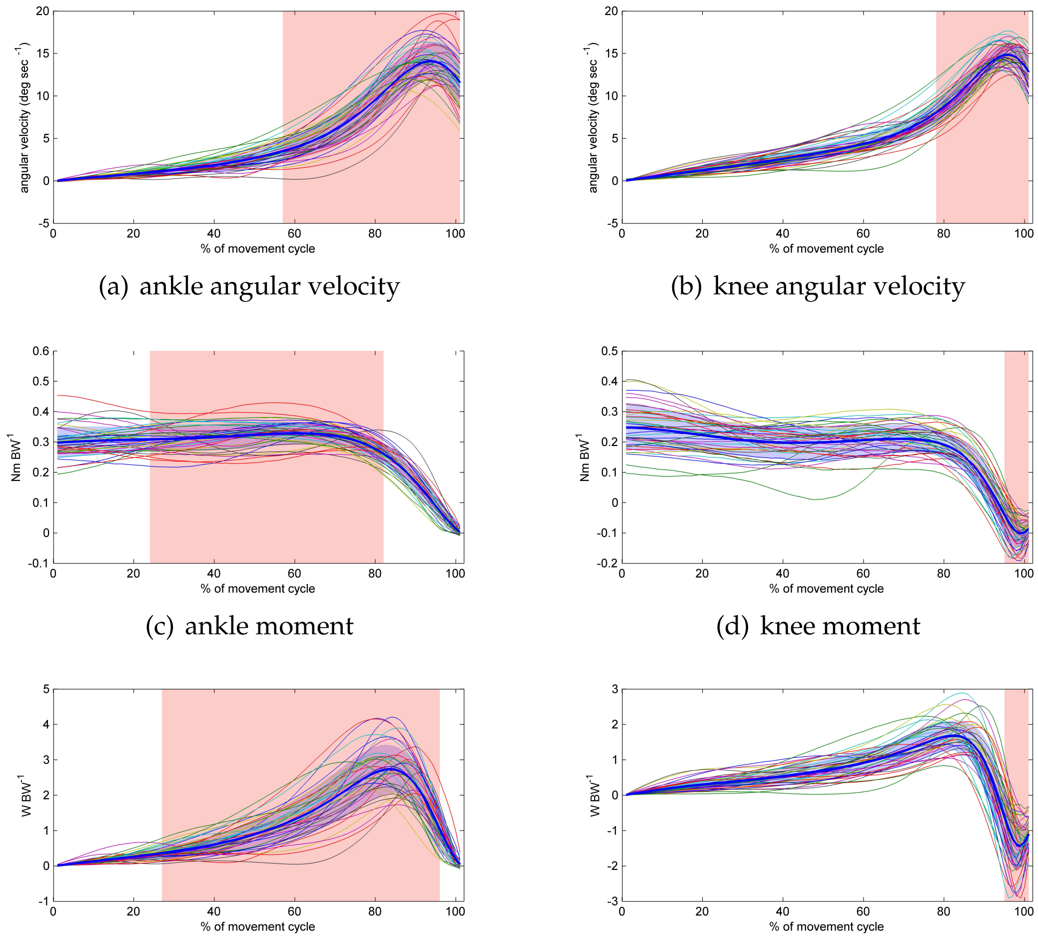
Table 7.1: Jump height (mean, standard deviation and 95 % confidence interval) of the four generated clusters

	mean	95% confidence interval
Cluster 1	38 cm	30.9 to 45.1
Cluster 2*	41 cm	39.0 to 43.1
Cluster 3	37 cm	34.0 to 39.9
Cluster 4*	37 cm	35.1 to 38.8

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

Cluster 1: Cluster 1 contained six subjects and the performed regression analysis explained 100 % of the variances in jump height ($r^2 = 1.00$). However, 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). Because of its small sample size, it was discarded for the statistical analysis.

Cluster 2: Cluster 2 contained 40 subjects and the performed regression analysis explained 96 % of the variances in jump height. Defining characteristics in cluster 2 ,in comparison to cluster 3 and 4, are low knee and hip joint angles throughout the movement cycle, the ability to generate large knee moments, to maintain hip moments in the end of the movement cycle and a delayed ankle, knee and hip peak power (AppendixD). Performance related factors were found in concentric ankle duration, ankle angular velocity (57-100 %), ankle moment (24-82 %), ankle power (27-96 %; Figure 7.2; Table 7.2), concentric knee duration, knee angular velocity (78-100 %), knee moment (95-100 %), knee power (95-100 %; Figure 7.2; Table 7.2), hip joint angle (1-100 %), hip angular velocity (30-100 %), hip moment (1-100 %) and hip power (12-100 %; Figure 7.3; Table 7.3).



(a) ankle angular velocity

(b) knee angular velocity

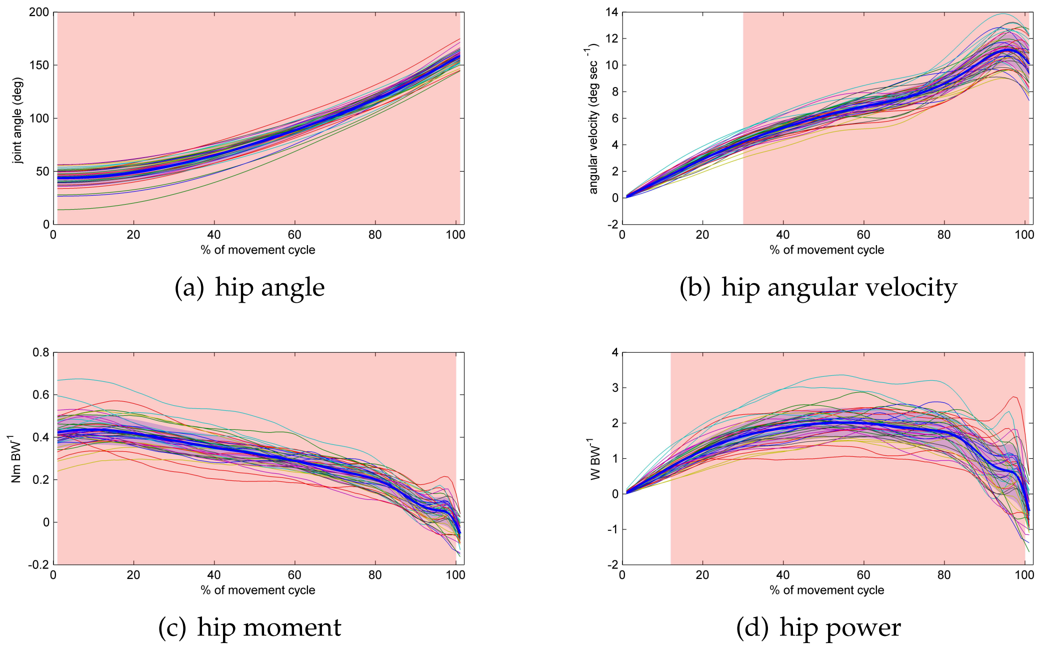
(c) ankle moment

(d) knee moment

(e) ankle power

(f) knee power

Figure 7.2: Ankle (left) and knee (right) joint kinematics (angular velocity, moment and power) of subjects in cluster 2. Red phases represent key phases with significant correlation to jump height



(a) hip angle (b) hip angular velocity

(c) hip moment (d) hip power

Figure 7.3: Hip joint kinematics (angular velocity, moment and power) of subjects in cluster 2. Red phases represent key phases with significant correlation to jump height

Table 7.2: List of descriptive statistics of phases that have been identified to be related to performance in subjects of cluster 2 in ankle and knee joint

Variable	Key phase			p value	r^2 value	confidence interval		
Ankle time domain	1	to	100	0.000	-0.28	-0.52	to	-0.07
Ankle Angle Velocity SS PC2	70	to	99	0.000	0.32	0.10	to	0.56
Ankle Angle Velocity SS PC3	89	to	100	0.001	0.25	0.05	to	0.49
Ankle Angle Velocity SS PC4	57	to	87	0.003	0.20	0.03	to	0.45
Ankle Moment SS PC1	36	to	82	0.002	0.23	0.04	to	0.48
Ankle Moment SS PC4	24	to	63	0.004	0.20	0.02	to	0.44
Ankle Power SS PC1	27	to	60	0.010	0.16	0.01	to	0.40
Ankle Power SS PC2	36	to	81	0.001	0.24	0.04	to	0.48
Ankle Power SS PC3	82	to	96	0.000	0.32	0.10	to	0.56
Ankle Power SS PC4	63	to	93	0.000	0.37	0.14	to	0.60
Knee Time Domain	1	to	100	0.035	0.11	-0.34	to	-0.01
Knee Angle Velocity SS PC1	92	to	100	0.000	0.29	0.08	to	0.53
Knee Angle Velocity SS PC3	78	to	99	0.001	0.27	0.06	to	0.51
Knee Moment SS PC2	95	to	100	0.017	-0.14	-0.38	to	0.00
Knee Power SS PC1	95	to	100	0.004	-0.20	-0.45	to	-0.03

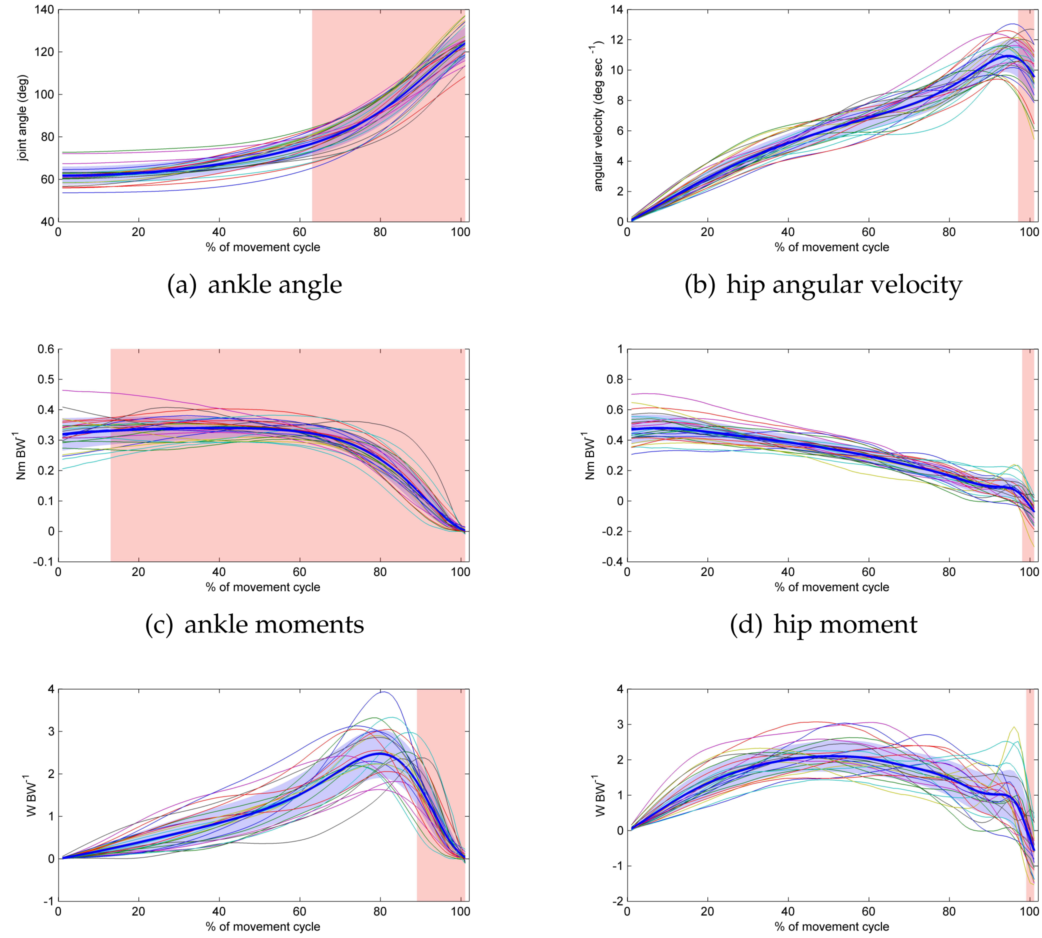
Table 7.3: List of descriptive statistics of phases that have been identified to be related to performance in subjects of cluster 2 in hip joint

Variable	Key phase			p value	r^2 value	confidence interval		
Hip Angle SS PC1	18	to	94	0.000	-0.34	-0.57	to	-0.11
Hip Angle SS PC2	67	to	100	0.000	-0.31	-0.55	to	-0.09
Hip Angle SS PC3	1	to	55	0.001	-0.26	-0.50	to	-0.06
Hip Angle Velocity SS PC2	89	to	101	0.002	0.23	0.04	to	0.47
Hip Angle Velocity SS PC3	30	to	64	0.001	0.24	0.04	to	0.48
Hip Angle Velocity SS PC4	49	to	84	0.000	0.33	0.10	to	0.57
Hip Angle Velocity SS PC5	70	to	99	0.000	0.30	0.08	to	0.54
Hip Moment SS PC1	90	to	100	0.011	0.16	0.01	to	0.40
Hip Moment SS PC2	1	to	27	0.001	0.26	0.05	to	0.50
Hip Moment SS PC3	71	to	98	0.000	0.30	0.08	to	0.53
Hip Moment SS PC4	37	to	88	0.000	0.44	0.19	to	0.65
Hip Moment SS PC5	6	to	65	0.000	0.37	0.13	to	0.60
Hip Power SS PC1	12	to	47	0.000	0.32	0.10	to	0.56
Hip Power SS PC2	92	to	100	0.007	0.17	0.01	to	0.42
Hip Power SS PC3	51	to	89	0.000	0.54	0.30	to	0.73
Hip Power SS PC4	79	to	98	0.000	0.29	0.07	to	0.53
Hip Power SS PC5	21	to	74	0.000	0.50	0.26	to	0.70

Cluster 3 (n = 25): Cluster 3 contained 25 subjects and the regression analysis explained 90 % of the variances in jump height. Defining characteristics of cluster 3 are, compared to cluster 2 and 4, high ankle and knee joint extension throughout the movement cycle, the inability to generate large ankle and knee moments, the ability to generate large initial hip moments and the inability to maintain large moments at the end of the movement cycle (Appendix D). Performance related factors were found in ankle joint angle (63-100 %), ankle moment (13-100 %), ankle power (89-100 %; Figure 7.4; Table 7.4), knee joint angle (88-100 %), knee angular velocity (95-100 %), knee moment (58-96 %), knee power (72-92 %; Figure 7.5; Table 7.5), hip angular velocity (97-100 %), hip moment (98-100 %) and hip power (98-100 %; Figure 7.4; Table 7.5).

Table 7.4: List of descriptive statistics of phases that have been identified to be related to performance in subjects of cluster 3 in ankle joint

Variable	Key phase			p value	r^2 value	confidence interval		
Ankle Angle SS PC1	76	to	100	0.002	-0.35	-0.64	to	-0.07
Ankle Angle SS PC3	63	to	97	0.009	-0.26	-0.57	to	-0.02
Ankle Moment SS PC2	33	to	88	0.000	0.43	0.13	to	0.70
Ankle Moment SS PC3	67	to	100	0.001	0.39	0.09	to	0.67
Ankle Moment SS PC4	13	to	63	0.005	0.30	0.04	to	0.60
Ankle Power SS PC2	89	to	100	0.010	0.25	0.02	to	0.56

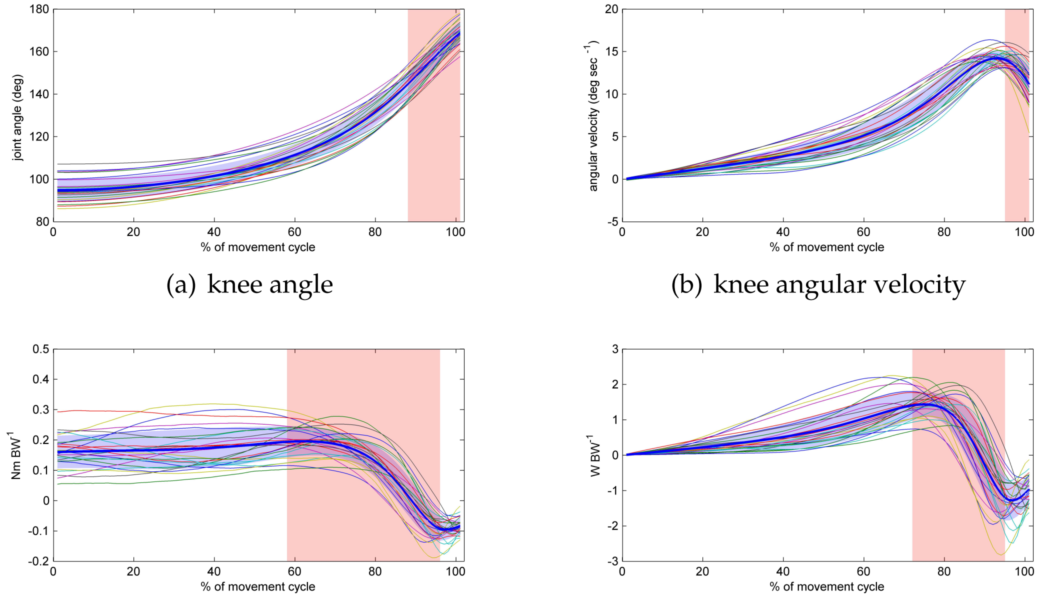


(a) ankle angle (b) hip angular velocity

(c) ankle moments (d) hip moment

(e) ankle power (f) hip power

Figure 7.4: Ankle (left) and hip (right) joint kinematics (joint angle, angular velocity, moment and power) of subjects in cluster 3. Red phases represent key phases with significant correlation to jump height



(a) knee angle (b) knee angular velocity

(c) knee moment (d) knee power

Figure 7.5: Knee joint kinematics (joint angle, angular velocity, moment and power) of subjects in cluster 3. Red phases represent key phases with significant correlation to jump height

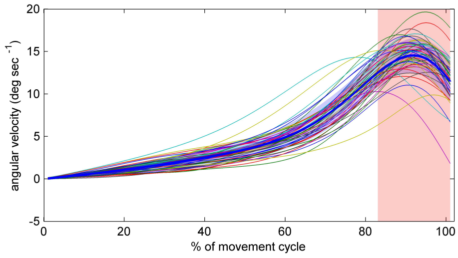
Table 7.5: List of descriptive statistics of phases that have been identified to be related to performance in subjects of cluster 3 in knee and hip joint

Variable	Key phase			p value	r^2 value	confidence interval		
Knee Angle SS PC1	88	to	100	0.007	-0.27	-0.58	to	-0.03
Knee Angle Velocity SS PC3	95	to	100	0.003	0.33	0.05	to	0.63
Knee Moment SS PC1	77	to	96	0.023	0.21	0.01	to	0.52
Knee Moment SS PC3	58	to	93	0.005	0.30	0.04	to	0.60
Knee Power SS PC1	81	to	95	0.025	0.20	0.00	to	0.51
Knee Power SS PC3	72	to	91	0.007	0.28	0.03	to	0.58
Hip Angle Velocity SS PC4	97	to	100	0.029	0.19	0.00	to	0.50
Hip Moment SS PC3	98	to	100	0.020	0.21	0.01	to	0.53
Hip Power SS PC2	99	to	100	0.008	0.27	0.02	to	0.57

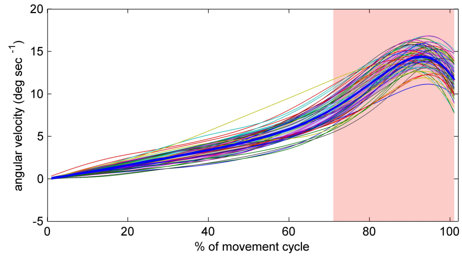
Cluster 4: Cluster 4 contained 51 subjects and the regression analysis explained 80 % of the variances in jump height. Defining characteristics of cluster 4 are high ankle moments throughout most of the movement cycle, the ability to generate large initial knee moments, and the inability to generate large hip moments (Appendix D). Performance related factors were found in ankle angular velocity (83-100 %), ankle moment (1-99 %), ankle power (66-100 %; Figure 7.6; Table 7.6), concentric knee duration, knee angle (88-100 %), knee angular velocity (71-100 %), knee moment (1-85 %), knee power (12-86 and 95-100 %; Figure 7.6; Table 7.6), hip joint angle (39-100 %), hip angular velocity (79-100 %), hip moment (10-88 %) and hip power (27-88 %; Figure 7.7; Table 7.7).

Table 7.6: List of descriptive statistics of phases that have been identified to be related to performance in subjects of cluster 4 in ankle joint

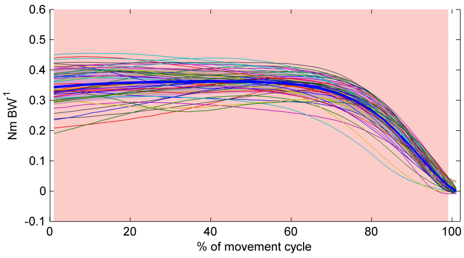
Variable	Key phase			p value	r^2 value	confidence interval		
Ankle Angle Velocity SS PC2	90	to	100	0.001	0.20	0.04	to	0.42
Ankle Angle Velocity SS PC3	83	to	99	0.002	0.18	0.03	to	0.40
Ankle Moment Ankle SS PC1	77	to	99	0.000	0.24	0.06	to	0.45
Ankle Moment Ankle SS PC2	1	to	35	0.000	0.30	0.10	to	0.51
Ankle Moment Ankle SS PC3	43	to	93	0.000	0.39	0.18	to	0.59
Ankle Moment Ankle SS PC4	9	to	74	0.000	0.40	0.18	to	0.60
Ankle Power Ankle SS PC2	83	to	100	0.000	0.34	0.13	to	0.54
Ankle Power Ankle SS PC3	66	to	93	0.000	0.40	0.19	to	0.60
Knee time domain	1	to	100	0.001	-0.15	-0.36	to	-0.02
Knee Angle SS PC1	88	to	100	0.015	-0.13	-0.58	to	-0.08
Knee Angle Velocity SS PC2	91	to	100	0.000	0.44	0.22	to	0.63
Knee Angle Velocity SS PC3	71	to	99	0.000	0.30	0.10	to	0.51
Knee Moment SS PC2	1	to	40	0.006	0.14	0.01	to	0.35
Knee Moment SS PC3	48	to	85	0.001	0.22	0.05	to	0.43
Knee Moment SS PC4	11	to	77	0.000	0.23	0.06	to	0.45
Knee Power SS PC1	95	to	100	0.001	-0.21	-0.43	to	-0.04
Knee Power SS PC2	12	to	61	0.001	0.20	0.04	to	0.42
Knee Power SS PC4	33	to	82	0.000	0.35	0.14	to	0.56
Knee Power SS PC5	66	to	86	0.000	0.24	0.06	to	0.45



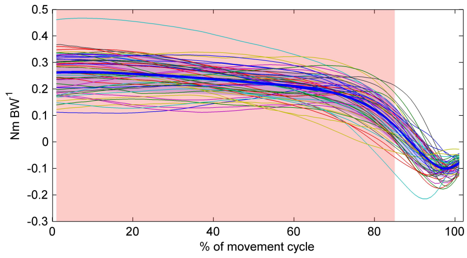
(a) ankle angular velocity



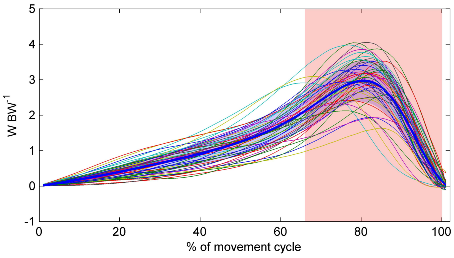
(b) knee angular velocity



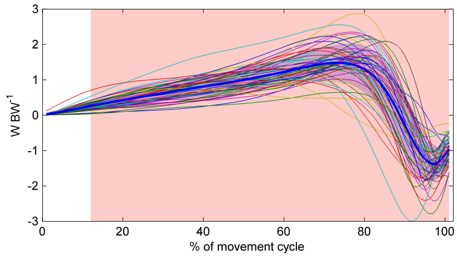
(c) ankle moment



(d) knee moment



(e) ankle power

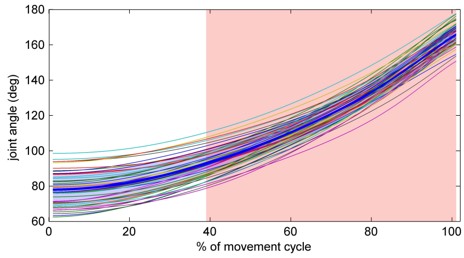


(f) knee power

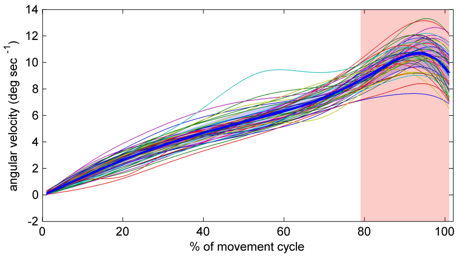
Figure 7.6: Ankle (left) and knee (right) joint kinematics (angular velocity, moment and power) of subjects in cluster 4. Red phases represent key phases with significant correlation to jump height

Table 7.7: List of descriptive statistics of phases that have been identified to be related to performance in subjects of cluster 4 in knee and hip joint

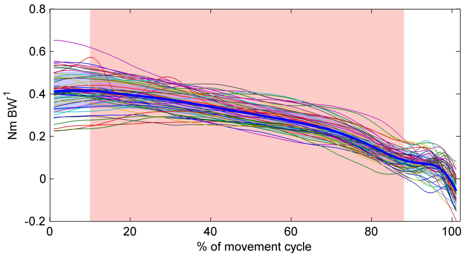
Variable	Key phase			p value	r^2 value	confidence interval		
Hip Angle SS PC1	70	to	100	0.004	-0.16	-0.37	to	-0.02
Hip Angle SS PC2	39	to	96	0.007	-0.14	-0.35	to	-0.01
Hip Angle Velocity SS PC1	92	to	100	0.000	0.23	0.06	to	0.45
Hip Angle Velocity SS PC4	79	to	99	0.001	0.20	0.04	to	0.41
Hip Moment SS PC1	43	to	88	0.000	0.28	0.09	to	0.50
Hip Moment SS PC5	10	to	73	0.000	0.23	0.06	to	0.45
Hip Power SS PC2	57	to	88	0.000	0.30	0.10	to	0.51
Hip Power SS PC6	27	to	75	0.000	0.25	0.06	to	0.46



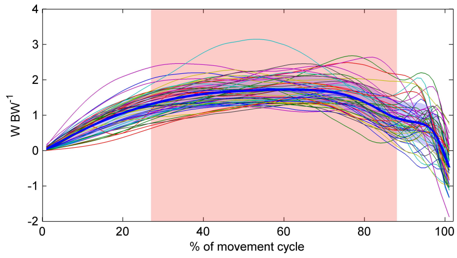
(a) hip angle



(b) hip angular velocity



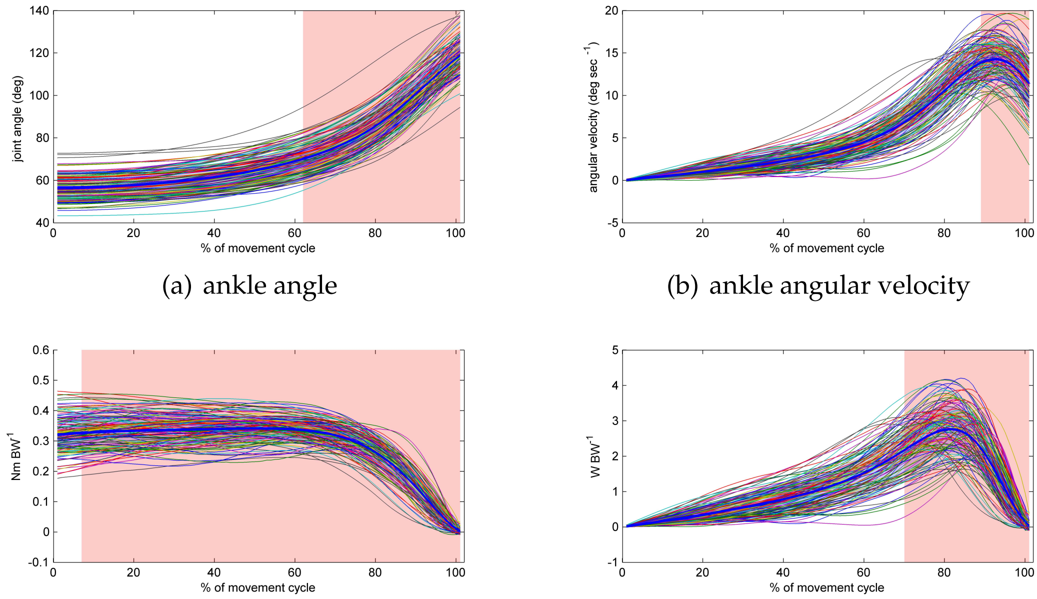
(c) hip moment



(d) hip power

Figure 7.7: Hip joint kinematics (joint angle, angular velocity, moment and power) of subjects in cluster 4. Red phases represent key phases with significant correlation to jump height

Single group analysis: Using the single group analysis, ACP identified performance related factors in ankle joint angle (62-100 %), ankle angular velocity (89-100 %), ankle moment (7-100 %), ankle power (70-100 %; Figure 7.8; Table 7.8), knee joint angle (47-100 %), knee angular velocity (86-100 %), knee moment (1-93 %), knee power (25-92 and 96-100 %; Figure 7.9; Table 7.6), hip joint angle (1-100 %), hip angular velocity (29-100 %), hip moment (1-100 %) and hip power (8-100 %; Figure 7.10; Table 7.7).



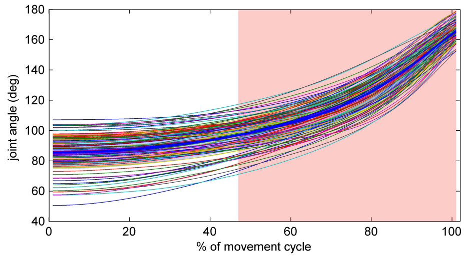
(a) ankle angle

(b) ankle angular velocity

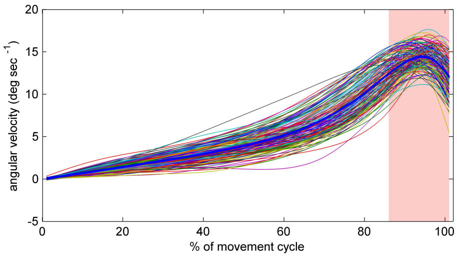
(c) ankle moment

(d) ankle power

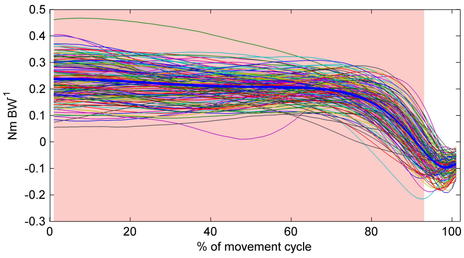
Figure 7.8: Ankle joint kinematics (joint angle, angular velocity, moment and power) using the single group analysis. Red phases represent key phases with significant correlation to jump height



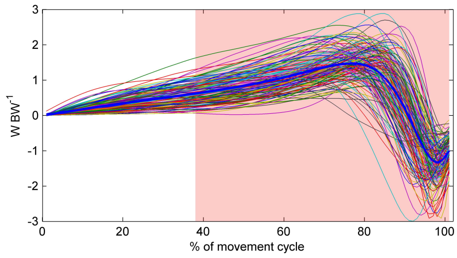
(a) knee angle



(b) knee angular velocity



(c) knee moment

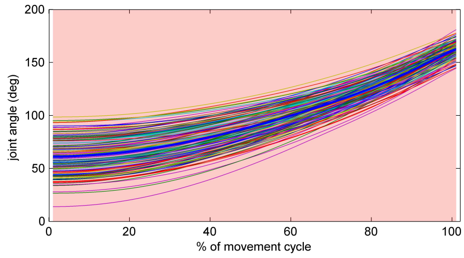


(d) knee power

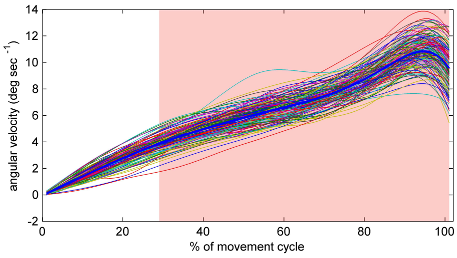
Figure 7.9: Knee joint kinematics (joint angle, angular velocity, moment and power) using the single group analysis. Red phases represent key phases with significant correlation to jump height

Table 7.8: List of descriptive statistics of phases that have been identified to be related to performance using a single group analysis in ankle joint

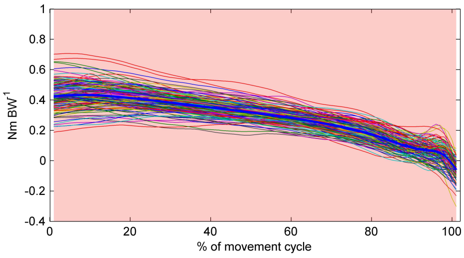
Variable	key phase			p value	r^2 value	confidence interval		
Ankle Angle SS PC1	80	to	100	0.00	-0.27	-0.42	to	-0.09
Ankle Angle SS PC3	62	to	97	0.01	-0.24	-0.40	to	-0.07
Ankle Angle Velocity SS PC2	89	to	100	0.00	0.28	0.11	to	0.44
Ankle Moment SS PC1	69	to	100	0.00	0.52	0.37	to	0.64
Ankle Moment SS PC3	37	to	89	0.00	0.52	0.38	to	0.64
Ankle Moment SS PC4	7	to	66	0.00	0.35	0.19	to	0.50
Ankle Power SS PC2	83	to	100	0.00	0.53	0.39	to	0.64
Ankle Power SS PC3	70	to	92	0.00	0.45	0.30	to	0.58



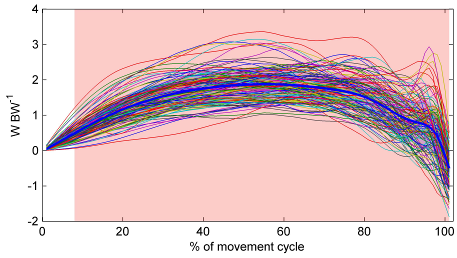
(a) hip angle



(b) hip angular velocity



(c) hip moment



(d) hip power

Figure 7.10: Hip joint kinematics (joint angle, angular velocity, moment and power) using the single group analysis. Red phases represent key phases with significant correlation to jump height

Table 7.9: List of descriptive statistics of phases that have been identified to be related to performance using a single group analysis in knee joint

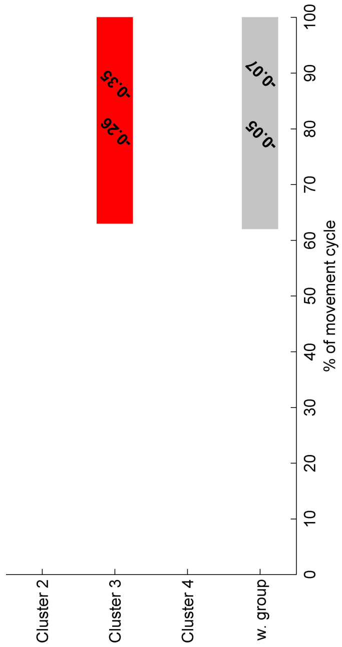
Variable	key phase			p value	r^2 value	confidence interval		
Knee Angle SS PC1	78	to	100	0.00	-0.31	-0.46	to	-0.14
Knee Angle SS PC2	47	to	97	0.01	-0.25	-0.41	to	-0.08
Knee Angle Velocity SS PC1	91	to	100	0.00	0.60	0.47	to	0.70
Knee Angle Velocity SS PC3	86	to	99	0.00	0.50	0.36	to	0.63
Knee Moment SS PC2	11	to	80	0.00	0.34	0.17	to	0.49
Knee Moment SS PC3	51	to	93	0.00	0.42	0.26	to	0.55
Knee Moment SS PC4	1	to	44	0.01	0.22	0.05	to	0.39
Knee Power SS PC1	25	to	38	0.07	0.16	-0.01	to	0.33
Knee Power SS PC2	96	to	100	0.00	-0.38	-0.52	to	-0.22
Knee Power SS PC4	38	to	83	0.00	0.39	0.23	to	0.53
Knee Power SS PC5	67	to	92	0.00	0.44	0.28	to	0.57

Table 7.10: List of descriptive statistics of phases that have been identified to be related to performance using a single group analysis hip joint

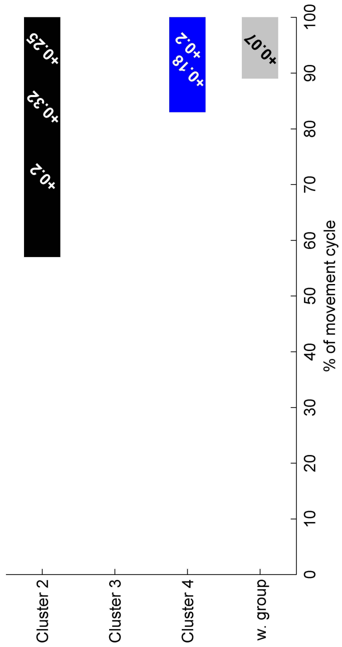
Variable	key phase			p value	r^2 value	confidence interval		
Hip Angle SS PC1	29	to	100	0.00	-0.40	-0.54	to	-0.24
Hip Angle SS PC2	1	to	82	0.00	-0.36	-0.51	to	-0.20
Hip Angle Velocity SS PC1	90	to	100	0.00	0.44	0.29	to	0.57
Hip Angle Velocity SS PC3	73	to	99	0.00	0.38	0.22	to	0.52
Hip Angle Velocity SS PC4	52	to	87	0.00	0.29	0.12	to	0.44
Hip Angle Velocity SS PC5	29	to	70	0.00	0.26	0.08	to	0.41
Hip Moment SS PC1	1	to	24	0.00	0.34	0.17	to	0.49
Hip Moment SS PC2	97	to	100	0.01	0.23	0.06	to	0.39
Hip Moment SS PC3	61	to	90	0.00	0.48	0.33	to	0.61
Hip Moment SS PC5	29	to	81	0.00	0.52	0.37	to	0.64
Hip Moment SS PC6	6	to	57	0.00	0.43	0.28	to	0.57
Hip Power SS PC1	8	to	47	0.00	0.37	0.21	to	0.51
Hip Power SS PC2	96	to	100	0.01	0.23	0.05	to	0.39
Hip Power SS PC3	74	to	91	0.00	0.45	0.30	to	0.58
Hip Power SS PC4	52	to	85	0.00	0.56	0.42	to	0.67
Hip Power SS PC6	23	to	72	0.00	0.49	0.34	to	0.62

The ability to describe jump height using the single group analysis, cluster 1, cluster 2, cluster 3 and cluster 4 was 85 %, 100 %, 96 %, 90 % and 80 %, respectively. The average ability to describe jump height across the subgroups was 91.5 % (the weighted mean[3] was 88 %). Comparing identified performance related factors across the generated clusters and the single group analysis demonstrated some commonalities between the identified factors. However, there were numerous dissimilarities in respect to whether performance related factors were present across clusters / analyses, and if they mapped in the identified phase and their relationship strength (Figure 7.11, 7.12 and 7.13).

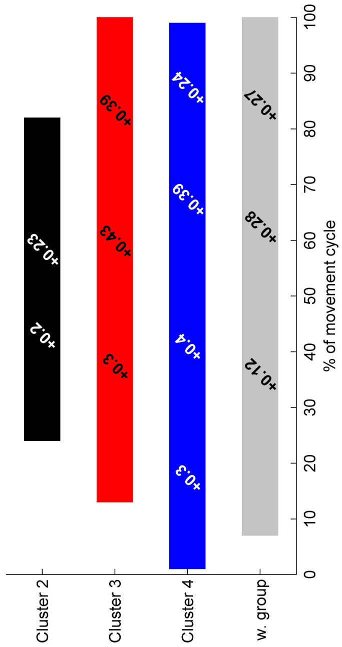
[3]The weighted mean is an average that takes the number of subject and the ability to describe jump height of a cluster into account. The weighted average was calculated as $\sum(\frac{members_{cluster}}{sample\ size\ data\ set)}) * \frac{ability_{clsuter}}{100}$



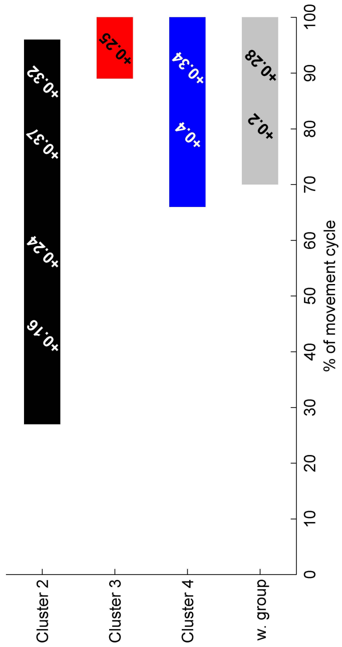
(a) ankle angle



(b) ankle angular velocity

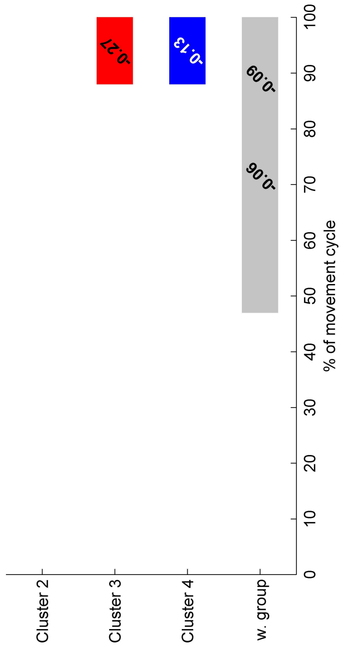


(c) ankle moment

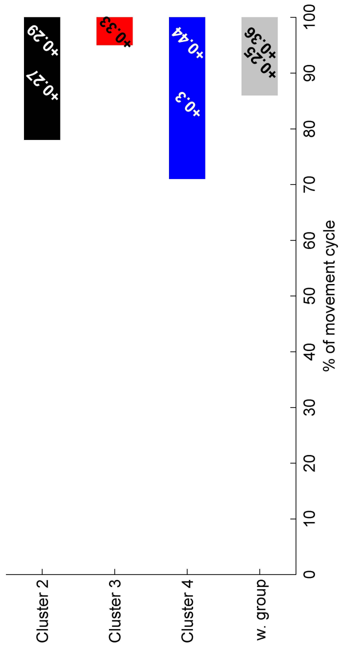


(d) ankle power

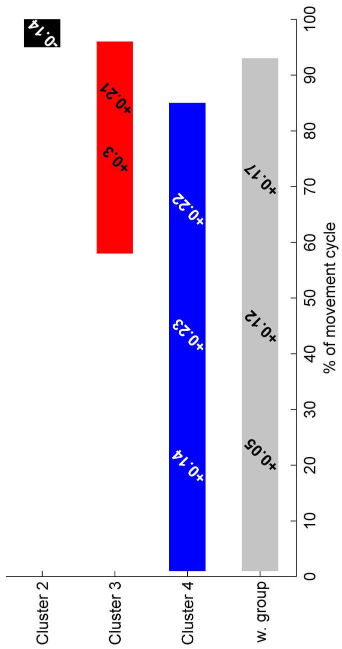
Figure 7.11: Cross comparison of performance related factors identified using a single group and subgroup analysis for kinematic and kinetic variables at the ankle joint



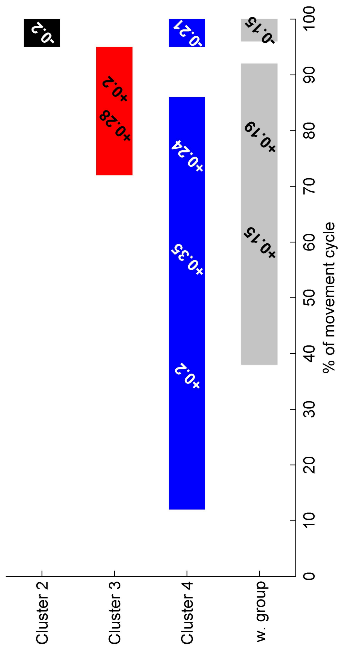
(a) knee angle



(b) knee angular velocity

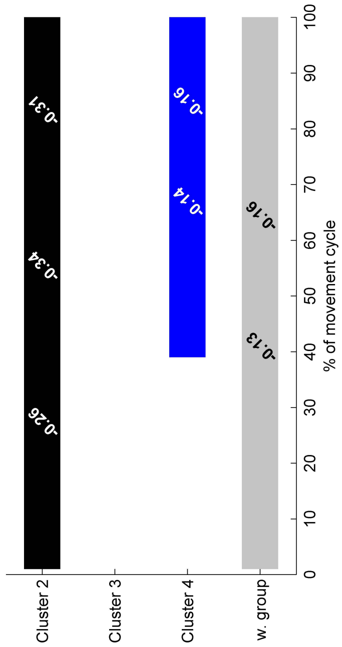


(c) knee moment

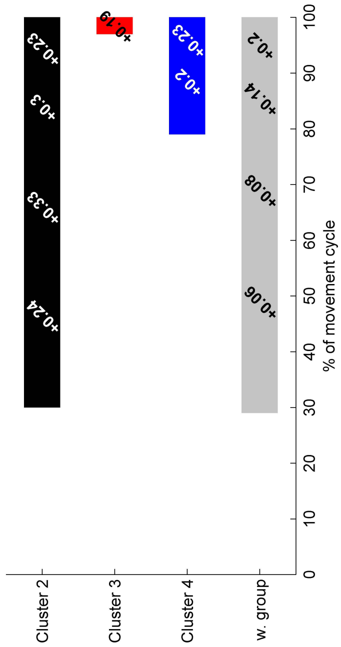


(d) knee power

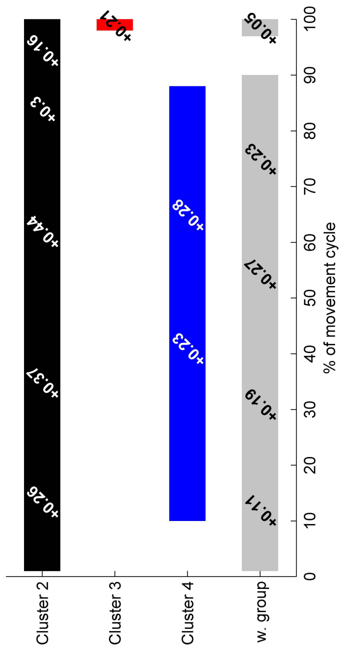
Figure 7.12: Cross comparison of performance related factors identified using a single group and subgroup analysis utilizing kinematic and kinetic variables of the knee joint



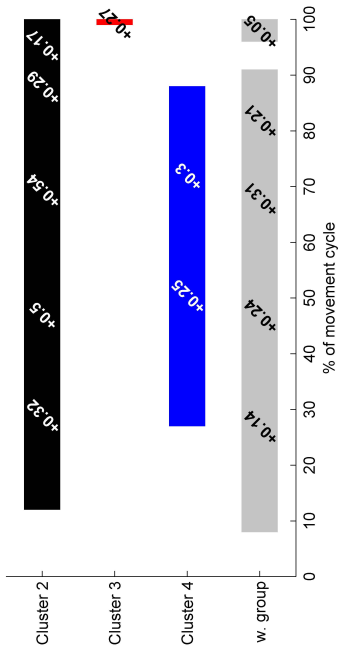
(a) hip angle



(b) hip angular velocity



(c) hip moment



(d) hip power

Figure 7.13: Cross comparison of performance related factors identified using a single group and subgroup analysis utilizing kinematic and kinetic variables of the hip joint

7.4 Discussion

Data clustering While the generated clusters display distinct movement strategies, the order of peak moments and peak powers is identical across the clusters[4]. The hip joint generated consistently the largest peak moments, which is in agreement with previous research (Vanezis and Lees, 2005; Bobbert et al., 1987; Vanrenterghem et al., 2008), and peak moments in the ankle joint were greater than the peak moments in the knee joint (as reported in Vanezis and Lees 2005; AragonVargas and Gross 1997b). Peak power was greatest in the ankle joint (AragonVargas and Gross, 1997b; Bobbert et al., 1986; Vanezis and Lees, 2005; Vanrenterghem et al., 2008) and the hip joint was greater than the knee joint across the clusters (Vanrenterghem et al. 2008, Table 7.11).

Table 7.11: Mean (95 % confidence interval) peak moment and peak power for cluster 2, 3 and 4

		Ankle joint	Knee Joint	Hip Joint	Order
Cluster 2	Peak moment (Nm\BW)	0.34 (0.33-0.35)	0.26 (0.24-0.29)	0.44 (0.42-0.47)	Hip > Ankle > Knee
	Peak power (Nm\BW)	2.87 (2.67-3.08)	1.77 (1.62-1.92)	2.14 (2.00-2.38)	Ankle > Hip > Knee
Cluster 3	Peak moment (Nm\BW)	0.35 (0.34-0.37)	0.21 (0.19-0.24)	0.48 (0.45-0.53)	Hip > Ankle > Knee
	Peak power (Nm\BW)	2.61 (2.40-2.84)	1.57 (1.39-1.74)	2.33 (2.16-2.50)	Ankle > Hip > Knee
Cluster 4	Peak moment (Nm\BW)	0.37 (0.36-0.39)	0.27 (0.25-0.29)	0.43 (0.40-0.45)	Hip > Ankle > Knee
	Peak power (Nm\BW)	3.07 (2.92-3.23)	1.61 (1.48-1.74)	1.84 (1.72-1.97)	Ankle > Hip > Knee

Cluster 2 demonstrated low knee and hip joint angles throughout the movement cycle and the ability to generate large initial knee moments. In addition, subjects were able to maintain high ankle, knee and hip moments for longer, which resulted in ankle, knee and hip peak power occurring closer to takeoff. Further, jump height was significantly higher in cluster 2 compared to cluster 4. Comparing jump heights between cluster 2 and 3 demonstrated the tendency

[4]Cluster 1 is not included in the discussion because of its small sample size (n = 6).

for higher jump heights in cluster 2. It should be noted that the 95 % confidence interval overlapped by only 0.9 cm between these clusters.

In contrast to cluster 2, both clusters 3 and 4 used large joint extension throughout the whole movement cycle in one or more joints, which may has a negative effect to jump height. A joint in greater extension may not be able to generate high moments in the beginning of the movement (strength-length relationship) and might have a limiting effect to generate high joint angle velocity due the rotational moment of inertia. This might explain the better jump performance of cluster 2. Subjects in cluster 3 performed the CMJ using high ankle and knee joint angles throughout the movement cycle and demonstrated an inability to generate large ankle and knee moments. This may be due to too large plantar-flexion in the ankle and knee extension in the latter phase of the jump, resulting in perhaps a less favourable force-length relationship for the muscle (Hill, 1939). Further, while cluster 3 was able to generate large initial hip moments; it was not able to maintain large moments for long. Subjects in cluster 4 generated high ankle moments throughout most of the movement cycle, were able to generate large initial knee moments, but were not able to generate large hip moments. The inability to generate large hip moments may be due to the significantly greater hip joint angles (greater joint extension) in cluster 4 compared to cluster 2 and 3 due possibly to the force-length relationship and/or the smaller range of motion of the hip joint.

The characteristics of cluster 2, 3 and 4 imply differences in performance related factors. For example, decreasing ankle and knee joint extension in cluster 3 may increase the performance outcome, while decreasing the hip joint angle may increase the performance of cluster 4.

Identified performance related factors - Ankle joint The ankle joint angle has a negative, moderate relationship with jump height in cluster 3. The single group analysis identified almost the same phase as cluster 3 to have a negative, but very weak, relationship between joint angle and jump height (63-100 vs. 62-100 %, $r^2 \approx$ -0.31 vs. -0.07). This indicates that the single group analysis was sensitive enough to identify the performance related factor of cluster 3 within the whole group. However, the single group analysis underestimates the influence of the performance related factor for cluster 3, and inappropriately suggests decreasing the joint angles (greater dorsi-flexion) for subjects in cluster 2 and 4. Given that cluster 2 and 4 have already lower joint angles, decreasing their joint angles further might have a negative effect on performance. The difference between cluster 2, 4 and 3 in respect to ankle angle at takeoff might explain why ankle angle at takeoff was not included in one of the best jump height predictor models reported by AragonVargas and Gross (1997b).

For joint angular velocity, larger values during the latter part of the movement cycle were found to be positively related to jump height in clusters 2, 4 and the single group analysis, while differences exist in the identified strength of the relationship. The single group analysis indicates only a weak relationship, cluster 4 indicates a moderate relationship, while cluster 2 indicates a strong relationship. The single group analysis again underestimated the effect of angular velocities in the latter phase of the jump. This is likely due to the effect of cluster 3, where no key phase in joint angular velocity demonstrated a significant relationship to jump height.

Ankle joint moments in the middle of the moment cycle (approximately 20-90 %) demonstrated positive moderate relationships with jump height for clusters 2, 3, 4 and the single group analysis, indicating the importance to maintain high moments to achieve maximal jump height. In contrast to cluster 2, 3 and the single group analysis, initial joint moments in cluster 4 were moderately related to jump height, which highlights the importance of the movement strategies in the loading phase for cluster 4. High initial moments may be generated due to a better use of the loading phase achieved by a greater stretch-shortening cycle[5]. While not examined within the present work, the following loading phase movement strategies may have resulted in high initial moment, as they are associated with enhancements of the stretch-shortening cycle: greater load and speed of stretch (Bosco et al., 1981; Cavagna et al., 1968; Bobbert et al., 1986) as well as short eccentric-concentric coupling times, and a smaller joint range of motion (Moran and Wallace, 2007). Findings of previous studies that examined initial or peak moment do not support the findings of the present work. In the study of AragonVargas and Gross (1997b) neither initial nor peak moment was included in one of the best jump height predictor models. In addition, in the study of Vanezis and Lees (2005) peak moment did not differ between 'poor' and 'good' jumpers.

Performance related factors identified in joint power differed between clusters 2, 4, the single group analysis and cluster 3. While in clusters 2, 4 and the single group analysis the phase *around* peak power was found to be strongly positively related to jump height, in cluster 3 only the phase after peak power was found to be strongly related. The contrast in findings might be related to a large phase shift variation in cluster 3 (Figure 7.4[e]). To examine this possibility, the discrete measure of peak power was analysed, but no significant correlation between peak power and jump height (r^2 = -0.01; p = 0.908) was found. The differences in performance related factors between the clusters might explain differences in previous findings. Vanezis and Lees (2005) identified peak power as a performance related factor, while Vanrenterghem et al. (2004) and AragonVargas and Gross (1997b) did not. This difference between the studies might have been caused by the number of individuals that used a cluster 3 type movement

[5]High initial moments are thought to be an indicator of greater stretch-shortening cycle utilisation (Bobbert et al., 1986; Bosco et al., 1981)

strategy in the studies of Vanezis and Lees (2005), Vanrenterghem et al. (2004) and AragonVargas and Gross (1997b).

Knee joint Knee joint angle had a negative moderate relationship with jump height in the latter phase of the movement in cluster 3, 4 and in the single group analysis. In contrast to the ankle finding, there is no difference in the classification to the strength of the performance related factors, but the single group analysis identified the relationship with jump height 40 % earlier than cluster 3 and 4. This difference may be caused by the combination of high joint angles in cluster 3 and 4. As stated for the ankle angle, the findings of the single group analysis cannot be generalized for cluster 2, which may have a more optimal knee angle. The performance related factors identified in cluster 3 and 4 are in agreement with findings of Chappell and Limpisvasti (2008). Chappell and Limpisvasti (2008) found an increase of the knee angle at takeoff after a 6 week training intervention, which increased jump height in a drop jump. However, findings of cluster 2 are in agreement with the study of AragonVargas and Gross (1997b), who found that knee angles at takeoff are not included in good jump height predictor models. In addition, it should be noted that the difference in magnitude of joint angles between cluster 2 and 3 decreased towards the end of the movement cycle, which implies a greater range of motion in cluster 2. A greater range of motion in cluster 2 implies a greater angular-impulse and greater CoM amplitude, both factors that are related to jump height (Winter 2009 and Cormie et al. 2009, respectively).

Performance related factors in knee angular velocity followed a comparable pattern across clusters 2, 3, 4 and the single group analysis, with similar strength (moderate) but differences in the starting point. The consistency across clusters 2, 3, 4 and the single group analysis indicates the importance of high knee angular velocity when performing a maximal CMJ. To the author's knowledge no previous study has examined the relationship between knee angular velocity and jump height. However, an increase in angular velocity will contribute to greater angular power, and also increase the vertical velocity of the body's centre of mass.

Performance related factors identified in knee moments differ remarkably across the clusters. In cluster 2, knee moments at 95-100 % had a *negative* moderate relationship to jump height. In cluster 3 moments from 58-93 % had a *positive* moderate relationship to jump height, while moments from 1 to ≈90 % in cluster 4 and the single group analysis had a *positive* moderate relationship. Cluster 3, 4 and the single group indicate the importance of the ability to maintain moments throughout the jump, while cluster 4 and the single group also indicate the need to generate high initial moments. High initial moments may be achieved by a greater stretch-shortening cycle in the hip joint (Bobbert et al., 1986; Bosco et al., 1981) and highlight the importance of the movement strategy of the loading phase in cluster 4. In contrast, cluster 2 identified a *negative* relationship between the moments magnitudes at the end of the movement and jump height. Inspecting moment curves visually indicates that moment curves of cluster 2 are highly inconsistent in their shape, and the location of the maximum moment prior to takeoff varies largely (Figure 7.2[d])[6]. Further, it should be noted that, due to the shape variation, no key phase covered the area of the maximum moment prior to takeoff (around 80 %). Hence, the identified performance related factor may reflect the maximum moment prior to takeoff, as the moment decreases rapidly towards takeoff. To test this possibility the discrete measure of maximum moment within 70-100 % was analyzed for its relation to jump height. Significant moderate correlation were found between 'maximum moment 70-100 %' to jump height ($p = 0.035$, $r^2 = 0.11$). To the author's knowledge, previous studies have not reported any discrete measure within knee moments to be a performance related factor. AragonVargas and Gross (1997b) did not identify either initial or peak moment to

[6]A landmark or phase shift registration approach could potentially be applied to overcome this limitation.

be included in a good predictor model of jump height. Vanezis and Lees (2005) did not find differences in peak moment between 'poor' and 'good' performances and visual inspection of plots published by Vanrenterghem et al. (2004) indicate a decrease of peak moment in maximal compared to sub-maximal CMJs (25, 50, 75 and 100 %). The differences between the findings of the present work and previous work are likely caused by the applied data analysis technique. Visual inspection of figure 7.2[d], demonstrates a large variety in moment curve shapes where peak could occur anywhere during the movement cycle. Therefore, the discrete measure 'peak moment' does not represent a comparable neuromuscular capacity across subjects. In contrast, ACP compared only moment variables that represent a comparable neuromuscular capacity across subjects.

Performance related factors identified in knee power demonstrate a similar behaviour to those identified in knee moments. Cluster 3, 4 and the single group analysis identified the area around the peak power as a moderate performance related factor. Differences between cluster 3, 4 and the single group analysis exist solely in the duration before the peak. In contrast, in cluster 2 the declining phase after the peak was positively related to performance, which may relate to peak power. The 'peak power' phase in cluster 2 was not covered by a key phase due to the variations in shape of the power curves. An additional test of peak power in cluster 2 demonstrated a moderate significant correlation with jump height ($p = 0.009$ $r^2 = 0.16$). This is in agreement with AragonVargas and Gross (1997b), who identified peak power to be included within multiple 'good jump height' predictor models.

Hip joint The hip joint angle has a negative moderate relationship with jump height throughout the whole movement cycle for cluster 2 and the single group analysis, but for only the latter 60 % of the movement cycle in cluster 4, and no relation to jump height in cluster 3. The variety of performance related factors reflects the contrast of those in previous research. AragonVargas and Gross (1997b) did not find hip angle at takeoff to be included in a predictor model. Chappell and Limpisvasti (2008) found no change in hip angle at takeoff after a trainings intervention that increased jump height of a drop jump, while Vanrenterghem et al. (2004) reported that the performance of a CMJ is greater with a less upright trunk (+ 10 %) than with an upright trunk (large hip extension angles). In addition, it should be noted that the magnitude of the joint angles between cluster 2 and 4 were significantly different, and decreased towards the end of the movement cycle, which implies a greater range of motion in cluster 2. This may result in a greater angular-impulse, and a greater CoM amplitude; the latter of which is associated with a greater jump height (Cormie et al., 2009).

Hip angular velocity at the latter part of the movement cycles in cluster 2, 3, 4 and the single group was identified as a performance related factor. Differences between them occur in respect of their starting location and their strength. Only cluster 2 demonstrated a strong relationship for hip angular velocity, while the influence in cluster 4 was close to a strong relation.

For joint moments, cluster 2, 4 and the single group analysis were found to hold moderate and strong performance related factors throughout most of the movement cycle; while in cluster 3 performance related factors (moderate) were found for only a short period prior to takeoff. Findings of cluster 2 and the single group analysis are in agreement with the study of AragonVargas and Gross (1997b), who found initial and maximal hip moment to be included in good jump height predictor models. The strength of the relation between maximal hip moment and jump height found by AragonVargas and Gross (1997b) is similar to the correlation strength of this work (r^2 = 0.23 vs. 0.28). In addition, visual inspection of plots published by Vanrenterghem et al. (2004) indicates an increase in initial and peak moment in maximal compared to sub-maximal CMJs (25, 50, 75 and 100 %). In contrast to the findings of the present work, Vanezis and Lees (2005) did not find differences in peak moment between good and poor jumpers.

For joint power, clusters 2, 4 and the single group analysis were found to hold moderate and strong performance related factors throughout most of the movement cycle, while in cluster 3 it was a performance related factor (moderate) for only a short period prior to takeoff. This is in agreement with the study of AragonVargas and Gross (1997b), who found peak hip power to be correlated to jump height with an r^2-value of 0.44, which is slightly higher than that of the present study (≈ 0.30)

Practical implications The variety of identified performance related factors support the assumption that people utilise different movement strategies and that these strategies in turn have different performance related factors. As such, they will require different training interventions. For example, training interventions for cluster 2 should aim to increase the magnitude of ankle kinetics in the middle of the movement cycle, knee kinetics at the very end and the majority of work should focus on increasing the magnitude of hip kinetics over the entire movement cycle. For cluster 3, a training intervention should aim to decrease ankle joint angles (greater dorsi-flexion) and increase the magnitude of knee kinetics at the end. However, training interventions for cluster 4 should focus to increase the magnitude of ankle kinetics, knee kinetics at the start and to increase the ability to maintain magnitudes of knee and hip kinetics in the middle phase. This highlights the benefit of using a subgroup analysis when identifying performance related factors. In contrast to the subgroup analysis, single group analysis does not account for different movement strategies and suggests only one training solution for all subjects. Further, different movement strategies can cause the identification of performance related factors that may decrease the performance of some individual movement strategies. For example, the single group analysis suggested a decrease in ankle joint angle to increase jump height. However, this is only the case for cluster 3, and decreasing the ankle angle (greater dorsi-flexion) in cluster 2 may result in decreasing in jump height. Another limitation of the single group analysis is that a movement strategy can artificially alter the strength of a performance related factor.

It should be noted that the joint angular velocity in the latter phase of the movement cycle was identified as a performance related factor across every joint and each group, except the ankle joint in cluster 3. This highlights the importance of the joint angular velocity towards takeoff, which can be explained by the direct relation of joint angular velocity at takeoff to the CoM velocity at takeoff, which determines jump height (Equation 2.1).

In terms of the employed data analysis techniques, the findings strongly support the use of continuous data analysis techniques. In contrast to continuous data analysis, discrete point analysis requires previous knowledge or experience of the user to identify key measures and can discard important information (Dona et al., 2009; Donoghue et al., 2008). For example, initial and joint angles at takeoff have demonstrated a relation to jump height in this work. To the author's knowledge only one study has examined joint angles at takeoff in the CMJ (AragonVargas and Gross, 1997b), while no study has examined initial joint angles. Consequently, the use of continuous data analysis can locate previously non-examined factors that relate to performance. The comparison of a single group and subgroup analysis demonstrates that the subgroup analysis alone was able to identify performances related factors that reflect specific characteristics of a movement strategy. This ability resulted in a greater capacity to describe variances in jump height (+6 %) and supports the use of a subgroup analysis over a single group level analysis. This is in agreement with previous gait studies who have also concluded that a subgroup analysis is more appropriate than a single group analysis (Stout et al., 1995; Carriero et al., 2009; O'Byrne et al., 1998; Kienast et al., 1999).

The findings of the study clearly show that different subjects (groups of subjects) have different performance related factors. However, jump height in cluster 2 was significantly greater than in cluster 4 and the jump height between cluster 2 and 3 was very close to statistical significance. Additionally, the movement patterns in 3 and 4 indicate limitations in the movement strategy used (large joint extension). The combination of greater jump height in cluster 2 and possible movement strategy limitations may imply that the movement strategy of cluster 2 is a more optimal strategy, which in turn may imply that the movement strategy of cluster 3 and 4 should be altered towards the movement strategy of cluster 2. This requires further examination using a training intervention design.

7.5 Conclusion

Hierarchical clustering utilizing normalized subject scores appears to be the most suitable technique for clustering kinematic and kinetic variables to detect movement patterns in the CMJ. Performance related factors differ across individuals, indicating that different training interventions should be used by different individuals / subgroups. In terms of the benefit of a subgroup analysis, it was able to provide a greater ability to describe jump height and give a much deeper insight into what factors relate to jump height. Consequently, the findings highlight the benefit of performing a subgroup analysis over a single group analysis and explain, at least in part, the contrasting findings between previous studies that examined vertical jumping at a single group level of analysis.

Chapter 8

Conclusion

8.1 Summary

The present work has aimed to enhance the capacity in identifying biomechanical based performance related factors in CMJs.

The performance related factors identified in previous CMJ studies are often inconsistent. One possible reason for this is the data analysis technique commonly used, discrete point analysis, which has significant limitations. Due to these limitations the use of continuous waveform analysis has increased (but is still used relatively little). One of the recommended continuous waveform analysis techniques is functional principal component analysis (fPCA). When employing fPCA the user has to choose a number of factors (n basis, h order and the number of principal component). The number of basis (n basis) and order (h order, degree of freedom - 1) are chosen during the transformation of the discrete observations and might influence the ability of fPCA to describe a dependent variable. Findings of chapter 3 indicated that the choice of n basis and h order have minor influence on fPCA's ability to describe a dependent variable if the functional data has a good fit to the discrete observations. However, chapter 4 demonstrated that the number of examined principal component has a significant influence on fPCA's ability to describe the dependent variable (jump height). The findings demonstrated that principal components that have a small effect on the data variance can have a large impact when describing the dependent variable. In chapter 5, I introduced a self-developed data analysis technique (Analysis of Continuous Phases; ACP) and compared its ability to both discrete point analysis and fPCA in describing a dependent variable. Findings demonstrate the superiority of continuous data analysis techniques (fPCA and ACP) over discrete point analysis, as they hold a ≈ 70 % higher ability to describe a dependent variable. In addition, ACP was more accurate (+ 8 %) than fPCA.

Another possible source of error and inconsistencies in identified performances related factors across previous studies is the commonly used single group analysis design. A single group analysis does not account for different movement strategies across individuals and has the potential to mask performance related factors. A possible solution to a single group analysis is a subgroup analysis, which uses clustering routines to identify different movement strategies. However, it is not clear which clustering techniques are best. In addition, it is unclear if and how the normalisation of the data that feeds into a clustering technique influences the ability to recognize movement strategies. Chapter 6 found that that a k-means approach and a hierarchical clustering approach, utilising normalized subject scores, have the greatest ability to identify different movement strategies. In addition, it was found that employing a subgroup analysis has a higher ability to describe a dependent variable compared to a single group analysis.

In the last chapter (chapter 7) the 'optimal data analysis solution', determined in the above mentioned studies of this PhD, was applied using a frequently employed movement task, the countermovement jump (CMJ). Performance related factors were identified and discussed in relation to previous studies and highlight the use of ACP and the importance of a subgroup analysis.

In conclusion, the findings of this PhD thesis strongly indicate the beneficial use of continuous waveform analysis, especially ACP, in combination with a subgroup analysis.

8.2 Future Research

The present work has highlighted the weakness of discrete point and single group analysis and has presented more powerful data analysis techniques (Analysis of Characterising Phases and subgroup analysis). However, these approaches may still be improved upon, creating a many possibilities for future research to enable the field of biomechanics to accurately identify performance related factors.

Analysis of Characterising Phases Analysis of Characterising Phases as presented in this thesis identifies phases of variation (key phases) using principal components, which identified solely linear patterns of variation within a data set. Relationships between performances related factors and jump height may 'hide' in non-linear patterns of variation within a data set and are not identified. The use of a kernel principal component analysis (a non-linear extension of PCA; Hoffmann 2007) might be able to provide a better insight than (f)PCA. In addition, the use of the Mahalanobis distance as subject scores rather than the generated subject scores (area between curves within key phases) might more accurately identify performance related factors than those found in the present work.

Another highly interesting field of continuous data analysis, which was not part of this thesis, is the use of a landmark or phase shift registration. Performing a registration approach might avoid the re-testing discrete points based on visual inspection of graphs, as it aligns curves to their distinctive characteristics. In addition, the author strongly believes that the benefit of examining the combined magnitude-time domain in registered curves will be much more helpful than in the non-registered curves, which is a research topic in itself.

Subgroup Analysis The chosen clustering solutions may not have been the optimal clustering solution. A factor that may have influenced the ability to detect movement strategies correctly is the high dimensionality of data input. Applying a dimension reduction approach prior to the classification might have a positive effect on the effectiveness of the classification process to identify different movement strategies. In addition, another theory of clustering is the use of fuzzy clustering, where an individual can belong to more than 1 cluster. The use of a fuzzy clustering technique might be more appropriate than the clustering approaches utilised here.

Intervention Study The identified performance related factors represent solely an association between performance outcome and a given phase of the movement cycles and might not have a causative effect. To examine if the identified factors have a cause effect, an intervention study should be performed.

Appendix A

Appendix A: Overview of How to Generate Functional Data

Introduction This section will give an overview how functional data can be generated and is dedicated to the reader who has not worked previously with functional data analysis. For further reading on functional data the reader is referred to the text of Ramsay and Silverman (2002).

The transformation from discrete observations into functional data is conducted using a mathematical model. This model represents a function of a curve [$f(t)$], where constants ($a1, a2, a3$ and $a4$) and individual variables (x, y and z) are represented by a basis system and a matrix of individual computed coefficients, respectively (Equation A.1).

$$f(t) = a_1 x^3(t) + a_2 y^2(t) + a_3 z(t) + a_4(t) \tag{A.1}$$

The Basis System The basis system remains the same across the sample of signals, holding a set of known (constant) functions P_i that are independent from each other. A basis system can contain different types of functions (e.g. monomial or polynomial function) which have different abilities to capture the behaviour of the multiple discrete observations. Ramsay (2006), reports that most functional data analyses involve either a Fourier basis for periodic data or a beta-spline basis (b-spline basis) for non-periodic data. This section will use a beta-spline basis as the example, as a beta-spline basis was used in the present work. The first step in generating a b-spline basis is the division of the basis system into i subintervals which are separated by knots (see Figure A.1). Knots connect a subinterval with the following subinterval, achieving the whole basis system. For example, a b-spline basis with 12 subintervals holds 13 knots. The position of the knots can be expressed by a vector of non-decreasing real numbers (at 0 %, 8.3 %, 16.6 %, 24.9 % ... 100 %), which define the start and end position of each subinterval. Subsequently, after the positions of the knots are known, spline functions for each subinterval have to be computed. These spline functions are represented by polynomial curves of chosen h order (degree of freedom - 1). The value of the h order describes the degree of the polynomial fit within each subinterval created by the polynomial curves. Equation A.2 and A.3 illustrate how to compute these polynomial curves N for each point t within the basis system, while figure A.1 visualizes the generated b-spline basis system.

$$N_i^0(u) = \{^{1, u_i < u < u_{i+1}}_{0, otherwise} \tag{A.2}$$

$$N_i^n(u) = \frac{u - u_{l-1}}{u_{l+n-1} + u_{l-1}} N_l^{n-1}(u) + \frac{u_{l+n} - u}{u_{l+n} + u_l} N_{l+1}^{n-1}(u) \tag{A.3}$$

Matrix of Coefficients After the basis system is computed, individual coefficients have to be calculated for each subinterval for a given signal. The De Boor algorithm can be used to compute these coefficients and can be reviewed in detail in De Boor (1978). The computed coefficients represent the functional data and are used within functional data analysis to extract information from a data set.

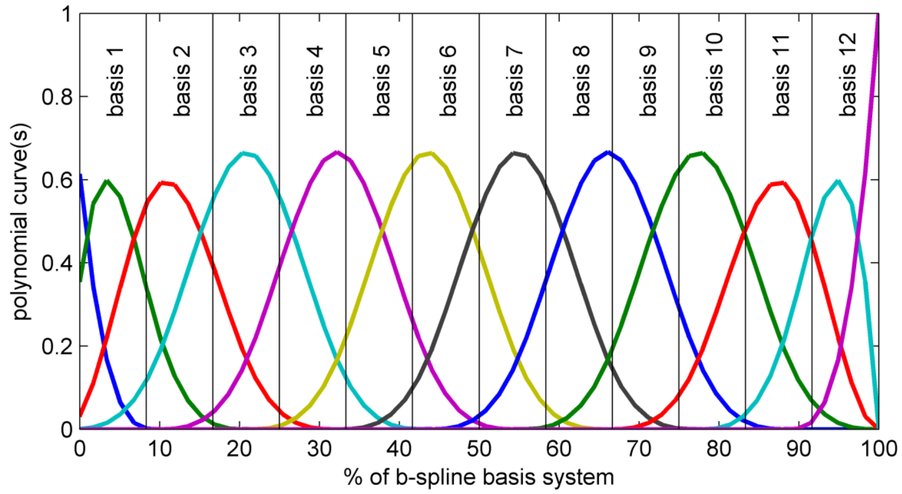


Figure A.1: Example of a b-spline basis system of order 4 with 25 bases over 100 % of the movement cycle

To evaluate a functional duplicate f(x) of a signal, a linear combination (Equation A.4) of basis system N and matrix of coefficients P needs to be conducted (Figure A.2).

$$f(x) = \sum_{j=0}^{L} P_j N_j^n(x) \tag{A.4}$$

To date no study has examined if the number of basis and the degree of freedom affects the ability to describe a dependent variable.

$$P_i^k(u) = (1 - \alpha_i^k) P_i^{k-1}(u) + \alpha_i^j P_i^{k-1} + 1(u) \tag{A.5}$$

with

$$\alpha_i^k = \frac{u - u_{I+i+1}}{u_{I-n+k+i} - u_{I+i+1}} \tag{A.6}$$

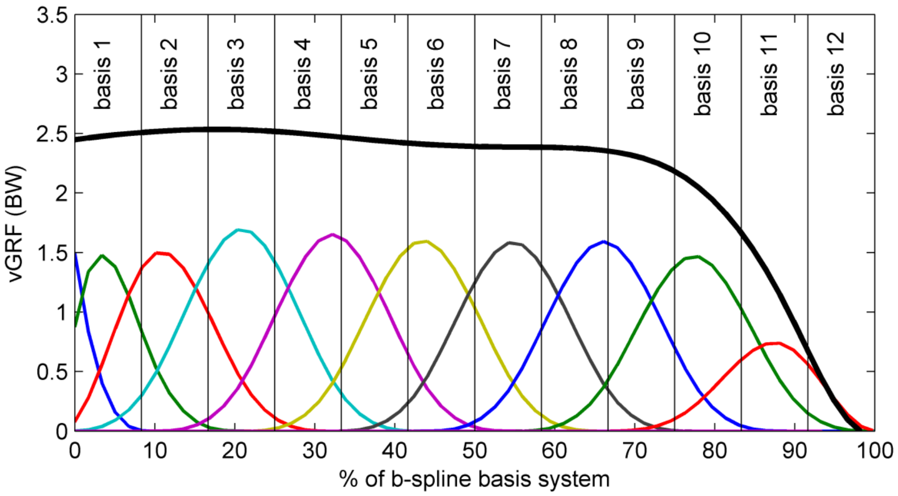


Figure A.2: Example of a b-spline basis system of order 4 with 25 bases over 100 % of the movement cycle and a functional duplicate f(x) of a signal

Appendix B

Appendix B: Overview of How to Perform a (Functional) Principal Component Analysis

Introduction This section will give an introduction to functional principal component analysis (fPCA) and is dedicated to the reader who has not worked previously with fPCA or PCA. For further reading on fPCA/PCA the reader is referred to the text of Jolliffe (2005) or Daffertshofer et al. (2004).

In fPCA, individual computed coefficients (functional data; Appendix A) are used for data analysis. The process of fPCA is explained, using a sample of 42 force curves (Figure B.1) and is separated in five sections: a) model of variance, b) Eigen analysis, c) score generating, d) test of variance and, e) visualisation.

Model of Variance In fPCA, the computed individual coefficients are used to create (in two steps) a variance-covariance matrix to describe the variation in the data, which can been seen as a model of variance. The first step in computing the variance-covariance matrix is to centre the coefficient matrix, achieving a variance matrix (Equation B.1). To achieve a variance matrix (X), the coefficients

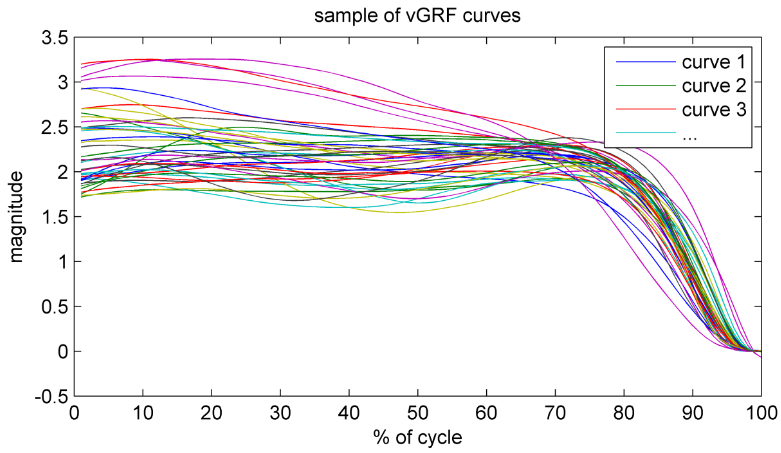


Figure B.1: Sample of 42 force curves to explain the principals of fPCA

(x) of every subinterval (t) and each subject (i), have to be subtracted from the overall mean coefficient (for each in the subinterval; Figure B.2).

$$X_i(t) = \bar{X}(t) - x_i(t) \tag{B.1}$$

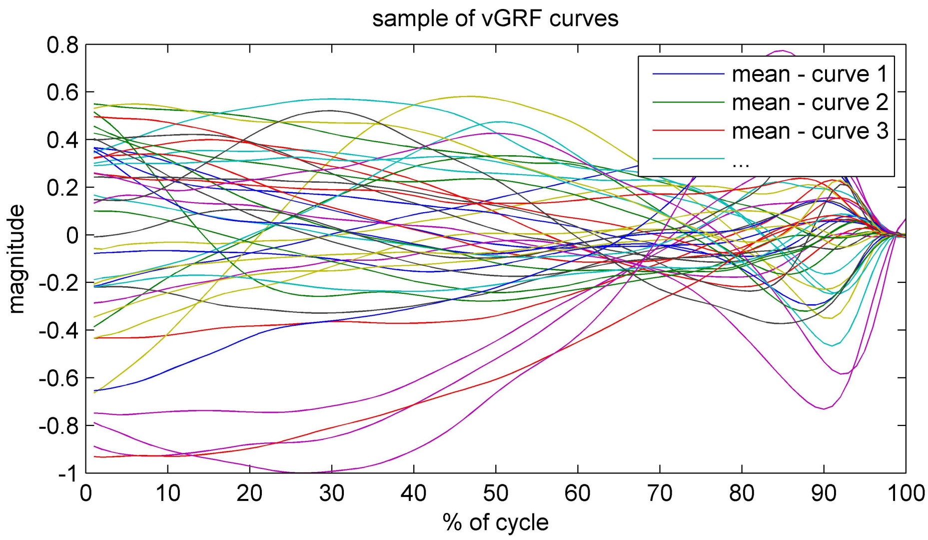


Figure B.2: Variance matrix created using a sample of 42 force curves

The second step to create a variance-covariance matrix is to calculate the covariance from the variance matrix. The covariance matrix V is computed by

Equation B.2, where N is the number of subjects, X the variance matrix and X′ the transposed variance matrix.

$$V = N^{-1} - XX' \tag{B.2}$$

Eigen Analysis To examine the generated model of variance, an Eigen analysis is performed to find a simplified expression of the variance-covariance matrix. This is achieved by solving the Eigen function of the variance-covariance matrix (Equation B.3), which discovers a coordinate system of variance and calculates (a) loadings along the computed axes and (b) scale factors for every generated axis in the coordinate system.

$$V\zeta = \rho\zeta \tag{B.3}$$

The Eigen analysis generates Eigen vectors (ζ), also called principal components, and Eigen values (ρ). Each generated principal components holds a series of loadings to an axis of variance. A loading can represent either a discrete factor (when PCA is applied to discrete data points) or a point in time (when PCA is applied to multiple continuous curve). The Eigen value of a principal component indicates its effect size. The process of solving the Eigen function can be described in three steps.

Firstly, the Eigen analysis generates an axis through the largest variance in the variance covariance matrix.

Secondly, the Eigen analysis computes further linear fits, orthogonal to the axis of largest variance generating a coordinate system of variance.

Thirdly, the Eigen analysis calculates (a) unit measures for each of the identified axes, so called loadings and (b) scale factors (Eigen values) for each of the identified axes of variance (Figure B.3).

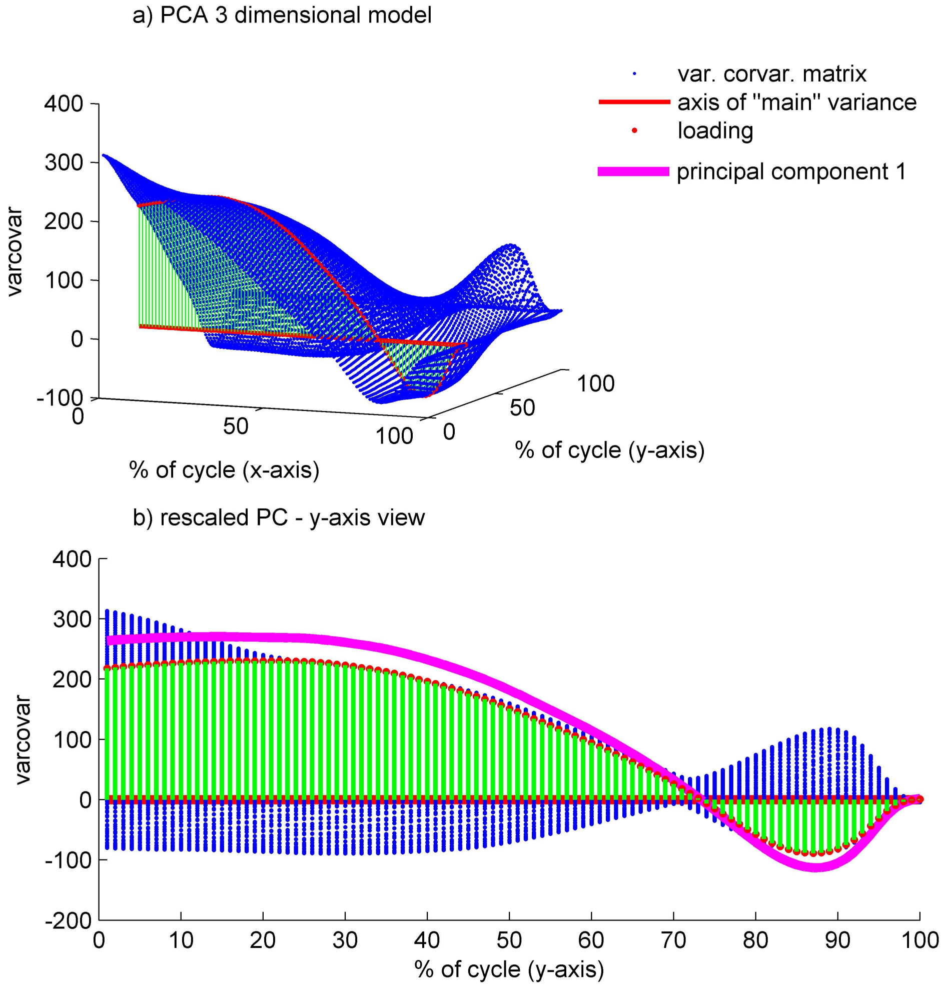


Figure B.3: Model of variance and the generated principal component using the example data. Plot (a) shows the model of variance (blue dots) and linear fit through the largest variance in the variance covariance matrix (straight red line). Plot (b) shows the model of variance, the linear fit through the largest variance and the loadings of the principal component (pink line)

The sum of all Eigen values fully describes the 'length' of the created coordinate system of variance, where each Eigen value indicates the effect size (ES) of its corresponding principal component (i; Equation B.4).

$$ES_i = (\rho_i / \sum \rho) * 100 \tag{B.4}$$

The interested reader is referred to Jolliffe (2005) for further information about the Eigen analysis. A VARIMAX rotation can be applied to both the principal component and Eigenvalue to increase their interpretability (Figure B.4; Donoghue et al. 2008; Harrison et al. 2007; Jolliffe 2005; Ramsay and Silverman 2002; Ramsay 2006; Ryan et al. 2006).

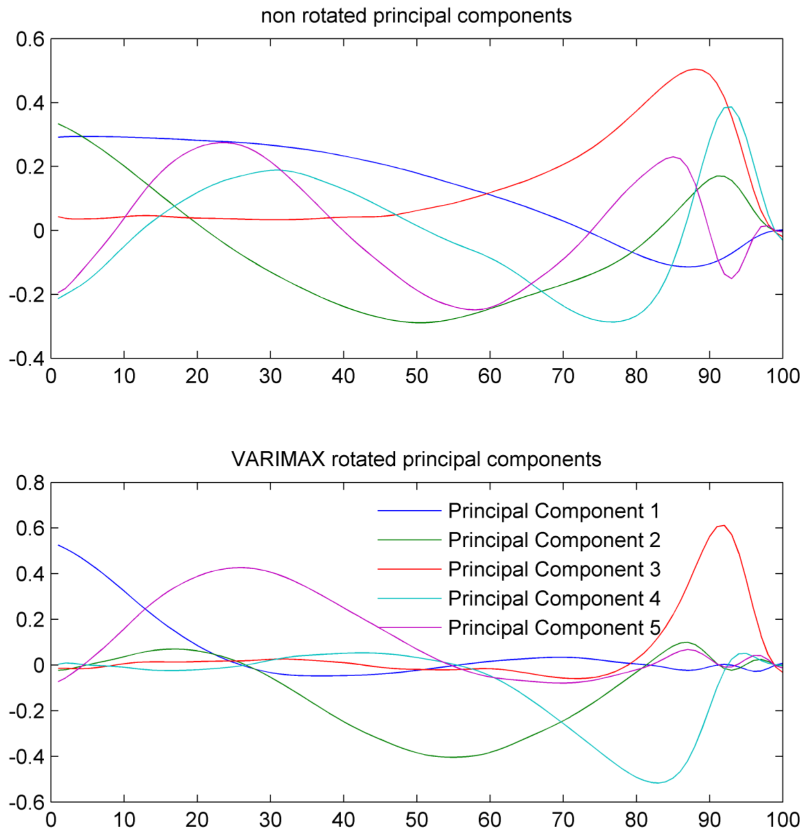


Figure B.4: Generated principal components (top row) and the examined VARIMAX rotated principal components. These five three principal components reflect the five patterns of variance and account together for 99 % of the variance within data

Score Generation The generated principal components give important information about the pattern of variance within the data but not how strong an individual is affected by a pattern. To assess how strong an individual is affected by a pattern, a principal component score has to be calculated (Equation B.5). Principal component scores are generated by the inner product (S) of a principal component (ζ) and variance from the mean of a signal (X) for a principal component (j) and each participant (i). A high principal component score indicates a large influence of the principal component, while the algebraic sign indicates the direction.

$$S_{i,j} = \int \zeta_j X_i \tag{B.5}$$

Figure B.5 illustrates the generation of a principal component score. It can be seen how the principal component score 'grows' over time and how strong it is influenced by the area around the peak in the principal component. A peak in a principal component indicates where the pattern of variance is strongest. Therefore, the use of the inner product of a principal component and the 'variance to the mean' of a curve can give a good indication of how strong a curve is influenced by a pattern of variance.

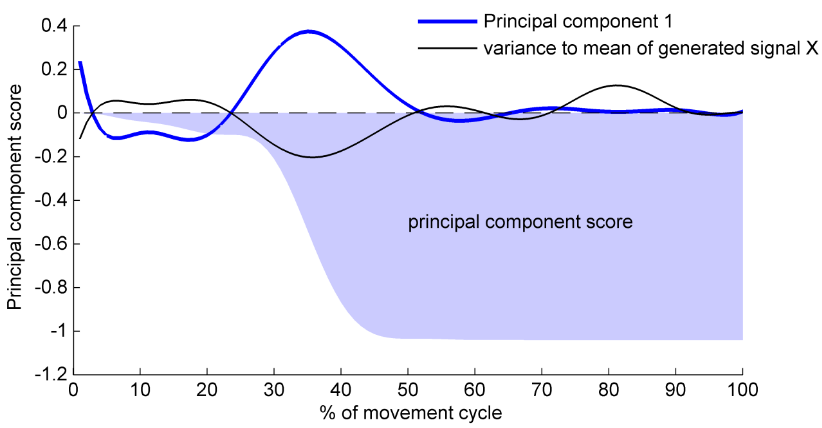


Figure B.5: Visualization of computing a principal component score

After the principal component scores have been computed, fPCA can use a variety of statistical analysis approaches to examine if principal component scores differ between groups (e.g. t-test, ANOVA) or if the principal component scores are related to the dependent variable (e.g. correlation, regression).

Visualisation

The information given by the principal component scores indicates the behaviour of each individual to a pattern of variance. However, principal components and their defined 'pattern of variance' are difficult to interpret without a visualisation tool. Ramsay (2006) suggests creating a plot consisting of three curves: a) the mean of the data, b) a multiple of the principal component added to the mean, and c) a multiple of the principal component subtracted from the mean (Figure B.6).

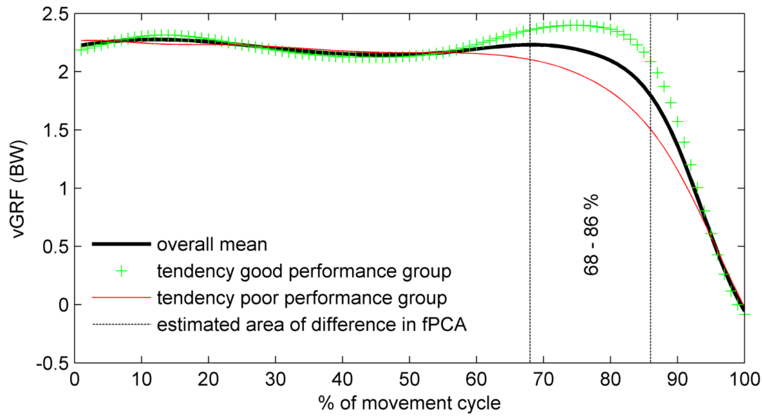


Figure B.6: Visualisation of principal component 1 generated using a sample of 42 force curves

The combination of the information given by principal component scores and the visualization tool allows the interpretation of the pattern of variance (Ramsay, 2006). For example, the sign of the principal component scores indicates the tendency of the behaviour of a subject, while the magnitude indicates how strong the subject is affected be the principal component.

Appendix C

Appendix C: Inverse dynamics

This section gives an overview how inverse dynamics are calculated using a free body diagram for generic body segment (Winter, 2009). As an example serves the shank segment of the used four-segment body model to calculate knee joint reaction forces and knee moments (Figure C.1).

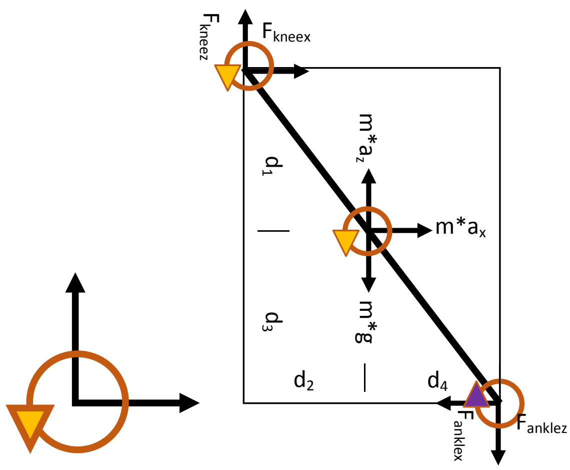


Figure C.1: Free shank segment diagram of the four-segment body model

Anterior-posterior (horizontal) knee joint reaction forces were calculated as follows:

$$\sum F_x = m * a_x \tag{C.1}$$

$$F_{knee_x} - F_{ankle_x} = m * a_x \tag{C.2}$$

$$F_{knee_x} = m * a_x + F_{ankle_x} \tag{C.3}$$

Proximal-distal (vertical) knee joint reaction forces were calculated as follows:

$$\sum F_z = m * a_z \tag{C.4}$$

$$F_{knee_z} - mg - F_{ankle_z} = m * a_z \tag{C.5}$$

$$F_{knee_z} = m * a_z + mg + F_{ankle_z} \tag{C.6}$$

Where F_{knee_x} and F_{knee_z} are knee joint (proximal) reaction force in the x or z direction. F_{ankle_x} and F_{ankle_z} are ankle joint (distal) reaction force in the x or z direction. The acceleration of the CoM shank segment in x and z direction is described by a_x and a_z, while m and g is the mass of segment and gravity, respectively.

Joint moments were calculated as follows were calculated as follows:

$$\sum Moment = -(I * \alpha) \tag{C.7}$$

$$-F_{knee_x} d1 - F_{knee_z} d2 + M_{knee} - F_{ankle_x} d3 - F_{ankle_z} d4 - M_{ankle} = (I * \alpha) \tag{C.8}$$

$$M_{knee} = F_{knee_x} d1 + F_{knee_z} d2 + F_{ankle_x} d3 + F_{ankle_z} d4 + M_{ankle} + (I * \alpha) \tag{C.9}$$

Where M_{knee} is the joint moment at the proximal end, M_{ankle} is the joint moment at the distal end, I is the moment of inertia and α is the segment angular acceleration

Appendix D

Appendix D: Data Classification of Chapter 7

The aim of this Appendix is to inform the reader about the generation and interpretation of the subgroups examined in Chapter 7. Appendix D is separated into two parts. The first part gives general information about the clustering approach and the numbers of cluster chosen to generate subgroups based on the kinematic and kinetic waveforms captured during a CMJ. The second part gives detailed information about differences between the generated clusters.

Part 1

To classify the captured kinematic and kinetic waveforms, subject scores were computed using Analysis of Characterising Phases (see section 5.3). Analysis of Characterising Phases detects phases of variation (key phases) within the sample of curves which are used to generate a subject's score (similarity score). Similarity scores were computed for key phases using the magnitude domain. Similarity scores were determined by calculating the area between a participant's curve (p) and the mean curve across the data set (q) for every point (i) within the key phases (Equation D.1).

$$similarity\ score = \int p_i - q_i \tag{D.1}$$

Key phases were identified using the information generated by the principal components needed to describe 99.5 % of the variances in the data (see section 4.4). To increase the interpretability of the retained principal components a VARIMAX rotation was performed (Harrison et al., 2007; Ramsay and Silverman, 2002).

To classify the data sets the computed similarity scores were input into a hierarchical classification algorithm (hierarchical classification) and a k-means approach (partitional classification) using normalized and non-normalized similarity scores (see section 6.4), and an Expectation-Maximization algorithm (model-based classification) using non-normalized similarity scores. The normalization of the input data was performed by transforming the similarity scores into their correlation matrix (Equation D.2), which quantifies numerically the relationship between them (section 6.4). The correlation matrix (corrMat) between curves was created by calculating the Pearson's r-value for the similarity scores ($SS1, SS2, \ldots, SSz$) for every curve ($i, j = 1, 2, \ldots$ number of curves).

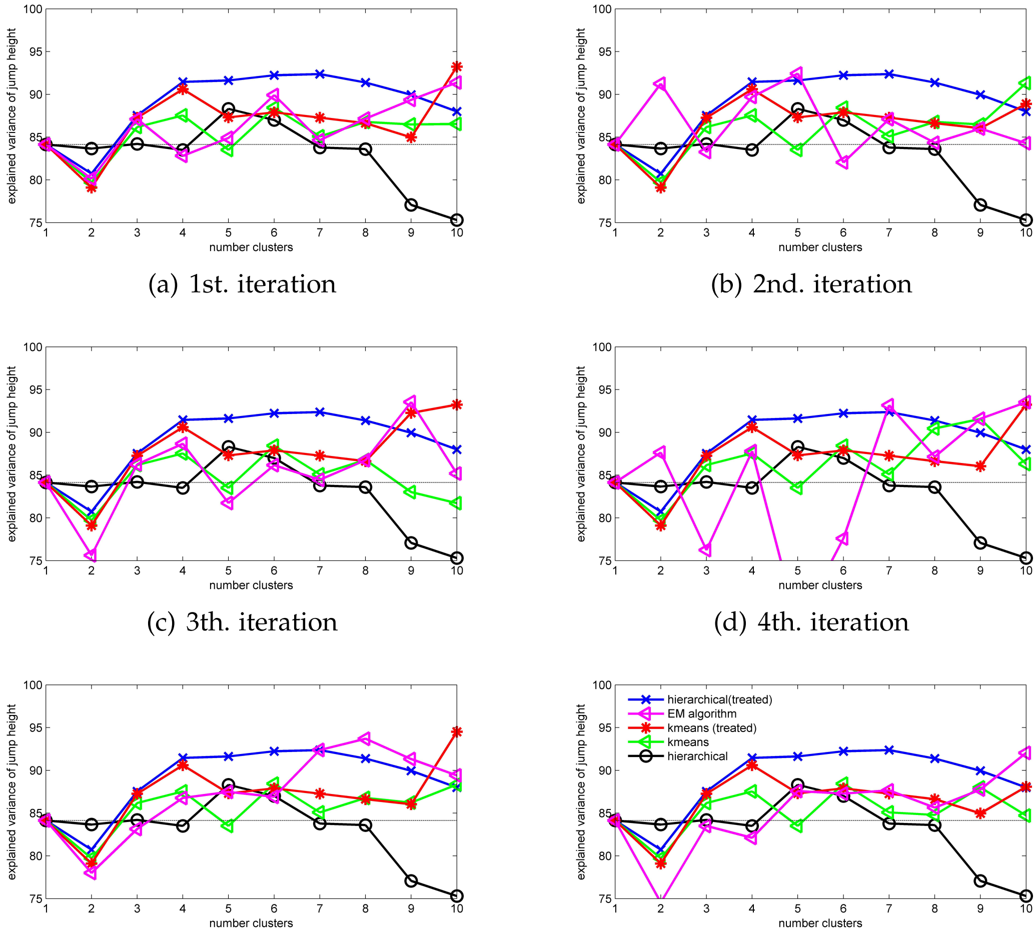
$$corrMat_{(i,j)} = \frac{\sum_{i=1}^{n}(SS1_i - \overline{SS1_{(i,j)}}) \ldots (SSz_i - \overline{SSz_{(i,j)}})}{\sqrt{\sum_{i=1}^{n}(SS1_i - \overline{SS1_{(i,j)}})^2} \ldots \sqrt{(SSz_i - \overline{SSz_{(i,j)}})^2}} \tag{D.2}$$

The hierarchical algorithm calculated pairwise distances using Euclidean distance, and created a hierarchical cluster tree using the nearest distance (Martinez et al., 2004). The k-means classification technique used the Euclidean distance as the distance measure and the Expectation-Maximization algorithm was applied using the Gaussian mixture model (Martinez et al., 2004).

The performance of each cluster technique was measured by assessing the ability to explain variances in jump height (dependent variable) across generated clusters. This approach was based on the assumption that an appropriate grouping of subjects does not mask performance related factors and hence enhances the ability to describe variances in jump height. In order to assess the ability to explain variances in jump height for a given number of clusters the average r^2-value of a stepwise regression analysis was computed across these clusters. Input variables for the regression model were similarity scores measured solely over the key phases of a cluster. If the stepwise regression analysis was not able to identify any predictor variables within a cluster, the highest r^2-value computed during the correlation analysis (between the generated similarity scores and jump height) was used. If a cluster technique assigned only one participant to a cluster, the cluster was discarded. The entire process was repeated 10 times using different random initial weights in the k-means and model based clustering to achieve a repeatable measure of the expected accuracy. The classification technique with x clusters that generated the highest stable ability to explain variances in jump height was considered the most appropriate classification technique for the captured force curves.

Results

Hierarchical clustering (normalized scores) reached its highest stable ability to describe jump height using seven clusters (92 %), k-means (normalized scores) reached its highest stable ability using four clusters (90 %), k-means (non-normalized scores) reached its highest stable ability using six clusters (88 %) and hierarchical clustering (non-normalized scores) reached its highest stable ability to describe jump height using five clusters (88 %). The Expectation-Maximization algorithm did not show a stable ability to describe jump height for any number of clusters (Figure D.1).



(a) 1st. iteration

(b) 2nd. iteration

(c) 3th. iteration

(d) 4th. iteration

(e) 9th. iteration

(f) 10th. iteration

Figure D.1: Ability to describe jump height for the two hierarchical clustering, the two k-means approaches and the Expectation-Maximization (EM) algorithm, at multiple numbers of clusters and for various iterations

Discussion and Conclusion

Hierarchical clustering (normalized scores) with seven clusters was able to describe jump height best. However, varying the number of clusters in hierarchical clustering (normalized scores) between four and eight clusters had no major impact to the ability to explain jump height (1 %), while using four clusters results in greater sample sizes within the clusters. Due to the insignificantly lower ability to describe jump height and the greater sample sizes using four clusters (allowing stronger statistical analysis), the author decided to use hierarchical clustering (normalized scores) with four clusters rather than seven clusters for the analysis.

Part 2

To understand the underlying neuromuscular capacities of the generated clusters the following section performed a one-way ANOVA (Bonferroni adjustment for multiple comparisons) to identify differences between the generated clusters using joint angle, angular velocity, joint moment and joint power of the ankle, knee and hip joint. All statistical analysis was performed using MatLab (R2012a, MathWorks Inc., USA).

Results

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 ($n = 6$) limits the statistical power of the cluster and increases the probability of committing a type II error (Cohen, 1988). Because of its small sample size, cluster 1 was not used in 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 performed regression analysis explained 90 % of the variances in jump height. Cluster 4 contained 51 subjects and the performed regression analysis explained 80 % of the variances in jump height. The statistical analysis for differences between the clusters found significant differences in jump height (cluster 2 > cluster 4; Table D.1) and over numerous key phases in joint angles, angular velocity, joint moment and joint power. Differences between cluster groups are detailed in Table D.2.

Table D.1: Jump height (mean and 95 % confidence interval) of the four generated clusters

	mean	95% confidence interval
Cluster 1	38 cm	30.9 to 45.1
Cluster 2*	41 cm	39.0 to 43.1
Cluster 3	37 cm	34.0 to 39.9
Cluster 4*	37 cm	35.1 to 38.8

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

Table D.2: Significant differences between clusters within kinematic and kinetic variables of the ankle, knee and hip joint

	Ankle Joint		Knee Joint		Hip Joint	
	key phase (%)	differences	key phase (%)	differences	key phase (%)	differences
Joint angle	1-25	cluster 3 > cluster 2, 4	1-25	cluster 3, 4 > cluster 2	1-21	cluster 4 > 3 > cluster 2
	67-84	cluster 3 > cluster 2, 4	67-85	cluster 3, 4 > cluster 2	65-83	cluster 4 > cluster 2, 3
	--	---	--	--		cluster 3 > cluster 2
	98-100	cluster 3 > cluster 2, 4	99-100	cluster 3,4 > cluster 2	99-100	cluster 4 > cluster 2, 3
Angular velocity	--	--	8-19	cluster 4 > cluster 2, 3	--	--
	29-41	cluster 3, 4 > cluster 2	37-50	cluster 4 > cluster 2, 3	31-41	cluster 2, 3 > cluster 4
	54-66	cluster 4 > cluster 2	--	--	51-60	cluster 2, 3 > cluster 4
	--	--	66-79	cluster 3 > cluster 2	--	--
	--	--		cluster 4 > cluster 2	--	--
	81-89	cluster 4 > cluster 2	--	--	--	--
	--	--	99-100	cluster 2 > cluster 3, 4	--	--
Joint moments	1-6	cluster 4 > cluster 2	1-7	cluster 2, 4 > cluster 3	1-6	cluster 3 > cluster 4
	29-45	cluster 4 > cluster 2	34-49	cluster 4 > cluster 2, 3	24-40	cluster 3 > cluster 4
	62-75	cluster 4 > cluster 3	--	--	71-78	cluster 2 > cluster 4
	89-96	cluster 2 > cluster 3, 4	89-95	cluster 2 > cluster 3, 4	85-89	cluster 2 > cluster 4
Joint power	--	--	1-2	cluster 4 > cluster 3	--	--
	9-19	cluster 4 > cluster 2	10-28	cluster 4 > cluster 2, 3	18-31	cluster 3 > cluster 4
	32-44	cluster 3, 4 > cluster 2	--	--	--	--
	57-68	cluster 4 > cluster 2	50-65	cluster 4 > cluster 2	49-60	cluster 2, 3 > cluster 1, 4
	79-86	cluster 4 > cluster 3	--	--	83-88	cluster 2 > cluster 4
	93-98	cluster 2 > cluster 3	91-96	cluster 2 > cluster 3, 4	--	--

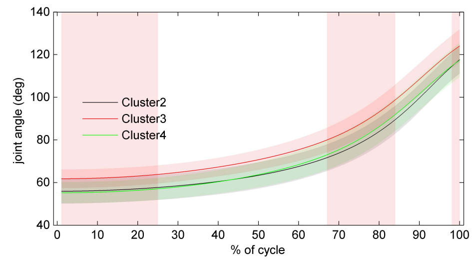
Discussion

Given the diversity and complexity of the findings, they are discussed separately for the ankle, knee and hip joint.

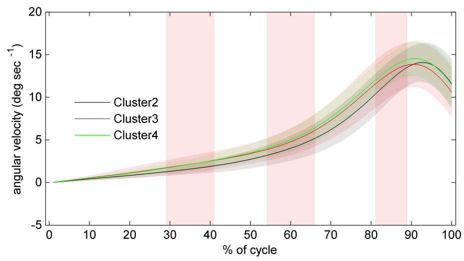
Ankle Joint: Statistical analysis indicated larger ankle joint angles in cluster 3 relative to clusters 2 and 4. Further, visual examination of joint angle curves indicates that cluster 2 and 4 follow an equal joint angle pattern (Figure D.2a). For angular velocity, cluster 4 had larger magnitudes than cluster 2 for $\approx$ most of the movement cycle over the phase 30-90 %. Cluster 3 had larger magnitudes than cluster 2 for 29-41 %. Visual examination of angular velocity curves indicates that cluster 3 and 4 follow a similar pattern. However, cluster 3 is not able to match the increase in slope of cluster 4 (visible at approximately 60 %). In terms of peak velocity, cluster 2, 3 and 4 have similar peak values (Figure D.2b).

For the ankle moment, findings indicate differences in initial magnitudes and the ability to maintain high moments. In the beginning of the movement cycle cluster 4 generates greater moments than cluster 2 (for much of the phase between 1 and 45 %). Visual examination of ankle moment indicates that cluster 3 tends generate moments between the magnitudes of cluster 2 and 4 (Figure D.2c). Cluster 3 and 4 are similar in curve shape and are not able to maintain moment as well as cluster 2 in the end of the movement. Cluster 3 losses the ability to maintain high moment earlier than cluster 4 ($\approx$ 59 vs. 75 %), which results in significant lower moments for the phase of 62-75% (cluster 4 > cluster 3). The ability of cluster 2 to maintain moments is indicated by significant largest moments for 89-96% of the movement cycle (cluster 2 > cluster 3, 4).

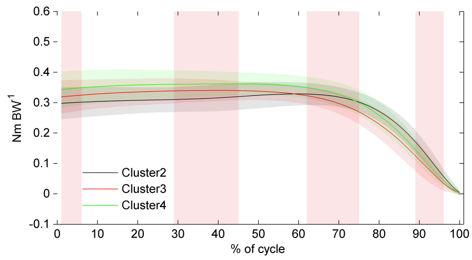
For ankle power, cluster 4 demonstrated higher ankle powers than cluster 2 for much of the phase between 9 and 68 %. Cluster 3, similar to cluster 4 demonstrated higher power magnitudes than cluster 2 in the first part of the jump (32-43 %). However, cluster 3 does not match the high positive slope of cluster 4, which results in lower power magnitude in the area around peak power (79-86%). An additional analysis of the discrete measure peak power supported this interpretation. Cluster 2 demonstrated higher power values than cluster 3 in the phase prior to takeoff. The difference between cluster 2 and 3 is caused by the tendency of cluster 2 to generate a greater and delayed peak. An additional test of the position (in %) of peak power indicated differences between cluster 2, 3 and 4 (cluster 2 > cluster 3, 4).



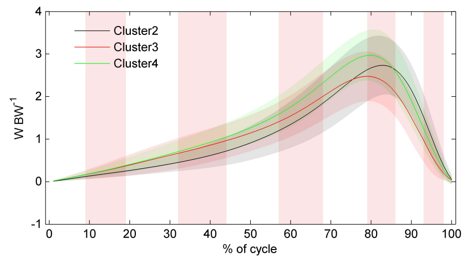
(a) joint angle



(b) angular velocity



(c) moment

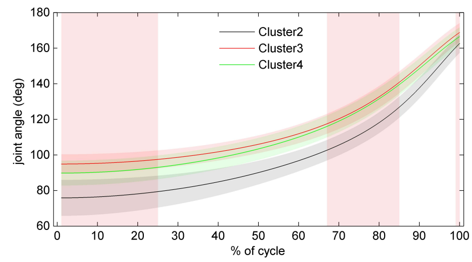


(d) power

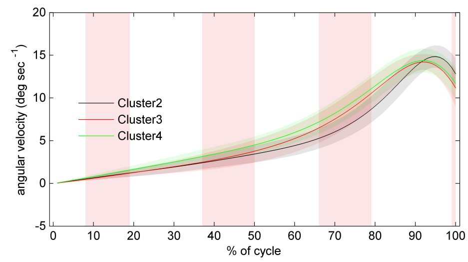
Figure D.2: Ankle joint kinematics and kinetics; red shaded area represent a key phase with significant differences between two or more clusters

Knee Joint: The analysis of knee joint angles indicated larger angles (larger extension) in cluster 3 and 4 compared to cluster 2 throughout much of movement cycle. Angular velocity was greater in cluster 4 than cluster 2 and 3 for the first part of the jump a lot of the phase between 8-50 %, greater in cluster 3 and 4 than cluster 2 for the middle part of the jump (66-79 %) and greater in cluster 2 than cluster 3 and 4 in the end of the movement cycle (99-100 %). The difference between the clusters can be explained, based on visual examination, by differences in the location of when the velocity starts to increase. Cluster 2 increased its velocity at approximately 66 % and cluster 3 at approximately 50 %, while cluster 4 maintains a similar rate of velocity development, which is highlighted by the position of the peak velocity (Figure D.3b). An additional test of the discrete measure position of peak velocity indicated differences between cluster 2, 3 and 4 (cluster 2 > cluster 3, 4).

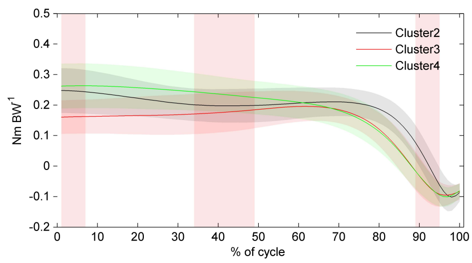
Initial knee moment were smallest in cluster 3 (1-7 %, cluster 2,4 > cluster 3), moments in the middle of the movement cycle were greatest in cluster 4 (34-49 %, cluster 4 > cluster 2, 3) and knee moments at the end were greatest in cluster 2 (89-95 %, cluster 2 > cluster 3, 4). This indicates that cluster 2 and 4 have similar initial moment magnitudes. For cluster 2, moments drop to similar magnitudes observed in cluster 3 shortly after the start, while cluster 4 is able the maintain high moments for longer (approximately 65 %; Figure D.3c). From approximately 65 %, cluster 2 is able to maintain moments towards the end of the movement cycle, while cluster 3 and 4 are not (89-95 %, cluster 2 > cluster 3, 4).



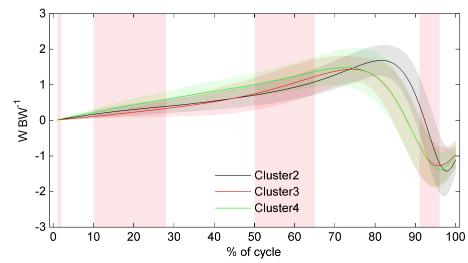
(a) joint angle



(b) angular velocity



(c) moment



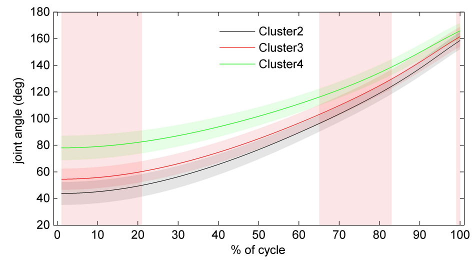
(d) power

Figure D.3: Knee joint kinematics and kinetics; red shaded area represent a key phase with significant differences between two or more clusters

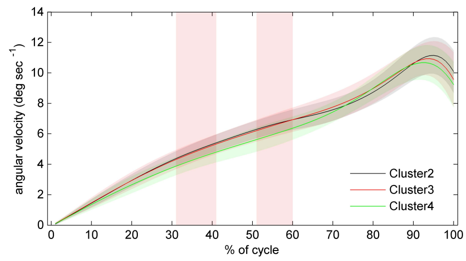
Hip Joint: The analysis of hip joint angles indicated larger angles in cluster 4 than cluster 2. Cluster 4 demonstrated significantly greater joint angles (knee joint extension) over much of the movement cycle (cluster 4 > cluster 2, 3 for much of the phase between 1 and 100 %).

Angular velocity was greater in cluster 2 and 3 compared to cluster 4 over most of the 31-60 % phase (Figure D.4b).

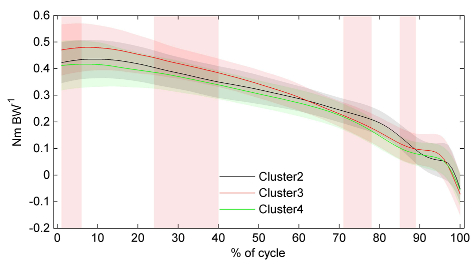
Hip moments were larger in cluster 3 for much of the phase from 1-40 % (cluster 3 > cluster 4) and largest in cluster 2 for most of the 71-89 % part of the jump (cluster 2 > cluster 3). While cluster 3 was able to generate high initial moments (cluster 3 > cluster 4 for 1-40 %), it is not able to maintain them. In contrast, cluster 2 demonstrated medium initial moments but greater ability to maintain them (cluster 2 > cluster 4 for 71-89 %). Based on visual examination, moments of cluster 4 tends to be the smaller throughout the movement cycle (Figure D.4d).



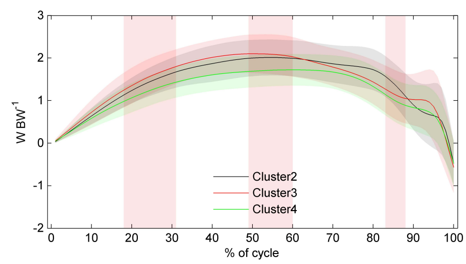
(a) joint angle



(b) angular velocity



(c) moment



(d) power

Figure D.4: Hip joint kinematics and kinetics; red shaded area represent a key phase with significant differences between two or more clusters

Conclusion

Defining characteristics of cluster 2 are low knee and hip joint angles (greater joint flexion), the ability to generate large knee moments, to maintain hip moments towards the end of the movement cycle and a delayed ankle, knee and hip peak power.

Defining characteristics of cluster 3 are high ankle and knee joint angles (greater joint extension) throughout the movement cycle, the inability to generate large ankle and knee moments, the ability to generate large initial hip moments and the inability to maintain large moments towards the end of the movement cycle.

Defining characteristics of cluster 4 are high ankle moment throughout much of the movement cycle, the ability to generate large initial knee moments, and the inability to generate large hip moments.

Bibliography

AragonVargas, L. E. and Gross, M. M. (1997a). Kinesiological factors in vertical jump performance: differences within individuals. *Journal of applied Biomechanics*, 13:45 – 65.

AragonVargas, L. F. and Gross, M. M. (1997b). Kinesiological Factors in Vertical Jump Performance : Differences Among Individuals. *Journal of applied Biomechanics*, 13(1):24–44.

Backman, C. and Harris, S. (1999). Case studies, single-subject research, and N of 1 randomized trials: comparisons and contrasts. *Am J Phys Med Rehabil*, 78(2):170–176.

Bates, B. T. (1996). Single-subject methodology: an alternative approach. *Medicine & Science in Sports & Exercise*, 28(5):631–638.

Bobbert, M. F., Gerritsen, K. G., Litjens, M. C., and Van Soest, A. J. (1996). Why is countermovement jump height greater than squat jump height? *Medicine and science in sports and exercise*, 28:1402–1412.

Bobbert, M. F., Huijing, P. A., and van Ingen Schenau, G. J. (1987). Drop jumping. I. The influence of jumping technique on the biomechanics of jumping. *Medicine and Science in Sport and Exercise*, 19(4):332–338.

Bobbert, M. F., Mackay, M., Schinkelshoek, D., Huijing, P. A., and Schenau, G. J. V. I. (1986). Biomechanical analysis of drop and countermovement jumps. *European journal of applied physiology and occupational physiology*, 54(6):566–573.

Bobbert, M. F. and Van Soest, A. J. (1994). Bobbert,1994_Effects of muscle strengthening on vertical jump height a simulation study.pdf. *Medicine and Science in Sports and Exercise*, 26(8):1012–1020.

Bosco, C., Komi, P. V., and Ito, A. (1981). Prestretch potentiation of human skeletal muscle during ballistic movement. *Acta Physiologica Scandinavica*, 111(2):135–140.

Carriero, A., Zavatsky, A., Stebbins, J., Theologis, T., and Shefelbine, S. J. (2009). Determination of gait patterns in children with spastic diplegic cerebral palsy using principal components. *Gait & posture*, 29(1):71–75.

Carugo, O. and Eisenhaber, F. (2010). *Data mining techniques for the life sciences*. Human Press.

Cavagna, G. A., Dusman, B., and Margaria, R. (1968). Positive work done by a previously stretched muscle. *Journal of Applied Physiology*, 24(1):21–32.

Chappell, J. D. and Limpisvasti, O. (2008). Effect of a neuromuscular training program on the kinetics and kinematics of jumping tasks. *The American journal of sports medicine*, 36(6):1081–6.

Chau, T. (2001a). A review of analytical techniques for gait data. Part 1: fuzzy, statistical and fractal methods. *Gait & Posture*, 13(1):49–66.

Chau, T. (2001b). A review of analytical techniques for gait data. Part 2: neural network and wavelet methods. *Gait & Posture*, 13(2):102–120.

Coffey, N., Harrison, A. J., Donoghue, O. A., and Hayes, K. (2011). Common functional principal components analysis: a new approach to analyzing human movement data. *Human movement science*, 30(6):1144–1166.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciencies*. Routledge.

Cormie, P., McBride, J. M., and McCaulley, G. O. (2009). Power-time, force-time, and velocity-time curve analysis of the countermovement jump: impact of training. *The Journal of Strength & Conditioning Research*, 23(1):177–186.

Crane, E. A., Cassidy, R. B., Rothman, E. D., and Gerstner, G. E. (2010). Effect of registration on cyclical kinematic data. *Journal of biomechanics*, 43(12):2444–2447.

Daffertshofer, A., Lamoth, C. J., Meijer, O. G., and Beek, P. J. (2004). PCA in studying coordination and variability: a tutorial. *Clinical Biomechanics*, 19(4):415–428.

De Boor, C. (1978). *A Practical Guide to Splines*, volume 27 of *Appl. Math. Sci.* Springer-Verlag., New York.

Deluzio, K. and Astephen, J. (2007). Biomechanical features of gait waveform data associated with knee osteoarthritis: an application of principal component analysis. *Gait & posture*, 25(1):86–93.

Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society.*, Series B((Methodological)):1–38.

Dixon, P., Stebbins, J., Theologis, T., and Zavatsky, A. (2013). Spatio-temporal parameters and lower-limb kinematics of turning gait in typically developing children. *Gait & Posture*, xxx(xxx):xxx.

Dona, G., Preatoni, E., and Cobelli, C. (2009). Application of functional principal component analysis in race walking: an emerging methodology. *Sports Biomechanics*, 8(4):284–301.

Donoghue, O. A., Harrison, A. J., Coffey, N., and Hayes, K. (2008). Functional data analysis of running kinematics in chronic Achilles tendon injury. *Medicine and science in sports and exercise*, 40(7):1323–35.

Dowling, J. J. and Vamos, L. (1993). Identification of kinetic and temporal factors related to vertical jump performance. *Journal of Applied Biomechanics*, 9(2):95–110.

Duhamel, A., Bourriez, J., Devos, P., Krystkowiak, P., Destee, A., Derambure, P., and Al., E. (2004). Statistical tools for clinical gait analysis. *Gait and Posture*, 20:204–212.

Eilers, P. H. and Marx, B. D. (1996). Flexible smoothing with B-splines and penalties. *Statistical science*, pages 89–102.

Epifanio, I., Avila, C., Page, A., and Atienza, C. (2008). Analysis of multiple waveforms by means of functional principal component analysis: normal versus pathological patterns in sit-to-stand movement. *Medical & biological engineering & computing*, 46(6):551–61.

Everitt, B., Landau, S., Leese, M., and Stahl, D. (2011). *Cluster Analysis*. Wiley, 5th. edition.

Feltner, M. E. and MacRae, P. G. (2011). Time Course of Changes in Novice Jumpers' Countermovement Vertical Jump Performance 1,2. *Perceptual and Motor Skills*, 112(1):228–242.

Ferraty, F. (2011). *Recent Advances in Functional Data Analysis and Related Topics*. Springer.

Floría, P. and Harrison, A. J. (2013). Ground Reaction Force Differences in the Countermovement Jump in Girls With Different Levels of Performance. *Research Quarterly for Exercise and Sport*, 84(3):329–335.

Gelman, A. and Hill, J. (2007). *Data analysis using regression and multi-level/hierarchical models*. ambridge University Press.

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

Han, J., Kamber, M., and Pei, J. (2006). *Data mining: concepts and techniques*. Morgan kaufmann.

Harman, E. A., Rosenstein, M. T., Frykman, P. N., and Rosenstein, R. M. (1990). The effects of arms and countermovement on vertical jumping. *Med Sci Sports Exerc*, 22(6):825–33.

Harrison, A. J., Ryan, W., and Hayes, K. (2007). Functional data analysis of joint coordination in the development of vertical jump performance. *Sports biomechanics / International Society of Biomechanics in Sports*, 6(2):199–214.

Hastie, T., Tibshirani, R., and Friedman, J. (2001). *The elements of statistical learning*. Springer, New York.

Hill, A. V. (1939). The mechanical efficiency of frog's muscle. *Proceedings of the Royal Society of London. Series B, Biological Sciences*, 127(849):434–451.

Hoffmann, H. (2007). Kernel PCA for novelty detection. *Pattern Recognition*, 40(3):863–874.

Howell, D. C. (2012). *Statistical methods for psychology*. adsworth Publishing Company.

Hubley, C. L. and Wells, R. P. (1983). A work-energy approach to determine individual joint contributions to vertical jump performance. *European Journal of Applied Physiology*, 50(2):247–254.

Jain, A., Murty, M., and Flynn, P. (1999). Data clustering: a review. *ACM computing surveys (CSUR)*, 31(3):264–323.

Jaques, J. and Preda, C. (2013). Functional data clustering: a survey. Technical report, Research Centre Lille Nord Europe, Lille, France.

Jolliffe, I. (2005). *Principal component analysis*. John Wiley & Sons.

Kaufman, L. and Rousseeuw, P. J. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis*. John Wiley & Sons, New York.

Kelso, J. A. (1995). *Dynamic Patterns: The Self Organization of Brain and Behaviour*. The MIT Press.

Kienast, G., Bachmann, D., Steinwender, G., Zwick, E. B., and Saraph, V. (1999). Determination of gait patterns in children with cerebral palsy using cluster analysis. *Gait & Posture*, 10(1):57.

Klavora, P. (2000). Vertical-jump Tests: A Critical Review. *Strength and Conditioning Journal*, 22(5):70.

Kollias, I., Panoutsakopoulos, V., and Papaiakovou, G. (2004). Comparing jumping ability among athletes of various sports: vertical drop jumping from 60 centimeters. *The Journal of Strength & Conditioning Research*, 18(3):546–550.

Laffaye, G. and Choukou, M. A. (2010). Gender bias in the effect of dropping height on jumping performance in volleyball players. *The Journal of Strength & Conditioning Research*, 24(8):2143–2148.

Laffaye, G. and Wagner, P. (2013). Eccentric rate of force development determines jumping performance. *Computer methods in biomechanics and biomedical engineering*, 16(1):82ß83.

Larsen, W. A. and McCleary, S. J. (1972). The use of partial residual plots in regression analysis. *Technometrics*, 14(3):781–790.

Lees, A. (2002). Technique analysis in sports: a critical review. *Journal of Sports Sciences*, 20(10):813–828.

Lenhoff, M., Santner, T., Otis, J., Peterson, M., Williams, B., and Backus, S. (1999). Bootstrap prediction and confidence bands: a superior statistical method for analysis of gait data. *Gait and Posture*, 9:10–17.

Mantovani, G., Lamontagne, M., Varin, D., Cerulli, G. G., and Beaulé, P. E. (2011). Is principal component analysis more efficient to detect differences on biomechanical variables between groups? In *ISBS-Conference Proceedings Archive*, volume 11, pages 911–914.

Marshall, B. (2010). *Can a pre-training biomechanical pathway identify the most effective exercise to enhance a given groups, subgroups or individuals countermovement jump height ?* . Phd, Dublin City University.

Martinez, W., Martinez, A., and Solka, J. (2004). *Exploratory data analysis with MATLAB*. CRC Press.

McBride, J. M., Triplett-McBride, T., Davie, A., and Newton, R. U. (2002). The effect of heavy- vs. light-load jump squats on the development of strength, power, and speed. *Journal of strength and conditioning research / National Strength & Conditioning Association*, 16(1):75–82.

McLachlan, G. and Peel D. (2000). *Finite Mixture Models*. John Wiley & Sons, New York.

Meylan, C. M. P., Nosaka, K., Green, J., and Cronin, J. B. (2010). Temporal and kinetic analysis of unilateral jumping in the vertical, horizontal, and lateral directions. *Journal of sports sciences*, 28(5):545–54.

Mojena, R. (1977). Hierarchical grouping methods and stopping rules: An evaluation. *Computer Journal*, 20:359–363.

Moran, K. A. (1998). *A biomechanical evaluation of the effect of the stretch shortening cycle in unconstrained and experimentally constrained vertical jumps*. Phd thesis, University of Ulster.

Moran, K. a. and Wallace, E. S. (2007). Eccentric loading and range of knee joint motion effects on performance enhancement in vertical jumping. *Human movement science*, 26(6):824–40.

Morgan, D. and Morgan, R. (2008). *Single-Case Research Methods for the Behavioral and Health Sciences*. SAGE Publications.

Morrissey, M. C., Harman, E. a., Frykman, P. N., and Han, K. H. (1998). Early phase differential effects of slow and fast barbell squat training. *The American journal of sports medicine*, 26(2):221–30.

Newell, J., McMillan, K., Grant, S., and McCabe, G. (2006). Using functional data analysis to summarise and interpret lactate curves. *Computers in biology and medicine*, 36(3):262–75.

Newton, R., Kraemer, W., and Häkkinen, K. (1999). Effects of ballistic training on preseason preparation of elite volleyball players. Technical Report 2, School of Exercise Science & Sport Management, Southern Cross University, Lismore, NSW, Australia. rnewton@scu.edu.au.

O'Byrne, J. M., Jenkinson, A., and O'Brien, T. M. (1998). Quantitative analysis and classification of gait patterns in cerebral palsy using a three-dimensional motion analyzer. *Journal of child neurology*, 13(3):101–108.

O'Malley, M. J., Abel, M. F., Damiano, D. L., and Vaughan, C. L. (1997). Fuzzy clustering of children with cerebral palsy based on temporal-distance gait parameters. *Rehabilitation Engineering, IEEE Transactions on,*, 5(4):300–309.

Pappas, E., Hagins, M., Sheikhzadeh, A., Nordin, M., and Rose, D. (2007). Biomechanical differences between unilateral and bilateral landings from jump gender differences. *Clinical Journal of Sport Medicine*, 17(4):263–268.

Petushek, E., Garceau, L., and Ebben, W. (2010). Force, velocity, and power adaptations in response to a periodized plyometric training program. In *ISBS-Conference Proceedings Archive*.

Preatoni, E., Devodier, E., Andreoni, G., and Rodano, R. (2009). Coordination in track & field sprinters while performing the countermovement jump. In *ISBS-Conference Proceedings Archive*.

Ramsay, J. O. (2006). *Functional data analysis*. John Wiley & Sons.

Ramsay, J. O. and Silverman, B. W. (2002). *Applied functional data analysis: methods and case studies*. Springer,, New York.

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

Schwartz, M., Trost, J., and Wervey, R. (2004). Measurement and management of errors in quantitative gait data. *Gait and Posture*, 20:196–203.

Segaran, T. (2007). *Programming collective intelligence: building smart web 2.0 applications*. O'Reilly Media.

Sheppard, J. M., Chapman, D. W., Gough, C., McGuigan, M. R., and Newton, R. U. (2009). Twelve-month training-induced changes in elite international volleyball players. *The Journal of Strength & Conditioning Research*, 23(7):2096–2101.

Sheppard, J. M., Cronin, J. B., Gabbett, T. J., McGuigan, M. R., Etxebarria, N., and Newton, R. U. (2008). Relative importance of strength, power, and anthropometric measures to jump performance of elite volleyball players. *The Journal of Strength & Conditioning Research*, 22(3):758–765.

Smith, J. P., Kernozek, T. W., Kline, D. E., and Wright, G. A. (2011). Kinematic and Kinetic Variations Among Three Depth Jump Conditions in Male NCAA Division III Athletes. *The Journal of Strength & Conditioning Research*, 25(1):94–102.

Sokal, R. R. and Rohlf, F. J. (1962). The comparison of dendrograms by objective methods. *Taxon*, 11(2):33–40.

Stergiou, N. (2004). *Innovative Analyses of Human Movement* . Human Kinetics, Leeds, U.K., 1 edition.

Stergiou, N. and Scott, M. (2005). Baseline measures are altered in biomechanical studies. *Journal of Biomechanics*, 38(1):175–178.

Stout, J. L., Bruce, B., Gage, J. R., and Schutte, L. (1995). Joint kinetic patterns in children with spastic hemiplegia cerebral palsy. *Gait & Posture*, 3(4):274.

Tibshirani, R., Walther, G., and Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society*, B(63):411–423.

Toro, B., Nester, C. J., and Farren, P. C. (2007). Cluster analysis for the extraction of sagittal gait patterns in children with cerebral palsy. *Gait & posture*, 25(2):157–165.

Tortora, G. J. and Derrickson, B. H. (2008). *Principles of anatomy and physiology*. Wiley.

Tuddenham, R. D. and Snyder, M. M. (1954). Physical growth of California boys and girls from birth to eighteen years. Publications in child development. *University of California, Berkeley*, 1(2):183.

Ullah, S. and Finch, C. F. (2013). Applications of functional data analysis: A systematic review. *BMC medical research methodology*, 1(13):13–43.

Vanezis, A. and Lees, A. (2005). A biomechanical analysis of good and poor performers of the vertical jump. *Ergonomics*, 48(11-14):1594–603.

Vanrenterghem, J., Lees, A., and De Clercq, D. (2008). Effect of forward trunk inclination on joint power output in vertical jumping. *The Journal of Strength & Conditioning Research*, 22(3):708–714.

Vanrenterghem, J., Lees, A., Lenoir, M., Aerts, P., and De Clercq, D. (2004). Performing the vertical jump: movement adaptations for submaximal jumping. *Human movement science*, 22(6):713–27.

von Tscharner, V., Enders, H., and Maurer, C. (2013). Subspace identification and classification of healthy human gait. *PloS one*, 8(7):e65063.

Walsh, M. S., Böhm, H., Butterfield, M. M., and Santhosam, J. (2007). ender bias in the effects of arms and countermovement on jumping performance. *The Journal of Strength & Conditioning Research*, 21(2):362–366.

Winter, D. A. (2009). *Biomechanics and motor control of human movement*. Wiley.com.

Witten, I. H. and Frank, E. (2005). *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann.

Wrigley, A. T., Albert, W. J., Deluzio, K. J., and Stevenson, J. M. (2006). Principal component analysis of lifting waveforms. *Clinical Biomechanics*, 21(6):567–578.

Zajac, F. (1993). Muscle coordination of movement: a perspective. *Journal of Biomechanics*, 26(1):109–124.