The application of functional data analysis to force signatures in on-water single sculling

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CANDIDATE SIGNATURE

I, John Samuel Warmenhoven, hereby declare that this thesis is my own work and does not, to the best of my knowledge, contain material from any other source unless due acknowledgement is made. The thesis was completed under the guidelines set out by The University's Faculty of Health Sciences, for the degree of Doctorate of Philosophy and has not been submitted for a degree or diploma at any other academic institution.

I, John Samuel Warmenhoven, hereby declare that I was the principle researcher of all work included in this thesis, including work published with multiple authors. An author contribution statement for published work is detailed at the beginning of each relevant chapter.

Signed: [redacted] *Date:* 21/04/2017

ABSTRACT

Biomechanics as a discipline of sports science has played an important role in on-water rowing over the last 150 years. In this time, substantial focus has been placed on understanding kinetic variables acting around the *oar-boat-rower* system, and how these variables interact to influence boat velocity. Of these variables, propulsive force applied at the oar has received considerable attention, and rowing instrumentation systems capable of measuring propulsive force have enabled coaches and sport scientists the ability to collect, assess and descriptively understand characteristics of rowing technique and performance. Propulsive force is usually observed through different continuous graphical representations, often referred to as *force profiles*. Large variations are present between athletes in the shape characteristics of force profiles, and subsequently these differences have led to propulsive force patterns being referred to as a rower's '*signature*'. The overarching aim of this thesis was to provide content that would build a more thorough understanding of differences in force profiles between rowers, using novel statistical approaches from the area of functional data analysis (FDA). In this thesis, chapter one provided theoretical and practical reasoning for the studies included in this body of work.

A review of literature in chapter two focused on a number of overarching sub-themes relevant to this body of work. These included the use of instrumentation systems for collection of propulsive force, qualitative and quantitative analytical approaches for understanding force profiles, and established associations between characteristics of force profiles and rowing performance. Shortcomings and limitations in contemporary literature were also provided and directions for further research were also highlighted, with these directed at concepts that could

further develop the scientific understanding of the relationship between force profiles and rowing performance.

Chapter three formed the first piece in a two part methodological series (the series spanned chapter three and four in this thesis), where insight into practical issues surrounding the use of two FDA techniques in biomechanics were explored. More specifically, the use of functional principal components analysis (*f*PCA) in biomechanics was explored using existing literature and sample data force profile data from an on-water rowing database. Propulsive pin force profile data was observed with force plotted relative to linearly increasing temporal scales such as time or percentage of the stroke cycle. The use of *f*PCA with regard to methodological considerations such as temporal normalisation of data, removal of experimentally introduced phase shifts in a data set and documented methods for retaining the original temporal properties within a group of curves, were explored in detail. Limitations and strengths of the statistical technique were outlined, and recommendations were provided to the reader ensuring that *f*PCA is used in the correct context, not only for rowing, but also for the broader discipline of sports biomechanics.

Chapter four followed as the second part of this series, and focused on an adapted version of *f*PCA, multivariate functional principal components analysis, also referred to as bivariate functional principal components analysis (*bf*PCA). This chapter demonstrated that FDA can be used effectively in the evaluation of continuous data, when differences in complex multivariate functional data are being assessed. Existing literature and sample propulsive pin force profile data were again used for the development of considerations and recommendations for the use of *bf*PCA in biomechanical contexts. In this chapter, force profiles were observed relative to the horizontal angle of the oar. When visualised together, force and the oar angle represent a complex structure of coordination between these two *technical* variables across the stroke cycle (and are also referred to as the force-angle profile).

Chapter five involved the application of *bf*PCA to propulsive pin force-angle profiles. Differences in pattern characteristics of force-angle profiles were explored relative to potentially constraining factors such as rower gender and side of the boat. Testing was conducted in a single scull for a group of highly skilled rowers (national and international level athletes), rowing at 32 strokes per minute. Discriminant function analysis demonstrated strong classification of rowers for gender across both sides of the boat. In this discriminant function model, force application leading into and away from the oar being perpendicular to the boat's longitudinal axis was identified as a key discriminating factor between male and female rowers. A mixed ANOVA exploring gender, boat-side and the gender-boat-side interaction revealed statistical trends for both boat-side and gender (but no interaction between boat-side and gender). For boat-side differences, bow side forces potentially acted as a driver of power and peak force production, while stroke side forces may have acted as a mediator of bow-side propulsive forces with a potential role in steering and maintaining boat control. Results in this chapter demonstrated that force profile differences relative to gender and boat-side must be acknowledged and accounted for, prior to exploring the relationship between patterns of the force-angle profile and known metrics of rowing performance.

In chapter six *bf*PCA was applied to propulsive pin force-angle profiles from a group of highly skilled female rowers at different competitive levels (national and international level), rowing at 32 strokes per minute in a single scull boat. Changes in the patterns of force-angle profiles between rowers were explored relative to two metrics of performance: level of competitive representation and average boat velocity. Discriminant function analysis showed moderate classification of rowers using force-angle graphs across both sides of the boat, with rate of force development identified as a potentially important characteristic for international rowers. Additionally for the bow-side, spending less time in the first half of the drive phase was also identified as an important feature for international rowers. Multiple linear regression of scores from the *bf*PCAs showed that a more pronounced front peaked profile was associated with a higher average boat velocity. The results of this demonstrate that different characteristics of the force-angle graph were associated with different metrics of performance in sculling.

Chapter seven explored force asymmetries across the rowing stroke cycle and assessed whether patterns of continuous asymmetry were associated with better rowing performance, (assessed relative to rower competition level). An established symmetry index (SI) and functional data analysis (FDA) techniques were applied to a continuous *difference* time-series, which described the fluctuating asymmetry in propulsive pin forces for each rower. A participant group of highly skilled female rowers (national and international competition level), rowing at 32 strokes per minute in a single scull boat were evaluated. Univariate ANOVAs revealed that differences in asymmetries were present as a factor of competition level for the SI and results of FDA. International athletes were more likely to utilise an asymmetry strategy with increased stroke-side force early in the drive phase, and increased bow side force through the second half of the drive. This was likely the result of international performers, modifying their movement strategies relative to known mechanical offsets in the boat. The first half of the drive phase was also found to be an adaptive part of the rowing stroke cycle, suggesting asymmetries may have a functional role in successful execution of movements during the rowing stroke.

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> "*An important quote like, 'The possession of anything begins in the mind…' would normally go here… but I'm not worried about that. I just need to shower because I smell offensive. Mainly because I'm a Llama. That's the main thing I'm worried about at the moment…*" (Yonn Llama, 2017)

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CHAPTER 1

Introduction and Thesis Overview

Background

Rowing has a competitive history spanning more than 150 years. Seiler (2015) demonstrated an early and sustained interest in monitoring basic biomechanical variables related to performance in rowing competitions across this time period. Results from historic races like the Oxford-Cambridge boat race (established 1829, with performance data being collected as early as 1845) and the world championships (established 1893 with data collection also beginning in 1893) have revealed a linear increase in boat velocity by approximately 2-3% per decade. A range of interacting factors have contributed to this increase in rowing velocity. Over time, the propulsive power capacity of elite rowers has increased, with part of this increase likely the result of changes to athlete anthropometry (i.e. athletes from becoming taller, 1-3cm per decade, and heavier over time). Increases to boat velocity have also been attributed to modifications in both boat and oar design, through changes in both the material composition and shape of oar blades and rowing boat shells (Seiler, 2015; Smith et al., 2015).

Modifications to rower technique has also substantially influenced progressions in boat velocity. Specifically a better understanding of kinetic variables, such as drag forces and propulsive forces acting around the boat, have contributed to changed coaching practices and better competition times. In on-water rowing, propulsive power (calculated as the product of propulsive force and velocity) is produced to overcome drag forces that are influenced by movement of the hull, rower and blades as they move through the water as a system (Soper & Hume, 2004). A greater understanding of the relationship between drag and propulsive forces and increased boat velocity has been made possible by the ability to measure such variables in an on-water environment (Spinks, 1996). In the training environment, substantial focus has centred on measurement and evaluation of propulsive forces, which contribute directly to increases in boat velocity. These propulsive forces (measured about the oar and most commonly at the pin or oarlock) are often visualised through the use of different graphical displays to explore differences between athletes for patterns force application. These graphical depictions are often referred to as '*profiles,*' (Spinks, 1996; Smith & Loschner, 2002; Coker, Hume & Nolte, 2008) or '*signatures*' (Ishiko, 1971), due to the large amounts of between athlete variability present in features related to the shape of these waveforms. For the purpose of clarity, these graphical depictions will be referred to as profiles for the rest of the background section of this introduction.

When visualising force profiles in the applied training environment two methods for graphical representation of force have been used (Spinks, 1996). Force can be observed relative to a temporal scale such as time, providing potentially meaningful information about the timing of different rowers in a crew (Roth, Schwanitz, Pas & Bauer, 1993) and the impulse generated across the stroke cycle (Hill, 2002). Force can also be observed relative to spatial measures such as the horizontal angle of the oar (Smith & Loschner, 2002), which can provide meaningful technical information to coaches regarding characteristics of force application across different phases of the rowing stroke cycle.

Historically, substantial research and applied interest has been shown in the considerable amount of between-athlete variability noted in these profiles (Ishiko, 1971; Seiler, 2015). Quantitative information has been derived from these different graphical representations and evaluated relative to metrics of better rowing performance or technique in attempts to understand how these force-profiles relate to rowing skill. This information has contributed to biomechanical and sports science literature reviews in rowing (Coker, Hume & Nolte, 2008;

Soper & Hume, 2004; Baudouin & Hawkins, 2002), which have found that a range of conflicting opinions regarding "*which*" features of these profiles are relevant for better performance.

Quantitative analyses of these graphical displays, have are often conducted in an effort to better understand these profiles from a performance or skill perspective. The analyses have centred on the use of simplistic discrete point analytical techniques or relatively crude data reduction strategies that assess differences in characteristics related to waveform shape (i.e. assessment of temporal features such as timing of key data points, assessment of amplitude features such maximal or peak force, area measures, smoothness measures, etc.). It is possible that the use of these techniques may have contributed in part to the lack of consensus surrounding "*which*" features of these profiles are actually important for performance. The use of discrete point variables or crude data reduction strategies in the analysis of human movement have been useful previously in sports biomechanics research (Preatoni et al., 2013), but may not be sufficient for providing an exhaustive description of the rowing stroke cycle, when it is observed through these graphical displays. When these analytical approaches are adopted in biomechanical research, often a large amount of data can be discarded and potentially useful information may be unaccounted for (Sutherland, Kaufman, Campbell, Ambrosini & Wyatt, 1996; Queen, Gross & Liu, 2006; Ryan, Harrison & Hayes, 2006).

The use of more complex statistical techniques that have the ability to preserve all potentially relevant characteristics and patterns present in the original data is becoming a more common practice, with a comprehensive review of such techniques used in sports biomechanics outlined by Preatoni et al., (2013). Within this review, one emerging area of statistics with some established use for analysis of continuous time-series data is functional data analysis (FDA). In FDA, observations arising from time-series are expressed in the form of a function, before statistical concepts (adopted from conventional multivariate data analysis) can be applied. By treating a time-series as a functional entity, generally no information is discarded from a waveform. Despite the increasing popularity of FDA techniques in biomechanics, at present there are still limited guidelines for the appropriate use of these techniques within sports biomechanics contexts. Data such as force profiles often possess novel complexities, which may make them difficult to analyse. For example, force observed relative to time (often referred to as a force-time profile) is a very useful method for assessing timing differences between rowers in multiple crew member boats and also provides rich contextual information regarding oar-impulse generated across each the drive phase of each stroke. Despite this, when each curve is analysed as a force-time profile, the original data representing these curves are likely to possess different lengths (in terms of data points), as the length of each time-series is likely to be affected by the amount of time spent in each phase of the stroke cycle or task constraints surrounding the activity such as a rower's stroke rate. This can often warrant temporal normalisation of data prior to analysis, due to methodological constraints imposed by some statistical practices (including FDA techniques). Similarly, force-angle curves have been demonstrated as important descriptors of rowing technique. These graphs incorporate information from two non-linear variables (i.e. neither variable is considered to be a linearly increasing scale such as time). plotted relative to each other. Analysis of pattern differences in force-angle graphs is difficult to achieve using conventional waveform statistical approaches such as principal components analysis (PCA) or spectral analysis techniques (Fourier and wavelet series analyses). Some FDA techniques may have the potential to circumvent some of these shortcomings, however a thorough evaluation of potentially appropriate FDA techniques and data preparation strategies is necessary prior to applying FDA to force-time or force-angle profiles.

In addition to these potential statistical limitations, it is also possible that other experimental factors may have contributed the lack of consensus surrounding characteristics of force profiles and their relevance with better rowing performance. Using Newell's (1986) conceptual model for constraints, movement patterns in rowing and subsequent rowing performance are likely to be affected by a range of concurrent and interacting factors, often referred to as constraints. Newell's model implies that the human body produces different characteristics of movement, often observed as coordination patterns, due to impositions of organismic, environmental and task constraints. Organismic constraints relate to the structural and functional constraints of the human body, and commonly include factors such as body weight, height, shape, muscular strength and power (Newell, 1986). Environmental constraints are external to the organism and can include gravity, ambient temperature, natural light, location, visual and auditory information (Handford, Davids, Benneth, & Button, 1997; Newell, 1986). Task constraints are related to the context of the skill or sport (Newell, 1986). Commonly, task constraints are specific rules or goals that are required for successful execution of skill within a particular sporting activity (Newell, 1985).

Results of contemporary experimental studies that have explored the importance of force profile characteristics for bettering rowing performance may have also been influenced by the presence of different constraints. It is possible that organismic constraints such as a rower's gender and anthropometric characteristics, as well as task constraints such as the type of rowing (sculling and sweep rowing), boat-side that the oar is relative to, boat type and also seat position may all individually, yet uniquely, influence characteristics of these force profiles. This could mean that characteristics of these profiles related to better rowing performance are potentially individualised according to the constraints within each context. In light of this, it becomes more difficult to synthesise findings from contemporary literature on the relationship between force profile characteristics and performance, given the different combinations of constraints present in each experimental study.

In terms of organismic constraints there has been a predominance of research conducted with male rowing athletes (Roth, Schwanitz, Pas & Bauer, 1993; Wing & Woodburn, 1995; Kleshnev, 1999; McBride, Sanderson & Elliot, 2001; Hill, 2002; Smith & Loschner, 2002; Smith & Draper, 2002; Baudouin & Hawkins, 2004; Smith & Draper, 2006; Hill & Fahrig, 2009), with a comparatively limited number of studies evaluating female rowers (Smith & Loschner, 2002; Draper & Smith, 2007). At present however, limited evidence exists to suggest that male and female rowers exhibit similar trends in characteristics of force profiles, or should be treated identically from the perspective of coaching interventions when observing these profiles. Further to this, known differences in gender exist in other kinetic and kinematic variables in on-water testing. A combination of variables including wasted finish time, stroke smoothness, rate of force development, propulsive power per kilogram of body mass and stroke length managed to correctly classify 88% of rowers according to gender in on-water sweep rowing (Smith, Galloway, Patton & Spinks, 1994). Thus it is plausible that differences in characteristic patterns of force profiles may exist between male and female rowers.

For task constraints, kinetic information derived from these profiles have been assessed in both sculling (Kleshnev, 1999; Elliot, Lyttle, Birkett, 2002; Smith & Loschner, 2002; Draper & Smith, 2007) and sweep boats (Roth, Schwanitz, Pas & Bauer, 1993; Smith, Galloway, Patton & Spinks, 1994; Wing & Woodburn, 1995; Kleshnev, 1999; McBride, Sanderson & Elliot, 2001; Hill, 2002; Smith & Loschner, 2002; Smith & Draper, 2002; Baudouin & Hawkins, 2004; Smith & Draper, 2006; Hill & Fahrig, 2009; Doyle, Lyttle & Elliot, 2010). Sweep boats have contributed considerably more to the literature, but these have also come in the form of both smaller (Roth, Schwanitz, Pas & Bauer, 1993; McBride, Sanderson & Elliot, 2001; Smith & Loschner, 2002; Smith & Draper, 2002; Baudouin & Hawkins, 2004; Smith & Draper, 2006; Hill & Fahrig, 2009; Doyle, Lyttle & Elliot, 2010) and larger (Wing & Woodburn, 1995; Hill, 2002) crew boats, or combinations of both (Kleshnev, 1999; Smith, Galloway, Patton & Spinks, 1994). This is interesting given that boat-side position of the oar in smaller crew boats is anecdotally known to affect descriptive characteristics of these profiles more markedly when compared to larger crew boats (inferred from Smith & Loschner, 2002). An offset in the rate of force development between the bow-side rower and stroke-side rower is an important feature of better performance in pair boats (the smallest sweep rowing boat) due to an unbalanced moment brought about from the staggered seat position found in pair sweep-oared rowing (Smith & Loschner, 2002). Conversely, synchronicity of force profiles is proposed as important for larger crew boats, irrespective of which side of the boat is analysed (Wing & Woodburn, 1995; Hill, 2002). The influence of seat position on kinetic characteristics have been explored in a limited capacity and only in larger sweep-oared crew boats, where the concept of synchronicity of force profiles have been supported across all seats (Wing & Woodburn, 1995; Hill, 2002). The differing organismic and task constraints present in contemporary research evaluating kinetic characteristics in on-water rowing may be contributing to the inconsistencies noted in literature reviews, regarding *which* important features of force profiles are related to better rowing performance.

Statement of the Problem

It is apparent that continuous biomechanical information, particularly propulsive force applied at the oar, has an accepted role in rowing biomechanics in both research and practice. Different graphical representations of propulsive force, often referred to as profiles or signatures, are accepted in the daily training environment and serve as tools for understanding and changing rowing technique for skilled rowers. Despite this, there is still limited consensus regarding "*which*" characteristics of these profiles are associated with better rowing performance or a higher level of rowing skill. This has been attributed to a combination of issues. Firstly, it is possible that conventional discrete point analytical strategies and simple data reduction approaches using information obtained from these graphs, may be inadequate at retaining all potentially relevant characteristics present in the original data. Secondly, other known factors, or constraints, may be influencing some characteristic differences between rowers, and these may be affecting the ability to identify characteristics that *are* directly relevant to better rowing performance. Consequently, the main objective of this thesis comes in two parts.

1. Firstly this thesis will explore new statistical approaches from the area of functional data analysis (FDA) for analysing continuous waveform variables such force profiles. Considerations and recommendations for the use of these techniques with force profile data will also be provided. It is intended that this will contribute to both the on-water rowing research/sports science community, and also the broader sports biomechanics community. This is necessary given that analysis of similar graphical displays may be warranted as a part of biomechanical research or practice in other sporting contexts.

2. Secondly, if proven applicable, this thesis will attempt to use FDA techniques for developing a new experimental and empirical evidence base. This evidence base will attempt to progress understanding of the factors that influence differences in force profiles between individuals in on-water rowing, and more specifically, single sculling. These factors will be inclusive of both potentially influential constraints as well as known performance metrics (once influential constraints are accounted for). Sculling will be the focus of this thesis, given the abundance of research that has already been conducted in sweep rowing. Single sculling, more specifically, has also been selected to control for the potential effect of task constraints such as rowing type and seat position, which may be considered in future research.

Specific Aims

Aim 1: To explore the applicability of the FDA technique, functional principle components analysis (*f*PCA), for use with on-water rowing force profile data (using force observed relative to time or percentage of the stroke cycle).

Aim 2: To explore the applicability of the FDA technique, bivariate functional principle components analysis (*bf*PCA), for use with on-water rowing force profile data (using force observed relative to the horizontal angle of the oar).

Aim 3: To assess whether changes in the characteristics of force profiles, when plotted relative the horizontal angle of the oar (force-angle profiles), are influenced by the organismic constraint of rower gender or the task constraint of side of the boat. This is conducted for on-water single sculling.

Aim 4: To assess whether changes in the characteristics of force-angle profiles are indicative of better rowing performance. Performance is assessed as both level of competitive representation and also as average boat velocity.

Aim 5: To assess whether differences in continuous asymmetries are indicative of better rowing performance, with performance measured as level of competitive representation.

Thesis Outline

In accordance with the outlined aims, eight chapters in total are presented in this thesis. A summary of chapters two through to eight are provided below:

Chapter 2: *Literature Review*

This section provides a comprehensive background for the succeeding research chapters. This literature review focuses on the importance of kinetic variables in on-water rowing; on-water rowing instrumentation systems measuring these kinetic variables; qualitative and quantitative analyses of continuous kinetic variables such as propulsive force; factors potentially affecting findings of contemporary research related to the relationship between force profiles and performance; and the potential for functional data analysis (FDA) techniques to be used in conjunction with on-water kinetic data.

Chapter 3: *Considerations for the use of functional principal components analysis (fPCA) in sports biomechanics: examples from on-water rowing.*

The use of functional principal components analysis (*f*PCA) in biomechanics is explored using existing literature and sample force profile data (force observed relative to time or percentage of the stroke cycle). The use of *f*PCA is investigated, with reference to known methodological considerations. Limitations and strengths of the technique are outlined and recommendations are provided to the reader to ensure that *f*PCA is used in the correct context within the field of applied sports biomechanics.

Chapter 4: *Bivariate functional principal components analysis (bfPCA): Considerations for use in coordination.*

The use of bivariate functional principal components analysis (*bf*PCA) is explored using a combination of existing literature and sample force profile data (force observed relative to the horizontal angle of the oar) from an on-water rowing database. The use of *bf*PCA is investigated, with reference to known methodological considerations. Limitations and strengths of the technique are outlined and recommendations are provided to the reader to ensure that *bf*PCA is used in the correct context within the field of applied sports biomechanics.

Chapter 5: *How gender and boat-side affect shape characteristics of force-angle profiles in single sculling: Insights from functional data analysis.*

Differences in the characteristics of force profiles (force-angle profiles) are assessed relative to gender differences and side of the boat differences in-on water single sculling. This is conducted using the FDA technique *bf*PCA. Highly skilled (national and international) rowers are tested in a single sculling boat rowing at 32 strokes per minute.

Chapter 6: *Assessment of propulsive pin force and oar angle time-series using functional data analysis in on-water rowing.*

Associations between force profile (force-angle profile) characteristics and performance are assessed. Performance is measured using two metrics: level of competitive representation and average boat velocity. Force profiles are analysed using *bf*PCA. Gender is controlled for through the evaluation of female participants only. Boat-side is controlled for through the use of separate *bf*PCAs being applied individually to each side of the boat. Highly skilled (national and international) rowers are tested in a single sculling boat rowing at 32 strokes per minute.

Chapter 7: *Kinetic coordination strategies in on-water single sculling: are asymmetries in propulsive pin-force functional?*

A new approach for the evaluation of both global and local asymmetries across the entire rowing stroke cycle is developed and used to identify whether particular asymmetries are associated with the performance metrics of competition level. An established symmetry index from previous literature is used in conjunction with a modified FDA technique, analysis of characterizing phases (ACP) to act as measures of global and local asymmetry respectively. Gender was controlled for through the evaluation of female participants only. Highly skilled (national and international) rowers are tested in a single sculling boat rowing at 32 strokes per minute.

Chapter 8: *Discussion and thesis conclusion*

This section summarises the key findings present in the five preceding methodological and experimental chapters, discusses the implications of the findings from the current body of work, outlines directions for future research and presents the final conclusions from results presented in the experimental studies conducted.

Significance of Thesis

Firstly, it is believed this thesis will provide an integral step forwards through contributing to the development of an evidence base for what has been a largely ‘anecdotal’ area of rowing biomechanics. The information gathered from experimental research in this thesis would aid in better understanding the important role of continuous propulsive force-application across the stroke cycle. This thesis will identify whether potentially influential organismic constraints such as gender, and task constraints such as side of the boat affect patterns of propulsive force when observed through force profile graphs. Subsequent to this, and if necessary, this thesis would then control for these potentially confounding factors and provide some insight into the role of force profiles with increased rowing performance, assessed through level of competitive representation and average boat velocity. Secondly, this thesis will also aim to assess and comment on contemporary and innovative methodologies, which may be more appropriate for identifying subtle, idiosyncratic differences between athletes. This includes the exploration and application of FDA techniques such as *f*PCA, *bf*PCA and ACP. This would likely benefit not only rowing biomechanics research, but also the broader sports biomechanics community.

The structure of this thesis also presents a novel framework for future doctoral dissertations in applied biomechanics. The analytical approaches explored as a part of this thesis are novel in the context of their application with human movement data. As mentioned in the "*Statement of the Problem*" section of this chapter, this aims to address two main themes. Firstly, there is an exploration of some FDA techniques (and associated data processing approaches) applied in the context of sports biomechanics data. Secondly, outcomes of these FDA techniques when they are applied in the context of a relevant research question (or theme) in sports biomechanics are discussed, with this being the concept of force signatures and their relevance in on-water rowing in this project. The emergence of new methods for analysing data in sports biomechanics is becoming more common, and it is a growing practice for using novel data analysis approaches to explore pre-existing data sets in applied biomechanical contexts (Hébert-Losier et al., 2015). It is believed that this thesis demonstrates a framework that can be used in the future, when similar adaptations of novel statistical concepts are of interest to a particular research question.

Dissemination of Results

At the time of submission, chapters within this thesis have been submitted for publication and/or presented as follows:

Submission to Journals

*Chapter 3 is **accepted for publication** as*: Warmenhoven, J. S., Smith, R., Cobley, S., Draper, C., Harrison, A. & Bargary, N. Considerations for the use of functional principal components analysis (*f*PCA) in sports biomechanics: examples from on-water rowing. *Sports Biomechanics*. Accepted (undergoing proofing).

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*Chapter 5 is **published** as*: Warmenhoven, J. S., Smith, R., Cobley, S., Draper, C., Harrison, A. & Bargary, N. How gender and boat-side affect shape characteristics of force-angle profiles in single sculling: Insights from functional data analysis. *Journal of Science & Medicine in Sport*. In Press.

Chapter 6 is ***published*** *as*: Warmenhoven, J. S., Smith, R., Cobley, S., Draper, C., Harrison, A. & Bargary, N. (2017). Assessment of propulsive pin force and oar angle time-series using functional data analysis in on-water rowing. *Scandinavian Journal of Medicine and Science in Sport*. In Press.

Chapter 7 is ***submitted (Scandinavian Journal of Medicine & Science in Sport)*** *as*: Warmenhoven, J. S., Cobley, S., Draper, C., Harrison, A., Bargary, N. & Smith, R. (2017). Force coordination strategies in on-water single sculling: Are asymmetries in propulsive pin-force functional? *Scandinavian Journal of Medicine and Science in Sport*. Submitted.

Conference Presentations

Pilot data collected during this thesis was presented as:

Warmenhoven, J. S., Smith, R., Cobley, S., Draper, C., Harrison, A. & Bargary, N. (2016). Force-angle charateristics and level of competitive representation in on-water rowing. In: *Scientific Proceedings of the XXXVth International Symposium on Biomechanics in Sports*. International Society of Biomechanics in Sport, Tsukuba.

Warmenhoven, J. S., Smith, R., Cobley, S., Draper, C., Harrison, A. & Bargary, N. (2015). The application of functional data analysis techniques for characterizing differences in rowing propulsive-pin force curves. In: *Scientific Proceedings of the XXXIVth International Symposium on Biomechanics in Sports*. International Society of Biomechanics in Sport, Poitiers.

Warmenhoven, J. S., Cobley, S., Draper, C., Harrison, A. & Bargary, N. & Smith, R. (2015). Asymmetry strategies and performance in on-water single sculling. In: *Scientific Proceedings of the XXVIth International Symposium on Biomechanics*. International Society of Biomechanics, Brisbane.

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References for this chapter are included in the list of references at the end of this thesis

CHAPTER 2

Review of Literature

Background

There has been substantial interest in the mechanisms underpinning the skilled movements of on-water rowing for more than 150 years (Seiler, 2015). Contemporary attention from biomechanical research has focused on the important relationship between kinetics (such as force application at the oar) and performance. A range of instrumentation systems have been developed and used in both academic and rowing training contexts to better understand this relationship. Both qualitative and quantitative analytical approaches have been used in conjunction with these instrumentation systems for observing differences in propulsive force patterns between rowers. Despite this, as of 2015 (see Seiler), there is still limited consensus as to what the '*ideal*' characteristics of propulsive force application are, and whether these exist at all. This literature review of theoretical and experimental studies aims to provide a contemporary position on the relationship between propulsive force applied at the oar and rowing performance. The lack of consensus will be explored through the identification of shortcomings or limitations that are present in contemporary literature. Finally, this review will also aim to provide some direction for further research, in an effort to enable a better understanding of the relationship between propulsive force and performance in rowing.

Rowing Stroke Cycle

The rowing action has been referred to as a cyclical whole-body movement (Dawson, Lockwood, Wilson & Freeman, 1998). The upper and lower limbs work simultaneously to apply force to the oar(s), with this force providing the propulsion necessary for boat movement. Motion of the rowing stroke cycle is divided into two phases, the *drive* and *recovery*. These phases are defined using horizontal angular displacement of the oar (see Figure 1). The drive phase begins with the *catch*, when the minimum oar angle is reached and the blade begins entry into the water. The drive phase ends with the release, when the maximum oar angle is reached and the blade exits the water. The recovery phase starts at the release, and ends at the catch.

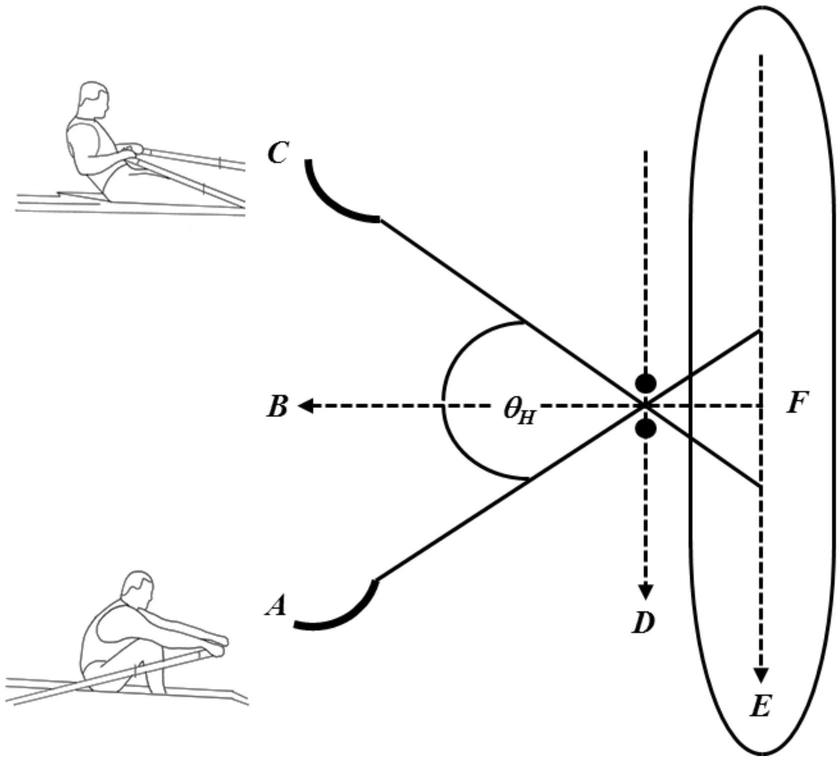

Figure 1. Diagram defining horizontal angular displacement of the oar. The horizontal angle of the oar (θ_H) is defined by the angular position of the oar in the transverse plane, relative to a vector (B) that is perpendicular to the longitudinal axis of the boat, which also follows the direction of water flow (E). When the oar is parallel to B, the horizontal oar angle is referenced as 0°, and often referred to as the square-off position (B). Movement of the oar blade towards the bow of the boat from the square-off position results in a negative angle, with the highest absolute negative angle referenced as the catch (A). Similarly, movement of the oar blade towards the stern of the boat from this perpendicular position results in a positive angle, with the highest absolute positive angle referenced as the finish (C). D is the direction of the boat's movement while rowing.

The primary aim of the drive phase is to achieve high boat propulsion through efficient force production to the handle over an optimal stroke length. At international competition level there are two main types of rowing: sculling (boats where each crew member uses two oars) and sweep rowing (boats where each crew member uses one oar). The main performance metric for these types of rowing is the time taken to move a boat translationally over a pre-determined competition distance, which is typically 2000m (Spinks, 1996). These competition times are dependent upon kinetic variables, such as drag forces and propulsive forces acting around the boat. This combination of kinetic variables directly interact to influence boat velocity (Smith & Loschner, 2002). Propulsive power (calculated as the product of propulsive force and velocity) must be produced to overcome drag forces that are influenced by movement of the hull, sculler and blades as they systematically move through the water (Soper & Hume, 2004).

Measurement of on-water kinetics

Given the relationship between kinetic measures and boat velocity, increased attention has focused on rowing instrumentation systems that can measure these kinetic variables. Spinks (1996) provided a thorough review of rowing data collection systems and processes since the 1950s (Soper & Hume, 2004). To summarise some common systems, kinetic variables (often in the form of continuous measures of force) have been measured at the inboard of the oar shaft (Schneider, Angst & Brandt, 1978; Smith, Galloway, Patton & Spinks, 1993; Smith & Spinks, 1989; Wing & Woodburn, 1995; Hill, 2002), the pin or oarlock (Roth, Schwanitz, Pas & Bauer, 1993; Smith & Loschner, 2002), and the oar blade (Elliot, Lyttle & Birkett, 2002). In addition to this, new technology is also available for measurement of force applied directly to the handle (Turner, Gravenhorst, Draper & Smith, 2015). Baca, Kornfeind, and Heller (2006) have also demonstrated the ability to capture information regarding force applied at the foot-stretcher. Both, Smith and Loschner (2002) and Baca, Kornfeind, and Heller (2006) have also demonstrated the ability to measure and use multidimensional force variables at the pin and foot-stretcher respectively, allowing for a more comprehensive understanding of kinetics influences on boat velocity.

Characteristics related to magnitude, timing and the interaction of these forces can be measured using these instrumentation systems and then changed through manipulation of a rower's technique (Spinks, 1996; Smith & Loschner, 2002). Thus knowledge of characteristics that relate directly to better rowing performance are of great benefit to enhance understanding of '*what*' biomechanically constitutes a high level of rowing skill. Spinks (1996) has noted that despite the presence of numerous measureable kinetic parameters influencing boat movement, the oar as the main propulsive element has received the most research attention. This is understandable given that the oar is used as a lever to apply force to the boat via the pin from force applied at the handle and with the blade-water interface being the fulcrum. As such, forces applied at the oar in different locations have been noted as the primary kinetic factors determining rowing performance (Baudouin & Hawkins, 2002; Sanderson & Martindale, 1986).

Qualitative analysis of on-water kinetics

A rower's ability to produce large or effective forces is dependent partly on their physical capacity and anthropometry (Soper & Hume, 2004). The largest and strongest individuals have been shown to produce higher boat velocities in on-water testing (Barrett & Manning, 2004). It may be difficult in some circumstances to increase a rower's physical capacity beyond particular limits, and in these instances performance gains are attempted through modifications to rowing technique. Coaching of rowing technique has traditionally involved visual analysis of kinematic and postural parameters, which represent aesthetic characteristics of movements executed during the rowing stroke cycle. Qualitative assessments of rowing technique have traditionally centred on the extent to which the rower's adopted style varies from an accepted style. There is an abundance of different rowing styles listed in the literature. Spinks (1996) has noted a number of rowing styles such as the English Orthodox, Fairbairn, Adam, German Democratic Republic (GDR or Modern Orthodox), Rosenberg and Tsukuba styles (Dal Monte & Komor, 1989; Edwards, 1963; Fukunaga, Matsuo, Yamamoto, & Asami, 1984; Klavora, 1982; Martin & Bernfield, 1979; Pannell, 1972; Schneider, 1980).

It is possible that visual inspection of these kinematic factors alone may not provide sufficient information to accurately quantify or analyse the rowing stroke, given that a range of kinetic factors are known to influence boat kinematics and overall rowing performance (Spinks, 1996). Effective coordination of forces across the stroke cycle (or *shape* of continuous force application), is a potentially meaningful yet difficult aspect of rowing technique to understand (Anderson, Harrison & Lyons, 2005; Rekers, 1999). Consequently, graphical displays of propulsive force have been used qualitatively to explore within-cycle coordination of force application, in the daily training environment. It should be acknowledged that similar qualitative analytical strategies can also be used for other kinetic variables such as forces observed at the foot-stretcher or pin in the non-propulsive planes (vertical and transverse planes) (Smith & Loschner, 2002). Despite this, the majority of literature demonstrating the applied utility of such graphing techniques in on-water rowing has focused on measures of propulsive force applied at the oar (often using systems measuring propulsive force applied to the pin). These graphical depictions are often referred to as '*profiles,*' (Spinks, 1996; Smith & Loschner, 2002; Coker, Hume & Nolte, 2008) and this term will be used to refer to such graphs throughout the remainder of this literature review. When visualising these profiles in the applied training environment two methods for graphical representation of force have been used (Spinks, 1996).

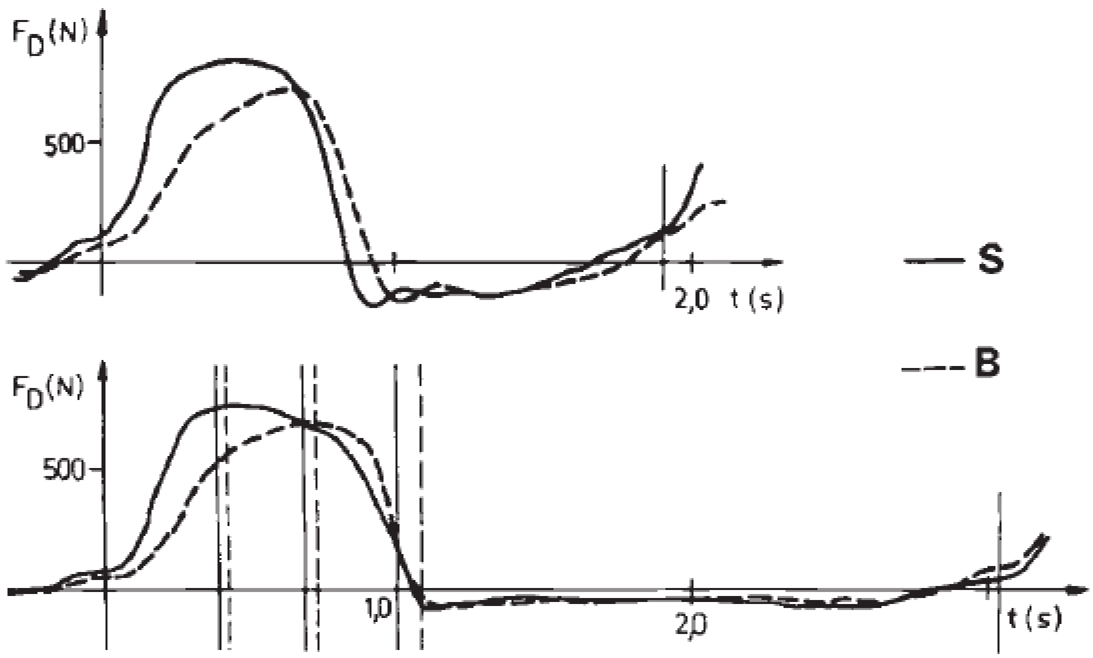

Figure 2. Example of *force-time* profiles in Roth, Schwanitz, Pas and Bauer (1993). This figure depicts curves for a rowers in the stroke seat (S, solid line) and bow seat (B, dashed line) of a coxless pair during rowing at different speeds. Top: competition speed, stroke rate of 32 strokes per minute. Bottom: endurance training, stroke rate 20 strokes per minute.

Temporal force profiles

These profiles involve force being plotted on the *y*-axis, relative to a linearly increasing temporal scale such as time (Roth, Schwanitz, Pas & Bauer, 1993; Spinks, 1996), or percentage of the stroke cycle after temporal normalisation (Smith & Loschner, 2002), which is plotted on the *x*-axis. As such these graphs can be referred to as *force-time* or *force-percentage* profiles respectively. Force-time profiles (see Figure 2) allow for the observation of meaningful temporal parameters that are related to force production such as a rower's stroke rate and ratio of time spent in the drive phase relative to the recovery phase. Differences in magnitude of force application and time taken to reach maximal force can be obtained from these profiles (Spinks, 1996). Force-time profiles are also used to obtain information regarding the impulse generated by a rower during each stroke cycle (Draper, 2005). Evaluation of force-time profiles is also a valuable tool when used in conjunction with video for assessing coordination within a crew (Christov & Ivanov, 1987; Draper, 2005; Kleshnev, 2007a). Force-time plots have also been noted as potential tools for maintaining training intensity and can be used as indicators of training load (Draper, 2005).

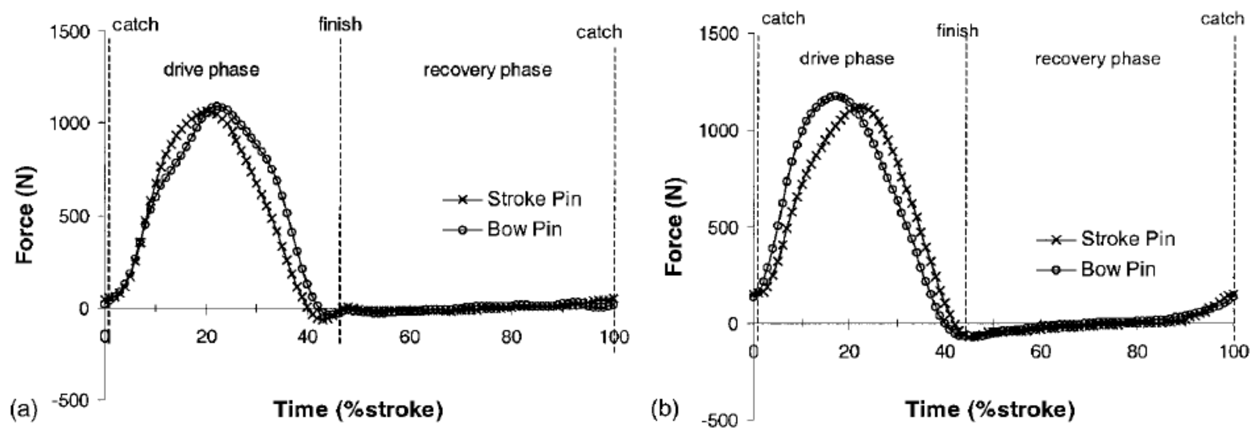

Figure 3. Example of force-percentage profiles in Smith and Loschner (2002). This figure depicts the relative timing between the stroke and bow pin propulsive forces in a pair for skilled (a) and less skilled (b) rowers. The curves are time-normalised and averaged data for 12 consecutive strokes at 30 strokes per minute.

Force-percentage plots (see Figure 3), although less frequently reported in the literature, are also used to observe qualitative changes in force application across the stroke cycle. Use of force-percentage profiles (Smith & Loschner, 2002) allows for assessment of force application relative to a common length for all profiles and also permits for the alignment of key events within the stroke cycle.

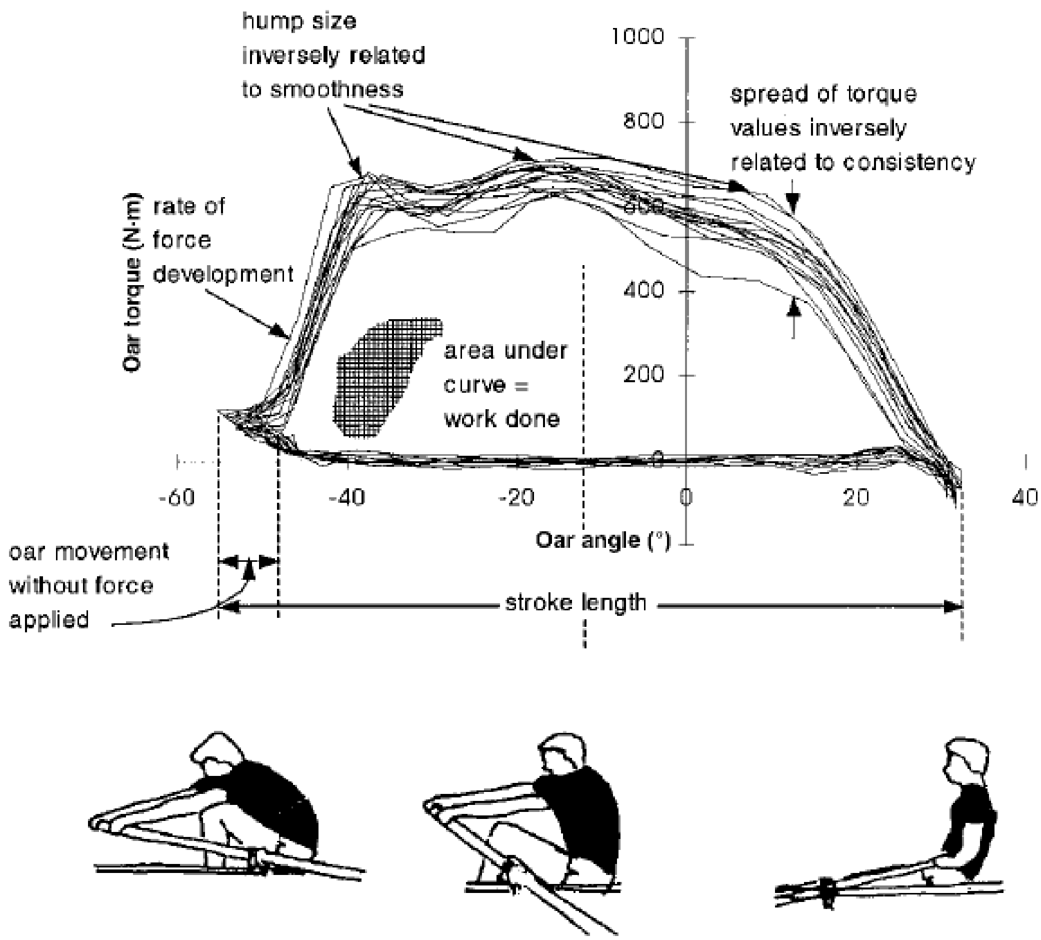

Figure 4. Example of force-angle profiles in Smith and Loschner (2002). This figure depicts a series of force-angle profiles of a club level rower. This graph also depicts a range of technical parameters that can be inferred from the shape characteristics of the force-angle profile.

The alignment of these events enables magnitude related characteristics of force application to be observed and qualitatively compared within key phases of the stroke cycle. Less inferences, however, can be made about the true temporal characteristics of force application using these plots, given that the relativity between strokes is lost as a part of normalization strategies applied to the data to create common time lengths for all time-series.

Positional force profiles

These bivariate graphical representations incorporate the force data plotted on the *y*-axis, relative to the corresponding *oar angle* on the *x*-axis. The horizontal oar angle (which is defined in Figure 1) can also be measured as a time-series through the use of on-water rowing instrumentation systems (Coker, Hume & Nolte, 2009; Smith & Loschner, 2002). When observed solely as a univariate time-series, the oar angle-time profile allows for analysis of continuous angular motion of the oar. This time series also allows for a range of relevant discrete kinematic variables to be explored such as, stroke length, angular speed of the oar, drive to recovery ratio, stroke rate and stroke rate variability (Spinks, 1996). When the force-time and oar angle-time profiles are plotted together in the form of a *force-angle* profile (see Figure 4), it becomes possible to visualise force spatially, by referencing the oar angle as a spatial measure of stroke length. The force-angle profile allows for inferences regarding the stroke by stroke work output for a specific rowing intensity (Kleshnev, 2007a; Spinks, 1996) and is also effective when comparison of profiles is required across different stroke rates (Spinks, 1996). The latter is possible because phase shifts that may result as a consequence of force-time profiles possessing different lengths (see Figure 2) will no longer distort visual interpretation of the profile, as force is plotted within a temporally independent spatial domain.

The inclusion of an oar angle measure in this profile also allows for a more intuitive assessment of phases in the stroke cycle than that provided by the force-time percentage profile. Use of the force-angle profile allows for visual examination of force application at different events during the stroke cycle (catch & release position, perpendicular oar position to longitudinal axis of the boat). This provides a meaningful platform for assessment of technical differences between or within rowers (see Figure 4), particularly with reference to the rowing movement phases and the (approximate) body positions associated with those phases (Draper, 2005). The force-angle profile is also useful, when assessing rowing crew set-up in the daily training environment (Coker, Hume & Nolte, 2008). It has been noted that if a rower's foot stretcher location is further to the bow relative to the other crew members, this rower's force-angle profile will be shifted to the right, relative to the rest of the crew. The opposite of this would be true if the foot-stretcher is located closer to the stern (Coker, Hume & Nolte, 2008).

Force signatures

Inspection of both temporal and positional force-profiles has introduced the concept of the force '*signature*' in rowing. This term was introduced by researchers in the nineteen seventies and is related to the unique athlete specific differences in shape characteristics of the pulling force on the oar handle (Ishiko, 1971) or on the oar gate (Nolte, 1979). This phenomenon has also been identified for force applied the foot-stretcher and has been referenced as "*footwriting*" (Koerndle & Lippens, 1988). These individual technical characteristics regarding patterns of force application are harmonically stable, yet unique for each rower (Wing & Woodburn, 1995; Smith & Loschner, 2002), with it being possible to identify rowers by their distinctive shape characteristics displayed in force-time and force-angle profile graphs. While some researchers have found these individualised signatures are stable and resistant to change (Schneider, Angst, & Brandt, 1978; Wing & Woodburn, 1995; Spinks, 1996), other research has demonstrated adaptability of these force patterns as a part of coaching and training interventions. Hill (2002) has demonstrated this notion with highly skilled rowers, whereby these athletes possessed the ability to adapt their own force signatures relative to the type of boat that they are performing in and crew they were rowing with. This demonstrates that, although rowers may self-organise their behaviour (Davids, Glazier, Araujo & Bartlett, 2003) in an effort to optimise force application at an individual level, there is still the possibility to perform technical interventions with an athlete, if optimal characteristics of these force profiles are known.

Quantitative analysis of on-water kinetics

Given the obvious idiosyncratic differences in force profiles or signatures between rowers, and high level of stability within rowers, a major point of interest in the literature, has centred on questions such as:

1. Is there a *signature* that will result in optimal rowing performance? Or;
2. Are there characteristics of a signature that will result in optimal rowing performance?

In an effort to answer these two questions, empirical information from temporal and positional force profiles has been used to develop theoretically and experimentally driven answers to these questions. This section of the literature review, will provide a summary of force profile characteristics known to be of potential importance for improved performance, and the associated underpinning quantitative methods for assessing these characteristics. Two main analytical strategies have been used to understand relevant performance related characteristics of force application. Firstly, discrete point analysis (DPA) (Richter, Marshall & Moran, 2014) has been used frequently through the examination of pre-selected *key* points on each of the force profiles (e.g. maxima or minima, etc.). Secondly, data reduction strategies where indexes or measures for particular characteristics are calculated, have also been used.

Discrete point analysis

It is logical that greater peak or maximal force application on the blades has been associated with greater boat velocity (McBride, 1998). Force-time profiles have supported this idea through experimental findings assessing peak force application at the handle, where athletes competing at a senior level of competitive representation were found to produce a higher amount of peak force relative to a junior cohort of participants (Kleshnev, 1999). Hill (2002) has however noted that assessment of peak force alone is unsuitable for making inferences related to technical differences between rowers, as patterns of force-time profiles can vary greatly for rowers who have similar measures of peak force.

For this reason, a number of researchers have investigated the biomechanical relevance of peak force location, using information derived from the force-angle profile (where maximal force can be observed relative to the oar's spatial position). It was traditionally thought that peak force should be applied when the blade is perpendicular to the longitudinal axis of the boat (Soper & Hume, 2004). Here the transverse component of the rowers force would be minimal and force would ideally be maximal in the propulsive direction (Celetano, Cortili, di-Prampero & Cerretelli, 1974; Martin & Bernfield, 1979; Spinks, 1996; McBride, 1998). Physiologically it has also been reported that a rower's metabolism operates at a higher efficiency if maximal force is applied across the middle of the drive phase, rather than increased force application at the beginning or end of force application (Roth, Schwanitz, Pas & Bauer 1993).

Theoretical arguments also exist for the use of '*front loaded*' profiles (where peak force occurs prior to the oar being perpendicular to the longitudinal axis of the boat). These force profiles are theoretically associated with a more evenly distributed power profile, which would in turn allow for reduced fluctuations in boat velocity and better rowing efficiency (Kleshnev 2006;

Nolte & Morrow, 2002). Soper and Hume (2004) also noted that in a case study by Fukunaga, Matsuo, Yamamoto and Asami (1984), a rower with a higher skill level was found to achieve peak force approximately 15° prior to the blade being perpendicular to the boat. In comparison, lesser skilled rowers reportedly achieved peak force in the second half of the drive phase (Fukunaga et al., 1984). The delay in reaching peak oar force by the unskilled rowers theoretically would limit the transfer of mechanical energy to the oar and result in deceased oar impulse compared to the skilled elite rowers (Kleshnev, 2007b).

Coker, Hume and Nolte (2008) have also highlighted theoretical support for increased force production at the catch and finish. The phases of the drive where the blade is furthest from being perpendicular to the longitudinal axis of the boat (catch and finish positions) are important for taking advantage of lift forces. In the earlier and later stages of the drive phase, the blade acts as a hydrofoil, creating a lift force with a considerable propulsive component (Caplan & Gardner, 2007a). These lift forces are linked through the middle section of the drive phase by increased drag forces at the blade. Therefore to make use of a rower's energy more effectively and achieve theoretical optimal efficiency, high lift forces should be generated at the beginning and end of the drive, in addition to high drag forces in the middle of the drive (Caplan & Gardner, 2007b). Although it is not biomechanically possible to create a completely rectangular force profile (as this theoretical notion suggests), theoretically by emphasizing the start of the drive, lift forces would be utilised more effectively and high internal joint loads on the upper extremities would be avoided.

Data reduction approaches

In addition to selecting discrete points from force-time or force-angle profiles, a number of data reduction strategies and subsequently derived discrete measures have been used to investigate characteristics of force application across the drive phase. Area under the force-angle and force-time profiles have been used to draw inferences about work outputted (Smith & Loschner, 2002) and impulse generated (Hill, 2002) over the drive phase. For the force-time profile, any increase in momentum (and therefore increase in boat velocity) will be determined by the size of this impulse, and as a consequence of this, the area underneath the force-time curve should be as large as possible (Coker, Hume & Nolte, 2008). Measures regarding area under the force-time profile can also be used to make inferences regarding the centre of the force-time graph. Hill (2002) devised a measure to determine whether patterns of force-time profiles could be assigned to a harder catch, harder finish or a neutral pattern. This centre-of-force measure was defined as the point at which the force graph would be divided into two halves of equal area during the drive phase.

Although shape characteristics were explored earlier in this review (through discrete point observations of peak force relative to the oar's spatial position), other analytical processes have been used to comment on shape characteristics of the force-time profile. It has been established that increasing average force relative to maximal force (referred to as mean to peak force ratio, or MPFR) or achieving a higher rate of force development at the beginning of the drive will result in a larger area (or impulse) for the same, or even lower amount, of peak force (Kleshnev, 1999; Kleshnev & Kleshnev, 1998; Millward, 1987). This ratio has been significantly higher in elite rowers when compared to a sub-elite cohort (Smith & Draper, 2006). Visually, this would create a more rectangular, rather than triangular shape (Coker, Hume & Nolte, 2008), through which assessment of peak force location alone would not necessarily have been able to detect.

Like assessments of area and shape, the smoothness of the force profile has been correlated to some degree with rowing level (Rekers, 1999; Smith & Spinks, 1988). This may be due to reduced fluctuations in boat velocity, which in turn increases rowing efficiency (Soper & Hume, 2004). Intermittent force application at the foot-stretchers and oars can result in increases to boat acceleration and deceleration during the drive and recovery phases. These in turn can lead to large increases in boat velocity fluctuations (Soper & Hume, 2004). Eliminating these deviations through use of a smooth continuous force application should also increase the area under the curve and optimise performance accordingly. Hill (2002) used a measure of smoothness to explore stability and variability of rowing technique with sweep oar rowers.

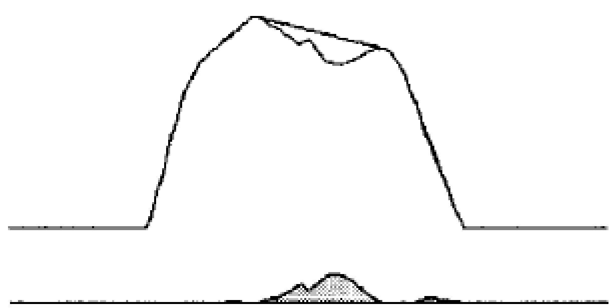

Figure 5. The smoothness measure as defined by Hill (2002). The shaded difference area relative to the force-time profile provides the value for smoothness, which in the present example is case 4%.

To compute smoothness, a line was drawn over the concave segments of the force-time profile (see Figure 5). All inflection points (local minima and maxima) across the force-time profile were located for the drive phase. An interpolated line was drawn between two subsequent maxima, and the area between the force-time profile and the interpolated line was derived. The smaller the area (or smoothness factor as referenced in Hill, 2002), the better the movement pattern was hypothesised to be. Previously, Hill also assessed the smoothness of force-time profiles of novice rowers during ergometer rowing (Hill, 1995). Performances of these novice rowers were inferior to that of elite rowers who were assessed in both on-water (Hill, 2002) ergometer conditions (Hill, 1995). The elite rowers in the on water testing did not see an improvement in the smoothness of force patterns during training camps (Hill, 2002). Hill concluded from this that smoothness is one potential discriminating factor between rowers of different abilities, but a large quantity of specific training is likely to be necessary for improvement of stroke smoothness.

Contemporary view on force profiles and rowing performance

Despite the significant contributions of researchers in attempts to understand the relationship between force application (force profiles) and rowing performance, there still remains a lack of clarity as to '*what*' exactly constitutes optimal propulsive force application in on-water rowing. In a list of five key recommendations for progressing biomechanics knowledge in on-water rowing, Baudouin and Hawkins (2002) noted the need for a better understanding of force-time profiles to identify specific components of a rower's biomechanics that can be modified to achieve greater force generation, and subsequent better performance. Similarly, after a comprehensive review of biomechanical factors associated with optimised rowing performance, Soper and Hume (2004) recommended that future research in rowing biomechanics, should be focused on understanding, what the ideal force-angle profile is (if it exists), particularly for sculling rowers. Soper and Hume also addressed a need for the investigation into whether force profiles could be used by coaches or selectors to reliably or validly to predict a rowers' current or future on-water performance. Perhaps, most interestingly, as a part of the "*World's Leading Rowing Sport Science and Medicine Conference - Improving Performance Naturally*," Seiler (2015) reviewed 150 years of rowing biomechanics research and concluded that "*real time measurement of boat kinematics and rower force application patterns open for new approaches to training and rower selection for team boats. It seems unlikely that one optimal force curve can be identified for all rowers in a team boat because the interaction of anatomical, muscular, and biomechanical factors probably constrains the optimal force curve for each rower*."

Newell's Model of Constraints

Seiler's (2015) comments regarding the decreased likelihood that *one* optimal force curve can be identified for all rowers in a team boat is logical, given that the performance of a skill is governed by the multifactorial integration of different variables (Newell, 1986; Glazier, 2015). According to Newell's dynamical model of constraints (1986), the underlying structure of coordination patterns for human movement is determined by the constraints imposed on the task. In this model a constraint is considered to be a boundary or feature that limits the number of potential degrees of freedom available to an individual (Newell, 1986). Newell's model implies that the human body produces different coordination patterns due to the impositions of organismic, environmental and task constraints. Organismic constraints relate to the structural and functional constraints of the human body, and commonly include factors such as body weight, height, shape, muscular strength and power. Individuals have their own unique organismic constraints that will affect their ability to interact with the environment and task constraints (Newell, 1986). Environmental constraints external to the organism and include factors such as gravity, ambient temperature, natural light, location, visual and auditory information (Handford, Davids, Benneth, & Button, 1997; Newell, 1986). Task constraints are often specific rules or goals that specify the kinematics requirements for successful movement during execution of a skill (Newell, 1985). In the present example of on-water rowing a considerable amount of between-athlete variation for shape characteristics of force-time and force-angle profiles or signatures is present (Hill, 2002). It is possible that performance characteristics (boat velocity, level of skill or competitive representation, etc.) will not account for all variation between individuals. Other constraining factors may influence these between-athlete differences.

Potential organismic constraints and force application

Rower anthropometry: One relatively common organismic constraint, which could affect characteristics of force profiles is athlete anthropometry. It has been recognised that athletes of a taller, larger stature hold a considerable physical advantage and possess a tendency to dominate rowing from a performance perspective (Bourgois et al., 2000). Consequently, a weight-limited category, Lightweight (LW), was introduced, restricting these crew boats to a maximum individual average mass of 70.0 kg, with no individual more than 72.5 kg (Doyle, Lyttle & Elliot, 2010). Doyle, Lyttle and Elliot (2010) compared a number of discrete kinetic measures between LW and heavy-weight (HW) rowers. These measures included peak handle force, average handle force, work per stroke and power-per-kilogram. All measures were found to be significantly different between weight categories, with heavyweight rowers possessing higher kinetic measures across all variables. Given three of the four measures evaluated by Doyle, Lyttle and Elliot (2010) were obtained from force-time or force-angle profiles, it is plausible that the shape characteristics of these profiles may be influenced by similar anthropometric constraints related to rower size differences. Additionally, anthropometric characteristics in the form of relative segment lengths, have also been noted to change characteristics of rowing technique. Greene, Sinclair, Dickson, Colloud and Smith, (2009) investigated the effect of shank to thigh length ratio changes between rowers, on timing and magnitude of joint power production during the drive phase of the rowing stroke. In this study, time to half lumbar power generation was significantly earlier in shorter shank rowers ($p < 0.05$) compared to longer shank rowers, who showed no lumbar power generation during the same period of the drive phase. Rowers with a relatively shorter shank also demonstrated earlier lumbar power generation during the drive phase resulting from restricted rotation of the pelvic segment requiring increased lumbar extension. Earlier lumbar power generation and extension did not appear to directly affect performance measures of the short shank group, and so can be attributed to a technical adaptation developed to maximise rowing performance. Similar adaptations of technique brought about from relative segment length differences between rowers may also be found through observation of changes to rowing force profiles.

Rower gender: There is also growing support for presence of biomechanical differences between male and female rowers (with gender acting as another organismic constraint, or potential cluster of organismic differences between groups of rowers). In addition to established peak force and power differences between males and females, ergometer research has established that females possess a more optimal lumbopelvic rhythm due to greater anterior pelvic rotation (McGregor, Patankar & Bull, 2008). Additionally, relative joint power differences between males and females have been noted, particularly for upper extremity joints, across the drive phase of the rowing stroke cycle (Attenborough, Smith & Sinclair, 2012). In this instance a reduced contribution of the angular shoulder energy expenditure to total energy expenditure has been demonstrated in female rowers across a range of stroke rates in ergometer testing. Despite these biomechanical differences between males and females in ergometer research, there is limited literature at present showing differences in characteristics of movement patterns, or biomechanical variables that are representative of these patterns, in on-water rowing.

Potential environmental constraints and force application

Environmental constraints are also likely to influence differences in force profiles. Given that on-water rowing testing takes place in an unstable aquatic environment, subtle changes relative to environmental constraints (normally temperature and wind conditions) are to be expected, and have the potential to account for differences in parameters of technique. Potential effects of environmental factors such as of temperature, tail-, head- and cross-winds on boat velocity are have been acknowledged in on-water testing environments (Smith et al., 2015), but these factors are not likely to account for consistent differences in skill execution between athletes (Hill & Fahrig, 2009).

Potential task constraints and force application

Rowing type: One notable task constraint in on-water rowing is rowing type. A drawback of contemporary literature evaluating characteristics of force-time or force-angle profiles, is the abundance of experimental studies assessing sweep rowers (Martin & Bernfield, 1979; Roth, Schwanitz, Pas & Bauer, 1993; Wing & Woodburn, 1995; Hill, 2002; Baudouin & Hawkins, 2002; Smith & Draper, 2006). Sweep rowing is somewhat easier to assess, given that a single unit of measure is recorded for force, rather than bilateral force collected in sculling. At present there isn't sufficient experimental evidence to suggest that sweep and sculling rowing styles require the same force profile characteristics for optimal rowing performance. Additionally, differences in technical biomechanical variables have been demonstrated when comparing sculling and sweep rowing in on-water testing. Burnett, Doyle and Elliot (2004) demonstrated significantly larger catch angles and stroke arcs for sculling on both sides of the boat when compared to sweep rowing. These were in agreement with other studies which have reported sculling arcs between 100° and 110° and sweep arcs of 80° to 90° (eg. Zatsiorsky & Yakunin, 1991). Burnett, Doyle and Elliot (2004) also demonstrated significant differences between scullers and sweep rowers for both catch and finish height. In this study, left side sweep rowers demonstrated a lower finish height in comparison with the left hand of scullers (sweep 5.0°; scull 7.9°) and the catch height for the right hand was significantly higher for scullers (5.3°) when compared to right oared sweep rowers (1.9°). It is plausible from these findings that characteristics of propulsive force application across the stroke cycle may also be affected by the type of rowing involved. This is particularly true for differences in the force-angle profile, as results demonstrated by Burnett, Doyle and Elliot (2004) were related directly to oar kinematic changes between the two rowing types.

Side of the boat: There is also evidence for potential differences in force application across each side of the boat in both on-water sculling and sweep rowing. The presence of differences in sculling is of particular interest given the assumption of symmetry in force application in this type of rowing. Due to the inboard length of the oars used during sculling, the oar handles must overlap when the blades are perpendicular to the boat, resulting in potential upper body asymmetry during force application. Boats are most commonly rigged so that when the handles overlap the left hand will be on top of the right hand. This asymmetry has been suggested as an attributing factor to large discrepancies reported (Elliot, Lyttle & Birkett, 2002;

Loschner et al., 2000) in stroke and bow side peak force measures. Both Loschner et al., (2000) and Elliot et al. (2002) reported greater force on the bow-side pin compared with the stroke-side pin. Greater force application on one blade may result in greater yawing (movement about the longitudinal axis of the boat), which is reported to negatively correlate to boat velocity. To account for unwanted yawing of the boat in sculling, it may be possible that shape characteristics purposefully differ between bow and stroke side forces to negate this asymmetrical offset in how the oars are mechanically rigged.

Differences across the two sides of the boat for sweep rowing has also been an area of interest in contemporary literature. McBride (1998) has reported that for stroke seat rowers in a highly skilled pair, an average of 13.8% greater peak oar-lock force was present when compared to bow seat rowers (Soper & Hume, 2004). Also, when rowing at 32 strokes per minute, Roth, Schwanitz, Pas & Bauer (1993) found greater power for stroke seat rowers when compared directly with bow seat rowers in a pair. Further to this, descriptive findings demonstrated a more *front peaked* force profile for the stroke seat. These findings regarding differences in the shape characteristics of force profiles were also supported by Smith and Loschner (2002) who found that for a highly skilled rowing pair, the stroke rower reached peak force earlier than the bow rower after applying a greater amount of force between 10% and 20% of the stroke cycle. The bow rower then applied a greater amount of force when compared to the stroke rower up to the finish. The opposite trends were present for an unskilled pair, demonstrating that this offset between the two sides of the boat were intentional for the highly skilled rowers. It was also highlighted that the skilled pair potentially compensated for the presence of an unbalanced moment that likely arose as a consequence of the seats being staggered relative to each other (Smith & Loschner, 2002).

Seat position: The task constraint of seating location may also affect force profile characteristics. For, sweep boats in particular, seating position in smaller boats are have already demonstrated differences in discrete kinetic measures. McBride (1998) has reported that well trained stroke seat rowers produced greater peak oar-lock force compared to bow seat rowers. Similarly, Roth, Schwanitz, Pas and Bauer (1993) have demonstrated significantly greater power by stroke seat rowers compared with bow seat rowers, illustrating that the issue of asymmetries in force production between rowers in a pair is just as much a factor of side of the boat, as it is a factor of seat position. In contrast to this, evaluation of force characteristics in larger sweep crew boats has often advocated for synchronous force application of all crew members. Synchronous coordination of crew members is generally thought the enhance efficiency of rowing, as poor synchronization will create a torque about the boat and subsequently increase drag (Baudouin & Hawkins, 2002). In highly skilled international rowers, differences between crew members in the shape of force profiles have been noted to be more detrimental to performance than differences in other measures such as area under the force profile (Wing & Woodburn, 1995; Hill, 2002). These findings have been noted for much larger crew boats such as racing eights. Thus the constraint of seat position is likely to affect characteristics related to asymmetrical offsets, or synchronicity of profiles between rowers, depending on the type of boat.

Constraints and force application summary

By combining the results of the aforementioned studies in this section of the literature review, it is plausible that a combination of organismic, environmental and task related constraints could affect patterns of force production across the rowing stroke cycle, through changes to characteristics of the force-time or force-angle graphs. The influence of these constraints could potentially mask relevant performance characteristics, which may be specific relative to the different conditions set-up by particular constraints. For example, when referring to organismic constraints, it is possible that an optimal force profile for males may differ to that of females. Similarly, when referring to task constraints, the way an athlete executes force application in single sculling on one side of the boat may be different to force outputted on the other side of the boat (as a consequence of known structural asymmetries). Thus it is imperative that these different, yet potentially influential constraints are explored and/or controlled for in future experimental research, for the assessment of performance differences in on-water rowing.

Analytical shortcomings from contemporary literature

There are also potential issues regarding the use established data analysis strategies that have attempted to understand differences in the coordination of force application displayed in force profiles. As is the case with a number of studies outlined within this review, an integral component of biomechanics is the analysis of biomechanical waveforms to identify features that relate to the performance of a movement. Commonly used approaches for identification of such features in force profiles have involved discrete point analytical (DPA) strategies and basic data reduction strategies, both of which aim to reduce the dimensionality of a time-series through examination of pre-selected measures or sections of a time-series. These selected data points or sections of a time-series are commonly chosen prior to analysis and often require substantial *apriori* knowledge of the skill being analysed. There are some limitations involved with these approaches. Pre-selection of features is strongly dependent on previous knowledge and has the potential to discard potentially relevant pieces of information (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Donoghue, Harrison, Coffey & Hayes, 2008). DPA and data reduction approaches used in contemporary rowing literature also do not necessarily preserve all structural aspects of the original data (characteristics of variability in a group of continuous time-series), often resulting in large sums of potentially important information being distorted or discarded.

Additionally, substantial research into relevant characteristics of force application has focused on force-time profiles, with minimal statistical rigor applied to the force-angle profile (other than assessment of peak force location). This is understandable given that the force-angle profile is a complex bivariate structure composed of two non-linear time-series variables. DPA techniques and simple data reduction strategies can be applied more readily to the force-time profile given its simpler univariate nature, but the same techniques are not as easily applied to the force-angle profile. This is disappointing, given that the force-angle profile has known practical utility for understanding important characteristics of rowing technique in ways that are different to observation of force-time and force-percentage profiles (Smith & Loschner, 2002). It is important that future experimental research looks to find suitable methodological and analytical approaches that can negotiate these shortcomings contemporary literature. More specifically, careful attention should be paid to identifying analytical strategies that preserve all of the original content and variability structure embedded in the original force profiles. Additionally, statistical techniques that can preserve all aspects of this original data for bivariate time-series would be warranted so that rigorous statistical processes can be applied to the force-angle profile and experimental evidence can be built for the role of the force-angle profile with understanding rowing performance.

An alternative analytical approach: Functional data analysis

Biomechanical data often take the form of a time-series or function, encapsulating information about an entire movement or skill. Appropriate statistical techniques are therefore needed to manage these large and complex forms of data, allowing for the integration of biomechanics into applied sports contexts. The use of novel statistical techniques for dealing with this type of data in biomechanics has grown substantially and comprehensive reviews on some of these techniques are already available (Chau, 2001a; Chau, 2001b; Wheat & Glazier, 2006; Preatoni et al., 2013). One emerging area of statistics in biomechanics is “Functional Data Analysis” (FDA), which is used to express observations arising from time series in the form of a function and then apply statistical concepts from conventional multivariate data analysis. This has advantages over conventional multivariate statistical models as all data points representing a given function are allowed to correlate with each other, and FDA also has applicability for use on data with irregular time sampling schedules (Ullah & Finch, 2013).

FDA has already been applied in various contexts within sports biomechanics, including evaluation of sports performance with jumping (Ryan, Harrison & Hayes, 2006; Harrison, Ryan & Hayes, 2007), race-walking (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009), on-water single scull rowing (Warmenhoven et al., 2015), front crawl swimming (Sacilotto, Warmenhoven, Mason, Ball & Clothier, 2015), running (Donoghue, Harrison, Coffey & Hayes, 2008; Liebl, Willwacher, Hamill & Brüggemann, 2014; Coffey, Harrison, Donoghue & Hayes, 2011), Olympic weightlifting (Kipp & Harris, 2014; Kipp, Redden, Sabick, & Harris, 2012a; Kipp, Redden, Sabick, & Harris, 2012b) and fatiguing exercises as a part of strength and conditioning research (Mallor, Leon, Gaston & Izquierdo, 2010). The growth of FDA in sports biomechanics literature to date was summarised in the International Society of Biomechanics in

Sport (ISBS) Geoffrey Dyson lecture of (2014), which provided an insight into the current use of FDA in sports biomechanics and called for further use, enhancement and refinement of FDA techniques when applied in sporting performance assessment and evaluation (Harrison, 2014).

Furthermore, FDA techniques have demonstrated utility in sports biomechanics with both univariate functional data (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Ryan, Harrison & Hayes, 2006), in the form of functional principal components analysis (*f*PCA), and multivariate functional data (Harrison, Ryan & Hayes, 2007), in the form of bivariate (or in some instances multivariate) functional principal components analysis (*bf*PCA). In the case of on-water rowing force profiles, *f*PCA could be applied to force-time or force-percentage profiles and *bf*PCA could be applied to force-angle profiles. The use of these FDA techniques could form the beginning of a newly improved methodological approach for handling and exploring the complex patterns of coordination that are embedded within force profiles.

Summary

Successful rowing performance is dependent upon the interaction of numerous kinetic variables, such as drag and propulsive forces acting on and around the boat. Given the existing relationship between these kinetic measures and boat velocity, a range of rowing instrumentation systems have been used to capture and assess continuous force application at the foot-stretcher, inboard of the oar shaft, the pin or oarlock and the oar blade. These rowing instrumentation systems have been used to qualitatively and quantitatively assess the role of force production in increasing or bettering rowing performance. Often qualitative analysis of rowing technique undertaken by coaches has involved observations of kinematic and postural aspects of the rowing skill, but strong evidence has also been demonstrated for observation of continuous kinetic variables. These variables are often related directly to measureable propulsive forces (commonly observed at the pin) and are visualised through the use of both *temporal force profile* and *positional force profile* graphs.

Qualitative inspection of these graphs possess benefits for understanding rower movement patterns and serving as a platform for development of more advanced coaching interventions in the daily training environment. Similarly, quantitative approaches have been used in attempts to understand differences in these profiles relative to known performance metrics. Quantitative analysis has often resulted in discrete point analytical strategies and data reduction processes being applied to force profiles in an effort to understand characteristics such as magnitude of peak force, peak force location, force profile area, force profile shape and force profile smoothness. Despite the substantial amount of literature available, there is still a lack of consensus in the literature regarding '*what*' exactly constitutes an optimal force profile, or optimal force profile characteristics, and whether such a profile or characteristics exist commonly for all rowers. Concerns regarding the influence of other existing constraints (particularly organismic and task constraints, using Newell's 1986 framework) on substantial amounts of between athlete variation in characteristics of temporal force profiles and positional force profiles have also been identified. Additionally, concerns regarding the use of established analytical and data reduction techniques on these graphs have been raised.

Further research is required to explore and understand the role of potential constraints (un-related to performance) on the characteristic differences between athletes in force profiles. Additionally, improved methodological approaches are required to more suitably handle the content and structure of data associated with these profiles. This is particularly true for the force-angle profile, which has received limited attention comparative to the force-time profile, given the added complexity of the former being a bivariate structure. By experimentally accounting for potentially influential constraints and optimising analytical processes, new research could be developed that would begin a more comprehensive, experimentally driven, evidence base for understanding the role of continuous force application in on-water rowing. Using such an approach is warranted to adequately understand the relationship between force profiles and performance metrics in this sport.

References for this chapter are included in the list of references at the end of this thesis

BRIDGING STATEMENT A

The literature review (in chapter two) has shown that qualitative graphical displays of force profiles such as force-percentage, force-time and force-angle graphs provide rich sources of technical information regarding skill execution in on-water rowing. Despite this, the literature review also highlighted that objective, experimental findings using information obtained from these graphs have provided conflicting opinions on '*which*' characteristics of these profiles or signatures, if any, are relevant for better rowing performance. This lack of consensus may be due in part to the use of statistical or analytical strategies, which do not adequately identify important characteristics if they do exist. Some statistical techniques with potential to circumvent such issues are from the *Functional Data Analysis* (FDA) family of statistical processes. In FDA, time-series data (represented by curves or waveforms) are considered in their entirety as a single functional entity, and all characteristics of variability present in groups of waveforms are retained when using these statistical processes. FDA techniques could have applicability for use across all documented graphical representations of force signatures (force-percentage, force-time and force-angle profiles, etc.). The following two chapters form a two part series, exploring the applicability of two FDA techniques. The first chapter in this series (chapter three) will explore the use of *f*PCA with force-percentage and force-time profiles. The second chapter in this series (chapter four) will look at the use of *bf*PCA with force-angle profiles. Considerations and recommendations regarding the correct use and administration of these techniques will also be provided. It is believed that these two chapters will be contributive to on-water rowing biomechanics literature and the broader sports biomechanics community.

CHAPTER 3

Considerations for the use of functional principal components analysis (*f*PCA) in sports biomechanics: examples from on-water rowing.

The following chapter was formatted for submission to the Journal of Sports Biomechanics and is currently accepted for publication.

Author Contribution Statement

As a co-author on the paper presented within this chapter entitled "*Considerations for the use of functional principal components analysis (fPCA) in sports biomechanics: examples from on-water rowing*," as well as being Primary Supervisor throughout the Doctor of Philosophy candidature of John Warmenhoven, I confirm John's contribution to the paper as follows:

- Conception and design of the research
- Data collation, database building and database management
- Analysis of data and interpretation of the findings
- Writing the paper and critically appraising content within the manuscript

Signed: [redacted]

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Considerations for the use of functional principal components analysis (*f*PCA) in sports biomechanics: examples from on-water rowing.

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Abstract

The proliferation of new biomechanical technology in laboratory and field settings facilitates the capture of datasets consisting of complex time-series. Statistical approaches for analysing and interpreting these data sets are needed and the functional data analysis (FDA) family of statistical techniques has emerged in the biomechanical literature. Given the use of FDA is currently in its infancy with biomechanical data, this paper will form the first of a two part series aiming to address practical issues surrounding the application of FDA techniques in biomechanics. This work focuses on functional principal components analysis (*f*PCA) of biomechanics data, which is explored using existing literature and sample data from an on-water rowing database. In particular methodological considerations for the implementation of *f*PCA such as temporal normalisation of data, control over artificially introduced phase variation into the results of an *f*PCA and documented methods for preservation of the original time domain within a set of curves are explored in detail as a part of this review. Limitations and strengths of the technique are outlined and recommendations are provided to encourage the appropriate use of *f*PCA within the field of applied sports biomechanics.

Key Words (3-8): Functional Principal Components Analysis; FDA; Biomechanics; Rowing.

Considerations for the use of functional principal components analysis (*f*PCA) in sports biomechanics: examples from on-water rowing.

Introduction

Despite the popularity of athlete performance monitoring in high-performance sport, a single definitive tool or variable that is accurate and reliable for prediction of performance or injury is not evident (Halson, 2014). The difficulty of identifying such a tool for quantifying predictors of sports performance or injury is logical, given that sport performance is governed by many interacting physiological, biomechanical and psychological variables (Glazier, 2015). Despite sports performance being multi-faceted, the majority of performance-oriented sports science research has been predominantly mono-disciplinary. Glazier (2015) has called for a unified theory of sports performance with multi-disciplinary input from a range of areas embedded within sports science. The practicality of implementing a framework as suggested by Glazier is becoming more likely, particularly since advances in technology allow for data capture of specific variables which have been too difficult to collect in the past. Biomechanics could be an important part of a multi-factorial model to describe sporting performance since the outcomes measured in biomechanics can provide meaningful and complex information on important characteristics such as control and coordination over a movement and can highlight how sporting technique can change relative to particular experimental and applied conditions (Glazier, 2015).

Since biomechanical data often take the form of time-series, encapsulating information about an entire movement or skill, appropriate statistical techniques are needed to manage these large and complex data sets. This would allow for biomechanics to be integrated effectively into sports monitoring. The use of novel statistical techniques in biomechanics has grown substantially and comprehensive reviews on some of these techniques are already available (Chau, 2001a; Chau, 2001b; Preatoni et al., 2013; Wheat & Glazier, 2006). One of the most common research activities in sports biomechanics involves the analysis of multiple time-series representing entire movements. Common methods have included comparisons of time normalised averaged curves with types of confidence bands (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Hamill, van Emmerik, Heiderscheit & Li, 1999; Preatoni et al., 2013), the coefficient of multiple correlation (CMC), which measures the overall similarity of waveforms taking into account the concurrent effects of differences in offset, correlation, and gain (Kadaba et al., 1989; Preatoni et al., 2013), traditional spectral analysis methods such as wavelet and Fourier decompositions (Chao, Laughman, Schneider & Stauffer, 1983; Chau, 2001b; Giakas & Baltzopoulos, 1997) and other similar data reduction strategies such as principal components analysis (Deluzio & Astephen, 2007; Deluzio, Wyss, Zee, Costigan & Serbie, 1997). One emerging area of statistics in biomechanics is functional data analysis (FDA), which represents the entire sequence of measurements in a time-series as a single functional entity (or curve) before applying functional versions of multivariate data analysis methods. This has advantages over conventional multivariate models since such treatment of the data appropriately handles correlation between data points that describe a curve or waveform. FDA also has applicability for use on data with irregular time sampling schedules (Ullah & Finch, 2013).

A review of FDA procedures on biomedical health data sets by Ullah and Finch (2013) found that the use of FDA techniques in biomedical research is still novel, but growing. A total of 84 articles were identified as a part of a systematic literature review, and 75% of the 84 articles were produced after 2005, with this likely occurring as a consequence of FDA being a more contemporary area of statistics. The growth of FDA is due in part to the abundance of literature and software available for using FDA techniques (also noted by Ullah & Finch, 2013). Ramsay and Silverman (2005) have provided an overview of the foundations and applications of FDA and also practical examples for the use of various FDA techniques were demonstrated in Ramsay and Silverman (2002). Supplementary software developed for MATLAB, S-PLUS and R by Ramsay and Silverman, specifically to support FDA processes, is also available from an FDA website: http://www.psych.mcgill.ca/misc/fda/ and are freely available for use. Graves, Hooker and Ramsay (2009) in conjunction with this software also provide guidelines for the use of FDA techniques using MATLAB and R, allowing users the opportunity to tailor and customise FDA processes to their own data sets.

These resources have facilitated the application of FDA in various contexts in sports biomechanics, including evaluation of sports performance with jumping (Harrison, Ryan & Hayes, 2007; Ryan, Harrison & Hayes, 2006), race-walking (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009), on-water single scull rowing (Warmenhoven et al., 2015), front crawl swimming (Sacilotto, Warmenhoven, Mason, Ball & Clothier, 2015), running (Coffey, Harrison, Donoghue & Hayes, 2011; Donoghue, Harrison, Coffey & Hayes, 2008; Liebl, Willwacher, Hamill & Brüggemann, 2014), Olympic weightlifting (Kipp & Harris, 2014; Kipp, Redden, Sabick & Harris, 2012a; Kipp, Redden, Sabick & Harris, 2012b) and fatiguing exercises as a part of strength and conditioning research (Mallor, Leon, Gaston & Izquierdo, 2010). The growth of FDA in the sports biomechanics literature to date was also summarised in the Geoffrey Dyson lecture (2014), which provided an insight into the current use of FDA in sports biomechanics and called for further adoption, enhancement and refinement of FDA techniques within a sporting performance assessment and evaluation setting (Harrison, 2014).

Despite the growth in use of FDA techniques within sports biomechanics, there is still limited literature concerning the appropriate use of specific FDA techniques with biomechanical data, particularly with reference to the various methodological approaches that are adopted. These methodological approaches include; (A) the preparation of data prior to using FDA and (B) how particular FDA techniques can be customised for more appropriate use with biomechanical data. Consequently, this review will focus on the use of functional principal components analysis (*f*PCA), the most common procedure within FDA. Since its first application in sports biomechanics research (Ryan, Harrison & Hayes, 2006), *f*PCA has been used in various sporting contexts, often adopting differing methodological approaches.

Prior to performing *f*PCA on biomechanical data, it is common practice for curves to undergo some form of temporal normalisation aligning all start and end points of curves to a common location (Donoghue, Harrison, Coffey & Hayes, 2008; Kipp & Harris, 2014; Kipp, Redden, Sabick & Harris, 2012a; Kipp, Redden, Sabick & Harris, 2012b; Ryan, Harrison & Hayes, 2006; Warmenhoven et al., 2015; Sacilotto, Warmenhoven, Mason, Ball & Clothier, 2015). More elaborate data preparation strategies such as curve registration techniques using time-warping functions have also been explored (Godwin, Takahara, Agnew & Stevenson, 2010; Page, Ayala, Leon, Peydro & Prat, 2006; Ryan, Harrison & Hayes, 2006), while in other cases curves are not normalised, and retained as a function of time (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Mallor, Leon, Gaston & Izquierdo, 2010; Page, Ayala, Leon, Peydro & Prat, 2006).

The use of *f*PCA in biomechanics has also resulted in some modifications to particular FDA practices. The use of rotations of the functional principal components in *f*PCA have been explored (Epifanio, Ávila, Page & Atienza, 2008; Sacilotto, Warmenhoven, Mason, Ball &

Clothier, 2015; Warmenhoven et al., 2015), as has the removal of sections of the time-series (also referred to as data truncation) prior to use of *f*PCA (Kipp & Harris, 2014; Kipp, Redden, Sabick & Harris, 2012a; Kipp, Redden, Sabick & Harris, 2012b; Warmenhoven et al., 2015), with both of these modifications designed to remove or adjust for unwanted variation in the data prior to analysis.

Despite the presence of different methodological approaches, little is documented on any limitations of these approaches when representing biomechanical data and their impact on the results of a subsequent *f*PCA. Consequently, this review will focus on the use of *f*PCA and will evaluate the effects of various methodological approaches on the outcome of the analysis. More specifically, the theoretical underpinnings of *f*PCA will be revisited so that temporal normalisation of data, removal of unwanted or erroneous forms of variation in a data set and documented methods for retaining the original temporal properties within a set of curves will be explored. To evaluate how these methodological approaches affect the results of *f*PCA, simple experimental data will be examined. Recommendations are also provided to the reader for future use of *f*PCA with biomechanical data.

Sample data sets

Two sample data sets were used in this review. These data sets were obtained as a part of a project between the New South Wales Institute of Sport and the University of Sydney. All data was collected after approval of the relevant tertiary institution's ethical board. Two highly skilled Australian female scullers were selected from this database and each athlete was assessed according to their competitive performance at the time of testing and classed as either 'national' level or 'international' level. National level athletes must have competed in Australian national age group championships or Australian national open championships prior to the testing and were deemed to be highly skilled, sub-elite rowers. International rowers must have competed as an Australian representative at an under 18, under 23 or open level prior to testing. One of the athletes was assessed as being national level (age = 25 years; height = 1.78 m; mass = 75.62 kg) and the other international level (age = 25 years; height = 1.82 m; mass = 79.58 kg). As a part of the testing, both athletes were directed to row a total of 1000 m, composed as 250 m at four ascending pre-selected stroke rates of 20, 24, 28 and 32 strokes per minute (also referred to as SR20, SR24, SR28, SR32 respectively). A short period of active rest (250m of light rowing) followed each stroke rate condition to ensure that fatigue was not a factor.

1. *Data set one* (DS1): For the first sample data set, data for both the national and international level athletes were selected and only SR32 was analysed.
2. *Data set two* (DS2): For the second sample data set, data for the international level rower only was selected and the SR 20 and SR32 data was analysed.

Within each data set, ten strokes were selected for each rower for both the bow side (left hand) and stroke side (right hand). Two variables were obtained for further analysis - horizontal angle of the oar and propulsive pin force. Twenty time-series (ten for each side of the boat) were entered into each analysis. For every individual time-series the drive and recovery phases were identified using the horizontal angle of the oar, with instrumentation for collecting these variables outlined in Smith and Loschner (2002).

Revisiting Classical PCA and Functional PCA

Principal components analysis (PCA) is a classical multivariate statistical technique used to reduce the dimensionality of a dataset and has been previously applied to human movement data (Deluzio, Wyss, Zee, Costigan & Serbie 1997). When applied to whole curves or time-series in biomechanics, this has been referred to as "*PCA of waveforms*" (Harrison, 2014), and has been used to transform an original set of variables into a smaller set of linear combinations that account for most of the variance in the original set of time-series (also referred to as principal components). The values of the linear combinations are called principal component scores, and the weighting of each principal component (PC) when it is applied to the original waveforms are often helpful in understanding what the principal components imply about the characteristics of specific participants (Ryan, Harrison & Hayes, 2006). Despite its use in biomechanics literature, PCA of waveforms carries some limitations. Firstly, smoothing and calculation of derivatives are carried out separately from PCA procedures resulting in unknown and potentially unwanted sources of variation entering an analysis. Secondly, in PCA of waveforms, the data points on each curve are assumed to be independent of each other, but in reality it is known that any point on a continuous time-series is correlated with the data points that precede and follow that point. Finally, it may be difficult to relate the waveforms described by each principal component (PC) to movement patterns of specific subjects in a particular experimental population (Harrison, 2014).

Functional principal components analysis (*f*PCA) is an extension of PCA of waveforms tailored for use with functional data, and as a consequence a number of preliminary FDA steps are necessary prior to using *f*PCA. The first step requires representing each time series as a function using a suitably chosen basis function procedure and smoothing these functions (usually B-splines or Fourier series, which will be discussed further in more detail within this chapter), with both processes generally being linked. The choice of basis functions selected to fit the data is often dependent on the nature of the data being analysed (i.e. in biomechanics, whether it is a discrete movement, a repetitive or periodic movement, or a movement that contains high frequency content within each time signal). The derived functions are smoothed by adding a roughness penalty to the fitting procedure. The roughness penalty term, controlled by a smoothing parameter "λ", ensures that the smoothness of each fitted curve is controlled, which is achieved by minimising the penalized residual sum of squares term (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Ramsay & Silverman, 2005). Generalized cross-validation is often recommended as a starting point for determining possible values of λ before a final subjective choice is made (a full outline of this process can be found in Ramsay & Silverman, 2005).

Once these functions are estimated and smoothed, *f*PCA can be applied. In *f*PCA a set of observed functions are represented as $\{x_1(t),..., x_N(t)\}$ (by applying basis expansions to the original vectors of data points). In this instance, x denotes the variable to be analysed, t is time and N is the number of waveforms. The mean function is defined as the average of all functions and is subtracted from all functions prior to calculation of the covariance function. The covariance function $v(s,t)$, is defined by $v(s,t) = \left(N-1\right)^{-1} \sum_{i=1}^{N} x_i(s)\, x_i(t)$, where s and t are time points. Subsequent to this the following eigenequation is used to find each functional principal component (*f*PC): $\int v(s,t)\, \xi(t) \mathrm{d}t = \rho\xi(s)$. As a part of this step, ρ is an eigenvalue and $\xi(s)$ is an eigenfunction of the variance–covariance matrix. *f*PCA produces principal components that are functions defined in the same domain as the original functional observations of the study, and are expressed with a mean of zero (Figure 6A), but have practical relevance when added to the mean of all original functions (Figure 6B). Each function is also weighted by the extracted *f*PCs, resulting in scalars referred to as *f*PC scores. As a result, for each original curve, one functional principal component score is calculated for each functional principal component extracted (Ryan, Harrison & Hayes, 2006). *f*PC scores corresponding to a particular *f*PC are computed by using the inner product rule for functional data: $\omega_i = \int x_i(t)\, \xi(t) \mathrm{d}t$.

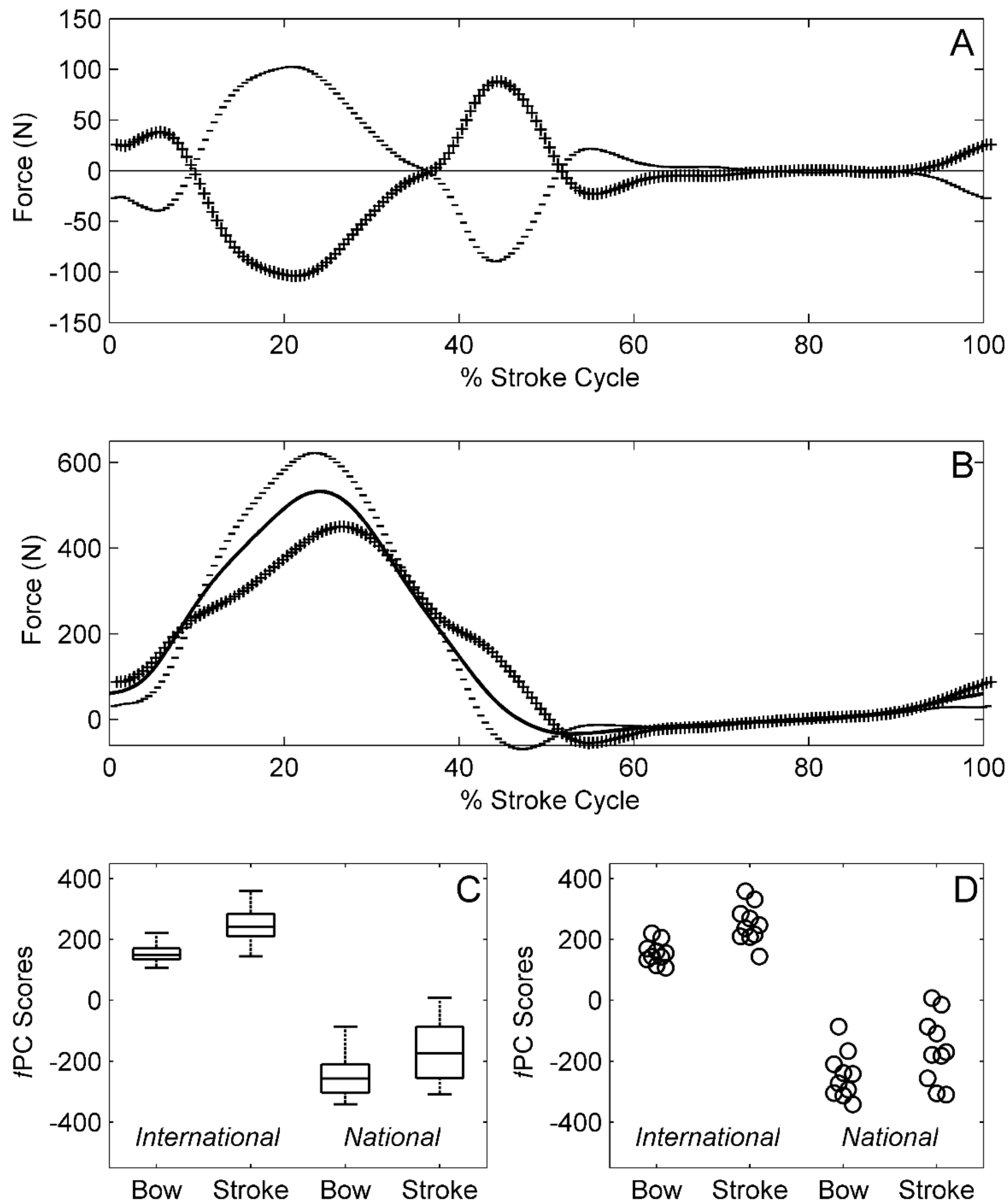

Figure 6. A sample functional principal component (*f*PC). A: the first functional principal component (*f*PC) function for sample data set one. B: the first *f*PC function added/subtracted to the mean function. C and D: boxplot and scatterplot of *f*PC1 scores for the international rower and the national level rower.

For visualisation of *f*PCs, Ramsay and Silverman (2005) have recommended the use of graphs that present the ensemble mean function, $\bar{x}(t)$, together with each *f*PC, $\xi(s)$. This is achieved by adding and subtracting a multiple (selected subjectively using visual inspection), in the form of a constant (c), of each *f*PC to the mean function and plotting them together so that they can be inspected relative to each other. Figure 6 displays this for DS1, when force is expressed as a percentage of the stroke cycle. In Figure 6 (A) the *f*PC function for the first *f*PC has been graphed independently of $\bar{x}(t)$ to demonstrate clearly where variability described by *f*PC1 is present across the stroke cycle. In Figure 6 (B) the *f*PC function has been added to $\bar{x}(t)$ to illustrate what this variation means from a biomechanical perspective, given that shape characteristics and notable landmarks of $\bar{x}(t)$ have known biomechanical relevance. When observed using this method, each of the retained *f*PCs demonstrate important structures of variability that are present within each *f*PC function. The interpretations of (A) and (B) in figure 6 is relatively simple. Positive scorers on the first functional principal component, illustrated by the plus (+) signs, are characterized by a force production that is lower than average near maximum force and this is followed by higher force production than average leading into 50% of the stroke cycle. Conversely, negative scorers (indicated by the minus (–) signs) exhibit the reverse characteristics and illustrate increased force production at the peak and reduced force application leading into 50% of the stroke cycle than average. It is also important to visualise the distribution of *f*PC scores in a similarly insightful way. Two methods for doing so are illustrated in Figure 6 (C and D), through the use of boxplots (C) (Harrison, Ryan & Hayes, 2007; Ryan, Harrison & Hayes, 2006) and scatterplots (D) (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009). Both of these can be seen in Figure 6 for DS1 where clear differences in the first *f*PC are noted between the international level rower and the national rower using both box plots and scatter plots, across both sides of the boat.

Standard data preparation for functional PCA

A prerequisite of using *f*PCA is that all curves are defined over the same time interval (Crane, Childers, Rothman & Gerstner, 2011). If curves do not start and finish at the same time point then there may be potential issues for smoothing over curves that have no data points beyond a particular time point. Some of these issues will be expanded upon further in this review. As a consequence of this constraint, a common method for aligning all curves to the same start and end point prior to conducting *f*PCA has been to use a linear length normalisation (LLN) strategy, used to express each curve as a percentage (0-100%) of a particular movement or cycle (Helwig, Hong, Hsiao-Wecksler & Polk, 2011). This typically involves the use of an interpolating cubic spline to resample each curve at a common number of time points prior to fitting functions to each curve. The use of an LLN approach linearly compresses or expands the time axis of a curve, in essence removing temporal differences between curves that are a result of the curves' lengths. A concern regarding this approach is that even after curves are aligned by an LLN procedure, temporal differences between events (e.g., peaks and valleys) may still exist, but may have shifted temporally relative to each other depending upon whether curves have been expanded or compressed. These new "within curve" misalignments will introduce new forms of variation at time points across the entire set of curves, and these will in turn affect the nature of variability between curves over an entire movement or cycle. This has already been highlighted as problematic, particularly when summary statistics are used to quantify variability between curves across an entire cycle (Helwig, Hong, Hsiao-Wecksler & Polk, 2011; Sadeghi et al., 2000).

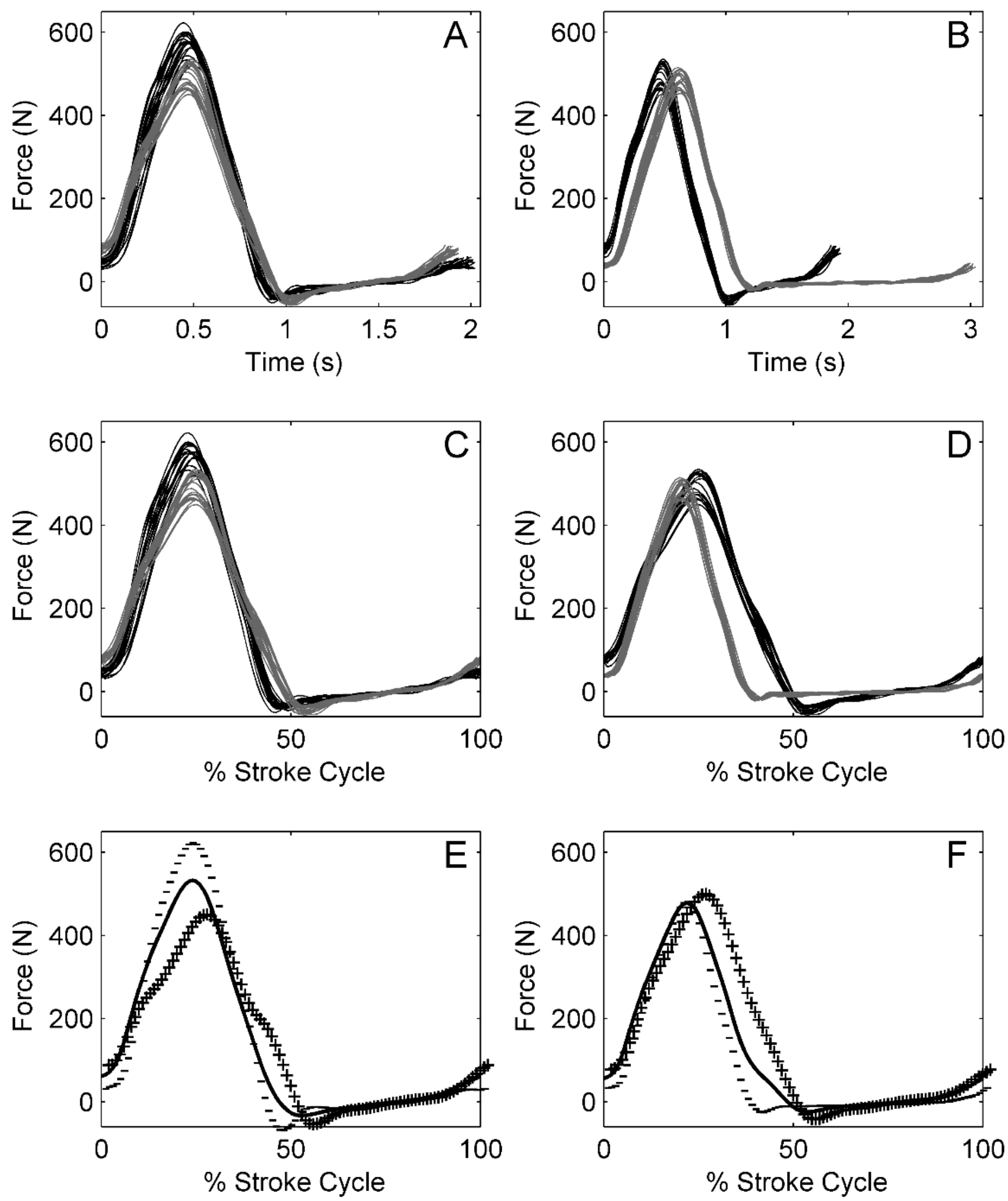

Figure 7. Standard data preparation strategies for *f*PCA. A: non-normalised propulsive force for sample data set one. B: non-normalised propulsive force for sample data set two. C: A LLN strategy applied to sample data set one. D: A LLN strategy LLN applied to sample data set two. E: the first *f*PC for sample data set one. F: The first *f*PC for sample data set two.

These new forms of temporal variability will also likely affect the principal components calculated using *f*PCA, with this becoming potentially problematic if the types of variation of interest are related directly to phase (or temporal) differences between curves, when curves are expressed in their natural time-domain.

In biomechanics, the ability to analyse differences in curves when expressed in the time-domain are important, particularly when differences noted between or within individuals may be needed to develop biomechanical or skill acquisition interventions for changing technique. In these cases, interventions may require that new technical changes are incorporated into a protocol in the original time-domain. A practical example of this problem is demonstrated via the rowing stroke cycle. The rowing stroke cycle can be broken into two phases: the drive phase and the recovery phase. The drive phase starts with the catch and involves placing the blade of the oar in the water, ready for application of force. The muscle actions that extend the ankle, knee, hip and lumbar joints and flex the shoulder, elbow and wrist joints control the drive phase. The end of the drive phase is called the finish and is defined by the removal of the blade from the water. The recovery phase is the return of the rower from an extended-body position at the finish to the flexed posture of the catch. This combination of actions, once optimised, is repeated throughout the course of a race or training interval (Smith & Loschner, 2002). Rowers are often trained to execute actions of the rowing stroke cycle at consistent and non-fluctuating stroke rates as a part of their training.

As a consequence, the amount of temporal variability from stroke to stroke when performed at a consistent stroke rate is minimal and the effects of a convention normalisation strategy (in this case a LLN strategy) when applied to all strokes at the same stroke rate may also be minimal. This is illustrated in Figure 7, where subplots (A) and (C) show non-normalised data and the use of this normalisation approach applied to DS1, with the international rower, represented by the grey lines and the national level rower, represented by the black lines. It can be seen that once a this normalisation is applied to this data set, the first *f*PC describing the majority of variance in these curves (E), characterizes a difference between curves that qualitatively resembles characteristics seen in the original data. In this first *f*PC, differences around peak force are still present, with the national rower maintaining a higher level of peak force. Differences are also noted towards the end of the drive phase with the international level rower spending a larger amount of time and a greater relative percentage of the stroke cycle in the drive phase when compared to the national level rower. The use of an LLN on rowing stroke cycle becomes problematic however, as the stroke rate changes. In rowing an interesting and well-documented phenomenon exists where, as stroke rate increases, the absolute time in the drive and recovery phases of the stroke cycle decreases; with greater reductions occurring in the recovery phase (Soper & Hume, 2004). This difference in the amount of time spent in each phase of the rowing stroke cycle can be seen in Figure 7, where (B), (D) and (F) respectively depict a the series of non-normalised curves for DS2, an LLN applied to these curves and the first *f*PC for these curves. By visual inspection it is noted that the majority of variation in the raw time-series can be seen as a form of phase variance between the two sets of curves at different stroke rates, with the SR32 curves, represented by the black lines, beginning force application in the drive phase, peaking at maximum force and finishing force application at the end of the drive phase, earlier than the SR20 curves, represented by the grey lines. However, when inspecting the curves after LLN and examining the content of the first functional principal component after LLN, it can be seen that the difference in the duration of the recovery relative to the drive phase between the two stroke rates has resulted in an expansion of the entire set of SR32 time-series relative to the SR20 time-series. Thus the main form of phase variation noted in the non-normalised data is now no longer present but has been altered to show that SR20 curves peak and finish force application earlier than the SR32 curves.

Dealing with temporal artifact as a result of normalisation

It is clear that the use of an LLN on DS2 has introduced an erroneous form of phase variability to the data set as a consequence of the time spent in the recovery changing between stroke rates. It may be appropriate to remove or 'neutralise' phase variation completely in this instance, so that the only variance reported between each of the curves is related directly to amplitude differences across the stroke cycle. In this case, functional data analysis (and *f*PCA) has advantages over conventional PCA, since several strategies are available which can align all curves at common time points, thus removing forms of potentially erroneous phase variation. These strategies, known as "registration" techniques, are designed to organise a series of curves, or functions, so that the analysis of phase or amplitude variation can be conducted independently prior to using *f*PCA (Marron, Ramsay, Sangalli & Srivastava, 2014). It is important to note that there are a large number of potential techniques for registering curves to remove phase variation and a comprehensive review of these techniques can be found in Marron et al., (2014). The most common of these registration techniques used with human movement data is landmark registration (Ryan, Harrison & Hayes, 2006). A series of smoothed curves may follow a similar overall pattern but the timing of certain important features or landmarks, for example, a global maximum or minimum, may differ among participants. Landmark registration identifies the location of visible features or landmarks and shifts each curve accordingly through the use of dynamic time-warping functions, so that these features occur at a fixed relative time, thus allowing for a more intuitive comparison between curves (Ramsay & Silverman, 2005; Ryan, Harrison & Hayes, 2006). If landmark registration is applied to DS2, it is possible to align all curves at notable landmarks that occur across the rowing stroke cycle. For example there are clearly identifiable minima, maxima and zero crossing points that could be used to align curves.

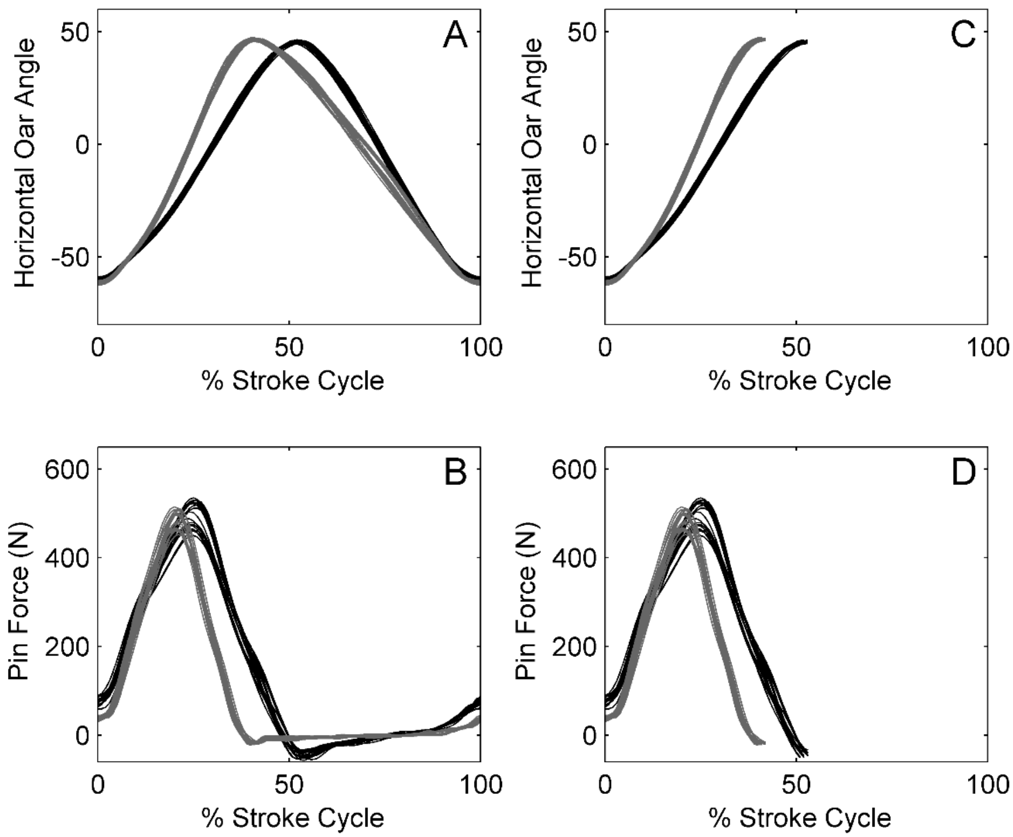

Figure 8. Defining the rowing stroke cycle. A: horizontal angle of the oar for the entire stroke cycle for all curves in data set two. B: horizontal angle of the oar for the drive phase for all curves in data set two. C: propulsive pin force for the entire stroke cycle for all curves in data set two. D: propulsive pin force for the drive phase for all curves in data set two.

This has proven to be effective in aligning features of kinematic waveforms before using *f*PCA to assess differences between individuals performing a vertical jump (Ryan, Harrison & Hayes, 2006). In the current example, the use of registration techniques to optimally neutralise *unwanted* phase variation is more difficult. The majority of unwanted phase variance in the curves is known to result from differences between the two stroke rates in the relative time spent in the drive phase relative to the recovery phase. Understanding differences in the relative shape characteristics (inclusive of both phase and amplitude variation) of force application during the drive phase is important information to retain and has been of interest in several previous applied biomechanical studies (Soper & Hume, 2004). One solution is to identify the location of each of the finish points (signifying the end of the drive phase) for all curves and then to use landmark registration to shift all of the finish locations to the same point, thus making all drive phases the same length and express these in the same percentage domain. The difficulty with landmark registration in this context is that it uses physical landmarks to identify the start and end of the drive and recovery phases, and in this case the landmarks are taken from a separate variable, the horizontal angle of the oar. The horizontal angle of the oar is used to separate out each phase of the rowing stroke cycle, with the catch noted as every subsequent oar angle minima and the finish noted as every subsequent oar angle maxima (see Figure 8). James (2007) has noted that when using landmark based registration techniques based on the location of markers that are not easily identified, the process of registration can work poorly. In this case, a more appropriate alternative to landmark registration may be needed.

Helwig, Hong, Hsiao-Wecksler and Polk (2011) evaluated a range of different strategies for temporally aligning gait data and assessed their performances relative to a target trajectory. In addition to conventional LLN, dynamic time-warping (DTW) was applied to the entire movement cycle, which non-linearly compresses or expands the time axis of a variable to identify the temporal alignment that best fits a target trajectory. Derivative based dynamic time warping (DDTW) was also explored, which mirrors DTW, however aims to identify the best alignment of the derivatives for both the original variables and the target trajectory. Additionally, piecewise linear length normalisation (PLLN), and piecewise dynamic time warping (PDTW), were also explored. Both of these apply LLN and DTW in a "piece-wise" manner to selected sections of a waveform, with these sections being identified by key landmarks or events across a movement cycle.

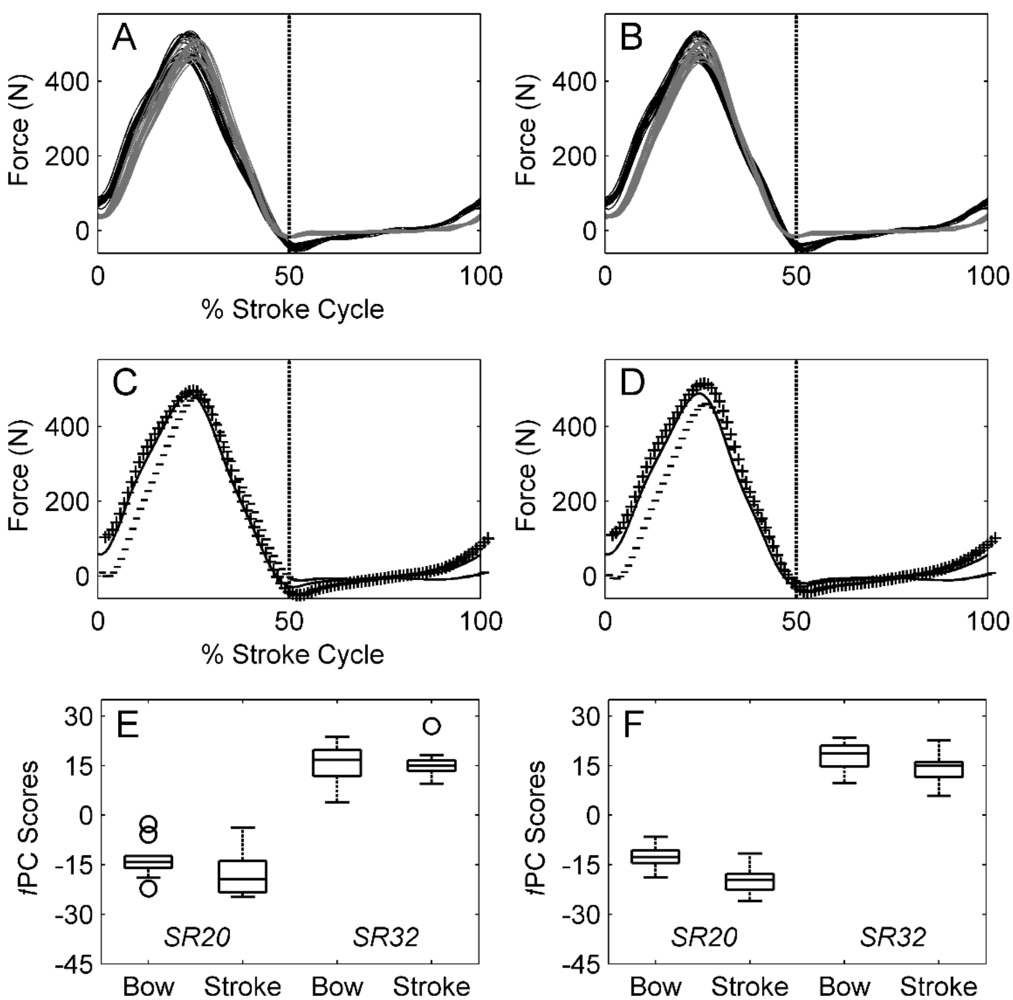

Figure 9. Temporally aligning key phases of a movement cycle. A: landmark registration (LR) applied to align the drive phases to 50% of the stroke cycle for data set two. B: PLLN applied to align the drive phases to 50% of the stroke cycle for data set two. C: first *f*PC of the landmark registered (LR) curves. D: first *f*PC of the PLLN shifted curves. E: Boxplot of *f*PC scores for the two stroke rates for landmark registration. F: Boxplot of *f*PC scores for the two stroke rates for PLLN.

Helwig concluded that specifically when phase variances were to be accounted for, as a result of temporal misalignment of phases within a cycle, both piecewise methods (PLLN and PDTW) outperformed all other data preparation methods. Furthermore, given the comparative simplicity of the PLLN algorithm, it is preferred to PDTW, which requires that a large number of experimental constraints be met prior to its use. PLLN segments cycle trajectories into sub-phases at user-determined points of interest (POI) and temporally aligns the POI with the corresponding POI of a target trajectory (Sadeghi et al., 2000).

This approach utilises LLN in a piecewise manner to align corresponding sub-phases of an overall time-series. POI can be characterizing points of any within-cycle features, so long as it is possible to identify these features across subjects and experimental conditions. The first and last POI in each trajectory should be the first and last time points of the overall cycle to ensure that all endpoints are aligned. In the present example, these POI could simply relate to the start and end of the drive and recovery phase with each making up 50% of the entire cycle by aligning all finish points at 50% of the stroke cycle. Similarly, a landmark registration shift could also be attempted by shifting all finish points of the stroke cycle to the 50% of the entire stroke cycle. This is illustrated with DS2 in figure 9.

When inspecting the effects of both landmark registration and PLLN on DS2, both techniques appear to remove the erroneous variation introduced into the first *f*PC after application of LLN to the data (and the introduced error can be seen in Figure 7, B and D). Despite this, there may still be limitations when trying to infer meaningful results from *f*PCA applied to landmark registered or PLLN applied curves, given the domain in which the curves are expressed is not the true time-domain. This is particularly relevant if retaining the original time domain is important for inferring biomechanical meaning from the results of an *f*PCA. Despite this, the use of either landmark registration or PLLN in conjunction with *f*PCA in the present review have demonstrated clear differences in patterns of force application between the two stroke rates. The *f*PC1 scores plotted in Figure 9 (E for landmark registration; F for PLLN), show that both the landmark registered curves and the PLLN curves were effective in discriminating between the two stroke rates, across both sides of the boat.

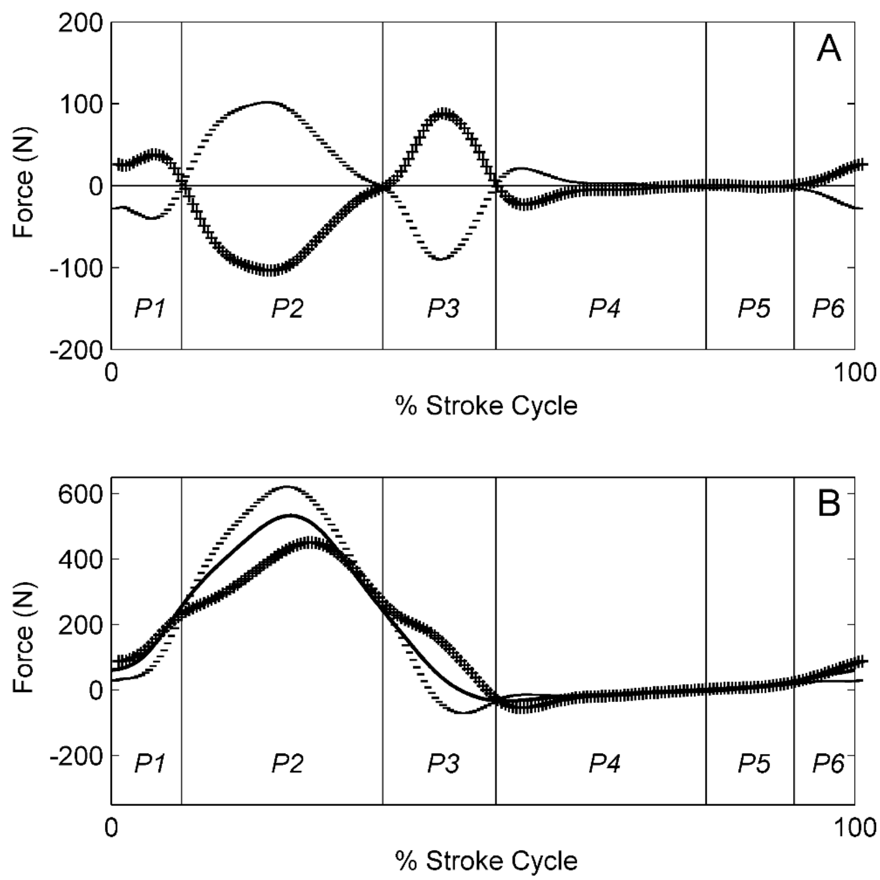

Figure 10. Phases of variation in an *f*PC. A: the first *f*PC function for data set one after LLN to 100%. B: the first *f*PC function added and subtracted on to the mean function for data set one. For both A and B, the first *f*PC has been broken into six phases of variation. Each phase is calculated using each zero crossing point and every subsequent zero crossing point.

The structure of variability displayed in the *f*PC1 functions for both landmark registered curves and PLLN were also very similar, where in both instances positive scorers were more likely to have an increase in force application in the first half of the drive phase (see Figure 9: C and D). Both landmark registered and PLLN curves demonstrated that for the first *f*PC, curves for the lower stroke rate (SR20) were more likely to have negative scores and a reduction in force across the first half of the drive phase (see Figure 9: E and F). The reverse trend was true for the higher stroke rate (SR32). Additionally, both landmark registered and PLLN curves also demonstrated that independent of stroke rate, a trend was present for bow side curves to possess a higher score than the stroke side curves.

Eliminating unwanted sources of variation

When using *f*PCA, it is common that an *f*PC can describe a particular characteristic of variability more than once on a curve. For example, in Figure 10, the *f*PC function when graphed alone (A) and the same *f*PC function added to and subtracted from the mean function (B), is displayed for DS1 (after a standard LLN has been applied). It can be seen that variability is present within this function in multiple locations across the stroke cycle, with the *f*PC function crossing zero five times from the start of the stroke cycle and dividing the stroke cycle into six different movement phases within the first *f*PC. The variability within some movement phases are much larger than others, with the first four phases (P1-P4) making up the majority of variation described by the first *f*PC with P2 and P3 visually presenting as the largest. P2 shows variation in the magnitude of force produced in the middle of the drive phase (near the peak) and P3 shows variation towards the end of the drive phase towards the finish point of the stroke cycle.

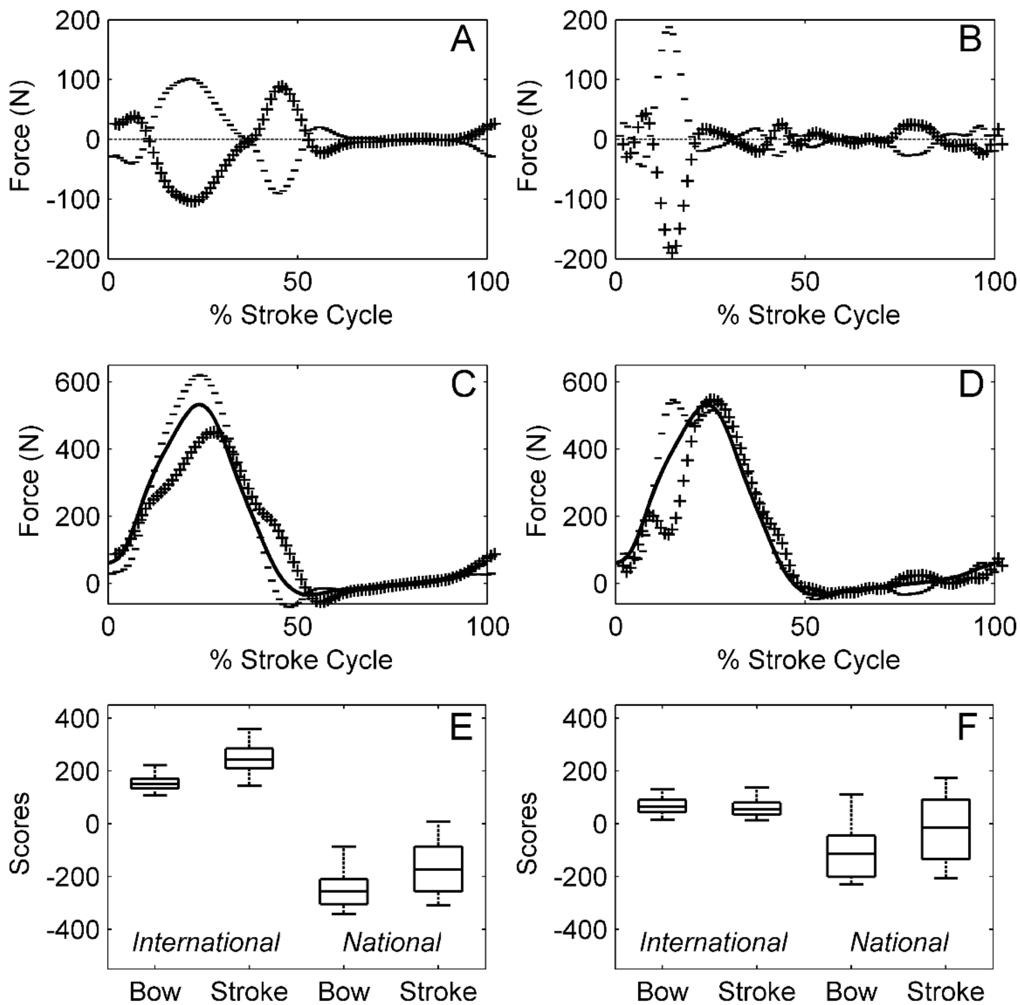

Figure 11. Varimax rotations in *f*PCA. A: the first *f*PC function for data set one after LLN to 100%. B: the first *f*PC function added and subtracted on to the mean function for data set one. C: the first *f*PC function for data set one after LLN to 100% and a varimax rotation has been performed. D: the first *f*PC function added and subtracted on to the mean function for data set one and a varimax rotation has been performed. E and F: boxplot of international and national rower *f*PC scores for both the normal and varimax rotated *f*PC1 (respectively).

If an individual receives a high positive score for this *f*PC, it would be assumed that they would have an increased rate of force production at the start of the drive phase (P1), a dip in force near the curves maxima (P2), increased force production leading into the finish (P3) and then a dip in propulsive force after the finish (P4). This is possible, but it is also likely that a particular curve can have a strong resemblance to one of these contributing phases within the *f*PC and minimal resemblance to the other movement phases (i.e. in Figure 10 a curve could strongly resemble P1, but does not resemble P2, P3, P4 or P5).

This would overly inflate the positive score for that curve, despite it only partly resembling the variation described by a single phase within that *f*PC. This is a limitation with the use of FDA and particularly *f*PCA. Firstly, it does not inherently identify *key* movement phases of importance within the *f*PCs; instead it tends to be applied to the whole function assuming that any phases of variability identified by an *f*PC will have an effect on the generated *f*PC score (Richter, O'Connor & Moran, 2014).

One method for focusing upon key movement phases contained within a single *f*PC is to use a rotation of the *f*PCs after *f*PCA has been conducted. In multivariate analysis, an appropriate rotation can produce components with more interpretable variability than the original components. A rotation method constructs new components based on *k* (the number of selected) principal components. *k* is normally selected prior to undertaking any type of PCA. The varimax rotation is the most common technique used with human movement data and has also been used in conjunction with FDA techniques (Epifanio, Ávila, Page & Atienza, 2008). Rotated *f*PCs tend to illustrate variability that is concentrated on part of the *f*PC function, thus expressing departures from the mean curve over a targeted part of a movement cycle rather than the whole of it. The rotated *f*PCs are still orthogonal, but the values of the *f*PC scores may now be correlated. Furthermore, the variability of varimax rotated components account for the same amount of variability as that found in the original components, but the variability is re-distributed and shared between components differently. This allows *f*PCs to change order in terms of each *f*PC's contribution of variability to all variability in the data (Ramsay & Silverman, 2002). In Figure

11, a varimax rotation is applied to DS1; this shows that each of the movement phases described by the first *f*PC have changed and only one form of variability is present on the curve early in the drive phase (B and D), compared with multiple forms of variation noted in the un-rotated principal components (A and C). This has illustrated the ability of a varimax rotation to target a selected region of the overall *f*PC function.

The scores for the varimax rotated and un-rotated first *f*PC also now differ in their ability to discern between the international and national rowers (E for un-rotated; F for varimax rotated), with the un-rotated *f*PC scores being better discriminators between the two athletes. This illustrates a cautionary point when using rotated *f*PCs. DS1 has some clear and interpretable differences between the two rowers as seen in Figure 7 (A and C). Those differences are also quite consistent from stroke to stroke. In this instance, changes between the two athletes may actually be reflective of the multiple phases of variability described by the un-rotated *f*PC1. In this instance the un-rotated *f*PC is more effective at representing the structure of the variability in the original data, thus making it better suited for identifying differences between these two series of curves. Some recent advances in the use of *f*PCA may have potential to negate some of the shortcomings noted when analysing either un-rotated or varimax rotated *f*PCs. Lin, Wang and Cao (2015), have recently devised a modified version of *f*PCA, *Interpretable Functional Principal Components Analysis*. This modified technique provides *f*PCs that possess better interpretability though a reduction in the number of non-zero coefficients in each *f*PC function. This sharpens the ability of an *f*PC to identify key areas of variability across an *f*PC function, without sacrificing major changes to the structure or shape of the variability in *f*PC functions, like that demonstrated when varimax rotations are used.

It should also be noted that when using varimax rotations applied to *f*PCs, careful consideration should be given to the *f*PC scores prior to their use in further analysis. Previous research using *f*PCA applied to biomechanical data has often subjected *f*PC scores to conventional multivariate statistical techniques, such as discriminant function analysis (Harrison, Ryan & Hayes, 2007; Ryan, Harrison and Hayes, 2006), for classification of curves into groups. Given that varimax rotations allow for scores from different *f*PCs to be correlated with each other, this could provide some issues for developing adequate multivariate statistical models, given that statistical techniques such as discriminant function analyses and are impacted by high levels of multi-collinearity in the data. When exploring the use of rotations applied to *f*PCs, it should be noted that the varimax approach is not the only approach available for use with human movement data. References on factor analysis and multivariate statistics such as Basilevsky (1994) may offer several other possibilities and details of these alternatives (including, but not limited to, the quartimax, equimax, direct oblimin and promax rotation options), although there is limited information regarding their use with functional biomechanical data.

Even after a varimax rotation is applied to the data, there is a possibility that meaningful forms of data will remain undetected. In *f*PCA the first group of *f*PCs are typically retained using a variability threshold (*x* % of the total variance in the data) as chosen by the user. While a variety of thresholds may be used, a 95% threshold appears to be the most frequent in recent biomechanical studies and principal components beyond the threshold of 95% are often discarded as they are assumed to have very little influence on the data (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Donoghue, Harrison, Coffey & Hayes, 2008). This can become problematic if one of the *f*PCs accounting for a smaller (but important) portion of the variability falls outside the subjective threshold for retaining *f*PCs. Additionally there is the possibility that particular key phases or 'parts' of an entire movement are of more, or sole, interest in the analysis.

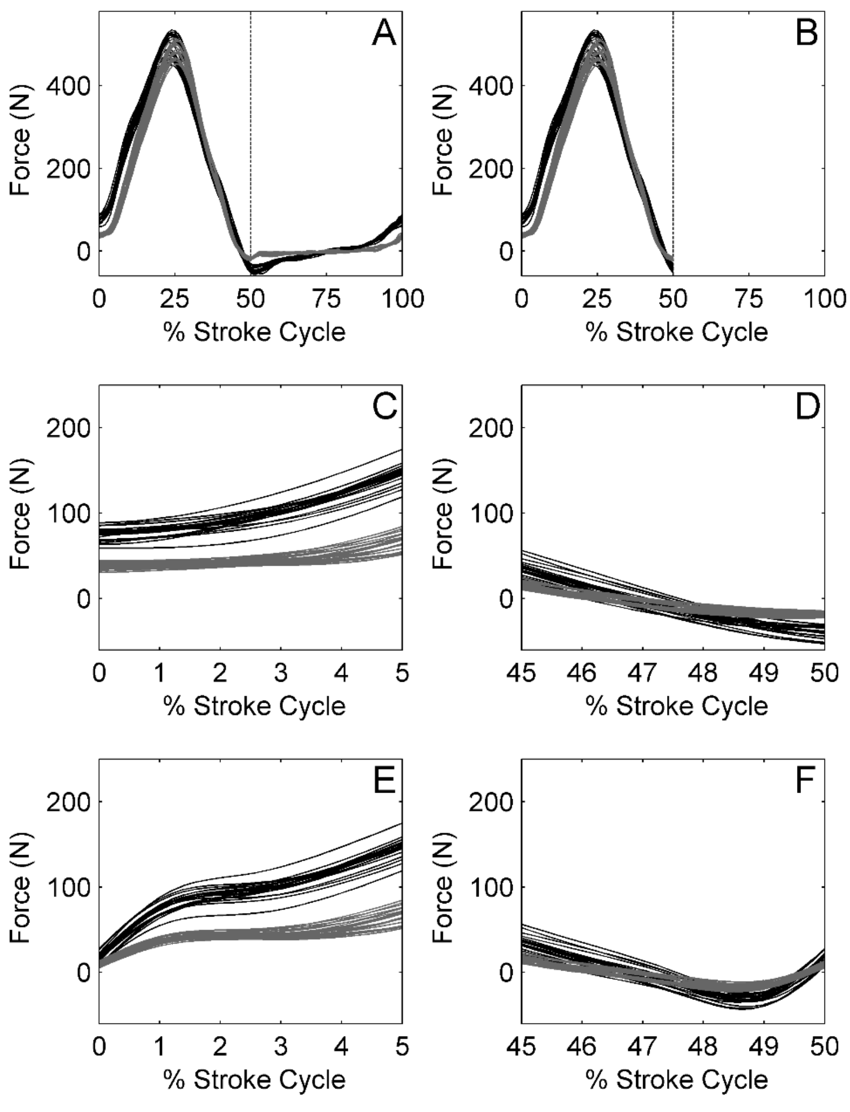

Figure 12. Applications of different basis functions. A: PLLN applied to align the drive phases to 50% of the stroke cycle for data set two. B: data set two truncated at 50% including only the drive phase. C: truncated raw data fitted using b-splines showing 0-5% of the stroke cycle (start of the drive phase). D: truncated raw data fitted using b-splines showing the 45-50% of the stroke cycle (end of the drive phase). E: truncated raw data fitted using Fourier for 0-5% of stroke cycle. F: truncated raw data fitted using Fourier showing the 45-50% of stroke cycle.

For example in rowing the two key phases of the rowing stroke cycle are the drive and recovery. If the relative shape characteristics of the propulsive pin-force curve and how those shape characteristics differ between athletes is the research question of interest, it may be appropriate to remove the recovery phase for each stroke. There can be a tendency for propulsive pin force to drift leading into the catch of a subsequent stroke cycle and differences in *f*PCs may be reflective of changes in the forces during the recovery phase. If this occurs, there is a chance that *f*PCs describing more subtle changes in force during the drive phase, which could be meaningful between groups of athletes, could be lost due to some *f*PCs describing recovery related differences. In this context, PLLN could be used to align each of the drive phases to 50% of the entire cycle and facilitate easy removal of the recovery phase.

Once a part of the curve has been removed it is possible that properties of the new altered curves may have changed from periodic functional data to discrete functional data. Figure 12 illustrates two options for basis functions being fitted to curves from DS2 after a PLLN was applied and the recovery phase was removed for each curve. Two separate procedures, B-spline basis functions (see figure 12, B and C) and Fourier basis functions (D and E) were used to fit these new truncated curves. B-splines are useful for smoothing as their structure is designed to provide a smooth function with the capacity to accommodate changing local behaviour. A B-spline consists of polynomial pieces joined at certain values of *x*, called knots and the process for using these in FDA (and underpinning theoretical justification) has been outlined in Ramsay and Silverman (2005). These are a more common basis expansion for discrete skills, given their ability to accommodate a range of non-periodic fluctuating changes across a curve (Epifanio, Ávila, Page & Atienza, 2008; Harrison, Ryan & Hayes, 2007; Kipp & Harris, 2014; Kipp, Redden, Sabick & Harris, 2012a; Kipp, Redden, Sabick & Harris, 2012b; Ryan, Harrison & Hayes, 2006).

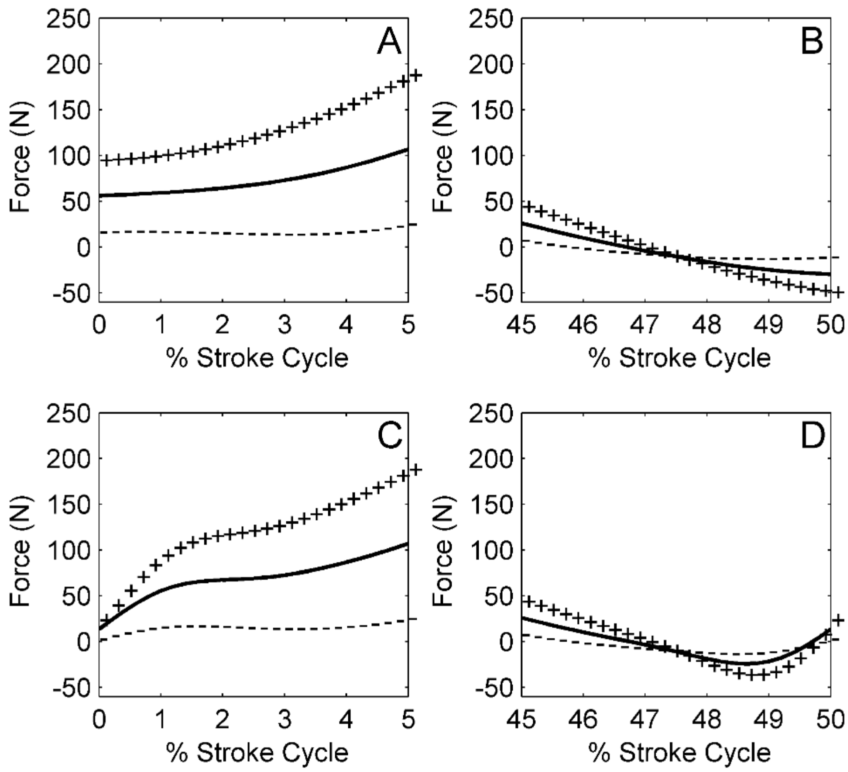

Figure 13. The effect of basis functions on *f*PCs. A: the first *f*PC for truncated raw data fitted using b-splines showing 0-5% of the stroke cycle. B: the first *f*PC for truncated raw data fitted using b-splines showing the 45-50% of the stroke cycle. C: the first *f*PC for truncated raw data fitted using Fourier functions for 0-5% of stroke cycle. D: the first *f*PC for truncated raw data fitted using Fourier functions showing the 45-50% of stroke cycle.

In Figure 12, it is noteworthy that once the recovery phases have been removed, the Fourier basis functions struggle to fit the data adequately as the signal is no longer periodic, particularly at the start (D) and end (E) of the drive phase. This artifact, a result of poor fitting, is also reflected in the first *f*PC for this data and can be seen in Figure 13 (C and D). The Fourier series approach is very useful for stable functions, where there are no strong local features and where the curvature tends to be of the same order throughout the curve. Fourier basis functions can however be inappropriate for use with data known or suspected to reflect discontinuities in the function itself or in low order derivatives (Ramsay & Silverman, 2005). By altering the actual function itself, through the removal of the recovery phases for each stroke, it is clear that this has affected the Fourier basis functions' ability to fit the data. These problems are not apparent for the B-spline fitted curves, or their first *f*PC, in Figures 7 and 8.

Preservation of the original temporal structure

So far this review has commented on methods for preparation and analysis of curves when they have undergone a normalisation strategy such as an LLN or PLLN, ensuring that all curves have the same start and end points. In some cases it may be important to preserve the natural time domain, but there are obvious drawbacks for doing this. Individuals spend differing amounts of time executing the same skill, which subsequently leads to curves of different lengths of data points. When dealing with discrete skills, truncation of data at a pre-determined location can be a simple executable process as some of these activities will finish at a common data point for all curves. This is true when examining activities such as the vertical jump, where vertical ground reaction force (GRF) is of interest. In this scenario there will be a point where all force curves will reach zero once the jumper has left the ground. If all curves were truncated at the point where the last curve reached its local zero point (thus the last individual leaving the ground) then truncation in this context would serve as a useful strategy for preservation of all necessary data in the original time domain. When evaluating curves of different lengths, curves that finish earlier can be stacked with either missing values or the corresponding final data point of the movement (Crane, Cassidy, Rothman & Gerstner, 2010; Crane, Childers, Rothman & Gerstner, 2011).

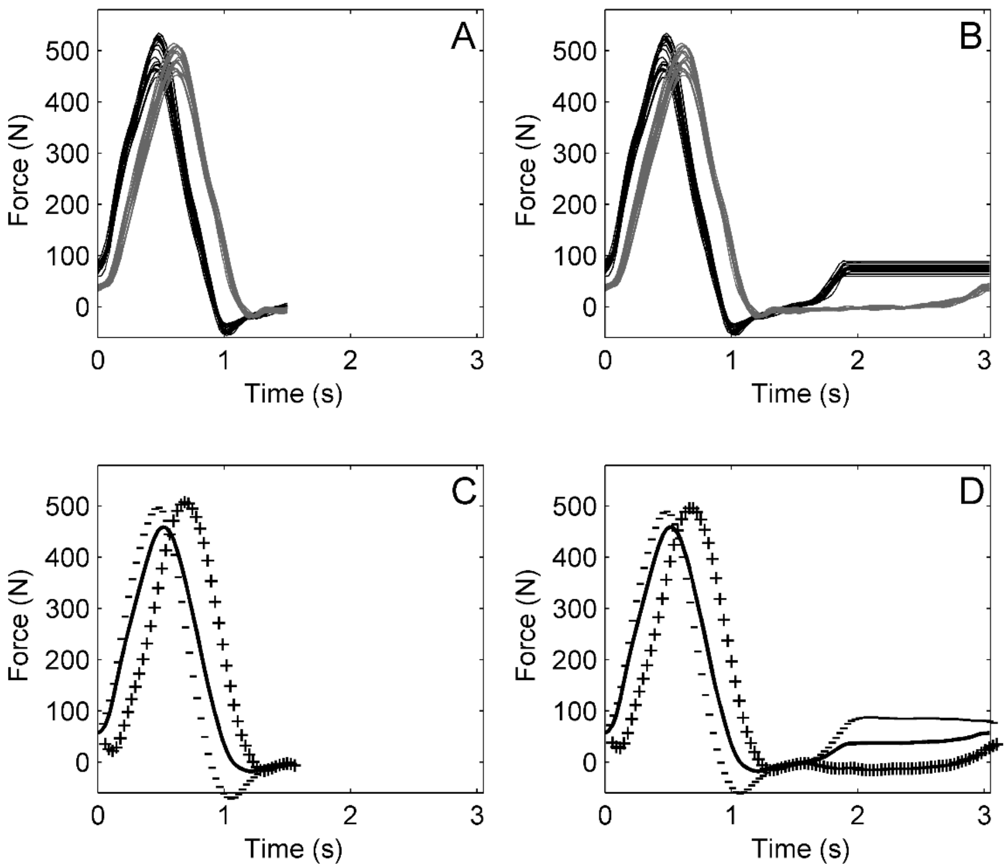

Figure 14. The effect of truncation on *f*PCA. A: raw time series for data set two truncated at an arbitrary time point of 1.5 seconds. B: raw time series for data set two with shorter curves padded by having the missing data points correspond to the stationary end point of each curve. C: the first *f*PC for truncated data. D: the first *f*PC for padded data.

This has been used successfully where all curves are likely to end up together at a fixed point (i.e. the final data point could be the local minima, maxima or zero point), and there is an assumption that this end point is meaningless to the analysis if it is to continue for the remainder of curves that finish earlier than others (Crane, Cassidy, Rothman & Gerstner, 2010; Epifanio, Ávila, Page & Atienza, 2008). Applying this approach for cyclical data is however more problematic. When cycles are padded at the end to create a common time interval, artifacts are created in the data that can change the interpretation of the actual behaviour (Crane, Cassidy, Rothman & Gerstner, 2010), consequently *f*PCA will provide inaccurate results. This can be seen when the raw curves for DS2 are each padded with points that correspond to the final data point of an individual cycle. This padding continues up to the location of the longest curve (see Figure 14). It is quite clear in this example, that artificial data padding at the ends of shorter curves has introduced a new form of variation to the first principal component function (Figure 14; D). An alternative option in an effort to preserve time could be to truncate the cyclical data at an arbitrary time point for each of the curves. Truncation of data at an arbitrary point for cyclical activities is possible, but is potentially undesirable as it could change the structure of a curve in much the same way as phase selection in the previous section of this review. This process would also leave some curves with phases intact, while others could have phases partly missing. Finding a suitable point to truncate all curves is therefore a difficult process and depending on the truncation point selected, the biomechanical interpretation of the results may be compromised.

Recommendations

Several recommendations can be made for the reader using information from both pre-existing literature and the sample data analysed in this review. If a standard LLN is to be used due to the simplicity and well documented use of the procedure, certain considerations should be made for how this could affect the results of a subsequent *f*PCA. If the overall structure of a series of curves is temporally consistent from both a global (length of the entire curve) and component (length of different phases within the curve), then the use of an LLN may be suitable as it will not impact the overall characteristics of temporal variability in a set of curves. If the structure is temporally inconsistent between curves, the user should be prepared for the introduction of temporal variability artifacts to the data.

To temporally shift different parts of a cycle as a means of neutralising erroneous temporal variation introduced by an LLN, it is recommended that a range of different techniques are trialled before a choice is made on which technique is most suitable for the data set. As James (2007) has noted, there may be problems in the shifting of curves using landmark registration when landmarks are not easily identifiable. The results of landmark registration and PLLN in the present example are very similar for capturing the main type of variance reported in these curves. As a general rule however, when landmarks are embedded within the original curve or one of its derivatives, landmark registration should be sought as the initial or preferred technique. If the landmarks and phases are contained within a separate variable, then a technique such as PLLN or PDTW may be of greater benefit with the remaining parts of the curves pieced back together at the relevant points of interest, with PLLN the best starting point given its simplicity for use.

Once a suitable normalisation strategy has been selected and *f*PCA has been conducted, if multiple forms of variation are present within one or more of the *f*PCs retained, then a suitable rotation can be used and the varimax rotation is an advisable starting point given its demonstrated use with functional human movement data (Epifanio, Ávila, Page & Atienza, 2008) and its availability in the FDA software repository. Careful consideration must, however be given to determine whether a rotation is warranted in view of how well a rotated set of *f*PCs represents the variability in the original data. If curves need to be altered to remove unwanted parts of a movement or cycle, careful consideration must be given to the functions used to fit the data, given that the properties of data may be altered.

If preservation of a time-series' original temporal properties is necessary for an analysis, *f*PCA can be quite limited in its ability to accurately manage this data, without there being some resulting form of experimental compromise. This is largely due to curves carrying different lengths (different numbers of data points) prior to any form of normalisation. Discrete skills are best suited to non-normalisation, particularly if each curve finishes at the same end point (local minima, local maxima or zero points). In these instances, stacking the missing data points with values that correspond to the stationary end point of the movement may be suitable and have demonstrated use in the literature (Epifanio, Ávila, Page & Atienza, 2008; Page, Ayala, Leon, Peydro & Prat, 2006). This however should not be performed for cyclical skills, as evidenced by Figure 14.

The majority of literature reported in this review and recommendations made to the reader are based upon literature that has used FDA with human movement data, and has utilised the pre-existing repository of software available on the FDA website. Other modifications to this statistical technique may be suitable to cover some short comings noted when using *f*PCA, but these would require additional programming beyond this repository. Nevertheless, it is important to acknowledge some of these adaptations in the event that they are interest to the reader. Wakim and Jin (2014) should be noted for their work with sparse and irregular data using the PACE technique for curves that have irregular measurement designs and may start and end at different time points.

Conclusion

The FDA technique *f*PCA can serve as a valuable tool for describing the main modes of variability in a data set, which can in turn, be used to assess differences between groups of individuals or associations with other variables. It isn't however, without its limitations, which have been outlined in this review. Depending upon the research question being asked or the practical application, *f*PCA may be a suitable technique for the assessment of curve characteristics in human movement data. Careful consideration should however, be given to the recommendations outlined in this review to ensure that *f*PCA is used in the correct context to answer particular biomechanical research questions of interest.

References for this chapter are included in the list of references at the end of this thesis

BRIDGING STATEMENT B

The previous chapter has explored the potential applicability of functional principle components analysis (*f*PCA) with force-percentage profiles (Smith & Loschner, 2002), and various potential derivatives of this profile (percentage profiles with the drive and recovery phases aligned using normalisation strategies or functional registration). When used with the force-percentage profile, *f*PCA was demonstrated to be effective in retaining structures of variability that were present in the waveform data. Considerations must be given however, to the use of different data preparation strategies such as temporal normalisation of data and removal of unwanted or erroneous forms of variation in a data set prior to using *f*PCA with this data. There also appear to be limitations for the use of *f*PCA with the force-time profile, as these profiles are likely to possess varying lengths of data points. This is problematic as some form of experimental compromise is required for *f*PCA to be applied to this data. As noted in chapter three, discrete skills are best suited for no use of normalisation, particularly if each of the curves eventually finishes at the same end point (local minima, local maxima or zero points). In these instances, stacking the missing data points with values that correspond to the stationary end point of the movement may be suitable. This however, is not the case with the rowing stroke cycle, with each curve potentially finishing with a different value of propulsive force. This makes it difficult to use *f*PCA on force time profiles, unless they undergo some form of data truncation as a way of standardising the lengths of all curves. Given that a more advanced version of *f*PCA, bivariate functional principal components analysis (*bf*PCA) has the ability to include an additional parameter with force (such as horizontal angle of the oar), there may potential for this technique to be applied to force-angle profiles, which are not affected by temporal normalisation.

CHAPTER 4

Bivariate functional principal components analysis (*bf*PCA): Considerations for use in coordination.

The following chapter was formatted for submission to the Journal of Sports Biomechanics and is currently in the accepted for publication.

Author Contribution Statement

As a co-author on the paper presented within this chapter entitled "*Bivariate functional principal components analysis (bfPCA): Considerations for use in coordination*," as well as being Primary Supervisor throughout the Doctor of Philosophy candidature of John Warmenhoven, I confirm John's contribution to the paper as follows:

- Conception and design of the research
- Data collation, database building and database management
- Analysis of data and interpretation of the findings
- Writing the paper and critically appraising content within the manuscript

Signed: [redacted]

Date: 21/04/2017

Professor Richard Smith

Discipline of Exercise and Sport Science

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Bivariate functional principal components analysis (*bf*PCA): Considerations for use in coordination.

By

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Abstract

Functional principal components analysis (*f*PCA) for multivariate data has demonstrated potential for analysing human movement. It has proven benefits in working with non-linear multivariate time-series and thus has an extended ability to explore differences between individuals for complex patterns of coordination in biomechanics. When applied to data composed of bivariate time-series, this technique (referred to as bivariate *f*PCA or *bf*PCA in this context) possesses a number benefits over conventional coordination measures such as vector coding and continuous relative phase. Despite this, given the infancy of *bf*PCA's use with biomechanical data there are still necessary considerations for its use with non-conventional or complex bivariate coordination structures. These non-conventional coordination structures are composed of variables that carry different units of measure or different magnitudes of within-variable variability (or in some cases both of these characteristics). This paper focuses on the issue of applying *bf*PCA in these contexts, and provides some considerations for the use of *bf*PCA in similar situations as a part of future biomechanical research.

Key Words (3-8): FDA; Biomechanics; Rowing.

Bivariate functional principal components analysis (*bf*PCA): Considerations for use in coordination.

Introduction

The identification of patterns that are present across multiple time-series variables is important for understanding underlying movement patterns in biomechanics. The way that movement patterns are measured can differ according to the type of time-series variables being assessed and can include analytical strategies related to muscle synergies (Hug, Turpin, Guével, & Dorel, 2010) and kinematic coordination structures (a comprehensive review of these can be found in Glazier, 2015). In sport, it is common for multiple time-series variables to be used concurrently for assessment of skill differences between athletes and understanding '*how*' some athletes are able to perform better than others. For example, in rowing, the potential for large captures of biomechanical data and the cyclical nature of the sport has resulted in the empirical exploration of multivariate time-series for the assessment of kinematic coordinative structures (Découfour, Pudlo, Barbier & Gorce, 2008; Découfour, Pudlo, Barbier & Gorce, 2010), muscle synergies (Shaharudin, Zanotto & Agrawal, 2014a, 2014b; Turpin, Guével, Durand, & Hug, 2011) and assessment of biomechanical asymmetries (Buckeridge, Bull & McGregor, 2014; Fohanno, Smith, Nordez & Colloud, 2015; Janshen, Mattes & Tidow, 2009).

The growth of functional data analysis (FDA), and particularly functional principal components analysis (*f*PCA), for analysing time-series data in biomechanics has been demonstrated extensively (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Donoghue, Harrison, Coffey & Hayes, 2008; Kipp & Harris, 2014; Kipp, Redden, Sabick & Harris, 2012a; Kipp, Redden, Sabick & Harris, 2012b; Liebl, Willwacher, Hamill & Brüggemann, 2014;

Mallor, Leon, Gaston & Izquierdo, 2010; Ryan, Harrison & Hayes, 2006). More advanced FDA techniques such as bivariate functional principal components analysis (*bf*PCA) have also started to provide a useful alternative for the analysis of multivariate time-series (or equivalently functional) data in sports biomechanics (Epifanio, Ávila, Page & Atienza, 2008; Harrison, Ryan & Hayes, 2007).

When assessing coordination structures present within bivariate data (i.e. two separate time-series), there may be some benefits for using *bf*PCA over other conventional coordination techniques, such as vector coding or continuous relative phase (CRP). Firstly, vector coding and CRP reduce coordination structures present in bivariate time-series data into univariate time-series, which are observed using measurement scales that may be difficult to interpret. Vector coding time-series are reported in the form of a vector coding coupling angle (in degrees) and are derived using angle-angle diagrams (Sparrow, Donovan, van Emmerik & Barry, 1987). Similarly, CRP time-series are also reported as a CRP angle (in degrees), and are derived using the difference between phase angles (taken from phase portraits) for individual variables (Hamill, van Emmerik, Heiderscheit & Li, 1999). When evaluating non-sinusoidal biological time-series such as body joint or segmental kinematics, changes in the CRP angle may not be accurately reflective of differences in the original data when observed in the temporal domain. This can make it difficult to interpret differences in the CRP angle between individuals and make meaningful inferences about patterns of coordination across a movement cycle (Peters, Haddad, Heiderscheit, van Emmerik & Hamill, 2003). Additionally, both vector coding and CRP also provide measures of coordination in a form that may be difficult for applied practitioners (coaches, sport scientists, medical staff, physiotherapists, etc.) to conceptualise and use practically for subsequent interventions that aim to modify characteristics of human movement.

Conversely, *bf*PCA preserves the original units of measure for each of the variables as a part of the analytical process. *bf*PCA also provides various options for visualisation of differences between individuals for bivariate coordination structures. Each variable can be displayed independently relative to time, or with each variable relative to the other in the form of angle-angle diagrams (Harrison, Ryan & Hayes, 2007). Irrespective of how coordination patterns are observed when using *bf*PCA, preservation of the original units may permit a more interpretable understanding of differences between individuals and be of more practical use for applied skill acquisition interventions or feedback strategies for athletes.

Secondly, analyses of vector coding or CRP time-series have often involved relatively simplistic data reduction approaches prior to any form of statistical analysis. Given the issues noted for interpretation of the CRP angle between individuals, vector coding angles are more frequently investigated for assessment of coordination patterns between individuals. Investigation of these angles has involved calculation of the mean coupling angle across particular phases of a movement cycle. These phases can be defined using known biomechanical landmarks or features (Chang, van Emmerik & Hamill, 2008), or arbitrarily by splitting the movement cycle into equally spaced sections (Wilson, Simpson & Hamill, 2009). Mean coupling angles across these phases are then compared statistically or can be used to classify coordination patterns into categories of movement patterns (Chang, van Emmerik & Hamill, 2008). Alternatively, *bf*PCA identifies different coordination strategies that are present across the entire movement cycle and allows for an intuitive comparison of these strategies between groups of the original bivariate time-series. In doing so, *bf*PCA does not sacrifice the functional form of the original data, which is a major strength of all FDA techniques.

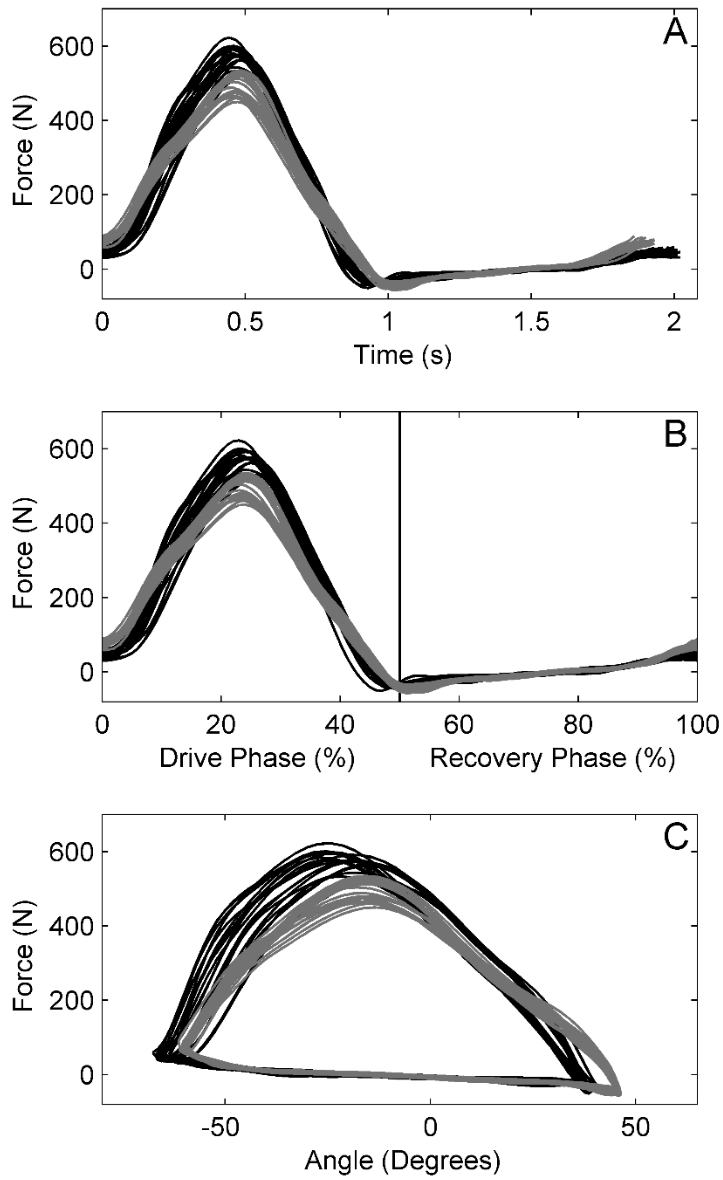

Figure 15. Different depictions of force application in rowing. Data for each of these subplots have been taken from the sample data set. International rower curves are plotted in grey; national rower curves are plotted in black. A: propulsive pin-force plotted relative to time. B: propulsive-pin force plotted relative to % of the stroke cycle (with the drive and recover phases making up 50% of the stroke cycle each). C: propulsive pin force plotted relative to the horizontal angle of the oar.

Finally, in practice it is possible that variables used to comment on coordination in different sporting contexts can be more complex than structures using body joint or segmental kinematics. In applied sports biomechanics, the ability to collect multiple time-series has led to improved strategies for qualitatively visualising combinations of different time-series variables that, when viewed concurrently, can serve as applied sport science tools for better understanding movement technique. These graphical representations can thus be used to provide valuable feedback for athletes and coaches (Smith & Loschner, 2002). In some instances, these graphical representations will have two variables that are measured using different units. Examples of these graphical representations include the force-velocity profile in vertical jumping (Cormie, McBride & McCaulley, 2009), which has been shown as an important tool for differentiating between better technical performance, and the force-oar angle (shortened to force-angle) diagram in on-water rowing, which is used in the evaluation of skilled rowing technique (see Figure 15) (Spinks, 1996; Smith & Loschner, 2002). For both of examples, the content of these graphical displays still describe coordination structures that are present between two variables, but in both instances, one is a kinetic variable and the other is a kinematic variable. In these particular contexts, the use of vector coding or CRP would be undesirable. Assessment of coordination structures using vector coding and CRP focuses on understanding the phasic or coupled relationship between two variables, and often aims to report whether synchronous, anti-phase or out-of-phase movement patterns were present during execution of a movement task using a given coordination structure. Understanding the phasic or coupled relationship between force and the oar angle, in on-water rowing, would likely not provide relevant technical information regarding the coordinated relationship between these two variables. Research analysing the importance of the force-angle coordination structure has previously centered on understanding patterns of co-variation between the two variables (i.e. shape or pattern characteristics of the whole force-angle curve) and how they can discriminate according to metrics of performance or skill (Spinks, 1996; Smith & Loschner, 2002). Unlike vector coding and CRP, *bf*PCA has the ability to analyse patterns of co-variation in bivariate structures such as the force-angle graph, allowing for discrimination of force-angle pattern differences between individuals. Despite this, there are some additional considerations that must be given to these more complex coordination structures prior to using *bf*PCA. Ramsay and Silverman (2005) has noted that *bf*PCA can be an applicable tool for analysing coordination structures when the two variables being considered are measured relative to the same argument (i.e. time for both variables), and each variable is also measuring quantities in the same units. This has also been practically demonstrated by Harrison, Ryan and Hayes (2007). If the variability in one variable is, however, substantially greater than that in the other, or the variables are measuring quantities in different units (i.e. the force-angle graph) then it is possible that one variable may dominate patterns of variation that are uncovered using *bf*PCA. In these instances it may also be advisable to account for such a discrepancy before analysing differences in such coordination structures. Consequently, this paper aims to provide some guidelines and recommendations for the use of *bf*PCA with this type of complex coordination structure in sports biomechanics. Initially *bf*PCA is revisited from a conceptual and theoretical view point. Considerations for the use of *bf*PCA are then explored relative to variables with different units of measure and different levels of within-variable variability. Examples are taken from sample data collected during on-water rowing testing, and the coordination structure of interest in this paper is the force-angle graph.

Sample data sets

The data sets was obtained as a part of a project between the New South Wales Institute of Sport and the University of Sydney. All data were collected after approval of the relevant tertiary institution's ethical board. Two highly skilled Australian female scullers were selected from this database and each athlete was assessed according to their competitive performance at the time of testing and classed as either 'national' level or 'international' level. National level athletes must have competed in Australian national age group championships or Australian national open championships prior to the testing and were deemed to be highly skilled, sub-elite rowers. International rowers must have competed as an Australian representative at an under 18, under 23 or open level prior to testing. One of the athletes was assessed as being national level (age = 25 years; height = 1.78 m; mass = 75.62 kg) and the other international level (age = 25 years; height = 1.82 m; mass = 79.58 kg). As a part of the testing, both athletes were directed to row a total of 1000 m, composed as 250 m at four ascending pre-selected stroke rates of 20, 24, 28 and 32 strokes per minute (also referred to as SR20, SR24, SR28, SR32 respectively). A short period of active rest (250m of light rowing) followed each stroke rate condition to ensure that fatigue was not a factor. Data for both the national and international level athletes were selected and only SR32 was analysed. Ten strokes were selected for each rower for both the bow side (left hand) and stroke side (right hand). Two variables were obtained for further analysis – horizontal angle of the oar and propulsive pin force. Twenty time-series (ten for each side of the boat) were entered into each analysis. For every individual time-series the drive and recovery phases were identified using the horizontal angle of the oar, with instrumentation for collecting these variables outlined in Smith and Loschner (2002).

Bivariate Functional Principal Components Analysis (*bf*PCA)

From this point onwards, since multiple variables are discussed in each section and variability within each of these variables will also be discussed, the term parameter will replace variable to avoid confusion. At present, few studies have explored *bf*PCA with human movement data (see Harrison, Ryan & Hayes, 2007 and Epifanio, Ávila, Page & Atienza, 2008). Ramsay and Silverman (2005) and Harrison, Ryan and Hayes (2007) have covered the theoretical steps for using this technique and thus only a summary is provided below. Each time-series parameter must be represented as a series of functions and this involves fitting each parameter contained within a multivariate functional object (in the case of the present study this is case bivariate data) with a suitably chosen set of basis functions and smoothing if necessary.

In *bf*PCA, the functions for the first and second parameters can be referenced as a and b for individuals $i = 1, \ldots, N$ as $a_1(t), a_2(t), \ldots, a_N(t)$ and $b_1(t), b_2(t), \ldots, b_N(t)$ respectively. Let $\bar{a}(t) = N^{-1}\sum_i a_i(t)$ and $\bar{b}(t) = N^{-1}\sum_i b_i(t)$ denote the mean curves of parameters a and b respectively. Assume that the data are mean-centered, i.e. $\bar{a}(t)$ has been subtracted from each $a_i(t)$ and $\bar{b}(t)$ has been subtracted from each $b_i(t)$. Covariance functions for a and b can be defined as $v_{aa}(s,t) = N^{-1}\sum a_i(s)a_i(t)$ and $v_{bb}(s,t) = N^{-1}\sum b_i(s)b_i(t)$ respectively and the cross covariance function can be defined as $v_{ab}(s,t) = N^{-1}\sum a(s)b(t)$, such that $v_{ab}(s,t) = v_{ba}(t,s)$. In each of these equations, s and t are time arguments. The functions $v_{aa}(s,t)$, $v_{bb}(s,t)$ and $v_{ab}(s,t)$ are then combined to construct the bivariate covariance function $v(s,t)$. A principal component in this context is defined by a vector of weight functions $\xi = (\xi_a, \xi_b)'$ where ξ_a denotes the variation in the parameter a (an example of this is Figure 16A), and ξ_b the variation in parameter b (Figure 16B). To extract principal components, the squared norm must be defined on the space of vector functions. The simplest definition for the squared norm in this context is to sum the squared norms of the two components. The principal components are then extracted as in the univariate case by finding the solutions to the eigen-equation system $v(s,t)\, \xi = \rho\xi$, which can be written in full as:

$$\int v_{aa}(s,t)\, \xi_a(t)dt + \int v_{ab}(s,t)\, \xi_b(t)dt = \rho\xi_a(s)$$

$$\int v_{ba}(s,t)\, \xi_a(t)dt + \int v_{bb}(s,t)\, \xi_b(t)dt = \rho\xi_b(s)$$

In practice, bivariate functional principal components (*bf*PCs) are calculated by replacing the first and second parameter functions, a_i and b_i with vectors of discrete values, effectively re-sampling data points from a functional form to a discrete form (Harrison, Ryan & Hayes, 2007; Ramsay & Silverman, 2005). For each individual *i*, these vectors of points for each parameter are concatenated into a single vector Z_i, which represents data for both parameters. A covariance matrix is then derived for Z_i, with this serving as an approximated version of the bivariate covariance function. A standard principal component analysis is performed on the Z_i vectors and principal component vectors $\xi^{(m)} = (\xi_a^{(m)}, \xi_b^{(m)})'$ for $m = 1, \ldots, M$ are extracted, each dividing into the parts corresponding to variation for parameter *a* and parameter *b*. The principal component scores or weights are also defined for each individual *i* on each principal component *m* via:

$$\omega_i^{(m)} = \omega_{ai}^{(m)} + \omega_{bi}^{(m)},$$

where $\omega_{ai}^{(m)} = \int \xi_a^{(m)}(t)\, a_i(t)\mathrm{d}t$, which denotes the ccontribution of parameter *a* to the *m*th *bf*PC score, and $\omega_{bi}^{(m)} = \int \xi_b^{(m)}(t)\, b_i(t)\mathrm{d}t$, which denotes the contribution of parameter *b*. Additionally, the amount of variation attributed to each *bf*PC is calculated by dividing each *bf*PC's eigenvalue by the sum of all retained *bf*PCs eigenvalues (similar to *f*PCA).

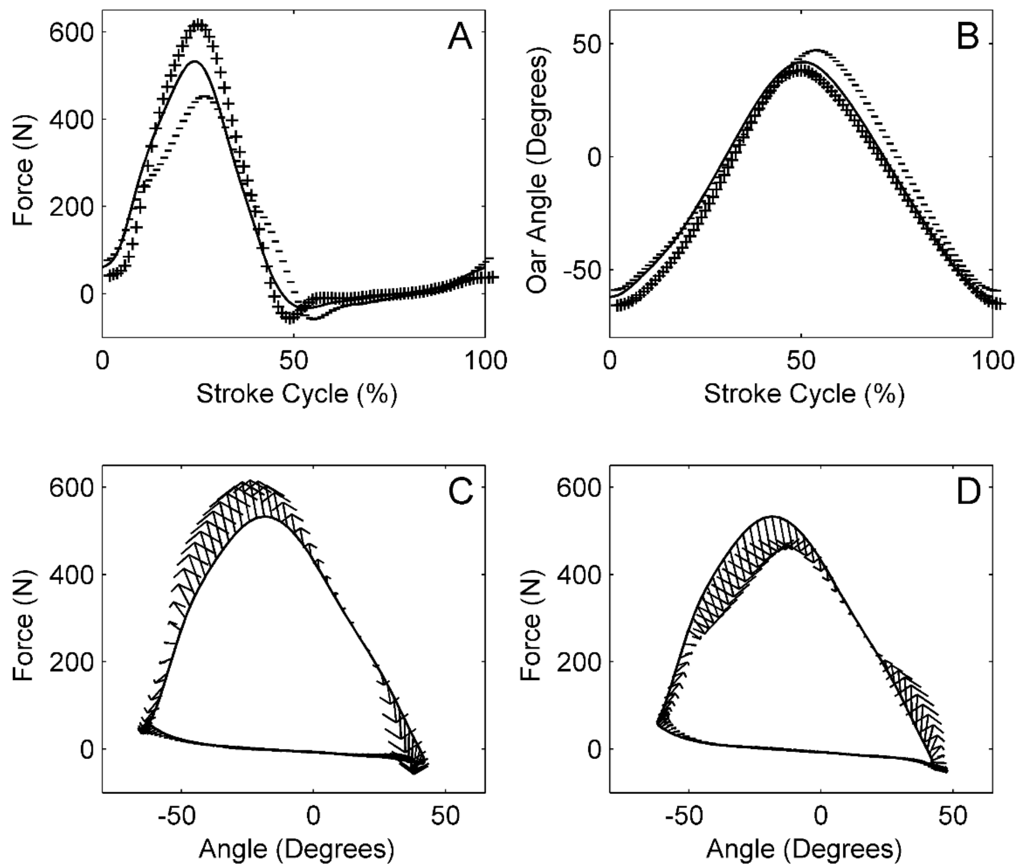

Figure 16. *bf*PCA applied to the force-angle profile. Data for each of these subplots have been taken from the sample data set. Each parameter analysed as a part of *bf*PCA can be visualised independently (as seen in A and B for force and the oar angle), or combined into a bivariate plot, which is a force-angle diagram in C and D. The bottom subplots show the combined interaction of both parameters for positive scorers (C) and negative scorers (D).

Visualising *bf*PCs

There are multiple ways that *bf*PCs can be visualised before the scores are interpreted. Epifanio, Ávila, Page and Atienza (2008) used an approach similar to standard *f*PCA graphical representations (see Warmenhoven et al., 2017 for a comprehensive review), where each part of the bivariate structure was graphed separately. An example is given in Figure 16, where Figure 16A displays $\bar{a}(t) \pm C\,\xi_a^{(m)}(t)$ while Figure 16B displays $\bar{b}(t) \pm C\,\xi_b^{(m)}(t)$. For each of these plots, a subjectively selected multiple in the form of a constant (C) is used to scale each parameter's part of the *bf*PC. An individual who is a positive scorer on this *bf*PC for parameter *a* and/or parameter *b*, will resemble the plus (+) signs moving away from the mean function for the appropriate plot. Similarly, the reverse will be true for negative scorers and the (–) signs.

Another effective method for displaying *bf*PCs is to construct plots of one parameter relative to the other. In this case, mean function values ($\bar{a}(t)$, $\bar{b}(t)$) can be displayed by a dot in the (x, y) plane with, for example in Figure 16, the horizontal oar angle (parameter *a*) on the *x*-axis and propulsive pin-force (parameter *b*) on the *y*-axis. These dots can be joined by arrows to the points corresponding to the location of ($\bar{a}(t) + C\,\xi_a^{(m)}(t)$, $\bar{b}(t) + C\,\xi_b^{(m)}(t)$), thus showing either positive scorers for both parts of the *bf*PC (Figure 16: C). The constant C is again chosen to give clarity to the figures and this process can also be repeated subtracting each part of the *bf*PC from each parameter's mean function ($\bar{a}(t) - C\,\xi_a^{(m)}(t)$, $\bar{b}(t) - C\,\xi_b^{(m)}(t)$) to show negative scorers (Figure 16: D) (Ramsay & Silverman, 2005).

Bivariate structures with different units of measure

The process for using *bf*PCA has been demonstrated in the assessment of coordination differences between groups using angle-angle diagrams (Harrison, Ryan & Hayes, 2007). This worked well for assessing coordination changes in vertical jump performance between groups of children at different developmental stages.

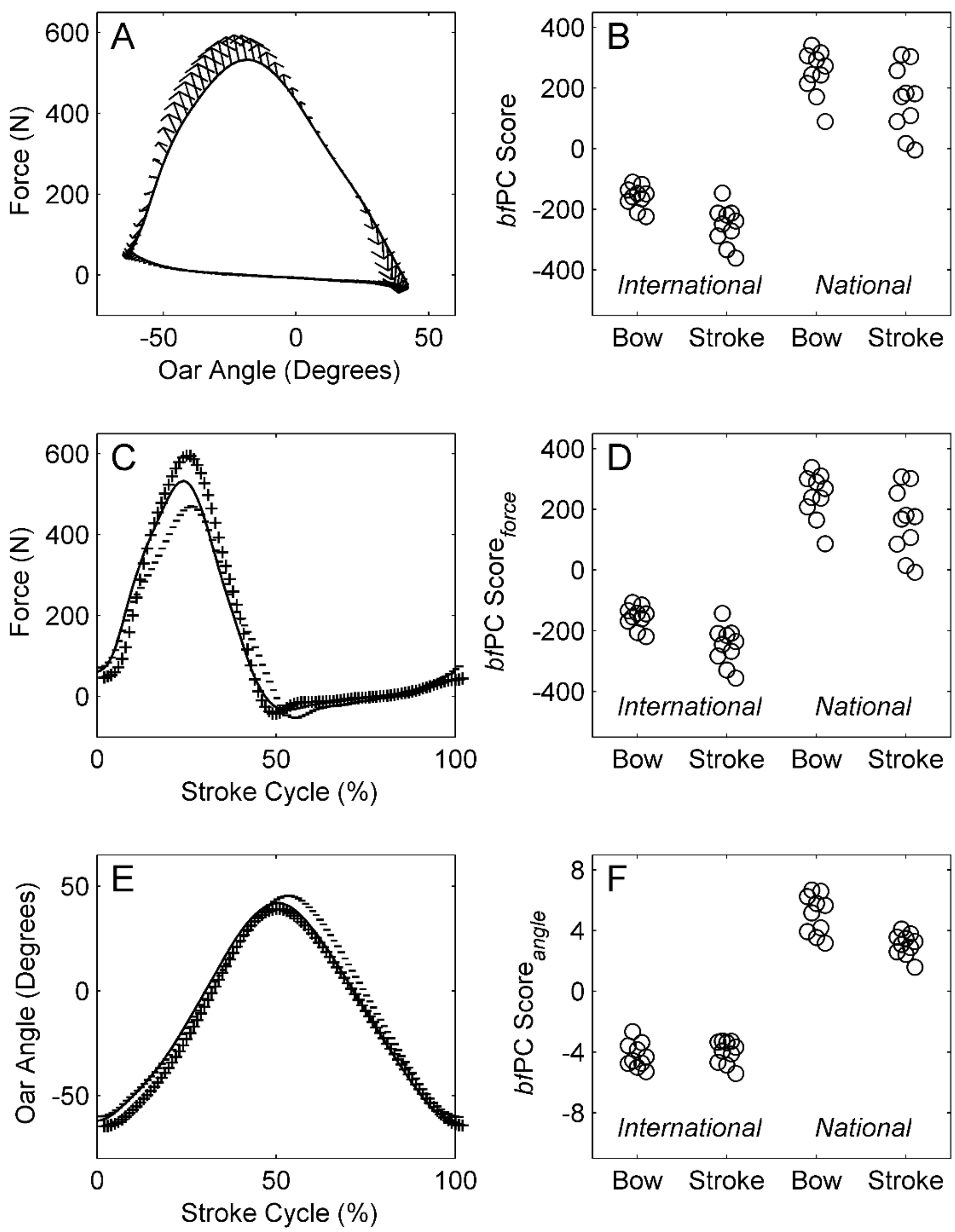

Figure 17. *bf*PCA before normalisation applied to the force-angle profile. Data for each of these subplots have been taken from the first sample data set. A: the first *bf*PC for force-angle curves using the sample data set. B: scatterplot of the first *bf*PC scores for the two rowers. C: force contribution to the first *bf*PC. D: scatterplot of the force contribution to the *bf*PC scores. E: oar-angle contribution to the first *bf*PC. F: scatterplot of the oar angle contribution to the *bf*PC scores.

The use of *bf*PCA has also been deemed appropriate when each parameter in a bivariate structure have the same units of measure (in the case of coordination both parameters are measured in degrees) and if the variance within each parameter is similar and not substantially different between parameters (Ramsay & Silverman, 2005). In some instances however, it may be important to evaluate differences between groups of coordination structures where the two parameters have either different units of measure, different levels of variability, or a combination of both. If *bf*PCA is used in any of these instances, the *bf*PC may not be truly reflective of each parameter's contribution to the overall *bf*PC, as a variable with a larger measurement scale or magnitude of variability may have a tendency to dominate the overall *bf*PC score calculation. This could be a potential problem for analysis of the force-angle diagram in on-water rowing (Smith & Loschner, 2002). The sample data set can be used to test whether these issues are apparent when *bf*PCA is applied to the force-oar angle graph. These sample data have been selected as the force-angle graph is typically used to compare technical characteristics between rowers (Smith & Loschner, 2002). This data set compares the force-angle profile of two rowers at differing levels of competitive representation. The original force-angle curves and the first *bf*PC for this data set can be seen in Figure 17. A scatter plot of the *bf*PC scores for each participants' curves and scatter plots for each parameters' contribution to the overall *bf*PC scores can also be observed in Figures 17. For this particular example, the first *bf*PC accounts for 65.6% of all variability in the data. It is clear in Figure 17, that the two rowers possess different force-angle coordination structures once the scores for the first *bf*PC are inspected (noted within the *bf*PC score scatterplot). It is also apparent, for both rowers, that the relative amount each parameter contributes to the overall *bf*PC score is different (from the different scales along the *y*-axis for Figure 17 D and Figure 17 F).

This difference in within-parameter variability between force and the oar angle, illustrated by Figure 17, can be confirmed empirically. In the present example, the first *bf*PC can be referenced as $\xi^1(t) = (\xi^1_{force}(t), \xi^1_{angle}(t))'$ with $\xi^1_{force}(t)$ representing the contribution of force to the first *bf*PC, and ξ^1_{angle} representing the contribution of angle to the first *bf*PC. In this example, $\left\|\xi_{force}(t)\right\|^2 + \left\|\xi_{angle}(t)\right\|^2 = 1$, and by definition calculating $\left\|\xi_{force}(t)\right\|^2$ will give the proportion of the variability in the first principal component accounted for by variation in the force time-series. The same can also be said for $\left\|\xi_{angle}(t)\right\|^2$ and the variance in the angle time-series. In the current example, $\left\|\xi_{force}(t)\right\|^2$accounted for over 99.99% of the variance in the bivariate functional structure and $\left\|\xi_{angle}(t)\right\|^2$ accounted for less than 0.01%.

Assessing differences in within-parameter variability in *bf*PCA

In the present example, it is important to understand what has contributed to the obvious imbalance in the contribution each parameter has made to the *bf*PC scores for the first *bf*PC. It remains unknown whether this difference can be attributed to true differences in the variability present in each parameter during execution of the skill, or whether the majority of variance is due to force and the horizontal angle of the oar measuring quantities using different units. To assess the nature of these within-parameter variability differences, a normalisation strategy can be used to provide both parameters with a consistent unit of measure prior to conducting *bf*PCA. This would preserve the internal structure of each parameter’s variability, but would remove larger differences that exist solely as a product of the units used for each.

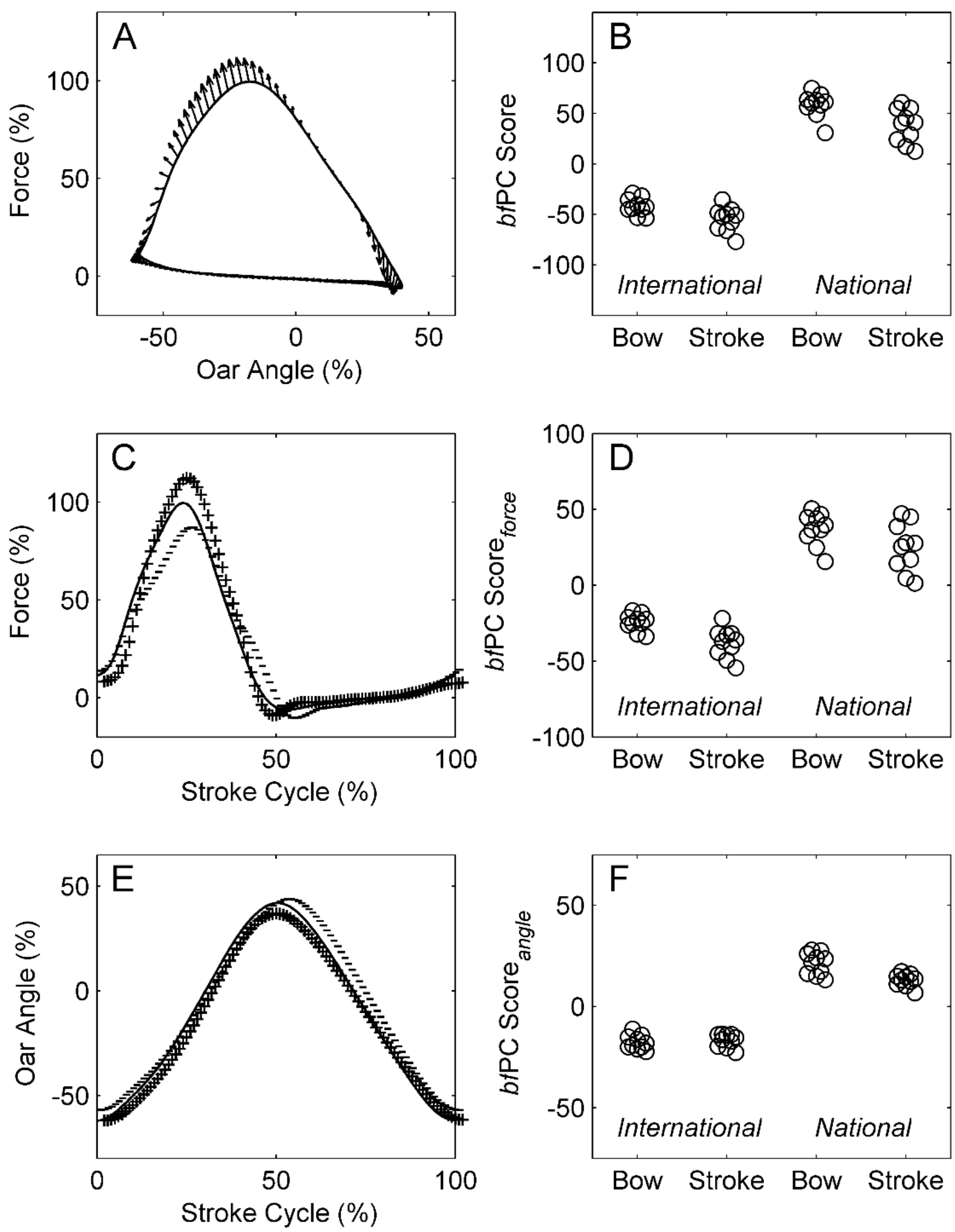

Figure 18. *bf*PCA after normalisation applied to the force-angle profile. Data for each of these subplots have been taken from the first sample data set. A: *bf*PC1 for force-angle curves after normalisation. B: *bf*PC1 scores for the two rowers after normalisation. C: force contribution to the first *bf*PC after normalisation. D: scatterplot of the force contribution to the *bf*PC scores after normalisation. E: oar-angle contribution to the first normalised *bf*PC. F: scatterplot of the oar angle contribution to the normalised *bf*PC scores.

In the present example, maximum force for each stroke could be used to create the mean for all maximal values ($F_{Average\ Maximum}$). Each stroke could be normalised to a percentage, relative to this mean maxima, and subsequently force would be centred, so that with a curve with a maximal force equal to $F_{Average\text{-}Maximum}$ would be weighted as 100%. The oar angle could also be normalised similarly as a relative percentage of stroke length. Both normalisation approaches are described by the equations below;

$$F_{Norm(i)} = \left(\frac{F_{(i)}}{F_{(Average\ Maximum)}}\right) \times 100(\%)$$

$$\theta_{Norm(i)} = \left(\frac{\theta_{(i)}}{\theta_{(Average\ Maximum)} - \theta_{(Average\ Minimum)}}\right) \times 100(\%)$$

Normalising the oar angle in this way would preserve important information about the spatial position of the oar. For example, *0* degrees would be maintained as *0* (when expressed as a percentage), in same way that the *0* point for velocity is maintained in specific phase portrait normalisation techniques (Hamill, van Emmerik, Heiderscheit & Li, 1999). The *0* point in both the force-angle diagram and a phase portrait have known biomechanical relevance, therefore it may be important to preserve these biomechanical landmarks. In the present example, it can be seen that after normalisation, the differences in within-parameter variability between force and the oar angle are substantially reduced (Figure 18). It is also possible to examine differences in the results of *bf*PCA after normalisation by defining $\left\|\xi_{norm\text{-}force}(t)\right\|^2 + \left\|\xi_{norm\text{-}angle}(t)\right\|^2 = 1$, where $\left\|\xi_{norm\text{-}force}(t)\right\|^2$ represents the variance attributed to force after normalisation and

$\left\| \xi_{norm\text{-}angle}(t) \right\|^2$ the variance attributed to the angle. After normalisation, $\left\| \xi_{norm\text{-}force}(t) \right\|^2$ accounted for 87.07% of variance in the first *bf*PC and the angle accounted for 12.93% for the first *bf*PC.

Accounting for differences in within-parameter variability

Once differences in multiple parameters (from a coordination structure) have been established, there are approaches that can be used to standardise variation between these parameters. Firstly, if the majority of differences in within-parameter variability is attributed directly to differences in the units of measure, a normalisation strategy such as that outlined in the present article can be considered as a potential solution. Once this normalisation strategy is used, *bf*PCA can be applied to this normalised data. If normalisation prior to the execution of *bf*PCA does not standardise differences in within-parameter variability adequately, it may be advisable to take steps in reducing these variances before or as a part of the execution of *bf*PCA. In the present example, the relative variance attributed to each parameter for the first *bf*PC changed substantially after each parameter was centred on a group mean. Ramsay and Silverman (2005) has noted that if variances within each of the two parameters in a bivariate structure are unequal, then the inner product of the corresponding parameter dominating variation in a *bf*PC can be down-weighted. This results in a reduction of the magnitude of that variable's contribution to the overall *bf*PC score. Generally with human movement data, this is a difficult process to execute accurately, since differences in the variability between two parameters may be important and meaningful forms of biological variation. Consequently, devising a multiple for which the most dominant mode of variation could be down weighted may affect the results of a *bf*PCA in a way that does not replicate how the movement was executed, particularly if the parameter which carried less variability, is a biologically '*less relevant*' part of a bivariate structure. In this case, it would be undesirable to increase the relative importance of its own variability. If the units of measure are to be unaltered for visualisation purposes, there are two different options for potential use of *bf*PCA. Firstly, a standard *bf*PCA could be carried out and instead of summing each parameter's contributive parts to form *bf*PC scores, the contributions from each parameter could be analysed separately. Any differences in within-parameter variability would thus be preserved. A second alternative approach could be to use a normalisation strategy to account for unit differences. *bf*PC functions from the normalised data could be added to the mean functions of the non-normalised data, with this being executed purely for visualisation of differences described by *bf*PC functions using the scale or units of measure of the original data.

It should be noted that this paper has focused on the use of *f*PCA for multivariate functional data as outlined by Ramsay and Silverman (2005) and used practically by Harrison, Ryan and Hayes (2007). Multivariate *f*PCA (or *bf*PCA for bivariate functional data in the present article) has been explored specifically in this article using software developed for MATLAB, S-PLUS and R by Ramsay and Silverman, and is accessible from an FDA website: http://www.psych.mcgill.ca/misc/fda/ and is freely available for use, in conjunction with a tutorial and sample biomechanical (gait) data set. There have been significant advancements made on the issue of analysing multivariate functional data since the development of *bf*PCA, and these may also provide the reader with some direction moving forwards. Both Jacques and Preda (2014) and Chiou Chen and Yang (2014) have provided normalised versions of multivariate *f*PCA for application to data with different measurement scales. Jacques and Preda (2014) introduced a clustering procedure for multivariate functional data based on an approximation of density within multivariate random functions. Chiou, Chen and Yang (2014) also proposed a normalised multivariate functional principal component ($m\text{FPC}_n$) method, which accounted for differences in degrees of variability and units of measurements among the components of multivariate random functions when defining *m*FPCs. This multivariate approach led to a single set of *m*FPC scores for each subject, which served well as a proxy of multivariate functional data. Both of these adaptations to multivariate *f*PCA (or *bf*PCA) may also have potential for use with human movement or sports biomechanics data, but investigation of these techniques is outside the scope of this article, and would require substantial additional programming beyond the established FDA software repository.

Recommendations for use of *bf*PCA

If *bf*PCA is to be applied to a bivariate coordination structure where each parameter is measured with different units, it is advised that differences in the variances between the parameters are assessed prior to analysis of *bf*PC scores. The normalisation approach outlined in this study is one method, which may be suitable for assessment of such differences. When the differences in within-parameter variability have been established, the data can be analysed in various ways. If the normalisation strategy used to assess the effect of differing units accounts for differences between the two parameters, then this normalised data can be used for subsequent *bf*PCA. If there is still a substantial difference between variances in the parameters of a bivariate structure, then down-weighting of the appropriate part of the inner product of *bf*PC functions could be undertaken, although this should be executed with caution. It is important preserve variation between biomechanical parameters in some cases and any further changes beyond the normalisation strategy used in this review may affect the outcomes of a *bf*PCA in ways that do not truly reflect structures of variability that were present in the original time-series data. If preservation of the original units for each parameter is essential, a standard *bf*PCA can be carried out but each parameter's contribution to the overall *bf*PC score should be analysed separately.

Conclusion

*f*PCA for multivariate data (*bf*PCA in the context of data used in this review) has demonstrated potential for use with human movement data. It has proven benefits for use with multivariate non-linear time-series and thus has an extended ability to explore differences between individuals for complex patterns of coordination in biomechanics. *bf*PCA carries a number benefits over conventional coordination techniques that are commonly applied to bivariate coordination structures (such as vector coding and continuous relative phase). Despite this, given the infancy of *bf*PCA's use with biomechanical data there are still necessary considerations for its use. In particular, diligence must be shown when differences in variation are present between parameters in a bivariate structure, particularly when structures have parameters that are scaled relative to different units. Different normalisation approaches, outlined in this review, could also be considered to standardise for these differences in within-parameter variation. These considerations are necessary to ensure that results from the use of this technique are interpreted in the correct context and accurately represent differences present in the original functional data.

References for this chapter are included in the list of references at the end of this thesis

Bridging Statement C

Chapter four demonstrated potential for the application of bivariate functional principle components analysis (*bf*PCA) to force-angle profiles. Concerns related specifically to differences in within-parameter variability were raised, but solutions to this potential problem were also offered. Within-parameter variability may be a concern with force-angle data due to the presence of different units of measurement for each parameter in the bivariate graph (force in Newtons and oar angle in degrees). Normalisation strategies were provided in an attempt to account for potential discrepancies in variability between the two parameters. In light of the well documented benefits of evaluating the force-angle profile in chapter two, and findings from chapter three regarding the difficulties applying *f*PCA to force-time profiles, experimental research assessing differences between rowers in force-time profiles will not be conducted within this thesis. It is believed that revisions and modifications of FDA techniques may be required before they are suitable for use with raw non-normalised and non-truncated force-time data. Further to this, such revisions to these techniques are beyond the scope of this thesis (as these would require substantial additional programming beyond the available software for using FDA at www.functionaldataanalysis.org). Given that *bf*PCA is not affected by these issues, differences between rowers in the characteristics of force-angle profile, will however be explored through using *bf*PCA. Chapter five will use *bf*PCA to explore the potential effects of gender (organismic constraint) and boat-side (task constraint) on differences in characteristics of the force-angle profile.

CHAPTER 5

How gender and boat-side affect shape characteristics of force-angle profiles in single sculling: Insights from functional data analysis.

The following chapter was formatted for submission to the Journal of Science and Medicine in Sport and is currently published (in press).

Author Contribution Statement

As a co-author on the paper presented within this chapter entitled "*How gender and boat-side affect shape characteristics of force-angle profiles in single sculling: Insights from functional data analysis*," as well as being Primary Supervisor throughout the Doctor of Philosophy candidature of John Warmenhoven, I confirm John's contribution to the paper as follows:

- Conception and design of the research
- Data collation, database building and database management
- Analysis of data and interpretation of the findings
- Writing the paper and critically appraising content within the manuscript

Signed: [redacted]

Date: 21/04/2017

Professor Richard Smith

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How gender and boat-side affect shape characteristics of force-angle profiles in single sculling: Insights from functional data analysis.

By

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Abstract

The graphical presentation of the propulsive force patterns applied at the pin plotted relative to the horizontal oar angle has been used extensively to evaluate rowing skill. However, how such patterns are related to gender and side of the boat in single sculling has not been determined. Bivariate functional principal components analysis (*bf*PCA) was used on force-angle data to identify the main modes of variance in curves of forty highly skilled male and female rowers (national and international level), rowing at 32 strokes per minute in a single scull boat. Discriminant function analysis showed strong classification of rowers for gender across both sides of the boat, with force application immediately prior to and after the oar being perpendicular to the axis of the boat demonstrating a difference for gender. A mixed ANOVA exploring gender, boat side and their interaction revealed that bow and stroke side forces were also statistically different from each other independently of gender. A main effect, independent of side of the boat, was also present for gender and no interaction was found between gender and boat side. Bow side forces seemingly acted as a driver of power and peak force production, while stroke side forces may have acted as a mediator of propulsive forces with an additional potential role in steering due to known asymmetrical offsets in boat rigging. Results demonstrate that propulsive force differences according to gender and boat-side must be acknowledged and accounted for before force-angle graphs are explored relative to performance measures.

Key Words (3-8): Bivariate Functional Principal Components Analysis; Gender, Shape Characteristics, Rowing.

How gender and boat-side affect shape characteristics of force-angle profiles in single sculling: Insights from functional data analysis.

Introduction

In rowing, 'signature' movements representing technical aspects of the rowing stroke cycle were first proposed in the 1970's, and are associated with execution of pulling force on the oar handle (Ishiko, 1971). Subsequently, studies have examined force characteristics measured at the oar handle, the pin (oarlock) and the oar blade (Soper & Hume, 2004). These forces are usually represented graphically with force plotted either against time (Smith & Spinks, 1995) or against the horizontal angle of the oar (Spinks, 1996). Rowers have been identified descriptively by their distinctive shape or harmonic structure on such graphs, with these shapes referred to as a rower's force profile (Spinks, 1996). Characteristics of these profiles are often utilised in training and performance contexts to assist in optimising rowing technique (Smith & Loschner, 2002; Spinks, 1996). Despite commonalities and idiosyncratic differences between rowers' force profiles, empirical research regarding the specific importance of shape characteristics in these signatures and their relationship with factors such as gender or the side of the boat in sculling is currently limited.

There is growing support for biomechanical differences between male and female rowers. In addition to peak force and power differences between males and females, ergometer research has established that females possess better lumbopelvic rhythm due to greater anterior pelvic rotation (McGregor, Patankar & Bull, 2008). Additionally, relative joint power differences between males and females have been noted, particularly for upper extremity joints across the drive phase of the rowing stroke cycle (Attenborough, Smith & Sinclair, 2012). Despite these gender differences in biomechanics, there is limited literature showing differences in movement strategies represented by biomechanical variables such as force profiles in on-water rowing.

There is also evidence for differences in force application on each side of the boat in on-water sculling. Due to the inboard length of the oars in sculling, the handles must overlap when the blades are perpendicular to the boat, resulting in upper body postural asymmetry. Boats are usually rigged so that when the handles overlap, the left hand will be on top of the right hand. This asymmetry has been attributed to large discrepancies reported in stroke and bow side peak force (Elliott, Lyttle & Birkett, 2002; Loschner, Smith, Barrett, Simeoni & D'Helon, 2000). Greater force application on one blade may result in greater yawing (movement about the longitudinal axis of the boat), which is reported to negatively correlate to boat velocity. To account for unwanted yawing, it may be possible that force profile characteristics purposefully differ between the bow and stroke sides to negate the asymmetrical offset in oar rigging.

Methodologically and analytically, there are benefits to visualising the force-angle graph over the force-time graph as it allows for inspection of force relative to stroke length, the area under the curve is a direct measure of the work done during the rowing stroke cycle and allows for an intuitive comparison of profiles across different stroke rates (Smith & Loschner, 2002; Spinks, 1996). Statistical data reduction strategies that retain properties from all aspects of the force-angle profile could provide additional insights into the role of key characteristics in force-angle shapes. One type of analysis with potential applicability to the force-angle graph is '*Bivariate Functional Principal Components Analysis*' (*bf*PCA), from the Functional Data Analysis (FDA) family of statistical techniques (Ramsay & Silverman, 2005).

The use of *bf*PCA for assessing trends in bivariate functional biomechanical variables have been highlighted (Harrison, Ryan & Hayes, 2007), where *bf*PCA has examined coordination differences between children for vertical jumping. In the present study *bf*PCA could be applied to explore gender and boat-side differences in force-angle profiles during on-water single sculling. Therefore, the aim of this study was to examine whether gender or side of the boat influenced shape characteristics of the force-angle profile in on-water single sculling. In this study force was expressed as a relative measure (a relative percentage of each individual's maximum force) ensuring that variability described in curves only was reflective of shape characteristics, and not already known amplitude differences in peak force as a result of gender (McGregor, Patankar & Bull, 2008) or boat-side differences (Elliott, Lyttle & Birkett, 2002; Loschner, Smith, Barrett, Simeoni & D'Helon, 2000). This is an explorative study and although there is a plausible case for differences to exist for both gender and boat-side, how each of these factors will influence the characteristics of continuous force application is unknown at this time.

Methods

Participants

Following institutional ethical approval and participant consent, twenty male (*M* age = 21.87 $\pm$ 2.55 years; *M* height = 1.91 $\pm$ 0.06 m; *M* mass = 87.16 $\pm$ 9.14 kg) and twenty female (*F* age = 20.73 $\pm$ 3.65 years; *F* height = 1.82 $\pm$ 0.06 m; *F* mass = 72.47 $\pm$ 7.08 kg) highly trained heavyweight and lightweight scullers participated. All rowers were required to have competed in an Australian national age group championship or an Australian national open championship (as a "national" level athlete) or represented Australia at an Under 18, 23, or open level event (as an "international" level athlete) prior to testing. In each group of male and female rowers, there were fifteen national and five international level athletes.

Procedures

Participants were instructed to row a total of 1000 m, composed of four 250 m segments at ascending pre-selected stroke rates of 20, 24, 28 and 32 strokes per minute. A short period of active rest (250m of light rowing) followed each stroke rate condition to ensure that fatigue was not a factor. Rowers used Nielsen-Kellerman © *Strokecoaches* to control stroke rate outputs. In this study, only the 32 strokes per minute data (i.e., highest stroke rate) were analysed. Rowing data was obtained using ROWSYS instrumentation (Smith & Loschner, 2002). Propulsive pin force was measured using three-dimensional piezoelectric transducers (Kistler, Switzerland). The pin was mounted on the rigger and was the axis of rotation for the gate. Horizontal oar angles were measured by low-friction potentiometers and a fiberglass arm attached to the inboard end of the oar.

Data Processing

The same ten strokes were selected for the bow and stroke side for each rower. These strokes were performed simultaneously and consecutively. For each participant, the drive and recovery phases were identified using the oar angle relative to the horizontal (Smith & Loschner, 2002) and only the drive phase was analysed in this study. A linear length normalisation strategy using an interpolating cubic spline was applied, normalising each curve to 100% of the drive phase. Amplitude normalisation was also applied, ensuring that variability described in the curves was only reflective of shape characteristics. For amplitude normalisation, force was converted to a percentage relative to each curve's maxima. Horizontal oar angle was normalised so that the length of all strokes was equal to 100%, and 0^{o} was reflective of the oar being perpendicular to the longitudinal axis of the boat. Both normalisation formulas are below;

$$F_{Norm(i)} = \left(\frac{F_{(i)}}{F_{(Maximum)}}\right) \times 100(\%)$$

$$\theta_{Norm(i)} = \left(\frac{\theta_{(i)}}{\theta_{(Average\ Maximum)} - \theta_{(Average\ Minimum)}}\right) \times 100(\%)$$

where F is the propulsive pin force and θ the horizontal oar angle. An average curve created from each participant's ten strokes was then used for analysis.

Data Analysis

Functional principal components analysis for bivariate data was implemented (Harrison, Ryan & Hayes, 2007; Ramsay & Silverman, 2005). The normalised force and the horizontal oar angle curves were estimated as functions using B-splines and smoothed by adding a roughness penalty to the fitting procedure, which was selected subjectively through visual inspection (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Ramsay & Silverman, 2005). The functions for propulsive force and the horizontal oar angle were referenced as a and b for individuals i = 1, . . . , N as $a_1(t)$, $a_2(t)$, . . . , $a_N(t)$ and $b_1(t)$, $b_2(t)$, . . . , $b_N(t)$ respectively. Bivariate functional principal components were calculated by replacing the propulsive force and oar angle functions a_i and b_i with a vector of values at a fine grid of points. For each individual i, these vectors were concatenated into a single vector Z_i. The covariance matrix of the Z_i is a discretised version of the bivariate covariance function. A standard principal component analysis was then performed on the Z_i vectors and principal component vectors $\xi^{(m)} = (\xi_a^{(m)}, \xi_b^{(m)})$ for the m = 1, . . . , M extracted, each dividing into the parts corresponding to a and b variation. The principal component scores or weights were defined for each individual i on each principal component m. A single *bf*PCA was conducted for all bow side and stroke side force-angle curves for all athletes. Bivariate force-angle functions were weighted by the first five bivariate functional principal components (*bf*PCs) with these resulting scalars being the *bf*PC scores.

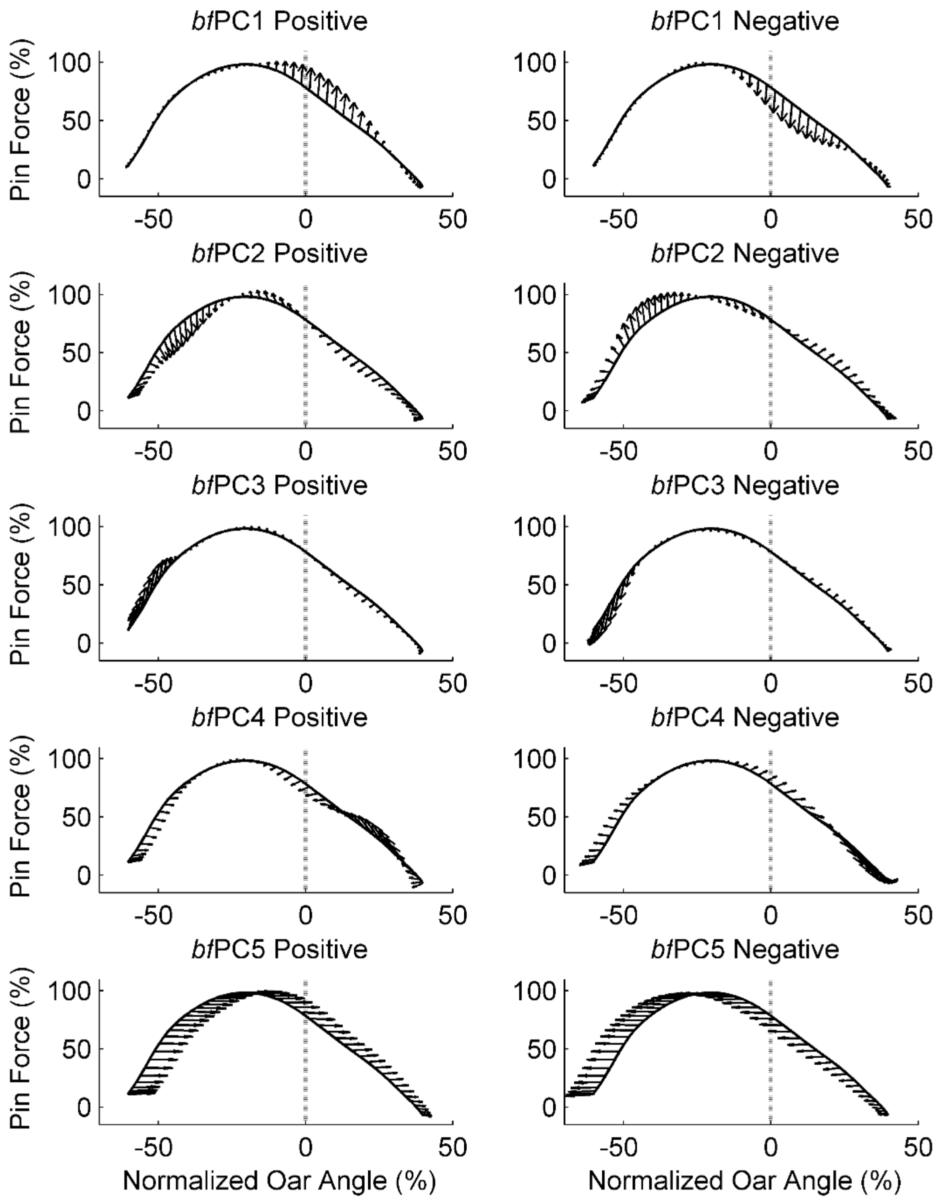

Figure 19. *bf*PC plots for relative force-angle profiles. Each plot is represented by a group mean profile in solid black. Positive scorers for each *bf*PC are displayed in the left set of subplots and negative scorers in the right set of subplots. Variability in each *bf*PC is indicated by the direction of the arrows away from the mean profile in each graph.

The ability of the *bf*PC scores to classify rowers according to gender was assessed using discriminant function analysis, with gender as the dependent variable and *bf*PC scores as the independent variables. For assessment of gender, separate discriminant function analyses were completed on *bf*PC scores for bow-side and stroke-side force-angle curves. A quadratic discriminant function was used to allow for heterogeneous variance–covariance structures. A 2 x 2 (side*gender) mixed-factor ANOVA was also used to compare between rower gender effects, within rower boat-side effects and the interaction of these for *bf*PC scores. α was set at 0.05 for all statistical tests.

Results

bfPCA

The *bf*PCs were varimax rotated to assist in interpretation of the results. The first five *bf*PCs for all force-angle curves accounted for 91.8% of variance in all curves. The individual contribution of each *bf*PC to this variation is illustrated in Figure 19. In the first *bf*PC, force contributed strongly and demonstrated a change in the magnitude of relative force application leading into and away from the square off position (0 degrees perpendicular to the longitudinal axis of the boat). This *bf*PC accounted for 36.8% of all variation in the data. Positive scorers for this *bf*PC possessed a larger application of force leading into square-off. The second *bf*PC accounted for 23.2% of all variation and demonstrated a change in the magnitude of relative force in the first half of the drive phase, and a phase shift relative to the angle position in the second half of the drive phase. Negative scorers for this *bf*PC were more likely to possess a front-loaded or front-peaked profile and an extended period of force application at the end of the drive. The third *bf*PC accounted for 21.8% of all variation in the data and demonstrated a change in the magnitude of relative force at the catch and early in the drive phase. Positive scorers possessed an increased rate of force development over this period.

Table 1. Descriptive statistics (mean and standard deviation) and linear discriminant function coefficients for comparison of *bf*PC scores across gender separately for bow and stroke side forces.

	Female *bf*PC Mean (SD)	**Male *bf*PC Mean (SD)**	**Discriminant Coefficients**
Bow *bf*PC1	-24.12 (35.87)	28.35 (51.86)	1.446
Bow *bf*PC2	-2.61 (34.50)	19.27 (38.47)	-0.395
Bow *bf*PC3	3.98 (28.11)	-13.28 (46.16)	-0.247
Bow *bf*PC4	-2.89 (22.28)	-7.76 (22.77)	-0.715
Bow *bf*PC5	-5.71 (28.91)	-5.24 (23.78)	0.932
% Classified	80.00% (n = 16)	70.00% (n = 14)	
Stroke *bf*PC1	-22.32 (45.87)	18.09 (52.33)	1.479
Stroke *bf*PC2	-15.88 (31.68)	-0.79 (34.13)	-0.627
Stroke *bf*PC3	11.98 (29.33)	-2.68 (36.78)	-0.148
Stroke *bf*PC4	10.89 (21.79)	-0.24 (24.74)	-0.950
Stroke *bf*PC5	9.08 (27.14)	1.87 (27.19)	0.662
% Classified	75.00% (n = 15)	80.00% (n = 16)	

The fourth *bf*PC demonstrated an increase in stroke length at the start of the drive phase for negative scorers, and a sustained period of increased force application directly after peak force. This accounted for 10% of all variation in the data. The fifth *bf*PC noted a change in the angle, demonstrating a phase shift with negative scorers being more likely to reach a deeper catch position and earlier finish position. This *bf*PC accounted for the smallest amount of data at <0.1%.

Gender

Means and standard deviations of *bf*PC scores for gender for each *bf*PC conducted can be seen in Table 1. Discriminant analysis of bow side *bf*PC scores demonstrated that the first *bf*PC discriminated most strongly according to its canonical discriminant function coefficient (Table 1). For this *bf*PC, female rowers featured more prominently as negative scorers.

Table 2. Descriptive statistics (mean and standard deviation) and mixed ANOVA results for comparison of bfPC scores across boat-side, gender and the interaction of boat-side with gender.

	Bow *bf*PC Mean (SD)	**Stroke *bf*PC Mean (SD)**	**Boat-Side (*p* Value).**	**Gender (*p* Value)**	**Boat-Side*Gender (*p* Value)**
*bf*PC1	2.12 (51.41)	-2.12 (52.70)	0.327	0.002	0.205
*bf*PC2	8.34 (37.73)	-8.34 (33.39)	<0.001	0.081	0.358
*bf*PC3	-4.65 (38.73)	4.65 (33.66)	0.012	0.253	0.712
*bf*PC4	-5.32 (22.37)	5.32 (23.70)	<0.001	0.147	0.171
*bf*PC5	-5.47 (26.13)	5.47 (27.06)	0.020	0.642	0.399

The bow side *bf*PC score discriminant function model was able to correctly classify 75% of all bow side force curves, with 80% of female and 70% of male athletes being correctly classified using *bf*PCs for bow side force application. Discriminant analysis of stroke side *bf*PC scores demonstrated that the first *bf*PC discriminated most strongly according to its canonical discriminant function coefficient (Table 1). For this *bf*PC, female rowers again featured more prominently as negative scorers. The stroke side *bf*PC score discriminant function model was able to correctly classify 77.5% of all stroke side force-angle curves, with 75% of female athletes and 80% of male athletes being correctly classified using *bf*PCs. The gender effect in the mixed ANOVA also demonstrated statistical significance for the first *bf*PC, demonstrating that independent of the statistical test used (discriminant function analysis or the mixed ANOVA), *bf*PC1 was indicative of potential differences between male and female rowers.

Boat-side

Means and standard deviations of *bf*PC scores for each side of the boat can be seen in Table 2. The mixed ANOVA demonstrated significant boat-side within subjects effects for the second, third, fourth and fifth *bf*PCs ($p < 0.05$, see Table 2). For the third, fourth and fifth *bf*PCs, bow side scores were more likely to be negative relative to stroke side scores. For the second *bf*PC, bow side scores were more likely to be positive. No statistically significant interactions were present for any *bf*PC as a factor of both side of the boat and gender (all *bf*PCs $p < 0.05$, see Table 2).

Discussion

The aim of this study was to assess whether *bf*PCA could be used to distinguish between gender or boat side using characteristics of force-angle profiles in single scullers. The results of this study suggest that systematic differences between athletes could exist for these variables. Irrespective of the side of the boat, discriminant function analyses and the gender effect from the mixed ANOVA revealed that males and females significantly differ from each other for the first *bf*PC. Relative to males, females were more likely to exhibit a reduction in relative force application leading into and away from the square-off position of the oar (oar being perpendicular to the longitudinal axis of the boat). This indicates, that for females, a noticeable peak in relative force application is reached earlier in the stroke cycle and then is not maintained through the second half of the drive phase. This is consistent with previous research, where females have been found to exhibit less arm power than males in on-water rowing (Kleshnev, 2000). This is supported in ergometer research where the proportion of angular shoulder energy expenditure to total energy was also demonstrated to be lower in females across a range of stroke rate testing conditions (Attenborough, Smith & Sinclair, 2012). It is known that reduced strength capabilities in females are more pronounced in the upper body when compared to males (Wilmore, 1973). This could contribute to the differences in upper extremity power between males and females (Attenborough, Smith & Sinclair, 2012) and also influence the drop in relative force production once upper-extremity joints become more highly involved later in the drive phase.

Table 3. Descriptive statistics (mean and standard deviation) for measures of peak force for female rowers, male rowers and all rowers across both sides of the boat.

	Female *Max Force* (N)	**Male *Max Force* (N)**	**Total *Max Force* (N)**
Bow Side	482.29 (57.46)	619.59 (62.64)	550.94 (91.40)
Stroke Side	456.53 (54.99)	588.66 (64.81)	522.60 (89.42)

In this study the mixed ANOVA revealed statistically significant differences between the bow and stroke side relative force patterns, independent of gender interactions. This was consistent across four of the five *bf*PCs. According to the third *bf*PC, bow side relative force application is less likely to have increased rate of force development at the catch. The second *bf*PC also shows that the bow side is less likely to have increased force application leading into peak force and the fourth *bf*PC shows that the bow side is more likely to have reduced force application at the end of the drive phase when relative to stroke side, while also showing a less pronounced peak in the first half of the drive phase. Differences in these three *bf*PCs between bow-side and stroke forces are potentially the result of an increased role of the bow-side force to act as a ‘driver’ of peak force application across the stroke cycle, with the bow side hand sitting over the top of the stroke side hand for every rower in this cohort. To support this, non-normalised peak bow-side forces were on average higher than stroke side forces for both males and females (see Table 3). The fifth *bf*PC also alluded to a deeper catch position and earlier finish position for the bow-side when compared to the stroke-side suggesting to a potential offset being present in angle of the oar. These differences indicate the stroke side potentially possessed a control or steering role over stroke mechanics, given that the force application on the stroke side is more likely to rise at different time points before and after maximum force and also start force application later relative to the bow side. This functional kinetic asymmetry in on-water sculling is logical as the oar handles must overlap when the blades are perpendicular to the boat due to the inboard length, resulting in upper body postural asymmetry. In this study all boats were rigged so that when the handles overlapped the left hand was on top of the right hand. This asymmetry may have led to the discrepancy noted in force patterns and peak forces in this study. These findings are of particular practical relevance because scullers have been considered to have symmetrical force outputs due to the assumed symmetrical rowing action of sculling, particularly when compared to sweep rowers (Buckeridge, Bull & McGregor, 2014).

This study also implemented a novel analytical approach for answering each of the experimental research questions. Relative force was used rather than normal force so that more subtle characteristics regarding shapes of force were detected and assessed. It is likely that if not normalised for amplitude these differences would have been lost and the majority of variation would have described known amplitude differences between male and female athletes around peak force (Table 3). Consequently, the oar angle was also normalised as a requirement of using *bf*PCA. This was done to account for non-uniform variation differences brought about as a consequence of each variable carrying a different unit of measure (Ramsay & Silverman, 2005). The great utility of *bf*PCA as a tool in the decomposition and evaluation of complex multivariate functional data in sports biomechanics has been demonstrated in this study, allowing for novel comparisons of force shape characteristics to be explored using conventional statistical approaches on the *bf*PC scores. Finally, understanding whether force profile characteristics are associated with optimal rowing performance is still of contemporary interest (Seiler, 2015). Despite this, it is acknowledged that there may be difficulties identifying one '*optimal*' force profile for all rowers as the interaction among anatomical, muscular, and biomechanical factors likely constrains the optimal force curve for each rower (Seiler, 2015). Results from this study support this notion.

Conclusion

Gender differences in force-angle profiles are evident and are present independent of boat-side. These differences are probably related to upper extremity or thoracic strength and power differences between genders. Boat-side differences in force-angle profiles are also demonstrated, and are present independent of any gender interactions. These differences are probably related to asymmetries in boat rigging during sculling. The function of systematic asymmetries relative to boat-side also requires further research in order to assess the importance of force profile shape to the efficiency and effectiveness of boat propulsion and whether they can be generalized or depend on individual rower technique.

Practical Implications

- Male and female rowers should be considered independently of one another when evaluating and modifying rowing technique using force profiles (i.e. force-angle graphs).
- Symmetry in on-water sculling should not be assumed. Differences in force profiles across both sides of the boat may be due to known mechanical or 'rigging' asymmetries that are present for sculling rowers.

- The '*ideal*' force profile for a rower may be dependent upon a number of interacting factors, which have the ability to influence and constrain characteristics of continuous force application, and the overall shape of a rower's force profile.

References for this chapter are included in the list of references at the end of this thesis

Bridging Statement D

Chapter five demonstrated that differences force-angle profile characteristics could be attributed in some capacity to rower gender. This was evident particularly for the first bivariate functional principle component (*bf*PC), which demonstrated that female rowers were more likely to have a reduction in relative force application leading into and away from the oar being perpendicular to the longitudinal axis of the boat. This gender effect was statistically contributive to the discriminant function analyses conducted (for both sides of the boat). A gender effect evaluated as a part of the mixed ANOVA also revealed statistical significance ($p < 0.05$). This indicates that, independent of boat-side, male and female rowers to appear to possess different strategies for relative force application when it is visualised relative to the oar angle. Similarly, boat-side also demonstrated significant within-subject differences ($p < 0.05$) as a part of the mixed ANOVA. This was present across four of the five retained *bf*PCs. The results of these four *bf*PCs alluded to the presence of consistent asymmetries in force production across the two sides of the boat for all rowers (independently of gender). The combination of these four *bf*PCs demonstrated that bow side forces seemingly acted as a driver of power and peak force production, while stroke side forces may have acted as a mediator of propulsive forces with an additional potential role in steering due to asymmetrical offsets that a present in sculling as a consequence of boat rigging. In light of these findings, the potentially constraining factors of gender and boat-side will be controlled for in chapter six, where changes in force-angle profiles will be explored relative to metrics of rowing performance. Chapter six will involve the use of separate *bf*PCAs applied individually to each side of the boat, to preserve important structures of variability present in force-angle profiles, which may be unique for each side of the boat. Only female athletes will be used, controlling for any gender effects. Rowing performance will be assessed using average boat velocity over the selected testing interval and also through evaluation of changes relative to a rower's level of competitive representation. Although boat velocity is the logical metric of performance, boat velocity in this instance is only directly relatable to performance in a single sculling boat. When athletes are selected to perform at an international level they are often selected for larger crew boats. It is possible that the characteristics required for selection in larger crew boats may be different to those required for increased velocity in a single sculling boat.

CHAPTER 6

Assessment of propulsive pin force and oar angle time-series using functional data analysis in on-water rowing.

The following chapter was formatted for submission to the Scandinavian Journal of Medicine and Science in Sports and is currently published (in press).

Author Contribution Statement

As a co-author on the paper presented within this chapter entitled "*Assessment of propulsive pin force and oar angle time-series using functional data analysis in on-water rowing*," as well as being Primary Supervisor throughout the Doctor of Philosophy candidature of John Warmenhoven, I confirm John's contribution to the paper as follows:

- Conception and design of the research
- Data collation, database building and database management
- Analysis of data and interpretation of the findings
- Writing the paper and critically appraising content within the manuscript

Signed: [redacted]

Date: 21/04/2017

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Assessment of propulsive pin force and oar angle time-series using functional data analysis in on-water rowing.

By

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Abstract

The graphical presentation of the propulsive force applied at the pin plotted relative to the horizontal angle of the oar has been used practically in on-water rowing for the qualitative assessment of skill. How the pattern is related to performance variables has not been well identified, particularly for highly trained sculling athletes. Bivariate functional principal components analysis (*bf*PCA) was used on force-angle data to identify the main modes of variance in curves representing twenty seven female rowers of different competition levels (national and international level), rowing at 32 strokes per minute in a single scull boat. Discriminant function analysis showed moderate classification of rowers using force-angle graphs across both sides of the boat, with rate of force development identified as a potentially important characteristic for international rowers. Additionally for the bow-side, spending less time in the first half of the drive phase was also identified as an important feature for international rowers. Multiple linear regression of scores from the *bf*PCAs showed that a more pronounced front peaked profile was associated with a higher average boat velocity. The results of this demonstrate that different characteristics of the force-angle graph may be associated with different metrics of performance.

Key Words (3-8): Bivariate Functional Principal Components Analysis; Biomechanics, Sport Expertise, Rowing.

Assessment of propulsive pin force and oar angle time-series using functional data analysis in on-water rowing.

Introduction

The idea of common techniques representing optimal and efficient movement has long existed in sport biomechanics. In rowing, ‘signature’ movements representing technical aspects of the rowing stroke cycle were first proposed in the 1970’s, associated with the execution of pulling force on the oar handle (Ishiko, 1971). Subsequently, force characteristics have been measured at the inboard of the oar shaft (Schneider, Angst & Brandt, 1978; Smith, Galloway, Patton & Spinks 1993; Smith & Spinks, 1989; Wing & Woodburn, 1995; Hill, 2002), the pin or oarlock (Roth, Schwanitz, Pas & Bauer, 1993), and the oar blade (Elliot, Lyttle & Birkett, 2002). In addition to this, new technology is also available for measurement of force applied directly to the handle (Turner, Gravenhorst, Draper & Smith, 2015). These forces are usually represented graphically with force plotted either against time (force-time) or against the horizontal angle of the oar (force-angle) (Spinks, 1996); and rowers have been descriptively identified by their shape or harmonic structure on such graphs. Despite these commonalities and idiosyncratic differences in force signatures, empirical research determining the specific importance of shape characteristics and their relationship with performance is currently limited. This issue is exemplified, when considering that presently there are no evidence-based guidelines for practitioners (e.g., coaches) on how to use patterns of force application to accurately evaluate a rower’s current performance and determine potential for future on-water performance (Soper & Hume, 2004).

Prior analyses of force-time and force-angle profiles in rowing have often used discrete time points (or frames) to sample and reduce data toward perceived indices of performance. This has included the use of measures such as mean to peak force ratio (Smith & Draper, 2006) and position of peak force (Smith & Loschner, 2002). From these methods, maximal force production from early in the rowing stroke cycle and maintenance of this maximal force, has been recommended, ideally leading to a ‘rectangular shaped’ force curve (Smith & Draper, 2006). However, it is acknowledged that such profiles are difficult to implement and sustain metabolically (Roth, Schwanitz, Pas & Bauer, 1993). There is also much conjecture regarding ‘what’ exactly constitutes a ‘good’ or ‘bad’ force shape, given that theoretical and experimental support for other shapes exists (e.g., front and middle peaked profiles; Kleshnev, 2006; Martin & Bernfield, 1979, Smith & Loschner, 2002).

A number of factors could have potentially contributed to the lack of consensus regarding the relevance of force profile characteristics. Firstly, substantial contributions have been provided through theoretical research (Millward, 1987; Kleshnev, 2006; Nolte & Morrow 2002; Caplan & Gardner, 2007b), where limited experimental evidence is provided to support these ideas. Similarly, some inferences have been made through the use of small sample sizes (i.e. case studies) or exemplar data (Baudouin & Hawkins, 2002; Smith and Loschner, 2002; Wing & Woodburn, 1995), which makes this difficult to extrapolate to different groups of rowers. Secondly, a drawback of contemporary literature is the abundance of studies assessing ‘sweep’ rowers (Smith & Draper, 2006; Wing & Woodburn, 1995; Hill, 2002; Martin & Bernfield, 1979; Roth, Schwanitz, Pas & Bauer, 1993), with this providing difficulty for understanding which characteristics of force profiles may be important for sculling boats. Thirdly, some experimental ergometer and on-water research has attempted to infer skill level differences, using measures derived from these profiles, both with very promising results (Smith, Galloway, Patton & Spinks, 1994; Smith & Spinks, 1995).

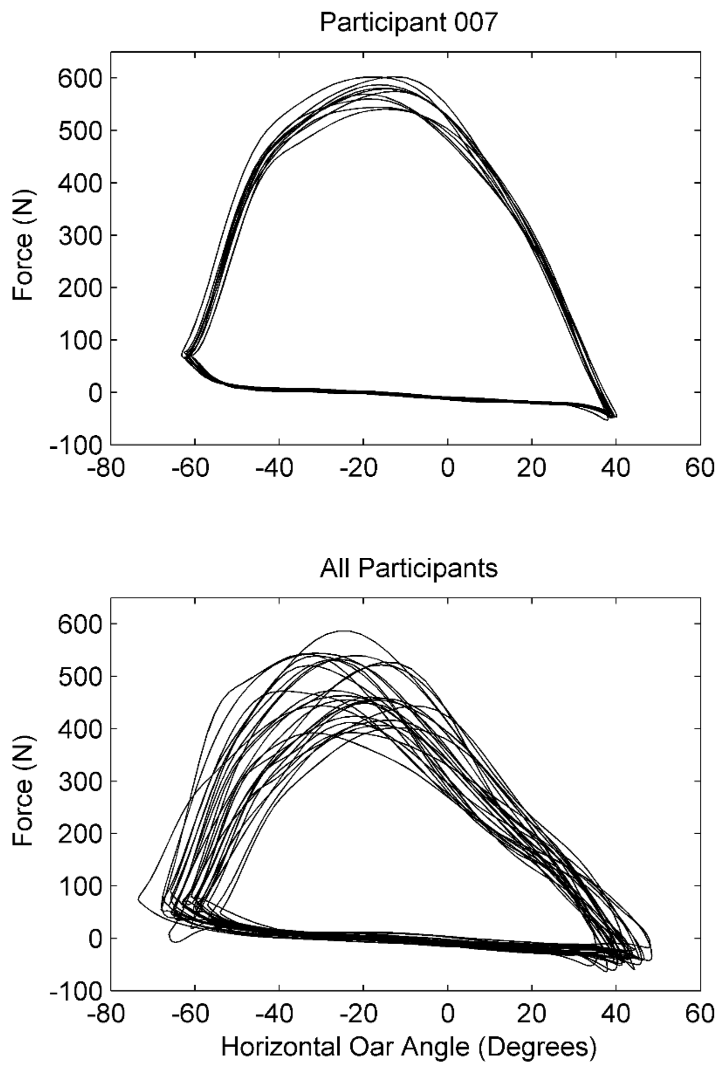

Figure 20. Ten bow-side propulsive pin force-oar angle curves for participant seven (top) and twenty seven mean bow-side propulsive pin force-oar angle curves for each participant (bottom). The mean profiles were derived from ten individual strokes per participant.

Despite this, these studies have only involved assessments of rowers with skill levels up to national level representatives. At present there is limited experimental evidence available for whether international performers row differently. Finally, it may also be difficult to answer this question adequately, using discrete point analytical strategies, as they discard a large amount of data from each curve, and may not correctly handle the complexity of variability within the original time-series data. To exacerbate this problem, there are increased benefits for visualising and analysing the force-angle graph over the force-time graph (Figure 20) as it acts as a measure of stroke length, has the ability to examine differences in the shape of force development and regression (independent of stroke rate) and the area under the curve is a direct measure of the work done during the rowing stroke cycle (Spinks, 1996). Despite this, statistical analysis applied to the force-angle graph is difficult given the bivariate nature of data in the plot. That said, statistical data derived from these graphs would potentially provide a more in-depth and richer insight on whether continuous force information, relative to stroke length, can for instance discriminate between different levels of rowing performance, particularly for more highly skilled performers, where the differences may be quite subtle.

Statistical data reduction strategies that retain information from all aspects of the force-angle curve could provide additional insight on important key characteristics of force curves. One such method is ‘Bivariate Functional Principal Components Analysis’ (*bf*PCA), which belongs to the Functional Data Analysis (FDA) family of statistical techniques (Ramsay & Silverman, 2005). The benefits of *bf*PCA for assessing trends biomechanically have already been highlighted. For instance, Harrison, Ryan and Hayes (2007) used *bf*PCA when examining coordination differences between children of different stages of development during a vertical countermovement jump. The use of *bf*PCA in this context allowed for the assessment of bivariate angle-angle plots and differences in these to be explored between developmental stages. Similarly, *bf*PCA could be applied to analyse performance level differences in force-angle curves during on-water rowing testing.

Table 4. Bivariate correlation results assessing the relationship between discrete performance outcomes to prognostic velocity of the boat (*denotes significance at p < .05).

	Pearson (*r*)	***p* Value**
Bow Peak Force	0.51	0.01*
Bow Average Force	0.55	<0.01*
Bow Peak Power	0.36	0.07*
Stroke Peak Force	0.62	<0.01*
Stroke Average Force	0.55	<0.01*
Stroke Peak Power	0.50	0.01*

In the present study, *bf*PCA was applied to force-angle data collected from a group of highly skilled female scullers to determine whether performance differences in these rowers could be inferred from characteristics of the force-angle graph. Performance was defined using two metrics: level of competitive representation and average boat velocity. Identifying force-angle characteristics related to these two metrics of performance was necessary for this participant group, as these rowers, independent of their level of competition, possessed similar capabilities for generating high boat velocities in single sculling. It would be plausible to assume that rowers in this participant group with a higher average velocity in single sculling would be implicitly associated with better performance outcomes related to level of competitive representation. Despite this some rowers with a faster single scull boat velocity may not be selected for larger crew boats at higher levels of competition. This could occur as a consequence of other factors with the capacity to influence performance characteristics in larger crew boats. Wing and Woodburn (1995) have noted the anecdotal and descriptive practice of matching rowers in terms of their individual force-time profiles as a part of crew selection in larger boats, and Hill (2002) has demonstrated evidence that crew members who have similar force patterns may result in a boat that is more efficient.

Table 5. Descriptive statistics (mean and standard deviation) and univariate ANOVA results for discrete performance outcomes for both national and international competition levels.

	International Mean (SD)	**National Mean (SD)**	***F* Value**	***p* Value**
Bow Peak Force	458.55 (54.48)	490.68 (54.62)	2.34	0.14
Bow Av Force	121.97 (11.00)	126.98 (13.59)	1.10	0.30
Bow Peak Power	663.14 (85.70)	705.53 (107.00)	1.28	0.27
Stroke Peak Force	448.98 (51.69)	454.28 (60.37)	0.06	0.81
Stroke Av Force	120.85 (12.23)	121.31 (14.07)	0.01	0.93
Stroke Peak Power	635.25 (94.03)	651.24 (106.96)	0.17	0.68

In further support of this, preliminary analyses from the participant group in the present study demonstrated that discrete performance outcomes expected to coincide with better performance in on-water rowing, such as maximum propulsive pin force (PPF), average PPF and maximum handle power, demonstrated significant predictive relationships with boat velocity (see Table 4) with bivariate correlations, but did not significantly differentiate between rowers according to their level of performance when assessed using univariate ANOVAs (Table 5).

As a consequence of this, an alternative method of analysis, such as *bf*PCA, is required to better understand the role of force application in more highly skilled rowing performance. This is particularly relevant for understanding differences between rowers who are similarly skilled in terms of boat velocity, but differ in terms of their level of competitive representation. The purpose of this study, is thus to assess whether *bf*PCA can be applied to data associated with the PPF-angle graph. Specifically, the potential of *bf*PCA to identify technical characteristics of propulsive force and potentially differentiate between levels of performance using these characteristics, will be explored. In the present study, level of performance is assessed through both average velocity of the boat and level of competitive representation. This research will aim to provide much needed experimental evidence, regarding the functional role of PPF-angle profiles for understanding skill differences between rowers in a highly skilled participant group.

Methods

Participants

Following institutional ethical approval and participant consent, data was collected for twenty-seven female rowing athletes (*M* age = 25.60 $\pm$ 4.88 years; *M* height = 1.74 $\pm$ 0.04 cm; *M* mass = 75.62 $\pm$ 4.61 kg). Participants were highly trained heavyweight and lightweight scullers. Competitive performance was assessed at the time of testing and each participant was categorised as either 'national' (n = 14) or 'international' level (n = 13). National level rowers must have been invited to compete in an Australian national age group championship or an Australian national open championship prior to the testing (with these competitions serving as a part of the selection process for international representation for under 18, 23, or open level). International rowers must have also competed at these domestic competitions, but also been successful in their selection and competed as an Australian representative at an Under 18, 23, or open level event, prior to testing.

Procedures

Participants were instructed to row a total of 1000 m, composed of 250 m at four ascending pre-selected stroke rates (SR20, SR24, SR28, SR32). Rowers used Nielsen-Kellerman © *Strokecoaches* to control stroke rate outputs. In this study only the SR32 data (i.e., highest stroke rate) was analysed. Rowing data was obtained using ROWSYS instrumentation as outlined in Smith and Loschner (2002). Propulsive pin force was measured using three-dimensional piezoelectric transducers (Kistler, Switzerland). The pin was mounted on the rigger and was the axis of rotation for the gate. Horizontal oar angles were measured by low-friction potentiometers and a fiberglass arm attached to the inboard end of the oar, enabling free rotation of the oar around its longitudinal axis. A magnetic turbine, pick-up coil and frequency-to-voltage converter were used to track boat speed, including intra-stroke fluctuations.

Data Processing

For data analysis, ten strokes were selected for each rower for the bow-side and stroke-side of the boat. The same ten strokes were selected for each side of the boat. For each participant the drive and recovery phases were identified using the angle of the oar relative to the horizontal (Smith & Loschner, 2002), and the drive phase was analysed in this study. A linear length normalisation strategy using an interpolating cubic spline was applied, normalising each curve to 100% of the drive phase. Amplitude normalisation was also applied, ensuring that variability described in the curves was only reflective of shape characteristics. For amplitude normalisation, force was converted to a percentage relative to each curve's maxima. Similarly, horizontal oar angle was normalised to a percentage relative to the length of each drive phase, with both normalisation formulas below;

$$F_{Norm(i)} = \left(\frac{F_{(i)}}{F_{(Maximum)}}\right) \times 100(\%)$$

$$\theta_{Norm(i)} = \left(\frac{\theta_{(i)}}{\theta_{(Maximum)} - \theta_{(Minimum)}}\right) \times 100(\%)$$

Where F is the PPF and θ the horizontal angle of the oar. Both variables were normalised using the following strategies to preserve important biomechanical landmarks. For force the zero point for relative force production indicated the landmark for which relative force changed from being positive to negative. For the oar angle the above normalisation formula preserved important spatial information regarding the oar's position relative to the boat. For example, the zero point for normalised oar angle resembles the point for which the oar is perpendicular to the longitudinal boat axis. An average curve created from each participant's ten strokes was then used for analysis.

Data Analysis

A full description of functional principal components analysis for multivariate functional data, or in this context bivariate data, can be found in Ramsay and Silverman (2005) and Harrison, Ryan and Hayes (2007). The normalised PPF and oar angle curves were estimated using B-splines. Functions were smoothed by adding a roughness penalty to the fitting procedure. The roughness penalty term, the impact of which is controlled by a smoothing parameter λ, ensured that the smoothness of each fitted curve was controlled, and this was achieved by minimising the penalized residual sum of squares term (Ramsay & Silverman, 2005). Generalized cross-validation was used to determine a starting point for possible values of λ before a final subjective choice was made. The smoothing coefficient used to fit the curves for both PPF and horizontal oar angles was 1*e*-14. The functions for PPF and the horizontal angle of the oar can be referenced as a and b for each individuals average curve $i = 1, \ldots, N$ as $a_1(t)$, $a_2(t), \ldots, a_N(t)$ and $b_1(t), b_2(t), \ldots, b_N(t)$ respectively.

Bivariate functional principal components are calculated by replacing the PPF and oar angle functions a_i and b_i with a vector of values at a fine grid of points. For each individual i, these vectors are concatenated into a single vector Z_i. The covariance matrix of the Z_i is a discretized version of the bivariate covariance function. A standard principal component analysis is then performed on the Z_i vectors and principal component vectors $\xi^{(m)} = (\xi_a^{(m)}, \xi_b^{(m)})$ for $m = 1, \ldots, M$ are extracted, which can be separated into the part corresponding to variation in PPF, $\xi_a^{(m)}$, and the part corresponding to variation in oar angle, $\xi_b^{(m)}$. The principal component scores on the m^{th} principal component can be defined for each individual i, and these scores can also be subdivided into parts corresponding to each variable's contribution to the overall score or added together to define an overall principal component score. Separate *bf*PCAs were conducted for bow-side and stroke-side PPF-angle curves. To aid interpretation a VARIMAX rotation of the *bf*PCs was performed and the corresponding *bf*PC scores were calculated (see Ramsay & Silverman, 2005, for full details).

Multiple linear regression was used to model the relationship between the *bf*PC scores and each athlete's average prognostic velocity across the ten strokes measured during the testing. This was conducted separately for bow and stroke-side PPF-angle data. Prognostic velocity normalises propulsive boat velocity to a percentage relative to a gold medal standard for the single scull in the year that the testing that was conducted. Prognostic times are used regularly as benchmarks for assessment of rowing performance in the normal training environment (Kleshnev & Nolte, 2011) and were used in this case rather than normal boat velocity as four of the international level rowers were lightweight, and lightweight and heavyweight rowers carry different time and velocity prognostic benchmarks.

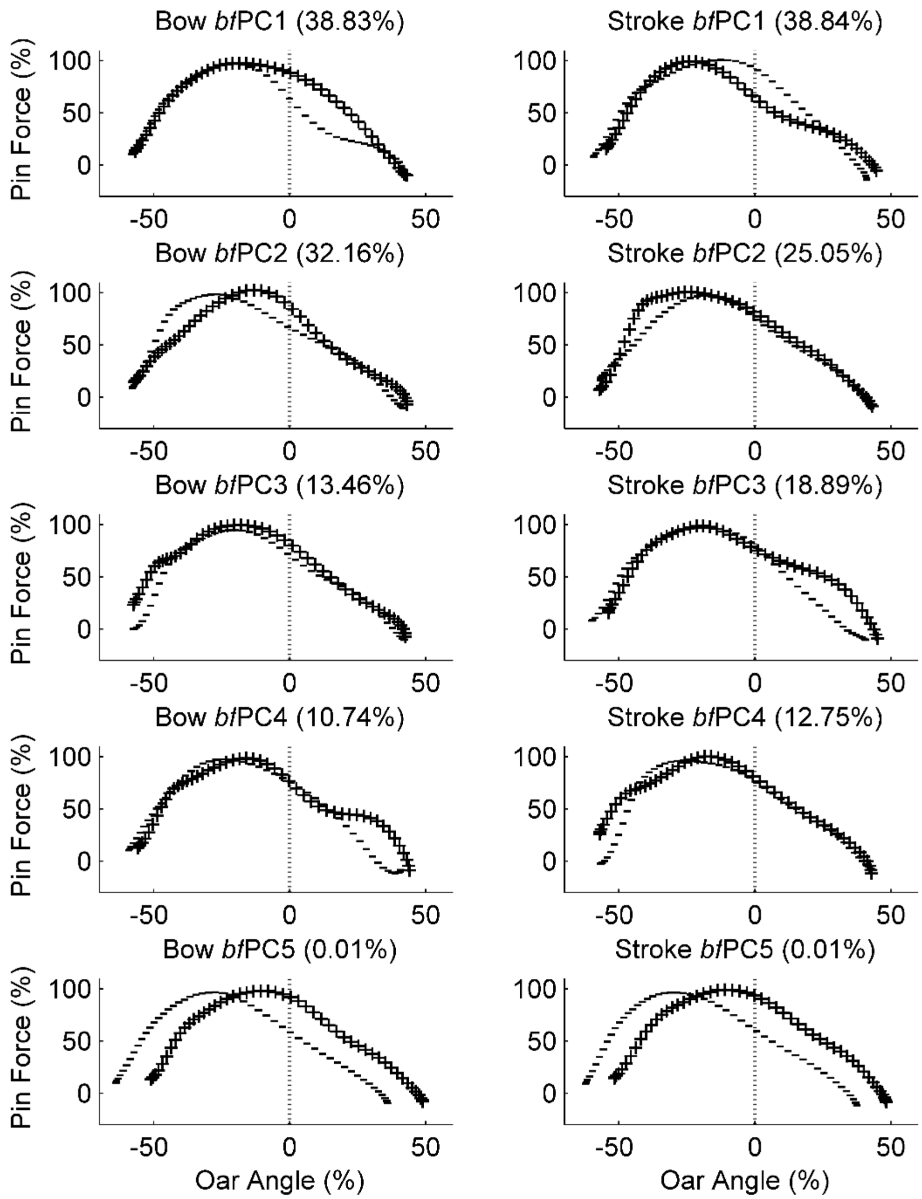

Figure 21. *bf*PC plots for each of the first five bfPCs for bow and stroke-side PPF-angle profiles. In plot positive scorers are indicative of the '+' line and negative scorers the '–' line. *bf*PC functions have been weighted using a suitably chosen constant to illustrate variability across the stroke cycle.

The ability of the *bf*PC scores to distinguish between different levels of competition was assessed using linear discriminant analysis, with the level of competition as the dependent variable and the *bf*PC scores as the independent variables. Separate discriminant analyses were completed on *bf*PC scores for bow-side and stroke-side PPF-angle data. The procedure was carried out by allocating each individual to a competition level category with the smallest Mahalanobis distance (D^2) using prior allocation probabilities for each competition level category.

Results

bfPCA

The first five *bf*PCs for bow-side PPF-angle curves accounted for 95.2% of all variance for the bow-side and each *bf*PC's individual contribution to this variation can be seen in Figure 21. In the first *bf*PC force contributed strongly and demonstrated a change in the magnitude of relative force application leading into and away from the square off position (0 degrees perpendicular to the longitudinal axis of the boat). For this *bf*PC positive scorers possessed a larger application of force leading into square-off. The second *bf*PC demonstrated a change in the magnitude of relative force in the first half of the drive phase with negative scorers more likely to possess a front-loaded or front-peaked profile. The third *bf*PC demonstrated a change in the magnitude of relative force at the catch and early in the drive phase, with positive scorers possessing an increased rate of force development over this period. The fourth *bf*PC demonstrated a change in the magnitude of relative force application at the end of the drive phase, with positive scorers more likely to possess increased relative force application leading into the release at the end of the of the drive phase. The fifth *bf*PC noted a change in the angle and demonstrated a phase shift with positive scorers being more likely to reach peak force closer to square-off, but retain similar force shape characteristics as negative scorers.

The first five *bf*PCs for stroke-side PPF-angle curves accounted for 95.9% of all variance and each *bf*PC's individual contribution to this variation can be seen in Figure 21. In the first *bf*PC force contributed strongly and demonstrated a change in the magnitude of relative force application leading into and away from the square off position, with positive scorers possessing a reduced application of force leading into square-off. The second *bf*PC demonstrated a difference in the magnitude of relative force in the first half of the drive phase with positive scorers more likely to possess an increased amount of force in this part of the drive phase.

Table 6. Descriptive statistics (mean and standard deviation) univariate ANOVA results and standardised linear discriminant function coefficients for discrete performance outcomes for comparison of *bf*PC scores across competition levels.

	International *bf*PC Mean (SD)	**National *bf*PC Mean (SD)**	**Discriminant Coefficients**	***F* Value**	***p* Value**
Bow *bf*PC1	8.48 (51.57)	-7.87 (31.82)	0.49	1.00	0.33
Bow *bf*PC2	11.18 (46.08)	-10.38 (45.16)	NA	1.51	0.23
Bow *bf*PC3	7.88 (22.05)	-7.32 (26.03)	0.79	2.66	0.12
Bow *bf*PC4	6.61 (22.8)	-6.14 (18.74)	0.18	2.53	0.12
Bow *bf*PC5	12.17 (19.08)	-11.3 (21.32)	1.00	9.04	0.01
% Classified	69.2% (n = 9)	78.6% (n = 11)			
Stroke *bf*PC1	9.75 (42.88)	-9.06 (40.47)	0.02	1.38	0.25
Stroke *bf*PC2	10.24 (40.24)	-9.50 (31.58)	NA	2.03	0.17
Stroke *bf*PC3	1.68 (24.89)	-1.56 (23.81)	0.30	0.12	0.73
Stroke *bf*PC4	10.45 (21.20)	-9.70 (21.50)	0.97	6.00	0.02
Stroke *bf*PC5	3.85 (27.43)	-3.58 (23.75)	0.14	0.57	0.46
% Classified	69.2% (n = 9)	50.0% (n = 7)			

The third *bf*PC demonstrated a change in the magnitude of relative force application at the end of the drive phase, with positive scorers more likely to possess increased relative force application leading into the release at the end of the of the drive phase. The fourth *bf*PC demonstrated a change in the magnitude of relative force at the catch and early in the drive phase, with positive scorers possessing an increased rate of force development over this period. The fifth *bf*PC noted a change in the angle and demonstrated a phase shift with positive scorers being more likely to reach peak force closer to square-off, but retain similar force shape characteristics as negative scorers.

Boat Velocity

Bivariate correlations between each *bf*PC score and velocity revealed that the first and second *bf*PC scores were moderately (but statistically significantly) related to velocity (Table 7). Multiple linear regression analysis showed that the bow-side *bf*PC scores significantly predicted prognostic velocity [$F(5,21) = 3.473$, $P = 0.019$], although only 32% of the variability in velocity was explained by the first five bow-side *bf*PC scores [R^2-adj. = 0.322]. In the regression model however, no specific *bf*PC score contributed significantly to the prediction of velocity, with the closest being the first *bf*PC score (Table 7). This indicated that there may be an issue with multi-collinearity, which arises after rotation since the *bf*PC scores are no longer uncorrelated (Joliffe, 2002). Examination of collinearity statistics (pairwise correlations between *bf*PC scores and variance inflation factors (VIFs) showed that the *bf*PC2 score exhibited moderate to high levels of correlation with the other scores in the model, along with the highest VIF ($VIF = 4.676$). Therefore the model was re-fitted after excluding the *bf*PC2 score. The reduced model remained significant at the 5% level ($F = 4.367$, $P = 0.009$), with a slight improvement in model fit [R^2-adj. = 0.341]. In addition the *bf*PC1 score contributed significantly to the prediction of velocity [$P = 0.033$], while there was also some evidence of a relationship between the *bf*PC5 score and velocity, although not statistically significant at the 5% level [$P = 0.067$]. Bivariate correlations between each *bf*PC score and velocity for the stroke-side revealed that the first and third *bf*PC score were significantly related to velocity (Table 7).

Table 7. Multiple linear regression and bivariate correlation results assessing the relationship between *bf*PC scores and prognostic velocity of the boat.

	Unstandardised Coefficients	**Standardised Coefficients**	***p* Value (model)**	**Pearson (*r*)**	***p* Value (variables)**
Bow *bf*PC1	-0.08	-0.47	0.03	-0.55	<0.01
Bow *bf*PC2	NA	NA	NA	-0.55	<0.01
Bow *bf*PC3	0.05	0.19	0.29	0.30	0.13
Bow *bf*PC4	-0.04	-0.11	0.61	-0.31	0.12
Bow *bf*PC5	-0.09	-0.31	0.07	-0.31	0.12
Bow Model			0.02		
Stroke *bf*PC1	0.10	0.62	0.01	0.43	0.03
Stroke *bf*PC2	NA	NA	NA	0.04	0.83
Stroke *bf*PC3	-0.07	-0.25	0.19	-0.40	0.04
Stroke *bf*PC4	-0.11	-0.37	0.08	-0.04	0.86
Stroke *bf*PC5	-0.05	-0.17	0.41	-0.01	0.95
Stroke Model			0.03		

Multiple linear regression analysis showed that the stroke-side *bf*PC scores significantly predicted prognostic velocity [$F(5,21) = 2.991$, $P = 0.034$], although only 28% of the variability in velocity was explained by the first five stroke-side *bf*PC scores [R^2-adj. = 0.277]. In the regression model only the first *bf*PC score contributed significantly to the prediction of velocity (Table 7). Again, there was some evidence of multi-collinearity in the model with the *bf*PC2 score exhibiting moderate levels of correlation with the other *bf*PC scores and the highest VIF ($VIF = 3.606$). After re-fitting the model excluding the *bf*PC2 score, the model remained significant at the 5% level [$F = 3.398$, $P = 0.026$, R^2-adj. = 0.27], the *bf*PC1 score again contributed significantly to the prediction of velocity [*P* = 0.013], however there was some additional evidence of a relationship between the *bf*PC4 score and velocity [*P* = 0.076].

Competition Level

Means and standard deviations of *bf*PC scores for each side of the boat and for each competition level are presented in Table 6. Univariate ANOVAs comparing *bf*PC scores between competition levels on the bow-side of the boat revealed that scores for the fifth *bf*PC were significantly different (p = 0.006) between competition levels, with international rowers featuring more prominently as positive scorers. Since multi-collinearity can also impact discriminant analysis, the bow-side *bf*PC2 score was excluded. Discriminant analysis of the remaining scores showed that the fifth *bf*PC score discriminated most strongly according to its standardised canonical discriminant function coefficient, followed by the third *bf*PC score (Table 6). Leave-one-out cross-validation was carried out to assess prediction performance. The bow-side *bf*PC score discriminant function model was able correctly classify 74.1% of all bow-side PPF-angle curves, with 69.2% of international athletes and 78.6% of national athletes being correctly classified using *bf*PCs for bow-side force application. Univariate ANOVAs comparing *bf*PC scores between competition levels on the stroke-side of the boat revealed that scores for the fourth *bf*PC were significantly different (p = 0.012) between competition levels, with international rowers featuring more prominently as positive scorers. Discriminant analysis of stroke-side *bf*PC scores (excluding the *bf*PC 2 scores) showed that scores on the fourth *bf*PC discriminated most strongly according to its standardised canonical discriminant function coefficient (Table 6). Leave-one-out cross-validation indicated that the stroke-side *bf*PC score discriminant function model was able correctly classify 59.3% of all stroke-side PPF-angle curves, with 69.2% of international athletes and 50.0% of national athletes being correctly classified using *bf*PCs.

Discussion

The aim of this study was to assess whether *bf*PCA could be used to identify characteristics of the PPF-angle graph that were related to performance outcomes for a group of highly skilled female rowers. The results of this study suggest that differences between athletes may exist in these performance outcomes when explored with *bf*PCA. For both bow and stroke-side *bf*PC scores, a pronounced early peak in relative force and a drop in relative force leading into square-off featured significantly in each multiple linear regression model. This showed that a more pronounced front loaded profile may be indicative of a faster boat velocity in single sculling. Although there is limited experimental evidence to support these findings, they are supported by the theoretical notion that a front “loaded” profile will result in a more evenly distributed power curve across the movement cycle (Kleshnev, 2006). This would in turn allow for reduced fluctuations in boat velocity, and better rowing efficiency (Kleshnev 2006; Nolte & Morrow, 2002).

Irrespective of the side of the boat, discriminant function analyses of *bf*PC scores revealed that rate of force development at the beginning of the drive featured as a discriminator for competition level, with the bow-side model discriminating more effectively than the stroke-side model. Coker, Hume and Nolte (2008) have highlighted theoretical support for these characteristics, where increased force application at the parts of the drive where the blade is furthest from being perpendicular to boat’s longitudinal axis (catch and finish positions), are important for taking advantage of lift forces occurring at the blade. In these parts of the drive, the blade is known to act as a hydrofoil while moving through the water, generating a lift force which has a large component moving in the same direction as the boat (Caplan & Gardner, 2007a). These lift forces are connected through the middle section of the drive phase by increased drag forces at the blade. Therefore to make use of a rower's energy more effectively, high lift forces should be achieved at the beginning and end of the drive phase, in conjunction with high drag forces in the middle of the drive phase (Caplan & Gardner, 2007b).

For the bow-side, spending less distance (oar-angle) in the first half of the drive phase, and more distance in the second half of the drive phase was also identified as strongly contributive to the discriminant function model. Results for this *bf*PC demonstrated that international athletes (indicative of positive scorers), were likely to possess both a decreased oar position at the catch and finish of the stroke for the bow-side. Burnett, Doyle and Elliot (2004) have noted that during single sculling, when the left hand is positioned above the right hand (as was the case with participants in the present study) the left hand will also sit forward of the right hand. In light of this, it is possible that a reduced oar position at the catch and the finish could indicate that international level participants row more symmetrically. This would, however require further investigation, as the two sides of the boat in the present study were analysed using separate *bf*PCAs.

Interestingly, the results of the multiple linear regressions and discriminant function analyses indicated that competition level and prognostic velocity, although both indicators of successful performance, were associated with different characteristics of the PPF-angle profile. From this, results of the present study indicate that performance in a single sculling boat, may not be truly indicative of a rower's potential for selection at international competitions, where the expectation to perform successfully in larger crew boats is more prevalent. The biomechanical findings from this study should, however, be interpreted with some caution. Results obtained using multiple linear regressions revealed bow and stroke-side models that could only account for 34% and 27% of variation in the boat velocity data (respectively), indicating that factors other than force pattern characteristics were also likely to substantially influence boat velocity. Similarly, discriminant function models for the bow and stroke-sides could only correctly classify 74% and 59% of rowers for competition level. These levels of correct classification were substantially lower than classification percentages for skill level classification using kinetic variables in previous ergometer (Smith & Spinks, 1995; where 82.9% of all rowers were correctly classified) and on-water research (Smith, Galloway, Patton & Spinks, 1994; where 95% of rowers were correctly classified). In these studies, the performance levels of rowers were substantially lower than in the present study, where the inclusion of novice rowers through to national representatives formed each of the participant groups. It can be expected that the differences demonstrated between performance levels in those studies were much larger, than the subtler differences found between competition levels in the present study.

There are also some limitations within the present study that should be acknowledged. Firstly, given the high level of skill of national performers in the present study, it is possible that these athletes may be selected for international level representation in the future, essentially making some of these athletes potential international level athletes "in-waiting." This may contribute in some capacity to the lower levels of correct classification between the two groups in the present study. Secondly, boat velocity in the present study was taken during a biomechanical testing session. Although this form of testing is used as a surrogate for evaluation of performance, it is not a race. As stipulated in the methods, the testing piece constituted rowing at a controlled stroke rating representative of a race pace scenario, however, this only occurred over a 250m period. In a real race conditions (taking place over 2000m), other factors such as effective pacing strategies and subsequent management of fatigue will also affect performance. Although a definite point of interest in future research, this is outside the scope of this study.

Irrespective of any biomechanical findings in the present study, *bf*PCA has proven to be an applicable tool for the assessment of relevant parameters describing rowing technique in on-water single sculling. Despite this, it is important to acknowledge some methodological considerations regarding use of *bf*PCA in further research biomechanical research. Firstly, once the *bf*PCs were reordered after a VARIMAX rotation, it was clear that a similar series of *bf*PCs were retained for both the bow and stroke-side, with the exception of the second *bf*PC for both sides, in which the structure was altered slightly. Normally when this occurs, it may be advisable to explore the use of more advanced functional data analysis techniques such as common functional principal components analysis (Coffey, Harrison, Donoghue & Hayes, 2011), but this technique is yet to be applied with multivariate functional data. Both force and angle data were also normalised in non-conventional ways in the present study. Force was normalised, to ensure more subtle harmonic components of force patterns were retained, and if the differences in peak amplitude were not accounted for, the majority of variance reported by *bf*PCA for either side of the boat would have been related to amplitude differences between rowers, which was already reported by the discrete outcome of peak force (Table 4). The oar angle was also normalised to a relative percentage of stroke length (while still accounting for 0 degrees to be preserved as the oar being perpendicular to the boat). This accounted for any undesirable differences in the amount of variability between force and oar angle, occurring solely as a consequence of the variables being measured in different units (Newtons and degrees). Accounting for between-parameter variability is a necessary step for correct use of *bf*PCA (Ramsay & Silverman, 2005).

This study also used a combination of lightweight and heavyweight rowers for the international group and as a consequence careful consideration was given to how lightweight and heavyweight differences could be controlled for in the present study. As force was normalised to a percentage of maximum force and boat speed was normalised to prognostic velocity, this should have accounted for known differences in discrete measures of performance between heavyweight and lightweight rowers (Doyle, Lyttle & Elliot, 2010).

Perspectives

The force-oar angle graph already has demonstrated potential for technical insights into successful rowing performance, as it graphically depicts the interaction of two key variables throughout the rowing stroke cycle (Spinks, 1996). Despite this it has been difficult to empirically evaluate performance using this graph, given the highly complex process required for exploring differences across two concurrent continuous time-series. The use of FDA and particularly the technique *bf*PCA has assisted in removing some of these barriers and has opened up potential for further exploration of this important biomechanical structure. Future use of this statistical method in on-water rowing research would allow for a comprehensive analysis of force profiles in more representative competition settings such as simulated races, which form part of the selection process for international competitions.

Results from the present study have also provided meaningful experimental evidence that supports established theoretical ideas that centre on "*what*" exactly constitutes "*good*" force application. Evidence from results in this study have also provided an important first step into the evaluation of force profile differences at a more higher level of skill, specifically for sculling athletes. Results in the present study can be used to drive future hypothesis driven questions in both research and practice environments, inclusive of questions such as, whether trends related to increased rate of force development at the catch, is present as a consistent feature across multiple rowers in a larger crew member boat at international competitions.

References for this chapter are included in the list of references at the end of this thesis

Bridging Statement E

Chapter six demonstrated that differences force-angle profile characteristics were also potentially attributed to metrics of rowing performance. Interestingly in this chapter, different metrics of performance were associated with different characteristics of the force-angle profile. Discriminant function analyses demonstrated that rate of force development was a potentially important characteristic for international rowers (with this present across both sides of the boat and more notably on the stroke side). Additionally for the bow-side, spending less time in the first half of the drive phase was also identified as an important feature for international rowers. Multiple linear regression of scores from the *bf*PCAs showed that a more pronounced front peaked profile was associated with a higher average boat velocity. This was present across both sides of the boat. These results support the notion that technical characteristics, identified using the force-angle profile, required better performance in a single sculling boat, may not align with the characteristics required to be a better performer in a larger crew boat. Although, at present these findings are speculative and further experimental research would be required to test this notion accurately.

As has been demonstrated in the literature (chapter two), and through the experimental findings of chapters five and six, force-time and force-angle profiles are established tools for enhancing and optimising rowing technique in the training environment. Despite this, it can be difficult to evaluate bilateral force measurements collected as a part of sculling. Current practices for displays of force profiles across both sides of the boat have involved the observation of the bow and stroke side forces together on the one plot (Smith & Loschner, 2002). Although these are interpretable when providing terminal feedback (provision of information at the completion of a task) to athletes or coaches, there may be some issues with providing information from both sides of the boat in the form of real-time concurrent feedback, which has been suggested as potentially beneficial in the applied training environment (Smith & Loschner, 2002). FDA techniques have the ability to identify and test the importance of particular characteristic patterns of force profiles that are associated with better rowing performance. As such, when an important pattern is identified, there is capability to provide targeted feedback in real-time to athletes in the form of a target trajectory. Thus, a graphical display, which reduces information from these two continuous measures of force into a single target trajectory would be useful, particularly if differences in the coordination or asymmetries of force production were found to be meaningful for better performance and subsequent interventions utilising real-time feedback were to be implemented.

In practice this could be achieved through the use of a force-force. Bow-side force could be observed relative to stroke side force (similar to an angle-angle diagram used in conventional coordination research), and then *bf*PCA could be applied to this bivariate functional force data. One issue with this approach is the scale of each parameter in a force-force plot and how these can affect a graph's ability to display meaningful differences in coordination of forces. Force (when measured in Newtons) is observed across a much larger scale than normal ranges of motion for joints or segmental angles in typical angle-angle diagrams. There is potential that differences in force application using a force-force plot may not be as obvious as those seen in kinematic research. This would affect an athlete's ability to use this information source for concurrent real-time feedback. Data reduction techniques from coordination research, such as continuous relative phase (CRP) and vector coding (VC) may also be useful for reducing complex information between two forces into a single univariate trajectory that can be analysed and displayed graphically. Despite this, there can be practical issues understanding differences in these waveforms, given that the final unit of measure in both instances a kinematic measure. For example a coupling angle is created between two variables as a part of VC, and a phase angle difference is created to describe coupling between variables using CRP. Although both are potentially suitable for concurrent feedback, this would make practical interpretation of findings from these waveforms difficult.

Thus in chapter seven, a simple *difference* function is used to reduce information from bow and stroke side forces into a single univariate time-series. In this function, for each rower, bow side force is subtracted from stroke side force at every stage of the stroke cycle, to create a time-series that reflects the fluctuating asymmetry present across both sides of the boat for single scullers. This provides a time-series measure that has interpretable units of measure (the original units are retained), is directional (in the sense that asymmetries are detected relative to the side of the boat) and structures identified in the time-series can serve as a simple target trajectory for real-time concurrent feedback schedules. When analysed using a modified FDA technique, analysis of characterizing phase (ACP), this difference function can also complement established measures of asymmetry from ergometer rowing research. Consequently, chapter seven uses a combination of existing rowing asymmetry measures, a force-difference time-series and FDA (with ACP) to more comprehensively and holistically account for the relationship between force asymmetry or coordination of forces, and better performance in on-water single sculling.

CHAPTER 7

Force coordination strategies in on-water single sculling: Are asymmetries in propulsive pin-force functional?

The following chapter was formatted for submission to the Scandinavian Journal of Medicine and Science in Sports and is currently submitted and awaiting the first round review.

Author Contribution Statement

As a co-author on the paper presented within this chapter entitled "*Force coordination strategies in on-water single sculling: Are asymmetries in propulsive pin-force functional?*" as well as being Primary Supervisor throughout the Doctor of Philosophy candidature of John Warmenhoven, I confirm John's contribution to the paper as follows:

- Conception and design of the research
- Data collation, database building and database management
- Analysis of data and interpretation of the findings
- Writing the paper and critically appraising content within the manuscript

Signed: [redacted]

Date: 21/04/2017

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Discipline of Exercise and Sport Science

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Force coordination strategies in on-water single sculling: Are asymmetries in propulsive pin-force functional?

By

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Abstract

Asymmetries of the rowing stroke cycle have been assessed with reference to kinematics and foot-force measures in laboratory testing environments. How asymmetries in propulsive kinetic measures are related to on-water rowing performance is not established. A new approach for the evaluation of both global and local asymmetries across the entire movement was used to assess the continuous role of asymmetries and whether these change according to level of competitive representation. An established symmetry index (SI) and functional data analysis (FDA) techniques were applied to a continuous *difference* time-series, which described fluctuating asymmetry in propulsive pin forces for each rower. A participant group of highly skilled female rowers (national and international competition level), rowing at 32 strokes per minute in a single scull boat were evaluated. Univariate ANOVAs revealed that differences in asymmetries were present as a factor of competition level for the SI and results of FDA. International athletes were more likely to utilise an asymmetry strategy with increased stroke-side force early in the drive phase, and increased bow side force through the second half of the drive. This was likely the result of international performers customising their movement strategies relative to known mechanical offsets in the boat. The first half of the drive phase was also found to be an flexible part of the rowing stroke cycle with high levels of between athlete and within athlete variation, suggesting asymmetries may have a functional role in successful execution of movements during the rowing stroke.

Key Words (3-8): Functional Principal Components Analysis; Biomechanics, Sport Expertise, Rowing.

Force coordination strategies in on-water single sculling: Are asymmetries related to competition level and functional?

Introduction

Coordination patterns have been analysed in a number of different sporting and human movement contexts including rowing (Découfour & Pudlo, 2004; Découfour, Pudlo, Barbier & Gorce, 2008), swimming, (Seifert et al., 2011), golf (Horan, Evans, Morris & Kavanagh, 2010), karate (Quinzi, Sbriccoli, Alderson, Di Mario & Camomilla, 2014), gymnastics (Irwin & Kerwin, 2007; Williams et al., 2016), athletics in disciplines such as triple jump (Wilson, Simpson & Hamill, 2009) and dancing (Armour Smith, Siemienski, Popovich & Kulig, 2012). In each of these instances coordination was explored relative to relationships between kinematic variables such as body joint or segmental kinematics. In practice it is possible that variables describing structures of coordination in sporting contexts can be more complex than solely kinematic measures. One such example is on-water rowing, where bilateral forces are collected during sculling.

It has been conventionally assumed that a high boat velocity is achieved through the production of large, *symmetrical* forces, which are efficiently delivered through the feet, up the human kinetic chain to the handle and oars (Hofmijster, Van Soest & De Koning, 2008; Buckeridge, Bull & McGregor, 2014). Despite this, recent advances in laboratory research have demonstrated evidence of lower limb asymmetries for different biomechanical variables. For kinematic measures, asymmetries have been identified at the hip and knee in ergometer rowing (Buckeridge, Bull, & McGregor, 2012). A growing evidence base also supports the presence of kinetic asymmetries. Asymmetries in foot-stretcher forces have been identified during ergometer rowing (Baca, Kornfeind & Heller, 2006; Buckeridge, Bull & McGregor, 2014; Colloud et al., 2001; Fohanno, Nordez, Smith & Colloud, 2015). Interestingly, the level of kinetic asymmetry noted by Buckeridge, Bull and McGregor (2014) was not significantly different between sweep rowers and scullers. These findings are of particular interest, given that scullers are considered to have symmetrical force outputs as a consequence of the assumed symmetrical rowing action achieved on-water, when compared to sweep rowers. Additionally, Fohanno, Nordez, Smith and Colloud (2015) demonstrated notable foot-stretcher asymmetries with low intra-stroke variability for elite scullers. These findings demonstrate that asymmetries in highly skilled rowers may actually be deliberate parts of a potentially underlying kinetic coordination structure across the stroke cycle.

As the majority of rowing training and rowing competition takes place on-water, it is possible that any intentional asymmetries, or coordination of forces, may be associated with movement patterns that are learned and practiced in an on-water environment. Evidence of asymmetries in on-water rowing is more limited however, with some differences in propulsive forces (measured at the pin) reported across both sides of the boat in sculling. Loschner, Smith, Barrett, Simeoni and D'Helon (2000) have reported greater peak force on the bow side pin compared with the stroke side pin. Similarly, Elliott, Lyttle and Birkett (2002) reported greater bow oar peak force of eight sculling rowers across three different stroke rates. Due to the inboard length of the oars used during on-water sculling, the oar handles must overlap when the blades are perpendicular to the boat, resulting in upper body postural asymmetry throughout the stroke cycle. This fixed mechanical asymmetry may lead to pin-force asymmetries such as those reported (Elliot, Lyttle & Birkett, 2002; Loschner, Smith, Barrett, Simeoni & D'Helon, 2000). It also may be possible that kinetic asymmetries may act to mediate the effects of the mechanical offset present in boat rigging. Despite the presence of established mechanical asymmetries during sculling and the growing evidence base of kinetic asymmetries in laboratory based research, there is limited evidence to suggest whether the nature of these asymmetries on-water is erroneous or functional, and if these asymmetries are consistent across the entire stroke cycle, or change according to specific phases of the movement.

Difficulties in building such an evidence base are partly due to the measures used to quantify force asymmetries in ergometer rowing. These have often involved indexes that describe the magnitude of asymmetry for each rower (Buckeridge, Bull & McGregor, 2014; Fohanno, Nordez, Smith & Colloud, 2015). Similarly differences in discrete points such as peak force have been reported in on-water research (Elliot, Lyttle & Birkett, 2002; Loschner, Smith, Barrett, Simeoni & D'Helon, 2000). Understanding the potentially functional role of asymmetries across the stroke cycle would be useful from a technical perspective (Soper & Hume, 2004). Different methods for analysing complex time-series data such functional data analysis (FDA) techniques (more specifically functional principal components analysis or *f*PCA) have been used in conjunction with biomechanical data in on-water rowing to explore patterns of variability in force-angle profiles across the rowing stroke cycle (Warmenhoven et al., 2015). In the present study FDA could be applied in conjunction with established approaches for measuring asymmetries (i.e. the symmetry index used by Fohanno, Nordez, Smith and Colloud, 2015), for a more holistic evaluation of asymmetries during on-water sculling. As such, the purpose of this study was to explore the potentially functional or coordinative role of asymmetries in on-water single sculling, and assess whether asymmetry patterns can are indicative of competition level differences in a group of highly trained single sculling rowers. It should also be acknowledged that this is an explorative study, and although differences between competition levels may exist, the structure of these differences and how they change across the rowing stroke cycle is relatively unknown.

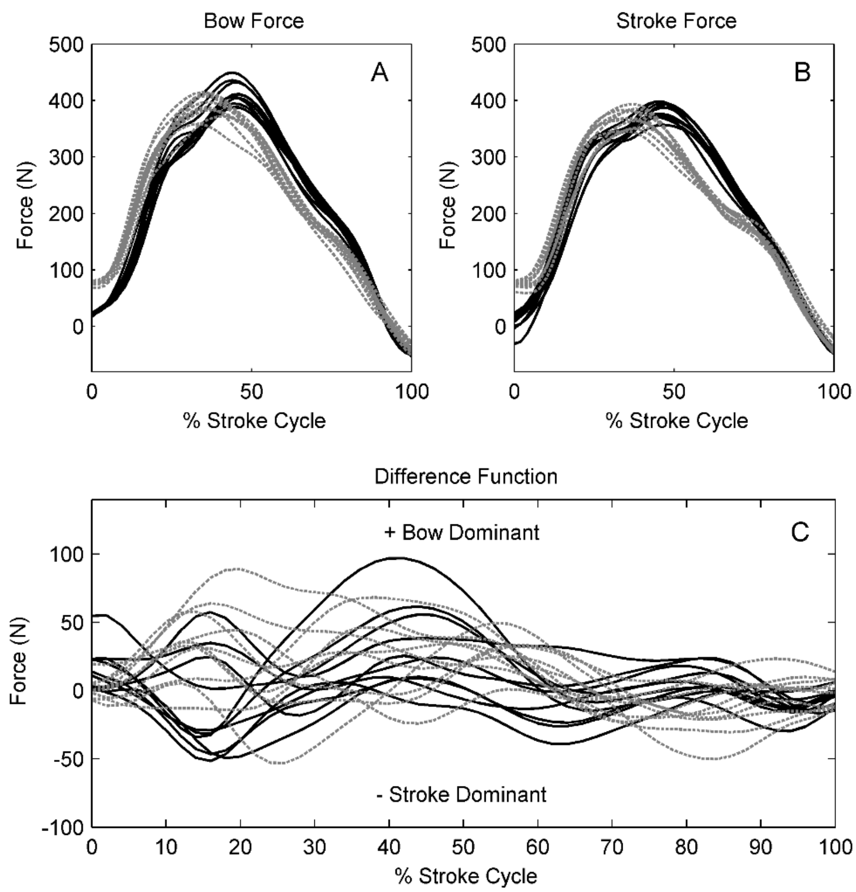

Figure 22. The asymmetry function. Top Left: Bow side force. Top Right: Stroke side force. Bottom: Difference time series created by subtracting stroke-side force from bow-side force. For all subplots ten strokes have been plotted for two athletes. International level rower in grey. National level rower in black.

Methods

Participants

Following institutional ethical approval, 27 female rowers voluntarily consented to participate (*M* age = 25.60 $\pm$ 4.88 years; *M* height = 1.74 $\pm$ 0.04 cm; *M* mass = 75.62 $\pm$ 4.61 kg). Participants were highly trained heavyweight and lightweight scullers. At the time of testing, competitive performance was used to categorise participants as either ‘national’ (n = 14) or ‘international’ level (n = 13) rowers. National rowers must have competed in an Australian national age group championship or an Australian national open championship. International rowers must have competed as an Australian representative at an Under 18, 23, an open level event or above.

Procedures

Participants were instructed to row a total of 1000 m, composed of 250 m at four ascending pre-selected stroke rates (i.e., 20, 24, 28 and 32 stokes per minute). A short period of active rest (250m of light rowing) followed each stroke rate condition to ensure that fatigue was not a factor. Rowers used Nielsen-Kellerman © Strokecoaches to control stroke rate outputs. For this study, only the 32 strokes/min data was analysed. Data was obtained using ROWSYS instrumentation as outlined in Smith and Loschner (2002). Propulsive pin force was measured using three-dimensional piezoelectric transducers (Kistler, Switzerland). The pin was mounted on the rigger and was the axis of rotation for the gate. Horizontal oar angles were measured by low-friction potentiometers and a fiberglass arm attached to the inboard end of the oar, enabling free rotation of the oar around its axis.

Data Processing

Data for ten strokes at 32 stokes per minute were selected for each rower on both boat-sides. For each rower, the drive and recovery phases of the stroke were identified using oar angle relative to the horizontal (Smith & Loschner, 2002), and the drive phase was examined further. A linear length normalisation strategy using an interpolating cubic spline was applied, normalising each curve to 100% of the drive phase. In addition to the ten individual curves, an ensemble average profile was created for each rower and for each boat-side.

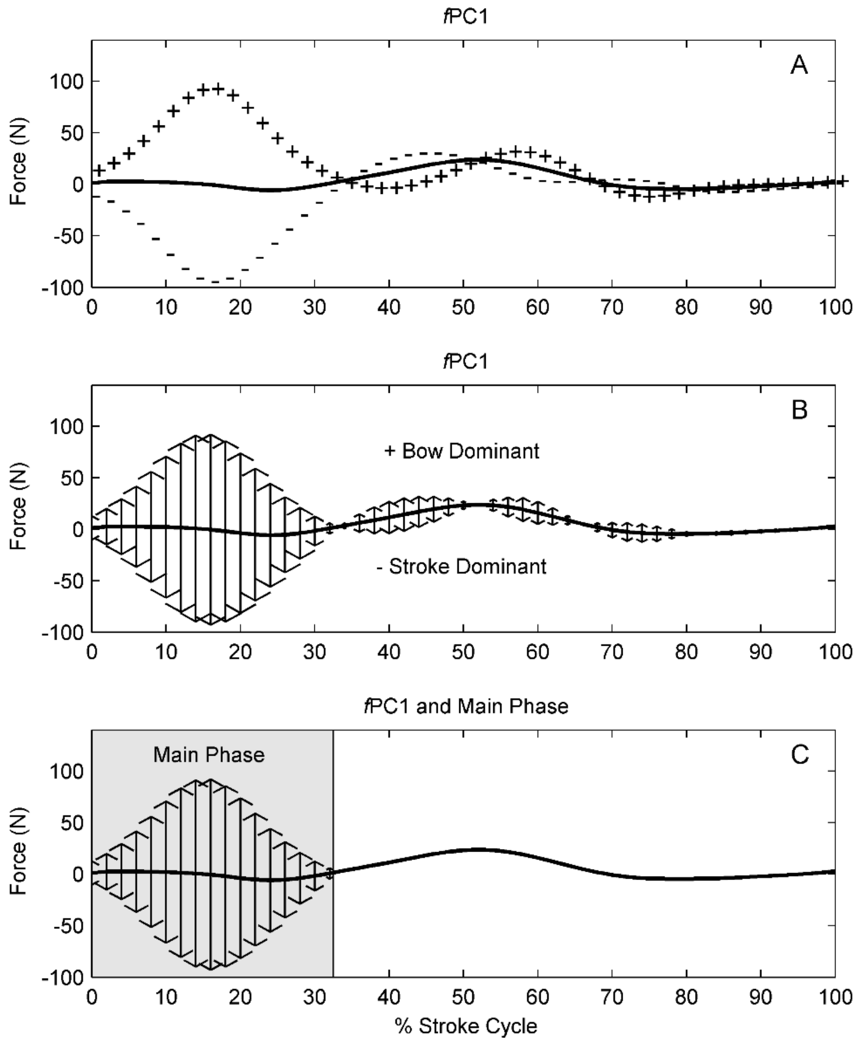

Figure 23. *f*PC of the asymmetry function with main phase. Top: *f*PC1 plotted using conventional illustration of positive and negative scorers (Dona et al. 2009). Middle: *f*PC1 plotted with positive scorers likely to bare characteristics of increased bow-side force and negative scorers increased stroke-side force. Bottom: *f*PC1 with main phase identified.

Difference Time-Series

A difference time-series was created for each individual stroke and ensemble average profile, for each participant. The difference time-series was created by subtracting stroke-side force from bow-side force across the entire drive phase. This resulted in a continuous waveform describing fluctuating force asymmetry across the entire movement. Zero, on the time-series, indicated perfect symmetry between boat-side forces; a positive value indicated higher force on the bow side; whilst a negative indicated a higher force on the stroke side (see Figure 22). Once all difference time-series were defined, the symmetry index (SI), *f*PCA and the modified FDA technique Analysis of Characterising Phases (ACP) were conducted (Richter, O'Connor & Moran, 2014).

Symmetry Index

The SI was defined as the root-mean-square difference between values of the bow and stroke side propulsive pin-force curves across the entire drive phase (Fohanno, Nordez, Smith & Colloud, 2015). Previously, Fohanno et al., (2015) normalised each curve relative to the maxima of the two parameters for each SI. This normalisation process ensured that SI values could be compared between different variables as a percentage. In this study, only a single variable and measure (i.e., force and Newtons) was used, thus no normalisation was necessary. An SI was calculated for each of the individual strokes and the average profile for each participant. Intra-athlete variability of SI was determined by calculating SI standard deviations (SI-SD$_{Intra}$) across ten strokes for each participant.

fPCA and ACP

Each of the difference time-series were represented as functions using B-splines. The derived functions were smoothed by adding a roughness penalty to the fitting procedure. The roughness penalty term was controlled by a smoothing parameter (λ), which was selected using a combination of generalized cross-validation and visual inspection. An outline of the data fitting and smoothing processes for *f*PCA can be found in Ramsay and Silverman (2005). Using all participant (ten) functions and each participant's ensemble average function, *f*PCA was conducted. The total number of functional principal components required to retain 95% of variance in the data set were used. Retained *f*PCs were also used to undertake ACP.

A requirement of ACP is that a VARIMAX rotation is performed on the data to optimise the interpretability of each *f*PC, and reveal a single *main phase* for analysis (Richter, O'Connor & Moran, 2014). Once each of the main phases were identified (see Figure 23), these portions of the rowing drive phase were isolated to calculate an ACP score for each retained *f*PC. To achieve this, each *f*PC was re-sampled from a function into a vector of data points using the same frequency to which the data was originally obtained (100Hz). The position and sign of each *f*PC's absolute maximum were used to establish the start and end point of each main phase. The last value differing in sign before and after the absolute maximum defined the start and end of the main phase for each *f*PC. The benefit of using an *f*PCA decomposition is that each *f*PC (and associated main phases) are directly reflective of structural variability in the original time-series data. The conventional equation for ACP score calculation is (Richter, O'Connor & Moran, 2014):

$$ACP_{Score} = \sum_{i=1}^{n}(q_i - p_i)$$

These scores are calculated using the point-by-point Euclidean distance defined *area* between a participant's curve (*p*) and the mean curve across the data set (*q*) for every point (*i*) within the main phase (identified using the VARIMAX rotation for each *f*PC). In the present study a modified ACP_{Score} equation was used, where each ACP_{Score} was reflective of the point-by-point Euclidean distance based *average* between a participant's curve and the mean curve using the equation below:

$$ACP_{Score} = \frac{\sum_{i=1}^{n}(q_i - p_i)}{n}$$

where (p), (q) and (i) referenced identically to the original equation and (n) is the number of data points in the main phase. Using this approach for score calculation permits for an intuitive comparison between the overall SI for each participant and the ACP_{Scores}. SI provides a measure of *average difference* between two curves across the entire waveform (measuring global asymmetry across the entire movement), and the ACP_{Score} for each *f*PC provides a measure of *average difference* between two curves, but is targeted at selected phases within the waveform (measuring local or '*phase related'* asymmetry). For the SI and ACP_{Scores}, both measures of asymmetry were observed using the same scale and units of measure (Force and Newtons). In this study, the direction of each ACP_{Score} is also referenced relative to the direction of differences noted in the original difference time-series. As such, a positive ACP scorer – for a given *f*PC - will have an average increase in bow force relative to stroke force across a key phase; while a negative scorer will have an average increased stroke force relative to bow force. ACP_{Scores} were also used to also calculate intra-rower asymmetry variability. Intra-rower asymmetry variability was as the ACP_{Score} standard deviation ($\mathrm{ACP\text{-}SD}_{Intra}$) of the ten strokes for each participant.

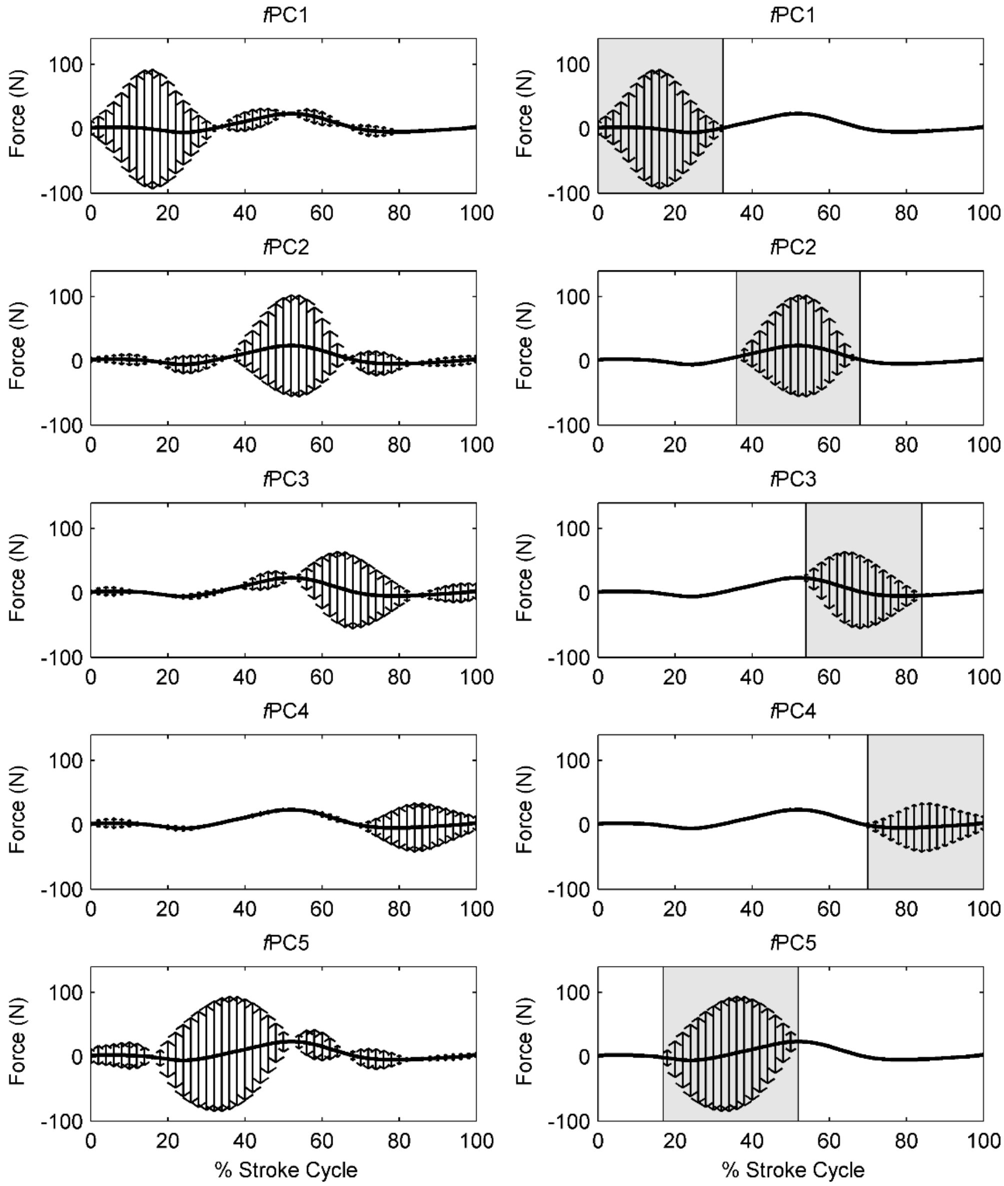

Figure 24. First five *f*PCs of the asymmetry functions. Left: *f*PC1, *f*PC2, *f*PC3, *f*PC4 and *f*PC5 plotted across the whole drive phase movement cycle with each *f*PC varimax rotated. Right: *f*PC1, *f*PC2, *f*PC3, *f*PC4 and *f*PC5 plotted with only the main phase for each *f*PC remaining.

Statistical Analysis

Differences in asymmetry according to competition level were examined using the measures of the global symmetry index (SI), global symmetry variability (SI-SD_{Intra}), local symmetry (ACP_{Scores}) and local symmetry variability (ACP-SD_{Intra}). To determine differences according to competition level, separate univariate ANOVAs were applied to measures of SI, SI-SD_{Intra}, ACP_{Score} and ACP-SD_{Intra} ($\alpha = 0.05$). Only the scores for the average difference curves were included in each ANOVA for SI and ACP_{Scores}.

Results

fPCA decomposition

The first five *f*PCs accounted for 95.2% of all variance in all curves. The content of these *f*PCs is demonstrated in Figure 24. The main phase from *f*PC1 described the presence of asymmetry starting from the catch position and continuing until approximately 35% of the drive phase. The main phase for *f*PC2 highlighted asymmetry in the middle of the drive phase. The main phase for *f*PC3 highlighted asymmetry beginning in the middle of the drive phase and continuing through the second half of force application. The fourth *f*PC's showed an asymmetry main phase at the end of the drive phase until the finish position. The fifth *f*PC's main phase showed asymmetry beginning early in the drive phase and continuing through until half way through force application.

Table 8. Descriptive statistics (mean and standard deviation) and univariate ANOVA results for SI, SI-SD_{Intra}, ACP_{Scores} and ACP-SD_{Intra}.

	International	**National**	***F* Value**	***p* Value**
SI	16.36 (9.54)	7.55 (5.66)	8.67	0.01*
SI-SD_{Intra}	8.41 (2.68)	9.40 (3.75)	0.62	0.44
ACP_{Scores} (*f*PC1)	-9.45 (27.46)	8.78 (15.48)	4.60	0.04*
ACP_{Scores} (*f*PC2)	-4.10 (32.81)	3.81 (13.62)	0.69	0.41
ACP_{Scores} (*f*PC3)	7.41 (19.09)	-6.88 (14.38)	4.88	0.04*
ACP_{Scores} (*f*PC4)	4.37 (8.10)	-4.06 (11.52)	4.77	0.04*
ACP_{Scores} (*f*PC5)	-13.70 (38.61)	12.72 (14.67)	5.69	0.02*
ACP-SD_{Intra} (*f*PC1)	21.82 (7.80)	23.31 (8.73)	0.22	0.64
ACP-SD_{Intra} (*f*PC2)	16.55 (5.45)	23.35 (9.97)	4.72	0.04*
ACP-SD_{Intra} (*f*PC3)	11.40 (4.89)	15.42 (5.81)	3.76	0.06
ACP-SD_{Intra} (*f*PC4)	8.61 (3.74)	9.98 (3.17)	1.07	0.31
ACP-SD_{Intra} (*f*PC5)	20.35 (8.21)	26.56 (12.52)	2.29	0.14

Table Notes: * = p<.05.

Competition Level

All descriptive statistics and univariate ANOVA results for global and local symmetry measures are shown in Table 8. SI differences were statistically significant between international and national level rowers ($p < 0.05$), as international level rowers possessed a higher SI. No statistical differences according to competition level were apparent for SI-SD_{Intra}. ACP_{Scores} demonstrated competition level differences, with scores for *f*PC1, *f*PC3, *f*PC4 and *f*PC5 reporting significance ($p < 0.05$). For *f*PC1 and *f*PC5, international rowers were indicative of negative scorers, while for *f*PC2 and *f*PC3 international rowers were indicative of positive scorers. ACP-SD_{Intra} measures also identified a difference for competition level for *f*PC2. International rowers reported a lower ACP-SD_{Intra} variability during the middle phase of the drive phase.

Discussion

Symmetry, Asymmetry and Performance

The purpose of this study was to explore the role of asymmetries in on-water single sculling and assess whether differences in asymmetry patterns were indicative of different performance levels, assessed using each rowers' level of competitive representation. The symmetry index (SI) used in this study revealed differences for competition level, where international athletes significantly differed from their national counterparts in the amount of global asymmetry across the entire movement cycle. International athletes were more likely to have an increased SI indicating that the total global asymmetry present in these athletes tended to be higher than that seen in national level athletes. The inclusion of the ACP_{Scores} also revealed that the structure of these asymmetries may have also differed as a factor of competition level. Four of the five retained *f*PCs (and their associated ACP_{Scores}) revealed statistical significance between international and national athletes. International athletes scored negatively on *f*PC1 and *f*PC5 indicating a trend for stroke-side pin force to lead bow-side pin force from the start of the drive phase until half way through the movement cycle. *f*PC3 and *f*PC4 were also more likely to be positive for international athletes indicating a trend for this early asymmetry to reverse through the second half of the drive phase, with the bow-side leading the stroke-side towards the finish. The reverse of these characteristics (described by the four *f*PCs) was true for national level athletes. One explanation for these differences in asymmetry patterns may be related to the fixed mechanical offset present in boat rigging during sculling (Smith & Loschner, 2002; Soper & Hume, 2004).

Smith and Loschner (2002) illustrated (descriptively through graphical depictions of the rowing '*hand curve*') that a vertical oar angle offset was present in a single scull, for an exemplar highly skilled rower. This offset was relatively consistent across the whole movement, but more prominent early in the drive phase. Burnett, Doyle and Elliot (2004) supported this finding and demonstrated increased vertical oar angles (and a subsequently higher handle position) for the bow side oar when compared to the stroke side oar for single scullers, at both the catch and finish positions of the drive phase. Burnett, Doyle and Elliot also found that sculling rowers possessed a tendency to drop their left hand downwards as they approach the catch to a larger extent than their right. It was suggested that this was likely a consequence of the same mechanical offset and as a sculling rowers approached the catch position, in order to keep the boat balanced, the left hand was dropped down towards the water to minimise the height difference between the hands. This indicates, that for the present study, stroke-side force application may have begun at the catch in a well '*anchored*' position and possibly allows for controlled, and increased force application early in the drive, relative to the bow side. It is possible that international athletes are more efficient at modifying their movement strategies relative to this mechanical constraint and are consequently anchoring strongly with the stroke-side oar early in the drive, with the bow-side then applying more force halfway through the stroke cycle to counterbalance for this early kinetic offset. When assessing changes in intra-athlete symmetry variability relative to level of competitive representation, the SI-SD_{Intra} did not show any significant differences. Additionally, only a reduction in intra-athlete variability for *f*PC2 (demonstrated through ACP_{Scores}) was shown to be significant for international athletes. This indicates that minimal asymmetric fluctuations halfway through the drive phase may be relevant descriptor of better rowing skill. This is logical as effective force application (oars being perpendicular to the longitudinal axis of the boat) occurs throughout the middle part of the drive phase (Soper & Hume, 2004) and stability in force application through this part of the stroke would likely be of benefit to rowers and increase rowing efficiency. It is important to note also that this difference between competition levels for asymmetry variability would not have been detected if SI was used alone, demonstrating the benefit of including *f*PCA and ACP for reducing the stroke cycle into specific phases of asymmetry patterns across the cycle.

Functional asymmetries and coordination

One interesting, yet co-incidental finding is related to the amount of variability within the international and national cohorts for local symmetry measures. It can be seen in Table 8 that the group standard deviations for ACP_{Scores} for international athletes for *f*PC1, *f*PC2 and *f*PC5 were considerably higher than group standard deviations for the national level rowers. The main phases for these *f*PCs describe different sections of asymmetry starting at the catch and continuing through until 50% of the way through the drive phase. This indicates that international rowers explored a broader range of asymmetry patterns in the first half of the drive phase. Further to this, once athletes have adopted a suitable asymmetry strategy, irrespective of the level of competitive representation, *f*PC1, *f*PC2 and *f*PC5 again reveal higher $ACP\text{-}SD_{Intra}$ scores for intra-rower asymmetry variability at each of these phases on the stroke cycle (when compared to *f*PC3 and *f*PC4). This indicates that the first half of the drive phase may be a functionally adaptive part of the stroke cycle, with larger amounts of between-athlete variation for asymmetry patterns (particularly for international athletes) and also large amounts of within-athlete variation. These higher amounts of variability (both between and within rowers) may be present to account for potentially large changes in boat acceleration during the early stages of the drive phase. Studies on a stationary ergometer have demonstrated increased lower limb joint loads as a consequence of higher inertial masses that the rower needs to overcome at the catch (Colloud, Bahuaud, Doriot, Champely & Che'ze, 2006; Greene, Sinclair, Dickson, Colloud &

Smith, 2013). It is possible that these loads will affect the dynamic stability of the boat and rower position in an on-water environment.

Findings from this study also imply that features of kinetic asymmetries in on-water rowing potentially should not be reviewed and observed just as asymmetry, but potentially coordination of forces across the stroke cycle as the rower adapts their mechanical output to the asymmetries of the rigging. Rather than increases in asymmetry measures being assumed as detrimental to performance, they may act a flexible parts of a dynamic system operating relative to the unique constraints imposed upon individual athletes and the environmental and task context of the skill (Newell, 1986). Finally regarding the concept of asymmetry variability in the present study, this study illustrates the importance of exploring movement patterns across multiple movement cycles. Force profiles when evaluated in isolation are generally assumed to be quite stable within each rower, and historically individuals have generally maintained the same harmonic structure of their own unique force signature with every repetition of the skill (Figure 22) (Wing & Woodburn, 1995; Hill, 2002).

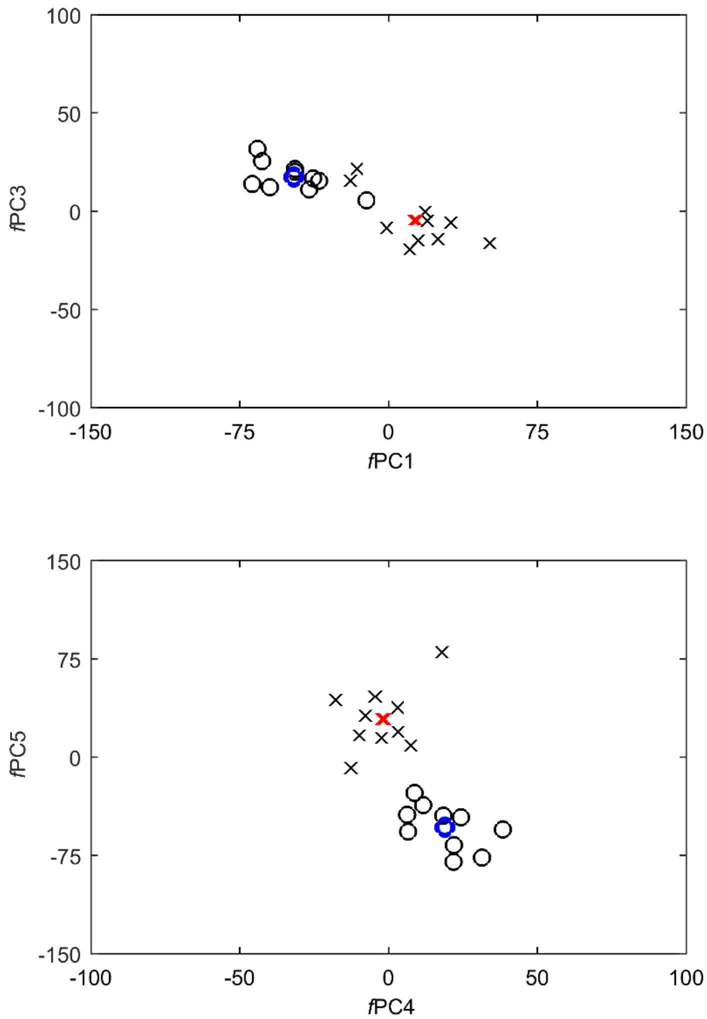

Figure 25. Sample scatter plot of ACP$_{Scores}$. Top: Scatter plot of ACP$_{Scores}$ for fPC1 and fPC3. Bottom: Scatter plot of ACP$_{Scores}$ for *f*PC4 and *f*PC5. In both plots, ACP$_{Scores}$ for mean asymmetry profiles are illustrated for two exemplar athletes (1 national in red, and 1 international in blue) in bold. The ACP$_{Scores}$ of each athletes' individual ten strokes are also plotted as '×' for the national athlete and 'o' for the international athlete.

It is clear from present results, however that the nature of within-rower asymmetry variability, when explored from a bilateral perspective, reveals a complex relationship in the structure of waveform changes in on-water rowing. This can be seen in Figure 25 where ACP$_{Scores}$ for the ensemble average difference curves are plotted in conjunction with ACP$_{Scores}$ of individual strokes for two exemplar athletes. For both athletes, there is a noticeable amount of intra-athlete variation present in ACP_{Scores} of the individual strokes when compared to the ACP_{Scores} of each rower's average.

The benefit of using a mixed analytical approach in the identification of symmetry differences has proven useful for understanding asymmetries as a complex but potentially necessary part of on-water sculling. The use of *f*PCA and ACP has built on previous work exploring the use of symmetry indexes. More specifically the symmetry index of Fohanno, Nordez, Smith and Colloud (2015) used in conjunction with *f*PCA and ACP has allowed for an intuitive comparison of global and local asymmetry differences, with all measures observed using the same scale and units of measure (in this instance: Newtons).

Conclusion

The purpose of this study was to use a novel analytical approach to explore the role of asymmetries in on-water single sculling and to assess whether asymmetries differ between athletes when assessed relative performance. Global and local measures of asymmetry were assessed across the entire movement cycle and differences were revealed for level of competitive representation. International athletes were more likely to utilise an asymmetry strategy with increased stroke-side force early in the drive phase, and increased bow side force through the second half of the drive. This is likely the result of international athletes, better modifying their movement strategies relative to known mechanical offsets that are present in sculling as a consequence of boat rigging. The first half of the drive phase was also found to be a functionally adaptive part of the rowing stroke cycle with higher levels of between athlete (particularly for international rowers) and within athlete (for all rowers) asymmetry variation reported for *f*PCs describing this part of the movement cycle. Results from this study, thus suggest it is possible that asymmetries have a functional role in successful execution of the rowing stroke, and rather than asymmetries be dismissed as a potential problem and detractor of performance, they are treated with the same care and evaluation as other coordination structures that are explored in biomechanics and human movement research.

References for this chapter are included in the list of references at the end of this thesis

CHAPTER 8

Discussion and Thesis Conclusion

Discussion

Overview of main findings

There were two main objective for this body of work. The first was to describe statistical approaches from functional data analysis (FDA) currently being used with continuous biomechanical waveform data. This exploration was conducted primarily to understand whether FDA techniques would be appropriate for the analysis of differences in patterns of propulsive force production between rowers. These patterns are often displayed using force-time or force-angle profile graphs (and often referred to as a rower's force signature). This was also conducted to provide the broader sports biomechanics community with guidelines for the appropriate use of these techniques, particularly where analysis of similar continuous biomechanical data may be of interest. The second was to use FDA techniques to demonstrate that rowers can be objectively categorized using their force-angle time series data. This empirical evidence base would contribute to a scientific understanding of differences in rowing performance through force profile characteristics.

For the first main objective, two particular FDA techniques were explored. Initially, functional principal components analysis (*f*PCA) was investigated using data from force-time and force-percent profiles. Considerations and recommendations for the use of *f*PCA in these contexts were provided, particularly with reference to different methodological approaches and data preparation strategies. Subsequently, the FDA technique *bf*PCA was explored for its potential applicability with bivariate functional biomechanical data (such as force-angle profiles in on-water rowing). Similarly, considerations for the use of this technique were provided.

For the second objective, known constraints with potential to influence differences between rowers in characteristics of force-angle profiles were explored using *bf*PCA, using data collected during testing conducted in a single sculling boat. These included constraining factors such as gender (organismic constraint) and boat-side (task constraint). Subsequent to this, and in light of findings from this thesis, these constraining factors were controlled for. The association between established performance metrics and characteristics of force-angle profiles were then explored using *bf*PCA. Finally, a modified version of *f*PCA, analysis of characterizing phases (ACP), was used for the development of a new comprehensive statistical approach for the measurement of functional asymmetries in on-water rowing. This statistical approach involved the reduction of bilateral propulsive force across both sides of the boat into a single functional measure. This new measure of continuous asymmetry was used to investigate the association of force asymmetry characteristics with different metrics of performance. In line with these two sections of the thesis' main objective, the primary findings from this thesis are summarised and are divided into two sections: *methodological findings* and *experimental findings*.

Methodological findings

Considerations for the use of fPCA: Several important considerations were noted regarding the use of *f*PCA on continuous univariate time-series variables such as the force-time or force-percentage profiles. A summary of these key findings are below:

i. If applying a standard linear length normalisation strategy (such as an interpolating cubic spline) to time-series data, careful evaluation of how this normalisation procedure will affect the temporal structure of the original data should be taken. This is with particular reference to time-series that differ in terms of their overall length or the length of their key phases.

ii. If length characteristics of time-series are substantially different between each curve, different piece-wise normalisation strategies or functional registration techniques can be used to remove any form of unwanted or distorted phase variation introduced as a by-product of standard linear length normalisation strategies.

iii. Once a suitable normalisation strategy has been selected and *f*PCA has been conducted, if multiple forms of variation are present within one or more of the retained *f*PCs, then a suitable rotation (such as the varimax rotation) can be used to sharpen the interpretability of the *f*PC scores.

iv. If preservation of a time-series' original temporal properties is necessary, *f*PCA can be quite limited in its ability to accurately describe variability in this data, without there being some resulting form of experimental compromise. Examples of compromise to data can involve "stacking" the remainder of shorter curves with missing values or stationary end points to standardise the length of curves, or truncation of data at designated time points.

Considerations for the use of bfPCA: Important considerations were also noted regarding the use of *bf*PCA on continuous bivariate or multivariate waveform variables such as the force-angle profile. A summary of these key findings are below:

i. If *bf*PCA is applied to a bivariate structure where each parameter is measured using different units, it is advised that differences in the within-parameter variances are assessed prior to analysing *bf*PC scores.

ii. If substantial differences in within-parameter variances are present, normalisation strategies should be considered to account for these differences, but executed with caution. In some instances it may be important not to "*over-process*" data, potentially leading to changes in the structure of variability displayed by *bf*PCs. This may lead to results that do not truly reflect characteristics that are present in the original data.

Experimental findings

First experimental study: The potential effects of conditions and/or constraints such as rower gender and side of the boat on differences in relative force-angle patterns were explored. This involved the use of *bf*PCA applied to an average relative force-angle profile for each rower. Both sides of the boat were included in this analysis. A summary of gender and boat-side findings are as follows:

Gender: Results of a gender effect tested within a mixed ANOVA revealed that males and females significantly differ ($p < 0.05$) from each for one pattern within the relative force-angle graph. In this pattern, females were more likely to exhibit a reduction in relative force application leading into and away from the square-off position of the oar (oar being perpendicular to the longitudinal axis of the boat). This indicated, that for females, a noticeable peak in relative force application is reached earlier in the stroke cycle and then is not maintained through the second half of the drive phase when compared to male athletes. Separate discriminant function analyses conducted independently for each side of the boat also revealed moderate to strong classification of rowers for gender, with 75% and 77.5% correct classification for the bow and stroke side curves respectively for gender classification. The same force-angle pattern demonstrating statistical significance in the mixed ANOVA for the gender effect also contributed most strongly in both discriminant function models (identified using the weight of discriminant function coefficients).

Boat-side: results of the mixed ANOVA revealed significant ($p < 0.05$) boat-side differences for four separate patterns identified in the relative force-angle profile. Differences in these patterns were likely the result of an increased role of the bow-side force to dominate the peak force application across the stroke cycle in single sculling. These differences also alluded to the stroke side potentially possessing a *control* or *steering* role, with force application on the stroke side more likely to rise at different time points before and after maximum force and also start force application later, spatially, when compared to the bow-side.

Second experimental study: In light of gender and boat-side differences noted in the previous experimental study, these factors were controlled for, and differences in female rowers' relative force-angle patterns were explored relative to established performance metrics, such as competition level and boat velocity. Separate *bf*PCAs were conducted for the bow and stroke sides. A summary of competition level and boat velocity findings are as follows:

Competition level: Irrespective of boat-side, separate discriminant function analyses revealed that rate of force development at the start of the drive phase contributed substantially to discrimination of performance when investigating competition level differences. The bow-side discriminated more effectively than the stroke-side through a higher correct classification of rowers (bow = 74.1% and stroke = 59.3% correct classification). For the bow-side, spending less time in the first half of the drive phase was also identified as an important characteristic, and alluded to a potential asymmetrical oar angle offset being present between the stroke-side and bow-side for sculling rowers at a higher level of competition.

Boat velocity: For both the bow and stroke-sides, a pronounced early peak in relative force and a drop in relative force leading into square-off featured significantly in multiple linear regression models, used across both sides of the boat. This demonstrated that a more pronounced '*front-loaded*' profile rather than a '*rectangular*' profile may be required for increasing boat velocity in a single scull boat.

Third experimental study: The previous two experimental studies investigated force observed as a relative percentage of each rower's peak force. Additionally, the previous study used FDA techniques to analyse each side of the boat independently in an effort to preserve important characteristics of force patterns that may be unique relative to the side of the boat being analysed. This study investigated asymmetry across the entire stroke cycle using a novel statistical approach. First a global measure of asymmetry across the entire stroke cycle was measured. This was defined using methods taken from previous research analysing foot-stretcher forces in ergometer rowing. Local measures of asymmetry (observed at different phases of the stroke cycle) were then explored using a difference function, defined as the difference between forces applied on both sides of the boat. This allowed for bilateral force application to be visualised as its own continuous structure and also displayed differences in an absolute unit of measure (Newtons, rather than a relative percentage). A modified FDA technique, analysis of characterizing phases (ACP) was applied to this difference function to identify phases of interest across the stroke cycle. Differences in these patterns of asymmetry were explored relative to competition level, with a summary of these findings below:

Competition level: International rowers significantly differed from national rowers for amounts of global asymmetry across the entire movement cycle, when assessed using univariate ANOVAs. International athletes were significantly ($p < 0.05$) more likely to have increased global asymmetry across the entire stroke cycle, indicating that these athletes use asymmetries in a more functional way during on-water sculling. ACP also revealed that the structure of these asymmetries could potentially differ relative to a rower's competition level. Four of the five *f*PCs (obtained using ACP) revealed statistical significance between international and national athletes. The combined findings of these four *f*PCs indicated asymmetric trends for international athletes, where stroke-side pin force led bow-side pin force at the start of the drive phase until half way through the drive phase. This trend then reversed through the second half of the drive phase, with bow-side force leading stroke-side force. Decreased within-athlete variability was also noted for international athletes near the middle of the drive phase.

Implications

Development of an evidence base

This thesis has begun the development of a much needed empirical evidence base, with potential to progress scientific understanding of differences in the characteristics of force profiles, measured during on-water rowing (Ishiko, 1971; Mallory, 1989; Wing & Woodburn, 1995; Hill, 2002). There have been numerous calls in contemporary literature for further research to be focused upon developing a better understanding of these profiles and how they relate to metrics of skill and performance (Baudouin & Hawkins, 2002; Soper & Hume, 2004; Seiler, 2015).

Previous literature has often focused on theoretical biomechanical concepts for understanding the relevance of force profile characteristics and how they relate to better rowing performance. For example, Millward (1987) used a mathematical model to represent different theoretical force-time profiles. Equations taken from this model shifted basic harmonic characteristics of each force-time profile in an effort to understand the link between force profile shape changes and boat velocity. Martin and Bernfield (1979) also noted the theoretical idea that force applied in the direction of the boat (perpendicular to the boat's longitudinal axis) was more effective and directly related to intra-cyclical increases in boat velocity. This assumption was made while assessing international level sweep rowers (in a racing eight). Similarly, Roth, Schwanitz, Pas and Bauer (1993) also speculated from a theoretical physiological perspective that that an increased rate of force application and faster velocity in the first half of the stroke would lead to acceleration of more body parts, which could trigger a higher metabolism and subsequently decreased work efficiency. Kleshnev (2006) and Nolte & Morrow (2002) have also theoretically proposed that a front loaded or front peaked force profile is mechanically associated with a more evenly distributed propulsive power profile. Finally, there is also theoretical support for the idea that increased force production, specifically at the catch or finish of the rowing stroke, is related to better rowing efficiency, as this theoretically takes advantage of lift forces occurring at the blade (Caplan & Gardner, 2007a).

In addition to the large amount of theoretical work presented, results from small cohort experiments, or use of exemplar data in the form of case studies, have also drawn upon in an effort to understand and rationalise differences in force profiles, when rowers are observed in the daily training environment. Smith and Loschner (2002) have used exemplar data from a skilled and unskilled pair and an elite junior single sculler to demonstrate the practical utility of novel rowing instrumentation systems and feedback methodologies that have potential to optimise on-water kinetics. Wing and Woodburn (1995) have also evaluated aspects of force profile consistency for four sweep rowers over a long training run, and Baudouin and Hawkins (2004) assessed whether a rowing crew's performance was predictable based on their total propulsive power, synchrony and total drag contribution using only a single rowing pair. Consequently, experimental design issues related to the use of small sample sizes could also have contributed to the present lack of consensus regarding '*which*' aspects of force profiles are relevant for better performance.

Content from this thesis has contributed directly to the development of an experimental evidence base in two ways. Firstly, work from this thesis has provided a suitable theoretical framework that can be used in subsequent research, to understand how different interacting factors influence differences between rowers in patterns of force profiles. In the present body of work, Newell's (1986) theoretical model of constraints has been referred to. In motor control literature this has served as an established theoretical framework for rationalising differences between and within individuals during execution of different tasks (Glazier, 2015). Secondly, by using this theoretical framework, this thesis has contributed hypothesis driven experimental findings, which can be used to understand why differences in these force profiles may be present between rowers.

In this thesis, the influence of gender as an organismic constraint was explored. Clear differences in characteristics of force profiles (when expressed as relative force) were demonstrated between rowers as a factor of gender, with females being more likely to resemble movement patterns where a reduction in relative force application leading into and away from the square-off position (oar being perpendicular to the longitudinal axis of the boat). This indicated, that for females, a noticeable peak in relative force application is reached earlier in the stroke cycle and then is not maintained through the second half of the drive phase when compared to male athletes. These findings support the idea in Smith, Galloway, Patton and Spinks (1994) that males and females can row differently on-water. These researchers were able to correctly classify 88% of athletes for gender using a range of discrete variables. These variables were also directly related to content derived from the force-angle profile in on-water sweep rowing.

The specific differences in this thesis, noted for gender are also supported by findings of other experimental research. Differences in relative joint energy and power contributions to overall propulsion have been noted between males and females during on-water rowing. Females have been found to exhibit smaller arm power than males (Kleshnev, 2000), and this finding was also supported in ergometer research where the proportion of angular shoulder energy expenditure to total energy was lower in females across a number of stroke rate conditions (Attenborough, Smith & Sinclair, 2012). It is known that reduced strength capabilities in females are more pronounced in the upper body when compared to males (Wilmore, 1974). This reduction in upper body strength for females could be contributive to differences noted in relative joint power contributions and could also be related to the drop in relative force production seen for females (within this thesis).

The presence of neuromuscular factors between male and female rowers may also assist in explaining why a gender effect was present in this thesis. In a study evaluating differences in muscle activity patterns in slide and stationary ergometer testing sessions, a gender effect in serratus anterior (SA) neuromuscular activity patterns was observed independently of any ergometer condition that was explored (Vinther et al., 2013). The neuromuscular activity pattern demonstrated that both male and female rowers possessed increased SA involvement in the second quarter of the drive phase, followed by a reduction in SA involvement towards the end of the drive phase. The increase observed during the second quarter of the drive phase was, however, twice the magnitude ($p < 0.05$) in female rowers when compared to males. Consequently, female rowers demonstrated peak SA n activity in the second quarter of the drive, whereas male rowers produced peak SA activity in the final quarter of the recovery phase (Vinther et al., 2013). Although this was a coincidental finding for Vinther et al., these results demonstrate that differences in the neuromuscular contribution of other parts of the body (thoracic region, etc.) exist between males and females, and these difference could also be contributive to differences found between male and female rowers in this thesis.

Acknowledging differences between male and female rowers in patterns of force production is crucial for correct administration of sports science (and particularly biomechanics) testing of female athletes in the daily training environment, and illustrates the need for normative data to be collected independently for each gender. If female rowers are likely to have different anthropometric constraints, relative strength differences across different sections of the body and also altered neuromuscular activity patterns during rowing skill execution, it cannot be expected that male and female rowers will possess the capability to perform identical movements. This will affect results on technical variables such as force profiles. These differences should be considered by coaches and sport science staff when administering feedback and training interventions that are designed to optimise performance in on-water single sculling.

This body of work also investigated the effect of boat-side on force profile characteristics. In this experimental research, boat-side acted as a task constraint, given that a mechanical rigging offset is present in single sculling, which has the potential to unbalance oar kinematic and kinetic characteristics during the stroke cycle (Loschner, Smith, Barrett, Simeoni & D'Helon, 2000). In this thesis a mixed ANOVA revealed statistically significant differences between bow and stroke side relative force patterns for four separate patterns of variation (identified through four separate *bf*PCs). These significant findings were also independent of any gender interactions. The combined findings for three of these patterns indicated that bow-side force may act as the driver of peak force application across the stroke cycle in single sculling. The fourth pattern also alluded to a deeper catch position and earlier finish position for the bow-side when compared to the stroke-side alluding to a potential offset being present in the horizontal angle of the oar. When observed together, these patterns alluded to the stroke side potentially possessing more of a control or steering role over stroke mechanics, given that the force application on the stroke side was more likely to rise at different time points before and after maximum force and also start force application later, spatially, in comparison with the bow side. This functional asymmetry in on-water sculling is logical as the oar handles must overlap when the blades are perpendicular to the boat due to mechanical constraints related to oar inboard length. Hypothetically, this could result in upper body asymmetry across the entire stroke cycle. In the present study all boats were rigged so that when the oar handles overlap the left hand was on top of the right hand. This mechanical asymmetry may have led to the discrepancy noted in force patterns and peak forces in the present study. Acknowledging differences in patterns of force application that can be attributed to boat-side characteristics in single sculling is important, given perfect asymmetry across both sides of the boat cannot be assumed. Differences noted for boat-side in this thesis should be considered by coaches and sport scientists when implementing technical intervention with athletes.

Methodological advancements

Statistical analysis of force profiles: In addition to the experimental advancements, this thesis has also contributed very important guidelines and recommendations for use of FDA techniques (*f*PCA and *bf*PCA) with biomechanical data. These recommendations can be used as a template for future research evaluating other factors that could influence differences in characteristics of force profiles. Statistical approaches from FDA used in this thesis, have managed to negotiate some of the shortcomings present in pervious analytical methods that were applied to force profile data.

Traditionally, two main analytical strategies have been used to understand performance related characteristics of force application. Firstly, discrete point analysis (DPA) (Richter, Marshall & Moran, 2014) has been used frequently through the examination of pre-selected key points on each of the force profiles. These have included magnitude of peak force and position of peak force temporally and spatially. Secondly, data reduction strategies involving the calculation of indexes that relate to relevant characteristics of force application have also been used. Such data reduction strategies have included measures of area under the force-time and force-angle profiles, mean-to-peak force ratio, and measures of smoothness. There are noted issues for using both of these data analysis strategies. Both discrete point analytical (DPA) strategies and basic data reduction strategies aim to reduce the dimensionality of a time-series through examination of pre-selected measures or sections of a time-series. These selected data points or sections of a time-series are commonly chosen prior to any form of analysis and require considerable apriori knowledge of the skill being analysed. There are some limitations involved with these approaches. Pre-selection of important features of characteristics is strongly dependent upon previous knowledge and has the potential to discard relevant pieces of information (Dona, Preatoni, Cobelli, Rodano & Harrison, 2009; Donoghue, Harrison, Coffey & Hayes, 2008). This was not the case with the experimental research conducted within this thesis, where the characteristics known to be affected by particular constraints, or deemed important for better rowing performance, were still unknown. DPA and data reduction approaches used in contemporary rowing literature also do not necessarily preserve all structural aspects of the original data (characteristics of variability patterns that are present in a group of continuous time-series), often resulting in large sums of potentially important information being distorted or misrepresented.

Additionally, substantial research into relevant characteristics of force application has focused on force-time profiles, with minimal statistical rigor applied to the force-angle profile as a part of previous studies (other than assessment of peak force location). This is understandable given that the force-angle profile is a complex coordinative structure, composed of two non-linear time-series variables. DPA techniques and simple data reduction strategies have the ability to be applied more readily to force-time data, given its simpler univariate nature. These same statistical approaches are however, not as easily applied to the force-angle profile. It is believed that thesis has provided suitable methodological and analytical approaches that can negotiate shortcomings of statistical approaches found in contemporary literature. Techniques from FDA preserve all aspects and structures (or patterns) of variability embedded in the original force profiles. Additionally, *bf*PCA has the potential to preserve all aspects of the original data in force-angle profiles, thus allowing for the development of experimental evidence related to this useful technical display of force across the stroke cycle.

Statistical analysis of asymmetries: A modification of the FDA technique functional principal components analysis was also successfully demonstrated to be a suitable data reduction tool, which could complement already existing strategies for assessing asymmetries in rowing. Previous research evaluating rowing kinetic asymmetry measures often involved the use of indexes, which describe the overall magnitude of foot-stretcher force asymmetry during rowing, in ergometer testing conditions (Buckeridge, Bull & McGregor, 2014; Fohanno, Nordez, Smith & Colloud, 2015). Similarly differences in discrete points such as peak force have been reported in on-water research (Elliot, Lyttle & Birkett, 2002; Loschner, Smith, Barrett, Simeoni & D'Helon, 2000). The use of analysis of characterizing phases (ACP) allowed for a more holistic investigation of asymmetries across the entire stroke cycle. It also allowed for the observation of asymmetry *direction* (i.e. tracking the side of the boat that was dominating the direction of force asymmetry). Chapter seven in this thesis demonstrated the benefit of adopting a mixed analytical approach for investigation of asymmetries. The use FDA (through *f*PCA and ACP) in conjunction with an established symmetry index, has built upon previous work exploring the presence of asymmetries in ergometer research, where only symmetry indexes were used. This approach has allowed for an intuitive comparison of global and local asymmetry differences all being described in the same unit of measure (in this instance: Newtons).

Limitations and Delimitations

Limitations

Environmental conditions: One known limitation of experimental research in this thesis, common to all on-water biomechanical testing, is the effect of environmental conditions on rowing performance. Potential effects of environmental factors such as of temperature, tail, head and cross winds on boat velocity are have been acknowledged (Smith et al., 2015). In the present study inconsistent weather conditions were avoided. The testing sessions used to collect data were performed early in the morning in calm water and minimal wind conditions to reduce any potential impact of environmental factors. The weather conditions were considered by coaches and athletes as acceptable and varied between still to a tail wind of 0.1-2.0ms^{-1}.

Measurement of pin-forces: Another potential limitation in this thesis is the location of where force was measured. It could be argued that the measurement of pin forces rather than actual propulsive force measured at the blade, was a mechanical limitation in this thesis. Characteristics of force applied at the blade can be inferred from force applied at the pin (measured using the ROWSYS system in this thesis). These inferences can be made as force applied at the handle of the oar is directly transferred to the blade via the pin. Blade force is however, the only source of boat propulsion (Soper & Hume, 2004). Known theoretical information regarding the way that oar stores elastic energy (Caplan & Gardner, 2007b) during the drive phase, may also result in different characteristics of how the blade applies propulsive force relative to how the pin measures the propulsive component of force at that location. Despite this, the use and acceptance of propulsive pin forces as technical measures in the daily training environment has been established (Spinks, 1996; Smith & Loschner, 2002). It is not believed that the collection of pin forces in this thesis will substantially affect findings, outcomes or practical implications from this body of work.

Analysis of characterizing phases: There are also potential statistical limitations from using analysis of characterizing phases (ACP) in chapter seven. One reason for using FDA techniques such as *f*PCA is that they can circumvent statistical problems that may be present when analysing waveforms as a set of discrete data points, rather than a functional entity. One major issue brought about from the application of multivariate statistical techniques such as conventional PCA, when applied to continuous waveform data, is related to independency of data points. In PCA points on a curve are assumed to be independent of each other, but in reality it is known that any point on a curve is correlated to the data points that precede and follow that point (Harrison, 2014). *f*PCA negotiates this problem by representing each curve as a functional entity, described by coefficients. ACP starts with the formation of a functional basis for each of the curves and performs an orthogonal decomposition on the data in a functional form (hence beginning *f*PCA). After this stage however, each original curve is re-sampled from function back into a set of discrete data points for the calculation of a modified *f*PC score, also referred to as a similarity score (defined as ACP_{Score} in chapter seven of this thesis) derived from Richter, O'Connor and Moran (2014). Resampling of the function takes place in an effort to identify all points within a *key* phase, with this phase being used for calculation of similarity scores. This shifting from a function to a set of discrete points, although intended to sharpen the accuracy of score calculation, is questionable, given that the points constituting each curve are considered to be independent measures again, and thus similar problems regarding the use of this technique (to that found for PCA) may exist. There is also the issue of what frequency (Hz) the data should be resampled at and whether lower frequencies may not sample at a high enough number of data points to get a score that is accurately reflective of the difference between each curve and the average curve for the key phase of interest.

Secondly, as a part of *f*PCA each original curve is weighted relative to the principal component function as a part of *f*PC score calculation. This occurs when the *f*PC function (expressed with coefficients that define the area under the *f*PC function as equal to one) is multiplied by each original function in the data set. In doing so, every structural aspect of the *f*PC function is taken into consideration for calculation of *f*PC scores. None of these structural aspects are taken into consideration when calculating similarity scores during ACP however, as similarity scores involve equations that describe area difference between two curves, for a key phase, expressed in the magnitude, time or magnitude-time domain. As such, this does not truly consider all structural components of variability described by *f*PC functions when similarity scores are calculated. In chapter seven of the present study, ACP was still preferred over *f*PCA as the equation used to calculate the similarity score was modified from a total area measure, as conventionally used, to an average Euclidean distance measure (similar to a root-mean-square-difference). This was preferable as the global symmetry index used in rowing research, and calculated across the entire stroke cycle (Fohanno, Nordez, Smith & Colloud, 2015), was also expressed as an average Euclidean distance. This allowed for a more intuitive comparison between the measures of global and local asymmetry, with them both being referenced in the same units of measure, and calculated using similar approaches.

Delimitations

On-water testing: Although athlete testing in a laboratory settings has the potential to create a controlled environment, comparative studies between on-water and ergometer rowing have highlighted that ergometer rowing is not truly representative of the on-water sculling movement (Dawson, Lockwood, Wilson & Freeman, 1998; Elliot, Lyttle & Birkett, 2002; Lamb, 1989; Li, Ho & Lin, 2007). More specifically, and with particular relevance to the present thesis, on-water force profiles are known to differ from those seen on the ergometers and it is therefore imperative that force waveforms were collected in a representative on-water environment (Li et al., 2007).

Stroke rate: Only a single stroke rate was selected for analyses in this thesis. This was put in place to act as a controlled task constraint. The potential effect of different stroke rates on force profile differences will be discussed further in the *future directions* part of this chapter.

Rowing and boat type: All experimental research in this body of work was conducted in single sculling boats. This was conducted to act as controlled task constraints, negating the effect of both rowing type and seat position. The potential effect of both of these factors will also be discussed further in the *future directions* part of this chapter.

Alternative FDA statistical tests: Although other statistical techniques could have been explored from within the FDA repository of statistical techniques, only *f*PCA and *bf*PCA were used. Other statistical techniques such a functional regression techniques, functional ANOVAs and functional *t*-tests (all available in Ramsay & Silverman, 2005) exist and may also have applicable use with biomechanical data. *f*PCA and *bf*PCA were used in the present study as they have had proven use with biomechanical data (Ryan, Harrison & Hayes, 2006; Harrison, Ryan & Hayes, 2007).

Future directions

Constraints

A number of other potentially constraining factors can be explored using the same experimental and statistical approaches outlined in this thesis. The following sections will cover some potential organismic and task constraints, which could influence characteristics of force profiles.

Organismic constraints: The main organismic constraint with potential influence over differences in force profile characteristics is anthropometry.

Anthropometry: Different anthropometric constraints could potentially influence shape characteristics of force profiles. A rower's anthropometric characteristics have been noted as determinants for better rowing performance (Soper and Hume, 2004). Highly skilled rowers are significantly taller and exhibit a greater overall body mass, as well as having longer segments (forearms and thigh lengths) compared to lower ranked rowers (Hahn, 1990). Barrett and Manning (2004) also correlated 2000 m rowing competition times with anthropometric measures and identified variables such as increased body mass, height, BMI, arm span, knee-floor height and hip compression angle as strong indicators of rowing performance. Anthropometry has also been noted as an influential factor on characteristics of rowing technique. Greene et al., (2009) investigated the effect of anthropometric differences, in the form of shank-to-thigh length ratio relative to the timing and magnitude of joint powers produced during the drive phase. Results of this study demonstrated that time to half lumbar power generation was earlier in shorter shank rowers ($p < 0.05$) compared to longer shank rowers. Rowers with a shorter shank also displayed earlier lumbar power generation as a consequence of restricted rotation of the pelvic segment, requiring increased lumbar extension. Earlier lumbar power generation and extension did not appear to directly affect performance measures of the short shank group in that study, and thus could be attributed to a technical adaptation developed relative to an anthropometric constraint, to optimise rowing performance. Identifying the presence of similar anthropometrically driven adaptations to technique displayed through characteristics of on-water force profiles would be of great interest in future research.

Task constraints: A number of task constraints (not explored through experimental research in the present body of work) should also be explored in future research. These constraints are inclusive of rowing cadence changes (or stroke rate), rowing type, side of the boat (particularly for sweep rowing) and seat position.

Stroke rate: Although not a task constraint in competition, different stroke rates are used frequently in the training environment as a moderator of training intensity. The stroke rate (strokes/min) is defined as the number of strokes divided by one minute of time (Soper & Hume, 2004). As the stroke rate increases peak force has been demonstrated to occur earlier in the drive phase (Schneider, Angst & Brandt, 1978; McBride, 1998). McBride has reported that peak oar force occurred 3.4% or 3 degrees earlier when the stroke cycle increased from 20 strokes per minute to a race pace rating of 35.7 strokes per minute in sweep rowing. These timing differences of peak force at different stroke rates indicates that shape characteristics may also be influenced by changes in rowing cadence.

Rowing type: It is also possible that rowing type (i.e. scull or sweep rowing) could influence characteristics of force profiles. Elaborate kinematic investigations of movement patterns in ergometer rowing have been conducted for simulated sculling and sweep ergometer rowing. Strahan et al., (2011) has demonstrated that movement patterns for these two types of rowing differ with sweep rowing demonstrating a greater lateral bend throughout the stroke, due to increased movement of the upper lumbar and lower thoracic regions. Sweep rowing also displayed a greater magnitude of axial rotation at the catch. Differences in other technical biomechanical variables have also been demonstrated when comparing sculling and sweep rowing in an on-water testing environments. Burnett, Doyle and Elliot (2004) demonstrated significantly larger catch angles and stroke arcs for sculling on both sides of the boat when compared to sweep rowing. The results of this study were similar to other studies, where sculling arcs between 100° and 110° and sweep arcs between 80° to 90° were noted (eg. Zatsiorsky & Yakunin, 1991). Burnett Doyle and Elliot (2004) also demonstrated significant differences between scullers and sweep rowers for both catch and finish height measures. Left side sweep rowers demonstrated a significantly lower ($p < 0.05$) finish height relative to the left hand of scullers. Additionally, the catch height for the right hand was significantly higher ($p < 0.05$) for scullers relative to right side sweep rowers. It is plausible from these findings that characteristics of propulsive force application across the stroke cycle may also be affected by the type of rowing involved. This is particularly true for differences in the force-angle profile, as results demonstrated by Burnett Doyle and Elliot (2004) were related directly to oar kinematic changes between the two rowing types.

Side of the boat: In the smallest boats for sculling and sweep rowing there are also some known differences for how forces interact across both sides of the boat. Sculling side-of-boat differences have been mentioned in the literature review and were also one focus of experimental findings in chapter four of this thesis. Differences across the two sides of the boat for sweep rowing has also been an area of interest in contemporary literature. McBride (1998) has reported that for stroke seat rowers in a highly skilled pair, an average of 13.8% greater peak oar-lock force was present when compared to bow seat rowers (Soper & Hume, 2004). Also, when rowing at 32 strokes per minute, Roth, Schwanitz, Pas & Bauer (1993) demonstrated greater power for stroke seat rowers relative to bow seat rowers in a pair. Further to this, descriptive findings demonstrated a more front peaked force profile for the stroke seat. These findings were also supported by Smith and Loschner (2002) who demonstrated that for a highly skilled rowing pair, the stroke rower reached peak force earlier than the bow rower after applying a greater amount of force between 10% and 20% of the stroke cycle. The bow rower applied a greater amount of force closer to the finish. The opposite trends were present for an unskilled pair, demonstrating that this offset between the two sides of the boat were possibly intentional for the highly skilled rowers. The skilled pair in this study, likely compensated for the presence of an unbalanced moment that was the result of the seats being staggered relative to each other (Smith & Loschner, 2002).

Seat position: The clear mechanical offset required for smooth boat movement in pair sweep rowing is as much boat-side issue, as it is a seat issue, given that the rowers are not aligned parallel to each other in the boat, but staggered relative to each other. This problem is very specific to pair rowing in sweep boats. Research evaluating characteristics of force application in larger sculling or sweep crew boats has often advocated for synchronous force application of all crew members. Synchronous coordination of crew members is generally thought the enhance efficiency of rowing, as poor synchronization will create a torque about the boat and subsequently increase drag (Baudouin & Hawkins, 2002). In highly skilled international rowers, differences between crew members in the shape of force profiles have been noted to be more detrimental to performance than differences in other measures such as area under the force profile (Wing & Woodburn, 1995, Hill, 2002). These findings have been noted for much larger crew boats such as racing eights. Despite this there is limited information available regarding the importance of force profile characteristics for different seat positions in other multiple crew member boats, such as racing fours in sweep rowing and quadruple sculling boats. Additionally for multiple crew member boats that are symmetrically rigged, Coker, Hume & Nolte (2008) alluded to the potential for using force profiles that enable the crew average force profile to resemble a longer level of high force production across a larger percentage of the drive phase, resembling more of a rectangular profile. These often conflicting ideas regarding the relevance of force application for different seat positions in different multiple crew member boats demonstrates this to be a very important area for future research.

Athlete monitoring

The statistical processes used, recommendations outlined and advancements in asymmetry measures within this thesis, could also assist in the development of more rigorous approaches for athlete monitoring. Traditionally athlete monitoring approaches have been dependent upon the measurement of variables related to training and competition workload

(Halson, 2014) and often focus on basic self-report measures or physiological variables. The statistical approaches used in the present body of work provide an avenue for the potential capture of movement quality measures during rowing performance. These could be collected and monitored in conjunction with training workload measures. With the capture of such information, there is potential for athlete monitoring to serve a dual purpose, working towards performance optimisation and reduction of injury risk.

Performance: Understanding the way that an individual athlete may vary their own force signature is an under-researched area and potentially important aspect of athlete monitoring. Research has largely assumed that because the harmonic structure of force signatures is stable, between-athlete differences in these signatures are of more importance (Wing & Woodburn, 1995). Some studies have advocated for the exploration of measures that comment on a rower's within profile variability, such as the propulsive force-time standard deviation curve, calculated using a series of rowing strokes (Wing & Woodburn, 1995; Hill, 2002). To date though there is limited information regarding the importance of within-rower variability characteristics (for force profiles), especially when investigated relative to metrics of better rowing performance. Force profiles or asymmetry functions used in this thesis can be monitored in a similar way to other variables (Halson, 2014) and normative data can be developed around individual athletes. This would allow for individualised changes to be assessed relative to other training factors such as periodization and coaching interventions.

Injury: There are already established relationships between kinetic variables and different rowing related injuries, in both ergometer and on-water rowing. A common rowing injury is the rib stress fracture. These are brought about as a consequence of different kinetic factors. Karlson (1998) noted that rib stress fractures in rowing are the result of contractions of the serratus anterior and external oblique muscles, with each muscle acting to cause a repetitive bending force to the lateral segment of the rib. The eccentric contraction of the serratus anterior muscle produces an ‘upward’ and ‘outward’ pull on the rib as the scapula is fixed relative to the load endured by the upper extremities (Karlson, 1998). The layback position and simultaneous exhalation pull the rib down and inward as a consequence external oblique muscle’s action. Athletes with rib stress fractures often report maximum pain at the finish of the stroke. It is known that rib stress fractures commonly occur during periods of intense training with a relatively low stroke rate and high load per stroke (often during long aerobic training pieces on the rowing ergometer) (Hosea & Hannafin, 2012). Although rigorous hypotheses would need to be built around the potential importance of force profile characteristics and features that could be associated with the aetiology or symptoms of kinetic based injuries such as stress fractures, some immediate starting points from the literature would be investigation of differences in force-angle patterns at the start of the stroke cycle due to the increased impulse (and subsequent kinetic load) generated at this part of the movement; and also force application at the end of the stroke cycle as this coincides with the problematic ‘layback position’ and also occurs at the point of the stroke cycle where pain is most commonly prevalent.

Feedback technology

If performance differences within-athletes are evident from monitoring of technique through evaluation of force profiles, there may also be potential for use of techniques such as *f*PCA or *bf*PCA in feedback protocols. Use of an FDA driven approach in this circumstance would involve the identification of core characteristics associated with better performance. These characteristics could then be used to develop targeted technical feedback interventions. The potential benefits of real-time or terminal feedback using information related to force profiles has already been demonstrated by Spinks and Smith (1994) and Smith and Loschner (2002). Spinks and Smith (1994) used a template and concurrent visual feedback of the force-angle profile in ergometer rowing to investigate whether concurrent feedback could improve the consistency of the rowing performance. The results of their study indicated that: (1) concurrent visual feedback can be used to modify patterns of work output during maximal rowing and to enhance maximal rowing performance; (2) there is biomechanical support for an even pace race strategy in competitive rowing; and (3) examination of the force-angle profile may allow coaches to identify biomechanical factors which *limit* rowing performance. Similarly, Smith and Loschner (2002) demonstrated that measurement and display of force-time and force angle profiles in on-water rowing provided unique high-quality augmented feedback, which provided rich information regarding aspects of rowing technique. Furthermore, this feedback was highly valued by coaches.

The use of force profiles in concurrent feedback protocols has proven useful for optimising performance in rowing in these contexts, but there may be potential for further refinements to rowing feedback interventions, particularly for on-water rowing. Anderson, Harrison and Lyons (2005) provided interventions using both summary and detailed feedback to rowers in attempts to improve rowing consistency. Information delivered during summary feedback was composed of a percentage score based on the time spent within an ‘acceptable’ performance bandwidth. As a part of summary feedback ‘100%’ indicated that all biomechanical data existed within the acceptable performance bandwidth and ‘0%’ indicated that no data existed within the acceptable performance bandwidth. Percentage scores were calculated for measures related to both the upper body (shoulder acceleration) and lower body (hip acceleration). The detailed feedback intervention in this study, involved a graphical representation of this same acceptable performance bandwidth across the stroke cycle, in real-time, their actual kinematic data superimposed on the acceptable performance bandwidth. Results indicated that performance consistency significantly increased for detailed feedback when compared to both no feedback ($p < 0.01$) and summary feedback ($p < 0.05$) interventions. These findings are particularly interesting, given that detailed feedback used a targeted zone (continuous performance bandwidth) in conjunction with real-time data.

The same premise could be investigated in future experimental research with force profile data, where FDA techniques such as *bf*PCA could be used identify important patterns in force-angle data that are relevant for better rowing performance. These patterns (displayed in the form of *bf*PC functions) could then be used to deform of modify a rowers' force-angle profile, by adding or subtracting the *bf*PC functions to a rower's average force-angle profile, thus creating a target trajectory to be followed by a rower within a concurrent feedback intervention. Constants directly proportionate to *bf*PC scores, which are commonly used to scale the amount of variability displayed in *bf*PC function graphs (Ramsay & Silverman, 2005) can also be used to expand and collapse the target trajectory to form appropriate target zones or thresholds for a movement to be executed within.

References for this chapter are included in the list of references at the end of this thesis

Conclusion

The five aims stated at the end of the *Introduction* have been achieved. The applicability of the FDA technique, functional principle components analysis (*f*PCA), for use with on-water rowing force profile data (using force observed relative to time or percentage of the stroke cycle) has been explored. When applied to the force-percentage profile, *f*PCA was effective in retaining structures of variability that were present in the original waveform data. It was noted however, that considerations must be given for the use of different data preparation strategies such as temporal normalisation of data and removal of unwanted or erroneous forms of variation prior to applying *f*PCA with these profiles. Limitations for the use of *f*PCA with the force-time profile were also present, mainly as a consequence of profiles possessing varying lengths of data points. Consequently, some form of experimental compromise is required for *f*PCA to be applied to this data. The applicability of the FDA technique, bivariate functional principle components analysis (*bf*PCA), for use with force-angle profiles was also explored. In this thesis, strong potential for the application of *bf*PCA to force-angle profiles was demonstrated. Concerns related specifically to differences in within-parameter variability were raised, but solutions to this potential problem were also offered through the form of within-parameter normalisation strategies.

The influence of the organismic constraint of rower gender and task constraint of side of the boat on patterns of force-angle profiles was also explored in single sculling testing data. Results demonstrated that differences in force-angle profile characteristics could be attributed in some capacity to rower gender. This involved female rowers displaying a reduction in relative force application leading into and away from the oar being perpendicular to the longitudinal axis of the boat, with this being present across both sides of the boat. Similarly, assessment of boat-side differences alluded to the presence of consistent asymmetries in force production across the entire stroke cycle. The results from this thesis indicated that bow-side forces seemingly acted as a driver of power and peak force production, while stroke side forces may have acted as a mediator of propulsive forces with an additional potential role in steering due to asymmetrical mechanical offsets that are present in sculling.

The relationship between characteristics of force-angle profiles and metrics of rowing performance was also explored. Performance was assessed using both level of competitive representation and also average boat velocity. Results from this thesis demonstrated that differences force-angle profile characteristics were potentially attributed to metrics of rowing performance. Interestingly different metrics of performance were described by different characteristic patterns of the force-angle profile. Rate of force development was demonstrated as a potentially important characteristic for international rowers (with this present across both sides of the boat and more notably on the stroke side). Additionally for the bow-side, spending less time in the first half of the drive phase was also identified as an important feature for international rowers. A more pronounced front peaked profile was associated with a higher average boat velocity during testing. This was present across both sides of the boat. These results support the idea that technical characteristics required for better performance in a single sculling boat, may not align with the characteristics required for selection in larger crew boats for international level competition.

The role of asymmetries, and their relationship with rowing performance, was also assessed, with performance measured using level of competitive representation. In this thesis, global and local measures of asymmetry were assessed across the entire movement cycle and differences were revealed for competition level. International level athletes were more likely to utilise an asymmetry strategy with increased stroke-side force early in the drive phase. The first half of the drive phase was also found to be a functionally adaptive part of the rowing stroke cycle with higher levels of between athlete and within athlete asymmetry variation being reported during this part of the stroke cycle.

To conclude, it is believed that this body of work has contributed significantly to the areas of both sports biomechanics and sports science of on-water rowing. Firstly, this thesis has identified, evaluated, added and critiqued particular techniques from functional data analysis, for suitability with sports biomechanics data. Secondly, this thesis has used an existing theoretical framework, reproducible experimental design features, and innovative statistical practices and provided relevant experimental findings, which together have progressed the ability to holistically understand the relevance of differences between rowers in characteristic patterns of force profiles or signatures. Implications related to the results of this thesis have been outlined and ideas for future research have also been listed.

APPENDIX

Appendix List

1. Appendix 1: Ethical Clearance
2. Appendix 2: Conference Presentations

Appendix 1

Data used in this PhD thesis was collected as a part of the PhD thesis, "*Improving Rowing Performance*" (2000) and was approved by the Human Research Ethics Committee (approval number 00/03/53). The Chief Investigator was Dr Richard Smith and the PhD student was Constanze Loschner (now Dr. Conny Draper). The project was completed successfully with no adverse events and the PhD thesis passed examination in 2005.

Advice was sought on the 17th of August 2016 by the postgraduate student (John Warmenhoven) and supervisory panel, from the University of Sydney Human Ethics Committee as to whether additional ethical approval would be sought. As the data is non-identifiable as per the NHMRC definition (i.e. data that have never been labelled with individual identifiers or from which identifiers have been permanently removed, and by means of which no specific individual can be identified), no further ethical approval was required.

Attached in this Appendix is the original *Ethical Approval*, *Subject Information*, *Protocol Information* and *Expression of Interest* for collection of this data.

Signed: [redacted] [redacted] Date: 21/04/2017

Professor Richard Smith John Warmenhoven

ETHICS APPROVAL

COPY

HUMAN ETHICS COMMITTEE
The University of Sydney
Room K4.01 Main Quad A14
Sydney 2006
Tel: (02) 9351.4474 Fax: (02) 9351.4812 E-mail:human.ethics@reschols.usyd.edu.au

Dr R Smith
School of Exercise and Sports Science
C42

05 April 2000

Dear Dr Smith

Title: *Improvement of rowing performance*

Ref No: ***00/03/53***

I am pleased to inform you that the Human Ethics Committee at its meeting on 28 March 2000 approved your protocol on the above study. Please note that the approved protocol is in accordance with the original protocol submission.

In order to comply with the National Health and Medical Research Council guidelines, and in line with the Human Ethics Committee requirements the Chief Investigator's responsibility is to ensure that:

(1) The individual researcher's protocol complies with the final and Committee approved protocol.
(2) Modifications to the protocol cannot proceed until such approval is obtained in writing.
(3) The confidentiality and anonymity of all research subjects is maintained at all times, except as required by law.
(4) All research subjects are provided with a Subject Information Sheet and Consent Form.
(5) The Subject Information Sheet and Consent Form be on University of Sydney letterhead and include the full title of the research project and telephone contacts for the researchers.
(6) The following statement appears on the Subject Information Sheet:
Any person with concerns or complaints about the conduct of a research study can contact the Manager of Ethics and Biosafety Administration, University of Sydney, on (02) 9351 4811.
(7) The standard University policy concerning storage of data should be followed. While temporary storage of audiotapes at the researcher's home or an off-campus site is acceptable during the active transcription phase of the project, permanent storage should be at a secure, University controlled site for a minimum of five years.
(8) A progress report is provided by the end of each year. Failure to do so will lead to withdrawal of the approval of the research protocol and re-application to the Committee must occur before recommencing.
(9) A report and a copy of the published material is provided at the end of the project.

Yours sincerely

[redacted]

pp *Professor Barry Baker*
Chairman
Human Ethics Committee

cc. *Ms C Loschner, U32/23 Charles St, NSW 2046*

SUBJECT INFORMATION SHEET

UNIVERSITY OF SYDNEY
Faculty of Health Sciences

School of Exercise and Sport Science,
East Street (P.O. Box 170), Lidcombe, NSW, Australia 2141
Tel: 61-2-9351-9137 or 9351-9612 Fax: 61-2-9351-9204

Improvement of Rowing Performance.

10 March, 2000

SUBJECT INFORMATION SHEET

Improvement of Rowing Performance

Constanze Loschner, Richard Smith
School of Exercise and Sports Science
University of Sydney-Cumberland Campus

Thank you for volunteering to take part in this research study that will examine the relationship between the forces applied on the pins and footstretcher and on-water rowing performance.

Since today there are no studies that have been done where the rowing performance in a Single Scull is analysed on the basis of three dimensional pin and footstretcher forces in combination with the seat position, the oar angles, boat acceleration and boat velocity. The aim of this study is to determine how important these forces and their interactions are to on-water rowing performance. From this it is hoped that the information can be translated into a valuable coaching and training tool.

During the course of this study your rowing stroke profile of the pin and stretcher forces, the seat velocity, the oar angles, the boat acceleration and boat velocity will be measured while you exercise in the Single Scull (Biomechanics testing boat). All data to be collected using a laptop, which is in the car following the athlete.

As a participant, we request that you attend the nominated training session (arranged with you and your coach) with your 'rigging chart' filled out (see attachment). All tests will be conducted in Penrith at the International Regatta Centre. All evaluations will be held at the University of Sydney, Cumberland Campus and the NSW Institute of Sport, Homebush Athletics Centre. Additionally, we will record your height, weight prior to the testing session. Once you are comfortable with the boat, testing starts after a 10 minute warm up.

UNIVERSITY OF SYDNEY
HUMAN ETHICS COMMITEE
APPROVED
2 MAY 2000

UNIVERSITY OF SYDNEY
Faculty of Health Sciences

School of Exercise and Sport Science,
East Street (P.O. Box 170), Lidcombe, NSW, Australia 2141
Tel: 61-2-9351-9137 or 9351-9612 Fax: 61-2-9351-9204

Improvement of Rowing Performance.

The protocol for the test is as follows:

1. Record height and weight of athlete
2. Adjust the boat to the athlete's requirement
3. 10 minutes warm-up

4. Part 1: 1x 2000meters rating 20, 24, 28 and 32 strokes per minute

i.	Start to 220meters	light rowing
ii.	220 – 250 meters	building up to 20 strokes/ minutes (full pressure)
iii.	**250 – 500 meters**	**Rowing 20 strokes/ minutes (full pressure)**
iv.	500 – 720 meters	light rowing
v.	720 – 750 meters	building up to 24 strokes/ minutes (full pressure)
vi.	**750 – 1000 meters**	**Rowing 24 strokes/ minutes (full pressure)**
vii.	1000 – 1220 meters	light rowing
viii.	1220 – 1250 meters	building up to 28 strokes/ minutes (full pressure)
ix.	**1250 – 1500 meters**	**Rowing 28 strokes/ minutes (full pressure)**
x.	1500 – 1720 meters	light rowing
xi.	1720 – 1750 meters	building up to 32 strokes/ minutes (full pressure)
xii.	**1750 – 2000 meters**	**Rowing 32 strokes/ minutes (full pressure)**

5. easy rowing back to the 1000m and turn around

6. Part II: 1x 250meters at race rating

i.	1000 – 1220 meters	light rowing
ii.	1220 – 1250 meters	building up to race rating (full pressure)
iii.	**1250 – 1500 meters**	**Rowing at race rating (full pressure)**

Where possible this test will be incorporated as part of your normal training session. Prior consultation will be held with your coach to determine the best session to attend in order that there is minimal disruption to your competition preparation.

The risk of injury or illness to you as a result of participation in this study is no different from the risks that you would experience during intense training.

The results of your tests are strictly confidential and while we will report the results of the study as a whole, we will not disclose any individual information without your written permission. If you wish, the results of this test can be discussed with your coach. You are free to withdraw from the proceedings at any time. Should you choose to withdraw, this will not be held against you. If you have any further questions or concerns please contact Conny Loschner on 9763 0206. This study is conducted with the approval of the University of Sydney Human Ethics Committee. Any person with concerns or complaints about the conduct of a research study can contact the Manager of Ethics and Biosafety Administration, University of Sydney, on (02) 9351-4811.

UNIVERSITY OF SYDNEY
HUMAN ETHICS COMMITTEE
APPROVED
2 MAY 2000
DATE:

Appendix 2

The following are the conference papers:

Warmenhoven, J. S., Smith, R., Cobley, S., Draper, C., Harrison, A. & Bargary, N. (2016). Force-angle charateristics and level of competitive representation in on-water rowing. In: *Scientific Proceedings of the XXXVth International Symposium on Biomechanics in Sports*. International Society of Biomechanics in Sport, Tsukuba.

Warmenhoven, J. S., Smith, R., Cobley, S., Draper, C., Harrison, A. & Bargary, N. (2015). The application of functional data analysis techniques for characterizing differences in rowing propulsive-pin force curves. In: *Scientific Proceedings of the XXXIVth International Symposium on Biomechanics in Sports*. International Society of Biomechanics in Sport, Poitiers.

FORCE-ANGLE CHARACTERISTICS AND LEVEL OF COMPETITIVE REPRESENTATION IN ON-WATER ROWING

John Warmenhoven[1], Stephen Cobley[1], Conny Draper[1], Andrew Harrison[2], Norma Bargary[3], Richard Smith[1]
Exercise and Sports Science, University of Sydney, Sydney, Australia.[1]
Physical Education and Sport Sciences, University of Limerick, Limerick, Ireland.[2]
Department of Mathematics and Statistics, University of Limerick, Limerick, Ireland.[3]

The graphical presentation of the propulsive force applied by the oar to the pin, plotted against the oar horizontal angle, has been used as a diagnostic tool for rowing skill. How the pattern is related to variables such as level of competitive has not been well identified. Bivariate functional principal components analysis (*bf*PCA) was used on force-angle data to identify the main modes of variation in curves representing twenty seven female rowers of two different competition levels (Australian Domestic and Australian International level), rowing at 32 strokes per minute in a single scull boat. Discriminant function analysis showed strong classification of rowers using force-angle graphs across both sides of the boat, with increased rate of force development identified as an important characteristic for international rowers. Additionally for the bow-side, spending less time in the first half of the drive phase was also identified as an important feature for international rowers. The results of this demonstrate that there are potentially some common characteristics of the force-angle that are important for selection in international level sculling boats.

KEY WORDS: principal components analysis, shape, waveform, on-water.

INTRODUCTION: A range of studies have examined force characteristics measured at the oar handle, pin (oarlock) and the oar blade (Soper & Hume, 2004). These forces are usually represented graphically with force plotted either against time (Smith & Spinks, 1995) or against the horizontal angle of the oar (Spinks, 1996); and rowers have been descriptively identified by their distinctive shape or harmonic structure on such graphs. Despite commonalities and idiosyncratic differences in the continuous force “signatures”, empirical research determining the specific importance of different shape characteristics and their relationship with performance is currently limited. There is much conjecture on what exactly constitutes a ‘good’ or ‘bad’ force shape, given that theoretical and experimental support for a range of different shapes exists (Kleshnev, 2006; Martin & Bernfield, 1980, Smith & Loschner, 2002). Functional data analysis (FDA) techniques such as bivariate functional principal components analysis (*bf*PCA) have been used effectively in the assessment of gender differences for these signatures in on-water rowing (Warmenhoven et al. 2015). This study aims to use *bf*PCA as a means of exploring potential differences in the propulsive pin force (PPF)-angle profile as a factor of level of competitive representation for a group of highly skilled female single scullers.

METHODS: Subjects: Following institutional ethical approval, data from twenty seven female subjects were analysed. The rowers consisted of highly trained heavyweight and lightweight scullers. Athletes were classified as Australian Domestic (AD) (n = 14), Australian International (AI) (n = 13) athletes according to their level of competitive representation in sculling boats.
Testing and Data Processing: Athletes were directed to row at four stroke rates in 250m steps (20, 24, 28, 32 Str min^{-1}), separated by one minute of light rowing. Ten strokes from the 32 Str min^{-1} data only were analysed. The drive and recovery phases were identified using the horizontal angle of the oar (Smith & Loschner, 2002), and only the drive phase was analysed for this study. A linear length normalisation strategy using an interpolating cubic spline was applied, normalising each curve to 100% of the drive phase. An amplitude normalisation (AN) technique was also applied, ensuring that variability described in the curves was only reflective of shape

characteristics independent of amplitude. For AN, force was converted to a percentage relative to each curve's maximum value. Similarly, horizontal oar angle was normalised to a percentage relative to the length of each drive phase. Both normalisation formulas are below:

$$Force_{Norm(i)} = \left(\frac{Force_{(i)}}{Force_{(Maximum)}}\right) \times 100(\%) \qquad Angle_{Norm(i)} = \left(\frac{Angle_{(i)}}{Angle_{(Maximum)} - Angle_{(Minimum)}}\right) \times 100(\%)$$

The horizontal oar angle normalisation strategy is expressed as a relative percentage of the drive phase length, but still preserves important information on where the oar is relative to the boat. An average curve created from each participant's ten strokes was used for further analysis.

***bf*PCA and Discriminant Analysis**: For *bf*PCA, B-spline basis functions were used for force-time and angle-time curves. A composite function was derived from the inner product of the bivariate functions. This composite function was then used to extract a set of bivariate functional principal components (*bf*PCs) and corresponding *bf*PC scores (Ramsay, 2006). A separate *bf*PCA was conducted for each side of the boat (bow-side and stroke-side). *bf*PC scores were input into separate stepwise discriminant function analyses (SDFA) for classification according to competition level. Univariate ANOVAs were also used in conjunction with SDFA to assess the significance of differences between *bf*PC scores for the competition levels.

Table 1: Descriptive statistics (*bf*PC scores means and standard deviations) univariate ANOVA results and linear discriminant function coefficients for discrete performance outcomes for comparison of *bf*PC scores across competition levels for both sides of the boat.

	International *bf*PC Mean (SD)	Domestic *bf*PC Mean (SD)	Discriminant Coefficients	*F* Value	Sig.
Bow *bf*PC1	8.48 (51.57)	-7.87 (31.82)	0.23	1.00	0.33
Bow *bf*PC2	11.18 (46.08)	-10.38 (45.16)	0.70	1.51	0.23
Bow *bf*PC3	7.88 (22.05)	-7.32 (26.03)	1.14	2.66	0.12
Bow *bf*PC4	6.61 (22.8)	-6.14 (18.74)	0.22	2.53	0.12
Bow *bf*PC5	12.17 (19.08)	-11.3 (21.32)	0.69	9.04	0.01
% Classified	76.9% (n = 10)	92.9% (n = 13)			
Stroke *bf*PC1	9.75 (42.88)	-9.06 (40.47)	0.28	1.38	0.25
Stroke *bf*PC2	10.24 (40.24)	-9.50 (31.58)	-0.48	2.03	0.17
Stroke *bf*PC3	1.68 (24.89)	-1.56 (23.81)	0.38	0.12	0.73
Stroke *bf*PC4	10.45 (21.20)	-9.70 (21.50)	1.14	6.00	0.02
Stroke *bf*PC5	3.85 (27.43)	-3.58 (23.75)	0.20	0.57	0.46
% Classified	69.2% (n = 10)	71.4% (n = 9)			

RESULTS: The first five *bf*PCs for bow-side and stroke-side force-angle curves accounted for 95.2% and 95.9% of all variance for bow side and stroke side curves respectively with each *bf*PC's individual contribution to this variation illustrated in Figure 1.

***bf*PCA and SDFA:** Univariate ANOVAs comparing *bf*PC scores between competition levels on the bow side of the boat revealed that scores for the fifth *bf*PC were significantly different (p = 0.006) between competition levels, with international rowers featuring more prominently as positive scorers. Discriminant analysis of bow side *bf*PC scores also showed that the third *bf*PC discriminated most strongly according to its canonical discriminant function coefficient (Table 1). The bow side *bf*PC score discriminant function model was able correctly classify 85.2% of all bow side force curves, with 76.9% of international athletes and 92.9% of national athletes being correctly classified using *bf*PCs for bow side force application.

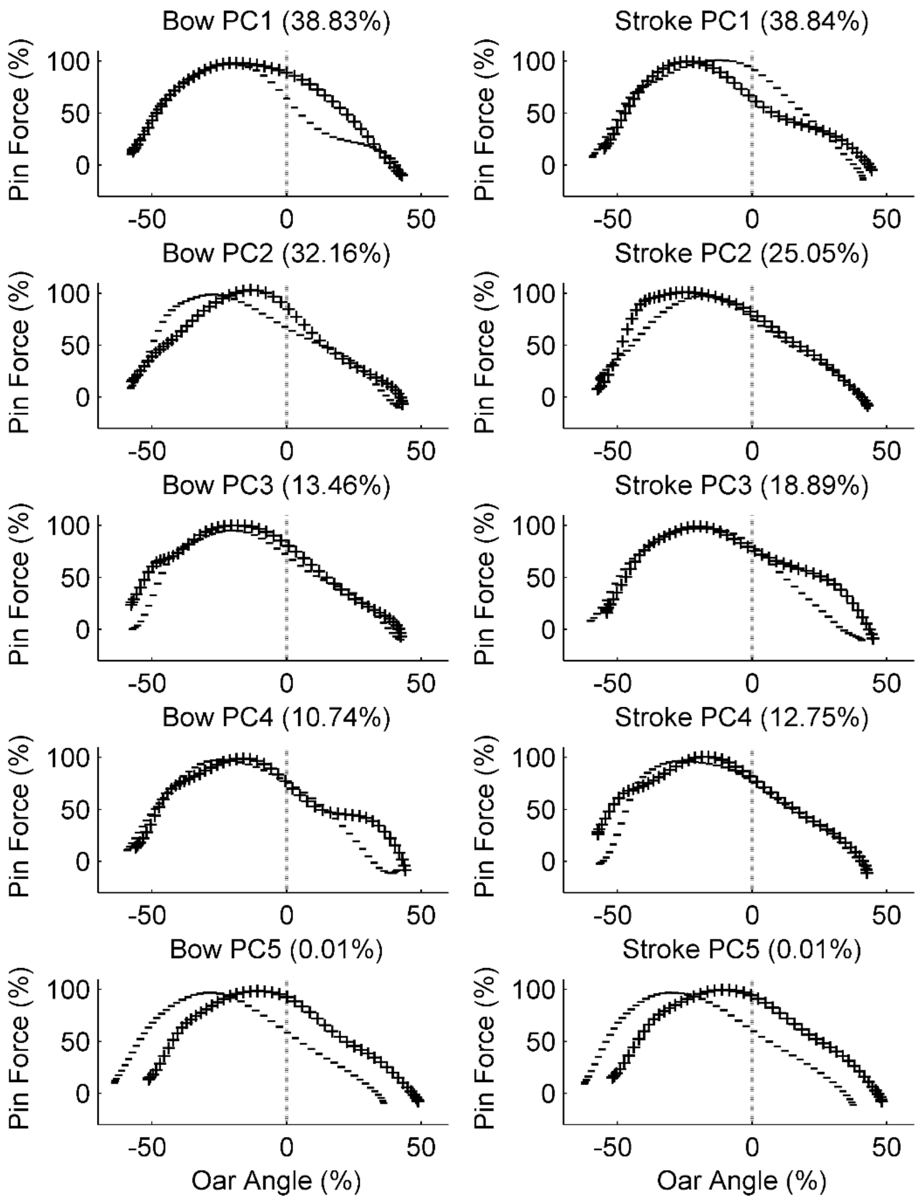

Figure 1: *bf*PC plots for each of the first five *bf*PCs for bow and stroke-side PPF-angle profiles. In plot positive scorers are more indicative of the '+' line and negative scorers the '–' line. *bf*PCs have been weighted as +/– 2 SD of the bfPC scores away from the mean function.

Univariate ANOVAs comparing *bf*PC scores between competition levels on the stroke side of the boat revealed that scores for the fourth *bf*PC were significantly different (p = 0.012) between competition levels, with international rowers featuring more prominently as positive scorers. Discriminant analysis of stroke side *bf*PC scores also showed that the fourth *bf*PC discriminated most strongly according to its canonical discriminant function coefficient (Table 1). The stroke side *bf*PC score discriminant function model was able correctly classify 70.4% of all stroke side force-angle curves, with 69.2% of international athletes and 71.4% of national athletes being correctly classified using *bf*PCs.

DISCUSSION: Irrespective of the side of the boat, discriminant function analyses of *bf*PC scores revealed rate of force development at the start of the drive phase as most important when examining differences between rowers as a factor of competition level, with the bow side discriminating more effectively than the stroke side of the boat. For the bow-side, spending less time in the first half of the drive phase was also identified as important, and alludes to a potential asymmetrical offset being present between the stroke side and bow side for rowers at a higher level of competition. This could be due in part to the different way that oars must move during the drive phase, as a consequence of how the boat is rigged for each athlete with the bow hand overlapping and sitting above the stroke side hand during the drive phase for this group of rowers (Smith & Loschner, 2002; Soper & Hume, 2004). The fact that this offset is only present on the bow side is also of interest given the ability to predict competition level using discriminant function analysis was different according to the side of the boat analysed. It is therefore important to establish whether consistent structural biomechanical offsets exist due to the boat rigging, influencing the need for rigid coordination structures, or whether a particular side of the boat, such as the bow side in the present study, often acts as a driver of motor pattern execution, with the other side acting more flexibly to account for steering of the boat and balance during skill execution. If the latter was true this would assist in explaining the larger amount of variability in the *bf*PC scores noted for the international level rowers for stroke side *bf*PC scores in the present study. Irrespective of the content of these findings, *bf*PCA has proven to be a powerful tool for assessing information in rowing biomechanics, particularly the novel adaptation for assessing the covariance structures that exist between the movements of the oar relative to the production of force. This allows for spatial application of force to be assessed empirically and any differences in these characteristics to be quantified between athletes.

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THE APPLICATION OF FUNCTIONAL DATA ANALYSIS TECHNIQUES FOR CHARACTERIZING DIFFERENCES IN ROWING PROPULSIVE-PIN FORCE CURVES.

John Warmenhoven[1], Richard Smith[1], Conny Draper[1], Stephen Cobley[1], Andrew Harrison[2], Norma Bargary[3].
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The pattern of propulsive force (measured at the pin), represented by force-time and force-angle graphs, typically differs among rowers. How the pattern differs according to competition level and gender has not been identified. Functional data analysis (FDA) techniques were used on force-time and force-angle data to identify the main modes of variance in curves representing thirty eight rowers of different competition levels (domestic, underage international and open international) and different gender. Stepwise discriminant function analysis showed strong classification of rowers using force-time and force-angle graphs and strong classification of female rowers. Male rowers, Underage rowers and Open International rowers showed weaker classification. Despite this, FDA provided useful information for the assessment of rowing performance.

KEY WORDS: principal components analysis, shape, waveform, on-water.

INTRODUCTION: The idea of a rowing technique ‘signature’ was first proposed by researchers in the nineteen seventies, and was associated with execution of the pulling force on the oar handle (Ishiko, 1971). A force signature is usually represented graphically with force either plotted against time (Smith & Spinks, 1995) or against the horizontal angle of the oar (Spinks, 1996); and rowers have been qualitatively identified by their distinctive shape on such graphs. However, empirical research analysing the specific importance of shape characteristics and their relationship with performance is currently limited. Yet the use and manipulation of ‘signatures’ to enhance performance is feasible. Two strategies for investigating differences in the shape of force-time and force-angle profiles are ‘Functional Principal Components Analysis’ (*f*PCA) and ‘Bivariate Functional Principal Components Analysis’ (*bf*PCA), from the Functional Data Analysis (FDA) family of statistical techniques (Ramsay, 2006). The benefits of *f*PCA and *bf*PCA for assessing trends in biomechanical variables have already been highlighted for use on vertical jump performance (Ryan, Harrison & Hayes, 2006; Harrison, Ryan & Hayes, 2007). In rowing the shape of the force-time curve could be analysed using *f*PCA, and the force-angle profile could be analysed using *bf*PCA. In the present study, data obtained on thirty eight athletes were processed to assess whether force trends in continuous data can be used to discriminate between rowers, and whether they can predict competition level and gender.

METHODS: Subjects: Following institutional ethical approval, data from thirty eight subjects were analysed (11 male, 27 female). The rowers consisted of highly trained heavyweight and lightweight scullers. Athletes were classified as Domestic (D) (n = 20), Australian International Underage (IU) (n = 7) or Australian International Open (IO) (n = 11) athletes.
Testing and Data Processing: Athletes were directed to row at four stroke rates in 250m steps (20, 24, 28, 32 Str min^{-1}), separated by one minute of light rowing. Ten strokes from the 32 Str min^{-1} data only were analysed. The drive and recovery phases were identified using the horizontal angle of the oar (Smith & Loschner, 2002), and only the drive phase was analysed for this study. A linear length normalisation strategy using an interpolating cubic spline was applied, normalising each curve to 100% of the drive phase. An amplitude normalisation (AN) technique was also applied, ensuring that variability described in the curves was only reflective of shape characteristics independent of amplitude. For AN, force was converted to a percentage relative

to each curve's maximum value. Similarly, horizontal oar angle was normalised to a percentage relative to the length of each drive phase. Both normalisation formulas are below:

$$Force_{Norm(i)} = \left(\frac{Force_{(i)}}{Force_{(Maximum)}}\right) \times 100(\%) \qquad Angle_{Norm(i)} = \left(\frac{Angle_{(i)}}{Angle_{(Maximum)} - Angle_{(Minimum)}}\right) \times 100(\%)$$

The horizontal oar angle normalisation strategy is expressed as a relative percentage of the drive phase length, but still preserves important information on where the oar is relative to the boat. An average curve created from each participant's ten strokes was used for further analysis.

***f*PCA and *bf*PCA**: For *f*PCA, B-spline basis functions were used for creation of force-time curves. The smoothing parameter was selected using a generalized cross validation (GCV) procedure and from these curves the functional principal components were derived. Each force-time curve was weighted by each of the first five functional principal components (*f*PCs), with resulting scalar averages referred to as *f*PC scores. For *bf*PCA, B-spline basis functions were used for force-time and angle-time curves. The smoothing parameter was again selected using a using a GCV procedure. A composite function was derived from the inner product of the bivariate functions. The composite function was then used to extract a set of bivariate functional principal components (*bf*PCs) and corresponding *bf*PC scores (Ramsay, 2006).

Discriminant Analysis: *f*PC and *bf*PC scores were input to separate stepwise discriminant function analyses (SDFA) for classification according to competition level and gender. The smallest Mahalanobis distance (D2) procedure was used in each case using prior allocation probabilities to account for the different sample sizes in each comparison.

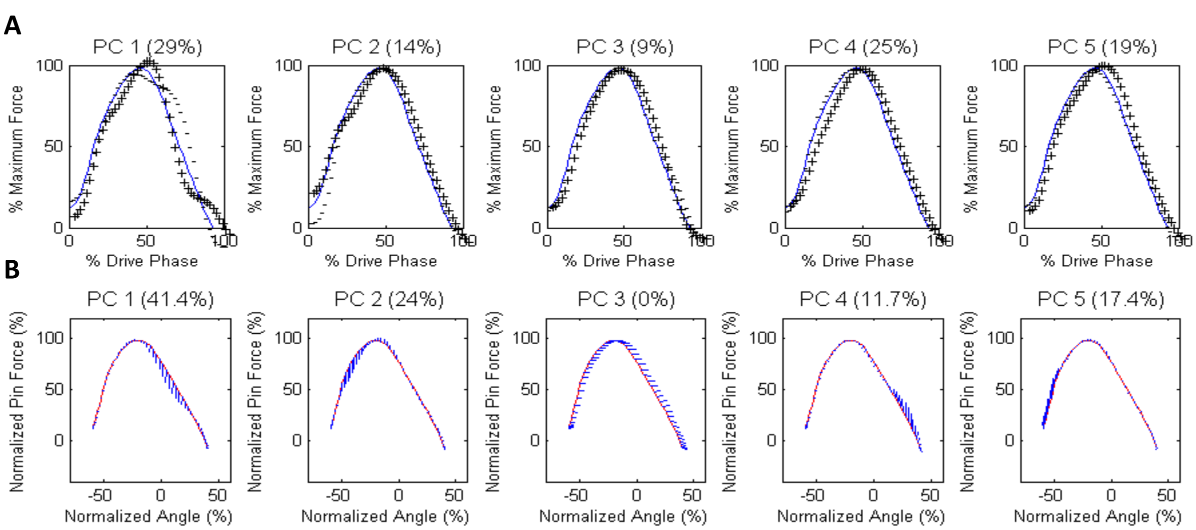

Figure 1. The first five varimax rotated *f*PCs (A) and *bf*PCs (B). For *f*PCs, the blue line represents mean force-time, the '+' line represents positive scorers who are +2SD and the '-' line represents negative scorers who are -2SD from the mean function. For *bf*PCs, the red line represents the mean force-angle function and the blue lines represent positive scorers +2SD from the mean function.

RESULTS: The corresponding percentage contribution for each *f*PC and *bf*PC to the total variability in all curves are shown in Figure 1. Mean scores for *f*PCs and *bf*PCs are in Table 1.

SDFA for competition levels using *f*PCA: *f*PC2 had the greatest discriminating power for the first step ($p < 0.001$), demonstrating a change in the pattern of force production in the first half of the drive phase. In the second step, *f*PC4 was identified ($p = 0.017$) showing a greater rate of force development early in the drive phase for negative scorers, and in the third step *f*PC3 was identified (p = 0.017), showing greater force production leading into the finish.

SDFA for competition levels using *bf*PC: Scores on *bf*PC2 had the greatest discriminant power for the first step (p = 0.002), demonstrating a lower rate of force development leading into maximum force, but a better ability to maintain a higher force closer to square-off for positive scorers. In the second step, *bf*PC4 was also identified (p < 0.001), showing a greater ability to produce force at the end of the drive phase.

SDFA for gender using *f*PCA: *f*PC5 (p < 0.001), *f*PC3 (p < 0.001) and *f*PC4 (p < 0.001) were discriminating variables for classification, with each identified in separate steps.

SDFA for gender using *bf*PC: *bf*PC1 (p < 0.001) and *bf*PC4 (p < 0.001) were discriminating variables for classification, with each identified in separate steps. *bf*PC1 showed a reduction in force production after reaching maximum force for positive scorers. The results of the discriminant analyses using *f*PC and *bf*PC scores for force-time and force-angle data as predictors of competition level and gender are shown in Table 1.

Table 1. *f*PCA and *bf*PCA mean (SD) scores for competition level and gender (A). Percentages of correct classification of *f*PCA (B) and *bf*PCA (C) for competition and gender.

(A) **Competition Level *f*PCA and *bf*PCA scores**

		***f*PCA**	***bf*PCA**
D	**PC1**	-3.4 (43.4)	-7.5 (52.1)
	PC2	-10 (26.9)	-2.4 (37.5)
	PC3	0.2 (19.6)	-6.5 (24.1)
	PC4	3.6 (35)	-2.3 (21.1)
	PC5	4.7 (31.1)	-10.7 (31)
IU	**PC1**	8.2 (24)	15.6 (35.3)
	PC2	24.4 (27.2)	-25.3 (32.4)
	PC3	-15.5 (16.2)	-2 (23.1)
	PC4	-26.3 (28.9)	13.8 (19.9)
	PC5	-13.6 (27.8)	27.9 (28.5)
IO	**PC1**	1 (41.9)	3.76 (53.1)
	PC2	2.6 (17.9)	20.5 (39.2)
	PC3	9.5 (24)	13.1 (19)
	PC4	10.1 (38.7)	-4.6 (27.9)
	PC5	0 (36.6)	1.8 (22.1)

Gender *f*PCA and *bf*PCA scores

		***f*PCA**	***bf*PCA**
F	**PC1**	9.2 (34.8)	14.9 (43.7)
	PC2	2.7 (24.1)	-6.6 (38.9)
	PC3	-5.1 (21.1)	0.7 (24.5)
	PC4	-6.8 (34.3)	4.5 (22.5)
	PC5	-11.3 (29.8)	3.6 (26.8)
M	**PC1**	-22.6 (43.2)	-36.4 (46.3)
	PC2	-6.6 (34.5)	16.2 (38.2)
	PC3	12.5 (18.8)	-1.8 (22.8)
	PC4	16.6 (39.1)	-11.1 (23.5)
	PC5	27.8 (20.1)	-8.9 (39.9)

(B) **Competition Level *f*PCA - % Classified**

	D	***IU***	***IO***
D	**87.5**	2.5	10.0
IU	50.0	**35.7**	14.3
IO	36.4	9.1	**54.5**

Gender *f*PCA - % Classified

	F	***M***
F	**90.7**	9.3
M	27.3	**72.7**

(C) **Competition Level *bf*PCA - % Classified**

	D	***IU***	***IO***
D	**85.0**	5.0	10.0
IU	42.9	**57.1**	0.0
IO	45.5	9.1	**45.5**

Gender *bf*PCA - % Classified

	F	***M***
F	**92.6**	7.4
M	27.3	**72.7**

DISCUSSION: The purpose of this paper was to see if FDA-analysed force-time and force-angle data from single scullers could be used to discriminate between their competition level and gender. If the analysis was successful it could be a method of identifying the 'ideal' force-angle shape characteristic of competition-winning scullers. Knowing the shape of the force-angle profile is critical for the development of strength and conditioning strategies (Korner and Schanitz, 1987). In the present study *f*PCs and *bf*PCs discriminated best between domestic and international open rowers. These results initially suggested that increased force near the start and the end of the drive phase may not be as important as increased force when the horizontal oar angle is closer to zero degrees, especially indicated by *bf*PC2. Despite this, both *f*PC and *bf*PC scores provided high correct classification percentages for domestic rowers but comparatively weaker percentages of classification for international underage and open rowers. It is possible that the skill in applying force to the oar is quite similar at lower performance levels, but international underage and open rowers have subsequently learned to adapt the shape of their force signatures with experience and potentially 'individualise' these shapes to fit other key performance characteristics. Both *f*PC and *bf*PC scores also provided high correct classification percentages for gender, particularly for female rowers. Female rowers demonstrated a better ability to develop force early in the stroke and maintain force leading into the release, but males demonstrated a greater ability to maintain a higher force production closer to the oar angle equalling zero degrees. As a result of these differences it is advisable to assess shape characteristic differences independent of gender, given that gender effects in the present study may have masked the discriminating ability of FDA at higher competition levels. Importantly, this preliminary investigation into shape differences has also been able to show the use of *bf*PCA in particular as a novel method for assessment of the force-angle profile, something which has traditionally been assessed qualitatively. It is known that the shape of the force/angle profile has reflected the seat that the rower occupies in a crewed boat (Smith and Loschner, 2002; Roth, Schwanitz, Pas & Bauer, 1998). The FDA method described here provides a quantitative analysis of curve shape that can clearly isolate and define time segments where changes can be made to better approximate an elite performance. The importance of segments of the force curves suggested by the *f/bf*PCA analysis provides a strong evidence base for discussions with coaches and athletes about how to increase performance in on-water rowing.

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