Quantifying the Functional Role of Discrete Movement Variability: Links to Adaptation and Learning

Submitted by

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Statement of Sources

This thesis contains no material published elsewhere or extracted in whole or in part from a thesis by which I have qualified for or been awarded another degree or diploma.

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All research procedures reported in the thesis received the approval of the Australian Catholic University Human Research Ethics Committee (Approval N2011 07).

The studies which constitute this thesis are predominantly my own work and as such I am, or will be, listed as primary author on all current and potential publications. External to that provided by my supervisory panel, assistance was received during the development of the algorithm and Matlab code for Study 3 of this thesis. The contributions from all secondary authors, supervisors or otherwise, comply with the regulations set out in the Australian Catholic University *Guidelines on the Preparation and Presentation of a Research or Professional Doctoral Thesis for Examination*. Specifically, the contribution of no author, other than the primary author, towards any of the included articles exceeds 50%.

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Preface

This thesis was prepared to fulfil the criteria for Doctor of Philosophy and is in the format of published and submitted manuscripts and manuscripts prepared for submission. It adheres to the guidelines outlined in "Guidelines on the Preparation and Presentation of a Research or Professional Doctoral Thesis for Examination – Australia Catholic University". The themes of the manuscripts presented in this thesis are closely related and form a cohesive and consistent research narrative.

Abstract

Introduction: Movement variability can be defined as the variance in human movement from one trial or cycle to the next, often when attempting to maintain dynamic equilibrium (in the case of continuous skills) or achieve consistent movement outcome (for discrete skills). Some theoretical perspectives of motor control consider movement variability to be deleterious. However, the dynamical systems perspective proposes beneficial and functional roles for movement variability. Within this view variability has developed as an independent theme of research that has gained momentum over the past 25 years, attracting focus from various sub-disciplines within the field with a major contribution from sports biomechanics. The previous research within the field of movement variability has proposed that these functional roles include reducing the risk of injury, enabling coordination change and facilitating adaptation to varying task or environmental constraints. This thesis is primarily constituted of four sequential studies designed to further the method-related approach to, and theoretical understanding of, the interaction between variability in discrete movement and adaptation.

Study 1: The first aim of this thesis was to review the previous work investigating variability in discrete sporting or sports derived movements. A systematic review was conducted which initially surveyed more than 19,000 articles before submitting 66 to final analyses. Data extracted identified participant age and gender, study design, sample size, population and movements studied in the included literature. Furthermore, the trial size, data collection equipment/methods, kinematic measures, filtering and variability quantification methods were reported. Results led to the suggestion that future discrete movement variability research should endeavour to do the following: implement longitudinal research designs; report justification for trial sizes using a valid means; consider using higher capture frequencies where possible;

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descriptively report any data manipulation and selection of critical values; consider the use of surrogate methods; and make use of emerging variability quantification techniques which adequately account for the deterministic nature of human movement time series. Furthermore, three levels of variability were proposed to seek a fuller understanding of its functional role: 1) variability in discrete and continuous measures of variables such as joints and segments, release/impact parameters and implement kinematics; 2) coordination variability; and 3) whole system variability. It was considered that assessment of variability at all three levels holds the best chance of further understanding the phenomenon of discrete movement variability.

Study 2: Based on the findings of Study 1, it was determined to utilise a longitudinal research design employing contextual interference to investigate discrete movement variability during the learning of a novel task. However, to address some of the method-related considerations raised in Study 1, Studies 2 and 3 focussed on trial size and surrogate methods of data collection. Study 2 addressed the recommendation that a valid determination of trial size be made a priori. This was conducted using sequential analysis. Considerable testing followed to ensure the valid application of this technique and to determine the number of throws required to achieve a stable mean. It was determined that a sample of at least 20 trials was required to make a determination of trial size using sequential analysis. Results suggest that a trial size between 13 and 17 provides stable means for overarm throwing kinematics.

Study 3: Another directive of Study 1 was that surrogate methods be considered, particularly when employing entropy measures, to highlight the presence of deterministic dynamics. Entropy measures quantify the regularity of both stochastic and deterministic signals. As such, a means of ensuring that collected data is deterministic in nature is required. This can be achieved using surrogate methods. However, no such surrogate method presently existed for use

with discrete human movement data. Study 3 outlines the development, validation and determination of reliability for a novel surrogate technique for this purpose. The proposed technique validly and reliably generated surrogates for discrete joint angle time series, destroying fine-scale dynamics of the observed signal, while maintaining macro structural characteristics.

Study 4: The final study addresses the overarching focus of the thesis - to investigate the interaction of discrete movement variability, adaptation and learning. Twenty participants were recruited into this study which employed a longitudinal design and contextual interference. Each participant was randomised into one of two experimental groups and attended nine training sessions where they practiced overarm throwing with their non-dominant hand. Surrogate methods and sample entropy were used to assess changes in movement variability at the first (joint) level while learning this novel discrete task. It was hypothesised that the contextual interference effect would be observed, such that those exposed to high contextual interference during skill acquisition would outperform those exposed to low contextual interference. The results indicated the presence of the contextual interference effect which enhanced adaptability in the high contextual interference group. Surrogate techniques effectively demonstrated the presence of deterministic dynamics. Movement variability (sample entropy) was not significantly different between the high and low contextual interference groups though several trends corroborated those reported by previous research. Combining longitudinal design, contextual interference and measurement of variability allowed several hypotheses to be formed which could enhance our understanding of the functional role of variability in motor learning and adaptation.

Conclusion: The four studies of this thesis provide a valuable contribution to movement variability research. Furthermore, the results offer useful guidance for future work. This includes, but is not limited to the following aspects: applying sequential analysis to other movements and

validating its use with time series data; applying the novel surrogate technique to other movements; and providing further exploration of emerging variability quantification methods and assessment of variability at all three levels across the entire span of motor learning. Potential applications of this and future work lay in the ability to effectively track and service athletes as well as to inform coaching techniques, particularly relative to task variability in training.

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Journal Publications

Taylor, P. G., Lee, K.-Y., Landeo, R., O'Meara, D. M., & Millett, E. (2015). Determining optimal trial size using sequential analysis. *Journal of Sports Sciences, 33*(3), 300-308. doi: 10.1080/02640414.2014.942679

Taylor, P. G., Small, M., Lee, K.-Y., Landeo, R., O'Meara, D. M., & Millett, E. L. (in press). A surrogate technique for investigating deterministic dynamics in discrete human movement. *Motor Control*. doi: 10.1123/mc.2015-0043

Four Page Conference Abstracts

Taylor, P., Lee, K.-Y., Landeo, R., O'Meara, D., & Millett, E. (2013). *Determining optimal trial size using sequential analysis*. Paper presented at the 31st International Conference on Biomechanics in Sports, Taipei, Taiwan.

Taylor, P., Lee, K.-Y., Landeo, R., Small, M., O'Meara, D., & Millett, E. (2015). *Changes in movement regularity during learning of a novel discrete task*. Paper presented at the 33rd International Conference on Biomechanics in Sports, Poitiers, France.

Taylor, P. G., Small, M., Lee, K.-Y., Landeo, R., O'Meara, D., & Millett, E. (2015). *A surrogate method for discrete movement data*. Paper presented at the 33rd International Conference on Biomechanics in Sports, Poitiers, France.

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List of Definitions

The following list includes the most commonly used terms within this thesis and are defined relative to their use within the context of the topic.

Adaptability: relative to movement is the ability of an individual to change their movement pattern in order to produce a successful outcome in the presence of changing task and/or environmental constraints.

Contextual interference: the randomisation of the task constraints (e.g., target, distance) under which a skill or set of skills is performed or practiced.

Continuous movement: a movement with a rhythmical or cyclical nature for which a definite start and end point are hard to determine.

Coordination variability: variability in the coupling or phasing of two or more biomechanical variables (e.g., shoulder and elbow angles).

Deterministic dynamics: defines the phenomenon whereby the state of a system at any given time (t_i) is determined by the state of the system immediately before (t_{i-1}) and determines the state of the system immediately after (t_{i+1}).

Discrete movement: a movement, usually short in duration, with a defined beginning and end point.

Discrete movement variability: variability in discrete movement profiles.

First level variability: variability of discrete or time series measures of individual segments and joint kinematic, release/impact parameters and implement/projectile kinematics. May include linear or angular displacement and its derivatives.

Learning: the acquisition and/or refinement of a motor skill.

Movement variability: the variance in motion from one trial or cycle to the next, often when attempting to maintain dynamic equilibrium (in the case of continuous skills) or achieve consistent movement outcome (for discrete skills).

Non-dominant hand: the hand which is not preferred by an individual for use in the majority of common tasks.

Overarm throw: a throw whereby the majority of the throwing arm is above the shoulder at the point of release and for much of the propulsion phase.

Sample entropy: a statistical technique for determining the regularity/complexity of a time series or set of time series based on the probability that an extraction from that time series will be repeated at any point across the rest of the time series or cycles.

Sequential analysis: a statistical technique for determining the point at which the mean of a certain variable has become stable.

Surrogate: a time series which resembles observed (real) data for macro characteristics (shape, amplitude, mean, variance, etc.) yet has had its micro structure (deterministic dynamics) corrupted or destroyed.

Trial size: the number of trials performed by a participant, or the number of trials analysed from a set of performances, for intra-individual analyses.

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Whole system variability: variability assessed across multiple coordinated

systems/structures such as coupled join and/or segment combinations through to the whole

human body.

List of Common Abbreviations and Symbols

Abbreviations

2D	Two dimensions/dimensional
3D	Three dimensions/dimensional
A	Analysed
ApEn	Approximate entropy
CI	Confidence interval
CMC	Coefficient of multiple correlations
CRP	Continuous relative phase
CV	Coefficient of variation
DyCoN	Dynamically controlled network
F	Female
FDA	Functional data analysis
fPCA	Functional principal component analysis
FIR	Finite impulse response
High CI	High contextual interference group
ICC	Intraclass correlation
IQR	Inter-quartile range
Low CI	Low contextual interference group
M	Male
MSE	Mean squared error
NoRMS	Normalised root mean squared
NR	Not reported
P	Performed
PCAw	Principal component analysis of waveforms
RMS	Root mean squared
RMSD	Root mean squared difference
SampEn	Sample entropy
SD	Standard deviation
SEM	Standard error of the mean
TE	Technical error
vs.	Versus

Symbols

~	Approximately
N	Total sample size
n	Sub-sample size
ρ	Rho. Critical value for the novel surrogate technique. Spearman's correlation coefficient

Chapter 1. Introduction

1.1 General Introduction

Movement variability, the variance in movement patterns from trial to trial or cycle to cycle, has garnered increasing interest over the past half century or more and has elicited several contrasting viewpoints. While the conflicting theoretical perspectives on movement variability are not the focus of this thesis, and some excellent resources already exist to cover it (c.f. Newell and Corcos [1993b]; Davids, Bennett, and Newell [2006]), they are nonetheless worth mentioning briefly.

Many early motor control theories modelled the human motor system in a computational manner where commands, or motor programs, were stored in memory, loaded when required and produced a desired output. Within these approaches, such as control theory, movement variability was seen as evidence of noise and error, arising in the neuromotor system between input and output, affecting the optimal execution of the motor program (Button, Davids, & Schollhorn, 2006). That is, movement variability was considered deleterious and to be avoided or eradicated where possible for optimal movement control and outcome.

For more than 20 years now though, adoption of different theoretical perspectives on motor control has seen a shift in thinking on the reason movement variability exists. These theoretical approaches, such as dynamical systems theory, regard variability as an omnipresent element of human movement. It arises, not due to error in transmission of a motor program, but rather because human movement is the outcome of all systems, from micro (e.g. cellular) to macro (e.g. segment, joint or whole body) levels, constantly evolving and re-organising under the pressure of external and internal constraints, to achieve desired motion outcomes (Newell &

Corcos, 1993a). That is, variability is an entirely natural and expected consequence of movement which may even have a functional role.

As acceptance of the newer theoretical perspectives grew and attitudes towards movement variability changed within the human movement sciences, it became an independent field of research. More authors began to include variability measures amongst dependent variables, more studies began to focus on variability exclusively and individual analysis designs, as opposed to traditional group-wise analyses, began to increase. This was no more apparent than in sports research. Sport provides an ideal context in which to investigate movement variability. At the least, sporting populations are proficient in the movements being studied, and at best are among the highest skilled in the world at their given task. Sports biomechanists became aware that even the most skilled athletes were unable to produce invariant movements (Bartlett, Wheat, & Robins, 2007). Individual analyses revealed even more, that movement patterns were often highly individualised. As such the following questions arise: (1) do the new theoretical approaches and evidence suggesting an optimal, invariant technique was no longer worth striving for change the way movement variability should be perceived?; and (2) Does movement variability have a role to play in facilitating movement and is it functional in any way?

Indeed, there have been several potential functional roles proffered for variability in movement. Two of these are well aligned with the primary goals of sports biomechanics – injury prevention and performance optimisation. Movement variability is thought to reduce repeated stresses on the same tissues, perhaps becoming a protective factor for injury. The potential for variability to optimise performance lies in another hypothesised function, the ability to facilitate adaptation, which may help achieve successful movement under dynamic task and environmental

constraints, such as those found in game situations. Furthermore, adaptation may be important to motor learning and skill acquisition.

This thesis has at its core four studies which document the process to further understand any functional role of variability in discrete movement and, in particular, its interaction with adaptation and motor learning. The first study establishes and justifies the use of the sporting context and focus on discrete (as opposed to continuous) skills as well as providing a systematic review of the current consensus. There is a particular focus on the collation and efficacy assessment of methodologies used to investigate this phenomenon. Furthermore, a synthesis of key findings and conclusions provides interpretation of the current theoretical understanding of variability, its potential function or role within discrete human movement and directs later research questions.

Studies 2 and 3 address method-related factors uncovered during the systematic review. Specifically, Study 2 documents the selection of appropriate trial size from pilot study data. This guides the method of the final two studies. Similarly, Study 3 outlines the development of a valid and reliable surrogate technique for discrete human movement. The potential effectiveness of surrogate analyses was raised within Study 1 but further investigation revealed no valid technique existed for the intended application. Hence the aim of Study 3 was to develop such a technique.

Finally, Study 4 describes the application of knowledge gained from Study 1 along with adoption of methodologies from Studies 2 and 3 to attempt to answer questions about the functional role of movement variability and its interaction with adaptation and learning. This experimental study details the use of emerging innovative analyses of variability coupled with effective research design and attempts to provide direction for further exposition of the question at hand. Combined, these studies provide new knowledge and perspective on what has been done

before as well as contributing new methods to variability research and imparting initial understanding on the interaction of discrete movement variability, adaptation and learning while detailing future research directions.

1.2 Aims and Hypotheses

Each study of this thesis builds on or adds to those before it to achieve the overarching aim of the thesis – to investigate the interaction of discrete movement variability, adaptation and learning. Yet, each study had its own hypotheses and/or aims related to the purpose of that specific investigation. Those aims and hypotheses are stated here.

1.2.1 Discrete Movement Variability in Sports and Sports Derived Tasks: A Systematic Review (Study 1)

Aims: To provide a systematic review of the design, methods and analyses of research into discrete movement variability and its role in sport or sports derived tasks. To collate any evidence for a functional role of variability in discrete movement and to provide guidance for further research in this field.

1.2.2 Determining Optimal Trial Size Using Sequential Analysis (Study 2)

Aims: To investigate the effect of using different trial numbers on the results of sequential analysis. To employ sequential analysis to establish the number of trials required for mean stability in discrete and time series kinematic data from an overarm throwing task.

1.2.3 A Surrogate Technique for Investigating Deterministic Dynamics in Discrete Human Movement (Study 3)

Aims: To propose a generalisation of the pseudo-periodic surrogate method, without time delay embedding, which can be applied to discrete movement data. To demonstrate the implementation of the surrogate technique including determination of critical values and the testing of surrogate output using sample entropy as a discriminating statistic.

Hypothesis: That this novel surrogate technique will produce outcomes similar to those of the Small shuffled surrogate method, whereby the sequence of data is shuffled on a fine scale, destroying the micro structure of the original data (relationship between each datum and those immediately surrounding it), while the macro structural elements of the data (mean, variance, length) are maintained.

1.2.4 Changes in Variability and Adaptability during the Learning of a Novel Discrete Task (Study 4)

Aims: To investigate the changes in movement variability during the learning of a novel discrete task under high and low contextual interference conditions using a surrogate method and sample entropy measures. To determine variability at the first (joint) level of the chosen activity as to begin understanding any relationship amongst variability, adaptability and learning.

Hypotheses: Those exposed to high contextual interference (task variability) during skill acquisition will outperform those exposed to low contextual interference in both retention and transfer tasks. Superior performance in the transfer task will provide evidence of adaptability in the high contextual interference group which will also display reduced movement variability at the first (joint) level.

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Chapter 2. Discrete Movement Variability in Sports and Sports Derived Tasks: A Systematic Review (Study 1)

2.1 Abstract

This review of literature sought to provide a systematic appraisal of the design, methods and analyses of research into discrete movement variability in sport or sports derived tasks. Four primary academic databases (Academic Search Complete, SPORTDiscus, Medline and CINAHL) were searched yielding 19,007 abstracts (duplicates removed). Following application of inclusion criteria 66 articles qualified for full analysis. Data extracted identifies participant age and gender, study design, sample size, population and, movements studied in the included literature. Furthermore, the trial size, data collection equipment/methods, kinematic measures, filtering and, variability quantification methods are reported. Results led to the suggestion for future discrete movement variability research: it should endeavour to implement longitudinal research designs; report justification for trial sizes using valid means; consider using higher capture frequencies where possible; descriptively report any data manipulation and selection of critical values; consider the use of surrogate methods; and make use of emerging variability quantification techniques which adequately account for the deterministic nature of human movement time series. Furthermore, three levels of variability are proposed to seek a fuller understanding of its functional role: 1) variability in discrete and continuous measures of variables such as joints and segments, release/impact parameters and implement kinematics; 2) coordination variability; and 3) whole system variability. It is proffered that assessment of all three variability levels holds the best chance of further understanding the phenomenon of discrete movement variability.

2.2 Introduction

Movement variability can be defined as the variance in motion from one trial or cycle to the next, often when attempting to maintain dynamic equilibrium (in the case of continuous skills) or achieve consistent movement outcome (for discrete skills). There have been two major theoretical perspectives on this phenomenon over the years. One view, for example, suggests that variability within biological systems is indicative of random "noise" within those systems (Newell, Deutsch, Sosnoff, & Mayer-Kress, 2006) and that minimisation of variability within movement is aspirational (Newell & Corcos, 1993a). A contrary opinion is proffered by the dynamical systems/ecological theory which models the human organism as a complex system whose interdependent components show nonlinear, self-organising behaviour (Glazier, Davids, & Bartlett, 2004). That is movement synergies and coordination can arise in human movement from the controlled and uncontrolled interaction of the various components (from the sub-cellular level up to larger components such as muscle) that make up the individual. This theory proposes a functional, rather than deleterious, role for variability in movement including the ability to adapt to perturbations in task and environmental constraints as well as to reduce injury by dispersing stresses over more soft tissue during repeated movements (Bartlett et al., 2007; Davids, Glazier, Araujo, & Bartlett, 2003).

Under the dynamical systems perspective, movement variability has developed as an independent theme of research that has gained momentum over the past 25 years, attracting focus from various sub-disciplines within the movement. Of these, sports biomechanists have taken a keen interest in movement variability due to its potential to enhance understanding of injury mechanics and to provide insight into questions around coordination, adaptability and performance (Bartlett, 2008). The focus of these investigations has been on the variability of

continuous and discrete movement classes. Research into continuous movement variability in sports biomechanics has been dominated by gait (Dufek, Mercer, Teramoto, Mangus, & Freedman, 2008; Hamill, Haddad, & van Emmerick, 2006; Preatoni, Ferrario, Dona, Hamill, & Rodano, 2010), whereas discrete movement variability has covered a broad spectrum of sports and sports derived movements with manipulative or ballistic tasks featuring prominently (Bootsma & van Wieringen, 1990; Button, MacLeod, Sanders, & Coleman, 2003; Chow, Davids, Button, & Rein, 2008; Fleisig, Chu, Weber, & Andrews, 2009; Langdown, Bridge, & Li, 2013; Taylor, Landeo, & Coogan, 2014; Whiteside, Elliott, Lay, & Reid, 2015).

Some reviews have been published on movement variability in sports biomechanics (Bartlett, 2008; Bartlett et al., 2007; Davids et al., 2006; Davids et al., 2003; Preatoni et al., 2013). However, variability in continuous and discrete movements has not been differentiated. There may be benefit in reviewing the previous work on each movement type separately, since differences in control, goal and outcome of the two movement classes require different research questions and methods. For example, it is often easier to ascertain movement success in discrete movements (e.g., shot accuracy or distance), compared to that in continuous tasks where variables such as economy of gait may be confounded by physiological factors.

The increased focus on movement variability has coincided with technological advances of the last two or three decades providing new and improved tools for data collection, notably increased camera speeds and three dimensional, multi camera, motion analysis systems. Similarly, novel methods of variability quantification have been employed (Davids et al., 2006; Deluzio, Harrison, Coffey, & Caldwell, 2013; Hamill, Haddad, & McDermott, 2000; Stergiou, Buzzi, Kurz, & Heidel, 2004; van Emmerick, Miller, & Hamill, 2013). Combined together, these elements are continually expanding the scope, importance and understanding of the link between movement

variability and performance measures in sports biomechanics. As such, the aim of this study is to

provide a systematic review of the design, methods and analyses of research into discrete

movement variability and its role in sport or sports derived tasks. In particular, we hope to collate

any evidence for a functional role of variability in discrete movement and to provide guidance for

further research in this field.

2.3 Method

2.3.1 Inclusion and exclusion criteria

Inclusion, and corresponding exclusion, criteria can be seen in Table 2.1. To be included in

this review literature must be in the form of peer reviewed journal articles, written in English,

detailing experimental or descriptive study designs, within discrete sport or sport derived

movements, quantifying intra-individual variability of kinematic or coordination variables. In order

to control the number of elements affecting reported variability, included studies must assess a

post-adolescent human population free of injury, illness or incapacity.

Table 2.1.

Inclusion and exclusion criteria for systematic review.

Inclusion Criteria	Corresponding Exclusion Criteria
1. Human Studies	Animal Studies
2. Variability in gross, discrete sporting or sports derived movements (jumping, throwing, catching etc.)	Physiological response variability (e.g., heart rate or blood pressure), kinetic or myographic variability, rhythmic or cyclical skills such as tapping and gait
3. Experimental and descriptive studies	Reviews, methodological, positional papers etc.
4. Intra-individual variability	Inter-individual variability including group analysis and reliability studies
5. Voluntary, goal directed movements	Involuntary, passive, assisted or constrained movements such as manipulation, spasms and tremors, orthoses, support mechanisms and data collection methods which constrain degrees of freedom
6. Healthy populations	Non-healthy populations including injured, ill and neurological or neuromuscular pathology
7. Healthy Adult/Fully developed/Non impeded	Children, aged, impeded or temporarily disabled (e.g., sight occlusion)

Where a paper has both elements that would and would not be included, the paper will be included and treated appropriately in analysis

2.3.2 Search strategy

Four primary research databases (Academic Search Complete, SPORTDiscus, Medline and CINAHL) were searched for the purposes of this review. Databases were accessed through EBSCO and searched using the following string with Boolean operators where the asterisk (*) symbol indicated the use of a wildcard:

"VARIABILITY AND (KINEM* OR BIOMECH* OR COORD* OR MOVEMENT* OR

SPORT* OR SKILL* OR MOTOR*)"

2.3.3 Search results, study inclusion and exclusion

The searching was concluded 23 December 2015 and results were exported to reference management software (EndNote; Thomson Reuters, New York, NY). The following processes were then employed: (1) the first author, working independently, removed all articles where ineligibility was clear from the title. (2) The first author, working independently, removed all articles where ineligibility was clear from the abstract. (3) Full text versions of the remaining studies were then sourced and the first and second authors, working independently, reviewed these articles against all inclusion criteria (Table 2.1). (4) The first author manually searched the reference lists of all included articles to identify any further studies which may meet inclusion criteria. These titles were then exported to EndNote and steps (2) and (3) were repeated. Using a standardised data extraction sheet, Microsoft Access (Microsoft Corporation, Redmond, WA), the first author reviewed all full text articles and extracted all desired data.

2.4 Results

The initial search yielded 19,007 results after the removal of duplicates. Following the processes outlined in section 2.3.3 a total of 66 studies were included in the review. A flow chart documenting the inclusions and exclusions at each step can be seen in Figure 2.1. The included articles spanned the year range 1986 – 2015.
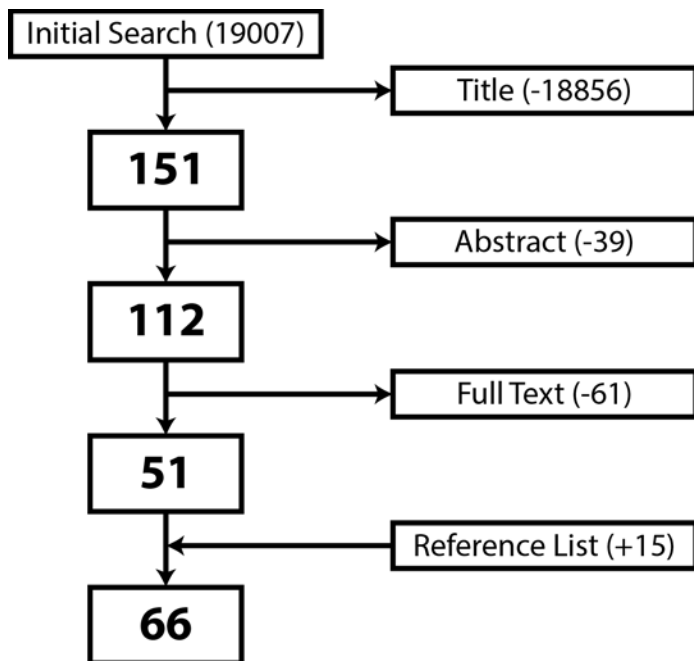
Figure 2.1. Study inclusion flowchart.

The key data extracted from the included articles are summarised in Table 2.2 and Table 2.3. The included articles were predominantly cross-sectional in their design (n = 38). Of these 25 were observational in nature, while the remainder included some form of comparison (e.g., across task conditions). Seventeen studies used a causal comparative design to investigate differences between groups. Repeated measures designs comprised 11 studies of which 7 were a pre-post intervention design, 3 were longitudinal interventions and there was 1 test re-test design.

Reported aims directly referred to variability in some form in 47 studies. The primary aim of these studies was quantification of variability (n = 34), either to form part of the knowledge base of the chosen movement, or, to compare variability between groups and/or conditions. Nineteen studies did not have variability as their focal point of the investigation with the majority using variability as a dependent variable to aid in the answering of their research question and/or testing of their hypotheses.

Reported sample sizes had a median value of 21.8 with an interquartile range (IQR) of 6 years. Sub groups were included in 22 studies where average group size was 9.9 ± 5.0 participants. The majority of research samples were combined genders (n = 26) or male (n = 25), with nine female only studies. Average age of adult participants was 23.4 ± 5.4 years, calculated from the studies where data was available and appropriate. Population samples were comprised of sport/skill specific groups (n = 55), general population (n = 9) or a combination of both (n = 2).

Tools for capturing kinematic data predominantly consisted of video (n = 22) or optoelectronic systems (n = 35). Other methods included active marker systems and goniometry (n = 9). Mean capture frequency for the video and optoelectronic studies was 211 ± 168 Hz, with a trend of increasing capture frequency with each subsequent year. There was also an increasing trend over the years in the adoption of optoelectronic data capture systems over traditional video.

Data smoothing/filtering methods were reported in 40 studies in which some form of Butterworth filter was most common (n = 24). Of those using smoothing, 32 reported the cut-off frequency or similar critical value. Two studies reported a cut-off frequency but not the type of filter implemented. Of the studies that reported critical values, 11 cited the method whereby those values were decided upon (e.g., residual analysis).

From 56 studies the median number of trials collected for each testing condition/time point was 10 (IQR 14). Five studies did not report the number of trials collected. Not all studies analysed all trials collected. The median number of trials analysed was nine (IQR 5). From the 48 investigations for which a determination could be made from the reported information, 14 studies reported analysing fewer trials than collected, while 34 studies reported analysing all collected trials.

The main kinematic variable types derived from collected data were relative joint angular displacements (n = 41), release/impact variables (n = 18), relative joint angular velocity (n = 16), marker linear displacement (n = 13) and implement (e.g., bat) kinematics (n = 13). Thirty studies reported some form of first derivative/velocity variable while four reported some form of second derivative/acceleration. Nineteen studies reported quantifying coordination of variables in some way. While these were the variables reported as being calculated or described, not all were submitted to variability analysis.

The most common method (n = 41) for quantification of variability was standard deviation (SD). Coefficient of variation (CV) was employed in 17 studies. Six studies used one or more of approximate entropy, sample entropy, principal component and cluster analyses. Other methods were reported in 14 studies. Investigation of variability in coordination was achieved using phase-plane plots (n = 2) and angle-angle plots (n = 9). Angle-angle plots were interpreted visually as well as often being further assessed using a quantitative measure, most commonly Normalised Root Mean Square (NoRMS; n = 7). Studies which quantified coordination using a vector coding technique (n = 9), assessed variability via methods such as circular SD or coefficient of correspondence. Variability of whole body or whole system output was assessed by methods such as variability ellipses, hierarchical cluster analysis and neural networks (n = 7).

Table 2.2.

Participant characteristics and movement investigated.

Article	Study Design	Sample Size	Population	Gender	Participant Age	Movement
Anderson et al. 1986	Observational case study	N = 1	General population	M	27	Dart throw
Armour Smith et al. 2012	Cross-sectional observational	N = 7	Experienced dancers	M (n = 2) F (n = 5)	19.4 ± 1.8	Sauté jumps
Barris et al. 2013	Cross-sectional observational	N = 5	Elite divers	M (n = 1) F (n = 4)	17.2 ± 1.6	Springboard dives
Barris et al. 2014	Longitudinal quasi-experimental	N = 4	Elite divers	F	20 ± 2.9	Springboard dives
Betzler et al. 2012	Causal comparative	N = 285	Intermediate golfers	M (n = 246) F (n = 39)	M: 46 ± 18 F: 50 ± 16	Golf drive
Bootsma et al. 1990	Cross-sectional observational	N = 5	Experienced table tennis players	M	18 - 24	Table tennis forehand
Bootsma et al. 1991	Longitudinal experimental	N = 20	General population	M (n = 12) F (n = 8)	21.9 (18 - 26)	Table tennis forehand
Bradshaw et al. 2007	Cross-sectional observational	N = 10	Experienced sprinters	M	20 ± 3	Sprint start
Bradshaw et al. 2009	Causal comparative	N = 20	High and low handicap golfers	M	25.4 ± 6.4	Golf iron shot
Button et al. 2003	Cross-sectional observational	N = 6	Basketballers of varying skill	F	19.8 ± 1.5	Basketball free throw

Article	Study Design	Sample Size	Population	Gender	Participant Age	Movement
Carson et al. 2014a	Cross-sectional observational	N = 3	Professional golfers	M	26.7 ± 2.9	Golf iron shot
Carson et al. 2014b	Cross-sectional observational	N = 9	Low handicap golfers	M	26.1 ± 8	Real and practice golf swings
Chow et al. 2005	Cross-sectional observational	N = 5	Skilled soccer players	M	20.0 ± 1.58	Soccer chip
Chow et al. 2007	Causal comparative	N = 15	Soccer players of varying skill	M	Skilled: 20.0 ± 1.58 Intermediate: 25.0 ± 2.65 Novice: 27.0 ± 3.54	Soccer chip
Chow et al. 2008a	Longitudinal	N = 4	NR (no soccer experience)	M	27.3 ± 4.03	Soccer chip
Chow et al. 2008b	Longitudinal quasi-experimental	N = 4	NR (no soccer experience)	M	27.3 ± 4.03	Soccer chip
Cicchella 2009	Observational case study	N = 1	National level gymnast	F	16	Gymnastic jumps
Cortes et al. 2014	Longitudinal quasi-experimental	N = 11	General population	NR	20.0 ± 0.9	Sidestep cutting task
Dai et al. 2013	Cross-sectional observational	N = 33	National level discus throwers	M (n = 18) F (n = 15)	NR	Discus throw
Dias et al. 2014a	Cross-sectional observational	N = 10	Low and intermediate handicap golfers	M	33.8 ± 11.89	Golf putting
Dias et al. 2014b	Cross-sectional observational	N = 10	Low and intermediate handicap golfers	M	33.8 ± 11.89	Golf putting

Article	Study Design	Sample Size	Population	Gender	Participant Age	Movement
Farana et al. 2015	Cross-sectional observational	N = 6	International gymnasts	F	21.0 ± 1.9	Gymnastic round off
Fleisig et al. 2009	Causal comparative	N = 93	Baseball pitchers	M	Youth: 13.6 ± 1.1 High school: 16.8 ± 1.1 College: 20.5 ± 1.1 Minor league: 20.8 ± 1.6 Major league: 27.6 ± 3.4	Baseball pitching
Gittoes et al. 2011	Cross-sectional observational	N = 4	National level gymnasts	F	20 ± 0.8	Gymnastic beam dismounts
Grassi et al. 2005	Cross-sectional observational	N = 9	Experienced gymnasts	M (n = 6) F (n = 3)	M: 20.3 ± 2.3 F: 18.7 ± 1.5	Gymnastic flic-flac
Gutiérrez-Dávila et al. 2013	Cross-sectional observational	N = 5	Handballers	M	22 - 27	Handball shooting
Hiley et al. 2013	Cross-sectional observational	N = 4	National level gymnasts	M	21 ± 4	Gymnastic high bar skills
Hodges et al. 2005	Longitudinal case study	N = 1	General population	M	26	Soccer chip
Horan et al. 2011	Causal comparative	N = 38	Low handicap golfers	M (n = 19) F (n = 19)	M: 26 ± 7 F: 25 ± 7	Golf drive
Irwin et al. 2005	Cross-sectional observational	N = 4	International gymnasts	M	22 ± 4	Gymnastic high bar skills
Irwin et al. 2007	Cross-sectional observational	N = 4	International gymnasts	M	22.5 ± 4.1	Gymnastic high bar skills
Jarvis et al. 2014	Causal comparative	N = 20	Professional dancers and general population	F	Dancers: 27.1 ± 3.5 Non-dancers: 24.8 ± 2.2	Sauté jumps

Article	Study Design	Sample Size	Population	Gender	Participant Age	Movement
Karlsen et al. 2008	Cross-sectional observational	N = 71	Low handicap golfers	NR	21.7 ± 7.1	Golf putting
Knudson 1990	Cross-sectional observational	N = 2	Collegiate tennis players	M	NR	Tennis forehand
Knudson et al. 2005	Cross-sectional observational	N = 7	Experienced tennis players	M (n = 6) F (n = 1)	NR	Tennis forehand
Kudo et al. 2000	Cross-sectional quasi-experimental	N = 8	General population	M (n = 4) F (n = 4)	20 - 24	Underarm throw
Langdown et al. 2013	Causal comparative	N = 20	High and low handicap golfers	M (n = 17) F (n = 3)	18 - 27	Golf iron shot
Lees et al. 2013	Cohort test re-test.	N = 10	Experienced soccer players	NR	23.4 ± 2.5	Soccer instep kick
Mackenzie et al. 2011	Longitudinal quasi-experimental	N = 31	Intermediate to high handicap golfers	M	22.3 ± 4.1	Golf putting
McDonald et al. 1989	Longitudinal	N = 5	Proficient darts players	M	19 - 30	Dart throw
McLean et al. 1999	Causal comparative	N = 30	Proficient sidestep cutters	M (n = 16) F (n = 14)	M: 19.4 ± 2.2 F: 19.1 ± 1.8	Sidestep cutting task
McLean et al. 2004	Causal comparative	N = 16	Proficient sidestep cutters	M (n = 8) F (n = 8)	M: 21.4 ± 3.2 F: 23.2 ± 3.8	Sidestep cutting task
McLean et al. 2005	Causal comparative	N = 20	Collegiate basketballers	M (n = 10) F (n = 10)	M: 20.2 ± 1.9 F: 21.3 ± 3.0	Agility tasks

Article	Study Design	Sample Size	Population	Gender	Participant Age	Movement
Meylan et al. 2010	Cross-sectional observational	N = 30	Recreational athletes	NR	21.9 ± 3.8	Jumping
Muller et al. 1999	Cross-Sectional observational	N = 6	Club and novice dart players	NR	NR	Dart throw
Mullineaux et al. 2010	Cross-sectional observational	N = 15	Collegiate basketballers	M (n = 9) F (n = 6)	M: 19.1 ± 0.8 F: 19.3 ± 1.4	Basketball free throw
O'Connor et al. 2009	Causal comparative	N = 33	Recreational athletes	M (n = 16) F (n = 17)	M: 22.7 ± 2.7 F: 20.9 ± 1.5	Sidestep cutting task
Pollard et al. 2005	Causal comparative	N = 24	Collegiate soccer players	M (n = 12) F (n = 12)	M: 19.7 ± 1.5 F: 19.3 ± 1.1	Sidestep cutting task
Pollard et al. 2015	Causal comparative	N = 20	Soccer players	F	Injured: 23.2 ± 3.4 Uninjured: 21.0 ± 1.2	Sidestep cutting task
Reeve et al. 2013	Cross sectional observational	N = 12	Experienced dancers	M (n = 5) F (n = 7)	19.5 ± 2.9	Drop landing
Robins et al. 2006	Cross sectional observational	N = 6	Experienced basketballers	M	21.83 ± 0.98	Basketball shooting
Salo et al. 1998	Cross-sectional observational	N = 7	National level hurdlers	M (n = 3) F (n = 4)	M: 26.9 ± 1.7 F: 20.1 ± 2.1	Sprint hurdling
Schmidt 2012	Cross-sectional observational	N = 21	Basketballers of varying skill	M (n = 16) F (n = 5)	17 - 38	Basketball free throw
Schorer et al. 2007	Cross-sectional observational	N = 5	Handballers of varying skill, general population and rugby players	M (n = 3) F (n = 2)	24.2 ± 6.5	Handball shooting

Article	Study Design	Sample Size	Population	Gender	Participant Age	Movement
Sevrez et al. 2014	Cross-sectional case study	N = 1	Experienced tennis player	M	33	Tennis serve
Sforza et al. 2000	Cross sectional observational	N = 7	Karateka	M (n = 3) F (n = 4)	M: 19.7 ± 0.6 F: 27.5 ± 10.4	Karate punches
Sforza et al. 2001	Cross sectional observational	N = 13	Expert Karateka	M (n = 8) F (n = 5)	M: 26.2 ± 5.5 F: 25.3 ± 5.9	Karate punches
Sforza et al. 2002	Cross sectional observational	N = 13	Experienced karateka	M (n = 8) F (n = 5)	M: 26.3 ± 5.5 F: 27.6 ± 6.4	Karate kick
Sheppard et al. 2007	Causal comparative	N = 24	Experienced table tennis players and general population	NR	Experienced: 21.7 ± 2.9 Gen. Population: 22.2 ± 5.6	Table tennis forehand
Slobounov et al. 1997	Cross-sectional observational	N = 6	Elite divers	M (n = 3) F (n = 3)	18 - 21	Springboard dives
Taylor et al. 2014	Cross-sectional observational	N = 7	Amateur water polo players	F	21.1 ± 2.7	Water polo penalty shot
Tucker et al. 2013	Cross-sectional observational	N = 16	Low handicap golfers	M (n = 6) F (n = 10)	26.3 ± 5.6	Golf drive
Urbán et al. 2015	Cross sectional	N = 25	Handballers	M	17.9 ± 3.7	Handball shooting
Wagner et al. 2012	Causal comparative	N = 24	Low, moderate and high skilled handballers	M	Low: 19.0 ± 5.2 Moderate: 19.1 ± 3.1 High: 25.3 ± 3.2	Handball shooting
Whiteside et al. 2015	Causal comparative	N = 31	Expert tennis players	F	Pre-pubescent: 10.5 ± 0.5 Pubescent: 14.6 ± 4.7 Adult: 21.3 ± 3.8	Tennis serve

Article	Study Design	Sample Size	Population	Gender	Participant Age	Movement
Wilson et al. 2008	Cross-sectional observational	N = 5	Experienced triple jumpers	M (n = 3) F (n = 2)	20.6 ± 1.5 years	Triple jump

Note: F = Female, M = Male, NR = Not Reported.

Table 2.3.

Trial size, methods and measures.

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Anderson et al. 1986	P = 114 - 122 A = 10	One (1) active marker camera system (312.5 Hz)	Marker linear displacement Marker linear velocity Relative joint angular displacement	Gaussian (19.2 msec window)	F-ratio SD
Armour Smith et al. 2012	P ≥ 20 A = 10	Passive marker optoelectronic system (250 Hz; # cameras NR)	Coordination Segment angular displacement	Butterworth (12 Hz)	Circular SD of coupling angle (vector coding)
Barris et al. 2013	P = NR A = 5	One (1) video camera (60 Hz) - manual digitisation (reliability reported)	Coordination Relative joint angular displacement Segment angular displacement Step/stride kinematics	Butterworth (NR)	Angle-angle plots NoRMS
Barris et al. 2014	P = NR A = 5	One (1) video camera (60 Hz) - manual digitisation (reliability reported)	Coordination Relative joint angular displacement Segment angular displacement Step/stride kinematics	NR	Angle-angle plots NoRMS SD
Betzler et al. 2012	P = 15 A = 10	Five (5) passive marker optoelectronic camera system (1000 Hz).	Implement kinematics Release variables	NR	CV Median absolute deviation
Bootsma et al. 1990	P = 40 A = 7	One (1) video camera (125 Hz) - manual digitisation	Implement kinematics	Butterworth (8 Hz - Frequency analysis)	CV SD
Bootsma et al. 1991	P = 40 A = 10	One (1) video camera (125 Hz) - manual digitisation	Implement kinematics	Butterworth (8 Hz)	SD

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Bradshaw et al. 2007	P = 4 A = 4	Two (2) synchronised video cameras (250 Hz) - manual digitisation (reliability reported)	Relative joint angular displacement Relative joint angular velocity Segment angular displacement Step/stride kinematics	Digital (8 Hz)	Biological CV
Bradshaw et al. 2009	P = 10 A = 10	Three (3) independent video cameras (50 Hz) Radar gun	Implement kinematics Segment angular displacement Stance kinematics Relative joint angular displacement	NR	Biological CV
Button et al. 2003	P = 30 A = 30	One (1) video camera (60 Hz) - manual digitisation (reliability reported)	Coordination Marker linear displacement Marker linear velocity Relative joint angular displacement Relative joint angular velocity Release variables	Filter type NR (9 Hz - Frequency analysis)	Angle-angle plots Phase-plane plots SD
Carson et al. 2014a	P = 10 A = 10	Inertial sensor motion capture suit (120 Hz)	Relative joint angular displacement	NR	SD
Carson et al. 2014b	P = 10 A = 10	Inertial sensor motion capture suit (120 Hz)	Marker linear displacement	NR	SD

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Chow et al. 2005	P = 5 or 10 A = 5 or 10	Six (6) passive marker optoelectronic camera system (240 Hz)	Ball backspin Centre of mass Coordination Relative joint angular displacement Relative joint angular velocity Release variables Segment linear acceleration Segment linear velocity Stance kinematics	Butterworth (7 Hz)	Angle-angle plots CV NoRMS SD
Chow et al. 2007	P = 5 or 10 A = 5 or 10	Six (6) passive marker optoelectronic camera system (240 Hz)	Ball backspin Centre of mass Coordination Relative joint angular displacement Relative joint angular velocity Release variables Segment linear acceleration Segment linear velocity Stance kinematics	Butterworth (7 Hz)	Angle-angle plots CV NoRMS SD
Chow et al. 2008a	P = 5 or 10 A = 5 or 10	Six (6) passive marker optoelectronic camera system (240 Hz)	Ball backspin Centre of mass Coordination Relative joint angular displacement Relative joint angular velocity Release variables Segment linear acceleration Segment linear velocity Stance kinematics	Butterworth (7 Hz)	Angle-angle plots NoRMS SD

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Chow et al. 2008b	P = 5 or 10 A = 5 or 10	Six (6) passive marker optoelectronic camera system (240 Hz)	Relative joint angular displacement Segment angular displacement	Butterworth (7 Hz)	Switch ratio (cluster analysis)
Cicchella 2009	P = 10 A = 10	Six (6) passive marker optoelectronic camera system (100 Hz)	Relative joint angular displacement Step/stride kinematics	NR	CV
Cortes et al. 2014	P = 5 A = 5	Eight (8) passive marker optoelectronic camera system (270 Hz)	Relative joint angular displacement	Butterworth (7 Hz)	Sample entropy SD
Dai et al. 2013	P = 3 A = 3	Two (2) synchronised video cameras (60 Hz) - manual digitisation - 3D analysis	Relative joint angular displacement Segment angular displacement	Butterworth (7.14 Hz)	SD
Dias et al. 2014a	P = 30 A = 30	One (1) video camera (210 Hz)	Implement kinematics	NR	SD
Dias et al. 2014b	P = 30 A = 30	One (1) video camera (210 Hz)	Implement kinematics	Sinusoidal smoothing function	Approximate entropy Lyapunov exponent
Farana et al. 2015	P = 10 A = 10	Eight (8) passive marker optoelectronic camera system (247 Hz)	Relative joint angular displacement	Butterworth (12 Hz)	Biological CV CMC
Fleisig et al. 2009	P = 10 – 15 A = 5	Six (6) to eight (8) passive marker optoelectronic camera system (240 Hz)	Relative joint angular displacement Release variables Segment angular displacement Segment angular velocity Step/Stride kinematics	Butterworth (13.4 Hz)	SD

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Gittoes et al. 2011	P = 10 A = 10	Two (2) co-aligned Cartesian optoelectronic dynamic anthropometers (200 Hz)	Centre of mass displacement Centre of mass velocity Relative joint angular displacement Relative joint angular velocity	Filter type NR (10 Hz - Residual analysis)	SD
Grassi et al. 2005	P = 15 A = 10	Eight (8) passive marker optoelectronic camera system (100 Hz)	Marker linear displacement	NR	3D SD SD
Gutiérrez-Dávila et al. 2013	P = 35 A = 35	Two (2) synchronised video cameras (500 Hz) - manual digitisation - 3D analysis	Marker linear displacement Release variables	Quintic spline	SD
Hiley et al. 2013	P = 10 A = 10	Fifteen (15) passive marker optoelectronic camera system (300 Hz)	Relative joint angular displacement Circle angle	Butterworth (20 Hz)	SD
Hodges et al. 2005	P = 25 A = 6	Three (3) passive marker optoelectronic camera system (240 Hz)	Coordination Relative joint angular displacement	NR	NoRMS SD
Horan et al. 2011	P = 5 A = 5	Passive marker optoelectronic system (500 Hz; # cameras NR)	Coordination Implement kinematics Segment angular displacement Segment linear displacement	Butterworth (6 to 10 Hz - Residual analysis)	Angle-angle plots Coefficient of correspondence (vector coding) SD Spanning set
Irwin et al. 2005	P = 15 A = 3	One (1) video camera (50 Hz) - manual digitisation (reliability reported)	Centre of mass Circle angle Relative joint angular displacement Relative joint angular velocity	Digital (6 Hz - Residual analysis)	SD of RMSD

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Irwin et al. 2007	NR	One (1) video camera (50 Hz) - manual digitisation (reliability reported)	Centre of mass Circle angle Coordination Relative joint angular displacement Relative joint angular velocity	Digital Gaussian kernel (bandwidth 0.15 - residual analysis)	RMS of CRP variance
Jarvis et al. 2014	P = 20 A = 10	Eleven (11) passive marker optoelectronic camera system (100 Hz)	Coordination Relative joint angular displacement Segment angular displacement	Butterworth (12 Hz)	Circular SD of coupling angle (vector coding) SD
Karlsen et al. 2008	P = 18.3 ± 5.1 A = NR	Active marker ultrasound system (70 Hz) - reliability reported	Implement kinematics	NR	Own algorithm SD
Knudson 1990	P = NR A = 8	Two (2) synchronised video cameras (100 Hz & 200 Hz) - manual digitisation (error reported) - 3D analysis	Relative joint angular acceleration Relative joint angular displacement Relative joint angular velocity	Butterworth (8 to 45 Hz)	Curve CV CV SD
Knudson et al. 2005	P = 40 A = 4 or 5	One (1) video camera (180 Hz) - manual digitisation (error reported)	Implement kinematics Release variables	Cubic spline	CV SD
Kudo et al. 2000	P = 30 A = 30	One (1) video camera (60 Hz) - manual digitisation (reliability reported)	Release variables	Linear square fitting	SD
Langdown et al. 2013	P = 10 – 15 A = NR	Thirteen (13) passive marker optoelectronic camera system (250 Hz)	Marker linear displacement Segment angular displacement Stance kinematics	NR	Variable error
Lees et al. 2013	P ≥ 20 A = NR	Eight (8) passive marker optoelectronic camera system (240 Hz)	Relative joint angular velocity Segment linear velocity	Butterworth (12 Hz)	CV SD SEM

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Mackenzie et al. 2011	P = 50 A = 50	One (1) active marker camera system	Implement kinematics	Butterworth (8 Hz)	SD
McDonald et al. 1989	P = 10 A = 10	Two (2) active marker camera system (100 Hz)	Relative joint angular displacement Relative joint angular velocity Release variables Segment linear displacement Segment linear velocity	Kalman recursive (5 Hz - Frequency analysis)	SD CV
McLean et al. 1999	P = 8 A = 5	Four (4) synchronised video cameras (500 Hz) - 3D analysis	Relative joint angular displacement	NR	CV
McLean et al. 2004	P = 10 A = 10	Six (6) passive marker optoelectronic camera system (240 Hz)	Relative joint angular displacement	Cubic spline (30 Hz)	SD
McLean et al. 2005	P ≥ 10 A ≥ 10	Six (6) passive marker optoelectronic camera system (240 Hz)	Relative joint angular displacement	Cubic spline (20 Hz)	SD
Meylan et al. 2010	P = 3 A = 3	Force plate (1000 Hz)	Centre of mass displacement Centre of mass velocity	NR	TE (as CV)
Muller et al. 1999	P = 17 - 46 (24 ± 10) A = 17 - 46 (24 ± 10)	Two (2) photographic cameras	Release variables	NR	SD
Mullineaux et al. 2010	P = 20 A = 3	Twelve (12) passive marker optoelectronic camera system (60 Hz)	Coordination Flight variables Marker linear velocity Relative joint angular displacement Relative joint angular velocity Release variables	Butterworth (8 Hz - Residual analysis)	Circular SD of coupling angle (vector coding) SD

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
O'Connor et al. 2009	P = 25 – 30 A = 4 or 5	Seven (7) passive marker optoelectronic camera system (200 Hz)	Relative joint angular displacement	Butterworth (12 Hz - Previous literature)	PCAw
Pollard et al. 2005	P = 7 A = 7	Seven (7) passive marker optoelectronic camera system (240 Hz)	Coordination Relative joint angular displacement Segment angular displacement	Butterworth (8 Hz)	SD of coupling angle (vector coding; presented as an angle)
Pollard et al. 2015	P ≥ 4 A = 4	Eight (8) passive marker optoelectronic camera system (250 Hz)	Coordination Relative joint angular displacement	Butterworth (12 Hz)	SD of coupling angle (vector coding; presented as an angle)
Reeve et al. 2013	P = 6 A = 6	Twelve (12) passive marker optoelectronic camera system (250 Hz)	Coordination Relative joint angular displacement	NR	h-value (vector coding)
Robins et al. 2006	P > 5 A = 5	Two (2) synchronised video cameras (25 Hz) - manually digitised - 3D analysis	Coordination Relative joint angular displacement Relative joint angular velocity Release variables	Quintic spline	Angle-angle plots CV NoRMS SD SD of CRP
Salo et al. 1998	P = 8 A = 8	Two (2) synchronised video cameras (50 Hz) - manually digitised (reliability reported) - 3D analysis	Centre of mass displacement Centre of mass velocity Relative joint angular displacement Relative joint angular velocity Segment linear displacement	Quintic spline	CV
Schmidt 2012	P = 20 A = 5	Four (4) video cameras (Hz NR) - manually digitised	Relative joint angular displacement Relative joint angular velocity	NR	DyCoN trajectories (artificial neural network)

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Schorer et al. 2007	P ≥ 80 A ~ 45	Three (3) synchronised video cameras (50 Hz) - auto tracked (reliability reported) - 3D analysis	Marker linear displacement	Butterworth (NR)	Euclidean distance matrices and cluster analysis Trajectory traces
Sevrez et al. 2014	P = 10 A = NR	Eight (8) passive marker optoelectronic camera system (500 Hz)	Implement kinematics Relative joint angular displacement	Moving average	CMC CV
Sforza et al. 2000	P = 10 A = 10	Eight (8) passive marker optoelectronic camera system (100 Hz)	Marker linear displacement	NR	3D SD
Sforza et al. 2001	P = 10 A = 10	Eight (8) passive marker optoelectronic camera system (100 Hz)	Marker linear displacement	NR	3D SD
Sforza et al. 2002	P = 10 A = 10	Eight (8) passive marker optoelectronic camera system (100 Hz)	Marker linear displacement	NR	3D SD
Sheppard et al. 2007	P = 75 A = 20	Thirteen (13) passive marker optoelectronic camera system (100 Hz)	Implement kinematics Release variables	Digital FIR (6 Hz)	SD
Slobounov et al. 1997	P = 5 A = 5	One (1) video camera (60 Hz) - manual digitisation	Marker linear displacement Relative joint angular displacement Step/stride kinematics	Fourier	CV SD

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Taylor et al. 2014	P = 10 A = 4 - 10	Six (6) passive marker optoelectronic camera system (250 Hz) One (1) video camera (250 Hz) - manual digitisation (reliability reported)	Coordination Relative joint angular displacement Release variables	NR	CV
Tucker et al. 2013	P = 10 A = 10	Six (6) passive marker optoelectronic camera system (400 Hz) Vector Pro launch monitor	Marker linear displacement Release variables	Butterworth (12 Hz - Residual analysis and previous literature)	CV Variability ellipsoids
Urbán et al. 2015	P = 16 A = 16	Three dimensional electromagnetic tracking system (240 Hz) Radar gun (50 Hz)	Marker linear displacement Release variables Segment linear velocity	NR	SD
Wagner et al. 2012	P = 12 ± 1 A = 10	Eight (8) passive marker optoelectronic camera system (250 Hz)	Relative joint angular displacement Relative joint angular velocity Release variables Segment angular displacement Segment angular velocity	Quintic spline (MSE = 10)	Phase-plane plots SD
Whiteside et al. 2015	P = 40 A = 5	Twenty two (22) passive marker optoelectronic camera system (500 Hz)	Coordination Relative joint angular displacement Segment angular displacement	Woltring (MSE = 2 - Residual analysis	Angle-angle plots Coefficient of correspondence (vector coding) Variability ellipsoids

Article	Trial Size	Kinematic data collection	Kinematic Measures	Filtering	Variability Quantification
Wilson et al. 2008	P = 10 A = 10	Twelve (12) passive marker optoelectronic camera system (100 Hz)	Coordination Relative joint angular displacement	Quintic spline	Circular SD of coupling angle (vector coding)

Note: P = performed, A = analysed, NR = Not reported ~ = 'approximately' (as reported by author); 3D = Three dimensional, CMC = Coefficient of multiple correlations, CRP = Continuous relative phase, CV = Coefficient of variation, DyCoN = Dynamically Controlled Network (a form of artificial neural network), FIR = Finite impulse response, MSE = Mean squared error, NoRMS = Normalised root mean squared, PCAw = Principal component analysis of waveforms, RMS = Root mean squared, RMSD = Root mean squared difference, SD = standard deviation, SEM = Standard error of the mean, TE = Technical error.

2.5 Discussion

Key method-related considerations surrounding the investigation and quantification of variability in discrete, sports-related movements will be addressed in the first part of this discussion. A summary of the key concepts and findings which have emanated from this field of research will be covered in the second part of this discussion.

2.5.1 Method

This section will discuss the main method-related issues within the sampled literature covering both what has been done, and, what may be beneficial future approaches. Starting with study design the section will cover sample and trial size selection, choice of capture frequency, filtering and normalisation and, variables for which variability was quantified. Finally, a discussion will cover the strengths and weaknesses of several common and emerging variability quantification techniques.

2.5.1.1 Study design

There were two general approaches to movement variability identified in this review. The first saw variability as the primary element of interest, documenting how it interacted with factors such as skill, gender, practice, etc. The second used variability simply as a dependent variable which was then analysed along with other variables to attempt to answer research questions and test hypotheses. Underlying the latter approach is an assumption that variability is an inherent outcome of movement and therefore may be affected by independent variables of interest. With this approach research design is governed by the overall aim of the study. When variability is the main focus of an investigation the predominant research designs resulted in a single contact with the participant(s) such as cross sectional descriptive and causal comparative studies. The

snapshots provided in these studies offered important information on the target populations and allowed further hypotheses to be developed. However, they lacked the ability to monitor change in variability, a strength of the longitudinal designs which were surveyed. Questions about the role of variability, particularly how it changes during motor learning/skill acquisition, and links to factors such as adaptability and injury are key current theoretical themes wherein a longitudinal design would facilitate greater insight and understanding.

2.5.1.2 Sample and trial size

The results indicate that differences exist in the number of participants recruited into each study as well as the amount of trials participants were asked to complete. Although large groups may not always be recruited in the sporting populations targeted by many of the surveyed studies, power analyses may be considered to determine sample size to ensure correct acceptance or rejection of null hypotheses (Cohen, 1992). Perhaps of more importance is trial size (i.e., the number of task repetitions analysed per subject) which also has implications for statistical power. Relative to trial size, in order to achieve power values upwards of 90% it has been suggested that researchers should consider employing 10, 5 and 3 trials for samples of 5, 10 and 20, respectively (Bates, Dufek, & Davis, 1992). However, determining trial size for variability analysis is not a simple task (Mullineaux, Bartlett, & Bennett, 2001) and ensuring statistical power for interaction analysis would require consideration of several characteristics of the task selected. The effects of elements such as fatigue and skill learning/familiarity on the dependent variable also need to be taken into consideration.

As movement variability can be expressed, at its simplest, as the amount of variance of individual performances around a mean performance, the number of trials required for this mean to stabilise may be an important factor to determine. Too few trials may result in an

unrepresentative mean and therefore, by association, result in unrepresentative variance. There

are methods to quantify the number of trials required to achieve mean stability such as intra-class

correlation and sequential analysis techniques (James, Herman, Dufek, & Bates, 2007; Racic, Pavic,

& Brownjohn, 2009; Rodano & Squadrone, 2002; Taylor, Lee, Landeo, O'Meara, & Millett, 2015).

Only a few of the studies in this review reported their method of selecting participant and trial

numbers. We suggest investigators may report justification for their selection and address the

issues raised herein when planning and conducting research on movement variability.

2.5.1.3 Capture frequency

Within the included studies a broad range of frequencies were used for motion capture

methods. Selecting an appropriate capture frequency for variability investigations is an important

consideration which has not been extensively addressed in the literature. Although a full

discussion is beyond the scope of this review some considerations are presented here. One

approach is to be guided by sampling theorem and selecting a sample frequency which is double

that expected to be present in the signal (Winter, 2005). For slower, cyclical movements, such as

human gait there has been general agreement that capture frequencies in the range of 25 – 60 Hz

are adequate (Ferber, Sheerin, & Kendall, 2009; Polk, Psutka, & Demes, 2005; Winter, 2005).

However, determining an appropriate frame rate for many discrete movements may prove

challenging due to the high frequency content arising from elements such as the movement of

implements and their projectiles. In addition, capture frequency needs to be sufficient to

accurately identify temporal elements. For instance, when attempting to determine elements of

timing, it has been shown that higher capture frequencies introduce less error than lower

frequencies (Ferber et al., 2009; Polk et al., 2005). Furthermore, the use of lower sampling rates

has been shown to result in misrepresentations of time series and peak values in derivatives of

displacement data (Harper & Blake, 1989). This may be reflected in the higher variability of

displacement derivatives reported in the variability literature (Knudson, 1990). Based on these

considerations, researchers may choose to adopt higher capture frequencies where constraints,

such as location or cost, allow. Data from this review suggest that higher capture frequencies are

gaining popularity with increasing adoption of optoelectronic systems, as they can operate at

higher frame rates than many older video systems and remove the need for manual digitisation.

Further investigation of the error introduced by both high and low capture frequencies may

enable a more informed selection for research into variability.

2.5.1.4 Filtering

The results of this review suggest that the majority of research into human variability

adopted some type of data transformation method and provided detailed information related to

the processes. It is good practice for researchers to ensure they report methods of data

manipulation used (e.g., filter type), any critical values and the processes for determining these

values so that readers may understand how data may have been transformed. Filtering/smoothing

of data is a very common convention within biomechanics which aims to remove noise and/or

error from an observed signal to allow analysis of the true signal. Appropriate selection of cut-off

frequency or similar critical value is important otherwise data distortion and loss of deterministic

biological variability information may occur. Several techniques exist for the purpose of selecting

an appropriate cut-off frequency (c.f. Derrick [2013] and Winter [2005]). Furthermore,

implementing surrogate methods can confirm whether a processed signal has had deterministic

elements removed after filtering (Small, Nakamura, & Luo, 2007; Theiler & Eubank, 1993).

Surrogate methods produce a signal which mimics the macro characteristics of an observed signal

such as mean, variance and amplitude (Stergiou et al., 2004). However, the micro structure of the

surrogate – the relationship between neighbouring data points – is destroyed, removing the deterministic nature of the signal. If differences between the observed (normally filtered) signal and surrogate can be confirmed, then we can be confident that the observed signal is representative of deliberate biological output and that any variability observed in collected signals can be stated to be a result of deterministic, not stochastic, processes (Taylor et al., in press). The comparison can be achieved using a discriminating statistics on the variables such as sample entropy estimate or Lyapunov exponent (Preatoni et al., 2010; Stergiou et al., 2004).

2.5.1.5 Analysed variables

The results revealed a broad spectrum of biomechanical variables for which variability was quantified. It was common to investigate factors such as release variables and other kinematic descriptors of sporting implements/objects (e.g., racquet/club face angles), often reported at or around points of impact or projection. Human kinematic variables included individual marker, segment or joint linear/angular displacement and derivatives, as well as measures of coordination. There were also studies which measured 'whole system' movement variability, describing variability within a group of coordinated structures (e.g., the striking and non-striking leg during a kick) or the whole body.

From the findings of this review, it is possible to divide these factors into three levels at which kinematic variability can be investigated. The first level consists of discrete or time series measures of individual segments and joint kinematic, release/impact parameters and implement/projectile kinematics. The second level sees two or more of these variables combined to form a coordinated unit. Finally, the combination of several coordinated structures allows examination of whole system movement. Specific research questions may direct investigators to one or the other of these levels according to an understanding of where changes in variability may

manifest. However, it is less clear at which level there should be a focus when attempting to

answer broader theoretical questions about movement variability, such as its interaction with

motor learning or links to factors such as adaptation. For example, a coupling of movement

between two joints may display little coordinative variability over a series of trials, yet certain

joints may be highly variable across the same period. Similarly, there may be increased variability

across several coordinated segments whereas whole body movement variability could show

decreased variability. This is potentially related to the concept of controlled and uncontrolled

variables within the uncontrolled manifold hypothesis (Latash, Levin, Scholz, & Schöner, 2010;

Schorer et al., 2007). Therefore when attempting to answer broader questions about movement

variability, it may be beneficial to consider all levels in order to see how and where variability

changes manifest across time. Of course, if results from a less complex analysis are suffice to

answer a question at hand, then there is lesser need to consider other levels of variability in the

investigation (Hamill et al., 2006).

2.5.1.6 Quantification method

Perhaps the major decision to make when studying movement variability is the selection

of the method used for quantification. Table 2.3 outlines the myriad measures available to

investigators that have been used previously. The most commonly employed methods were SD

and its derivative, CV, which is most commonly calculated by dividing the SD by the mean

(Atkinson & Nevill, 1998). One of the strengths of SD is that the variance is presented in the same

unit as the original measure, but as a result, it lacks the capacity to compare variation across

values of differing units or scale (Hopkins, 2000; Hopkins, Schabort, & Hawley, 2001). CV can

overcome this drawback through standardisation of variance across different units. Nevertheless,

CV is not without its limitation, as it has difficulty in validating variance in values which are not

bound by a true zero (Atkinson & Nevill, 1998). Both SD and CV have been employed primarily to quantify variability of discrete points extracted from time series. It can be questioned whether their use in this manner is an optimal measure of the variability as they only provide the magnitude of the variability without any consideration of its structure (Slifkin & Newell, 1999). Perhaps their best use is quantification of elements which only occur discretely, such as throw release parameters (height, angle, etc.), rather than discrete extraction of single values from time series data.

Another valid application of SD and/or CV is to describe the variance in measures of coordination. This review identified several methods employed to describe coordination, which covered both qualitative (e.g., angle-angle plots) and quantitative means. Although the methods chosen to quantify coordination variability within the included studies are documented (Table 2.3), and the close relationship between coordination and variability studies acknowledged, it is not the intention of this review to provide a discussion on the selection of an appropriate method for quantifying coordination. There is no doubt that a valid means of quantifying coordination is required to determine variability of coordination and several excellent resources provide ample guidance on this matter (c.f. Deluzio et al. [2013]; Hamill et al. [2000]; Sidaway, Heise, and Schoenfelder-Zohdi [1995]; van Emmerick et al. [2013]). In other studies, SD was used either in standard or circular form to determine variability of coordination measures using vector coding and relative phase analyses. Other methods for quantifying variability of coordination included normalised root mean square (NoRMS) for use with angle-angle analyses and coefficient of correspondence for vector coding techniques.

Current advances in data collection technology within biomechanics often results in large amounts of high dimensional data being obtained. One of the issues with the use of SD and CV is

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the reduction of high dimensional data to a single value based on a discrete extraction from time series. This can result in the loss of structural information, treating the extraction as an independent datum and neglecting the deterministic nature of biological time series. To allow for data reduction without loss of information, there is an emerging trend to adopt statistical techniques which consider entire time series. One such approach is the Lyapunov exponent which is a nonlinear measure that determines system stability by assessing the rate of divergence of elements within a state space (Stergiou et al., 2004). Greater instability results in an increased rate of divergence which yields a larger exponent.

Other nonlinear methods include approximate entropy (ApEn) and sample entropy (SampEn) which quantify regularity across a time series or family of time series. Those methods assess the probability that two sequences of points extracted from a time series of length N, which have similar values for a period of m points within a tolerance r, will remain similar for a period of $m + 1$ points (Richman & Moorman, 2000). The tolerance r is generally a fraction of SD in the time series. Both ApEn and SampEn return a value of 0 for those that are totally regular (e.g. sine waves) and higher values for those which are less regular (Richman & Moorman, 2000). Since they provide a single value measure of variability that is derived by assessing an entire time series or set of time series (when applied to discrete movement data, all time series from a set of trials are usually concatenated), this ensures that all data points are assessed and no information is discarded in the quantification of movement variability. Both entropy estimates and Lyapunov exponent can then be submitted to inferential statistics. However, similar to SD and CV, they only provide a measure of magnitude, and thus no information is offered on the structure of variability.

Where an exposition of the structure as well as magnitude of variance is desired, a different data reduction technique is required. Principal component analysis of waveforms (PCAw)

is one technique which can achieve these aims, reducing data dimensionality by determining the

number of unique components which contribute to the total waveform. These components are

themselves waveforms and exist across the same time domain as the sampled waveform which

can allow meaningful qualitative analysis of the structure of variance (Deluzio et al., 2013). The

percentage of total variation attributed to each component is also identified. Generally, only a few

components are required to account for the vast majority of variation in the original waveform,

allowing the remainder to be discarded. Subsequently, a relatively accurate reconstruction of the

original waveform can be estimated from the few retained principal components. In addition the

process produces principal component scores (the coefficients of the individual principal

components) which may be submitted to inferential statistics to facilitate hypothesis testing

within or between individuals, groups or interventions (Deluzio et al., 2013). However, a potential

source of data distortion might arise from this technique as it works pointwise across a time

normalised waveform thereby operating on the assumption that each time point is independent

(Harrison, 2014). Yet, biological time series are deterministic in nature, which can be confirmed

using surrogate analysis mentioned in a previous section (2.5.1.4), meaning there is a direct

relationship between each point and its neighbours (Taylor et al., in press). A method which

addresses these concerns and maintains the benefits of PCAw in quantifying the variability of total

waveform is functional principal component analysis (fPCA). As a component of functional data

analysis (FDA), fPCA transforms each time series into a single, functional entity through the use of

groups of basis functions (Ramsay, Hooker, & Graves, 2009; Ramsay & Silvermann, 1997).

Moreover, FDA and fPCA can assess coordination variability using a bivariate form of the analysis.

While both PCAw and fPCA provide ample opportunity to produce informative analyses, they

require careful progression through several steps to produce valid results, which can be quite

complex. Researchers should ensure they are fully acquainted with these processes before

implementing such analyses.

Finally, some authors sought to assess what may be termed as 'whole system' variability,

describing variability within a group of coordinated structures during movement, such as the

striking and non-striking leg or even the whole body during a kick. One method used calculated

variance volume, where an ellipsoid is created with the lengths of its three axes derived from the

variance (SD) of the linear displacement of markers in x, y and z axes (Sforza et al., 2002; Tucker et

al., 2013). The volume of the ellipsoid is therefore a measure of total variance at that site which

can be normalised by dividing by the total distance travelled by each marker in each axis to allow

comparison across sites (Tucker et al., 2013). While these markers are often placed on bony

landmarks at joints, they represent whole system variability since their position in space at any

time is reliant on the organisation of all intra-individual structures. As such, a mean or sum of all

scaled volumes may provide a single value measure of whole system variability.

Other approaches of note to assess whole system variability involve the reduction of the

dimensionality of data. The first of these is hierarchical cluster analysis where many biomechanical

variables can be entered and a criterion, such as Euclidean distance, used to determine whether

individual trials are similar and therefore sit within the same cluster. The hierarchy can be

represented using a dendogram at the top of which all trials form one cluster. Based on the

criterion, this cluster and subsequent clusters split until all trials sit in their own cluster (Chow,

Davids, Button, & Rein, 2008). The key decision to be made is at which level to cut the dendogram,

yielding n clusters (c.f. Everitt [1979]; Romesburg [2004]) which may represent the number of

individualised movement patterns of the whole system presented during any set of trials. In a way,

this number can denote the variability present. A further determination of variability can be

attained by calculating the switch ratio, the frequency of change in the classification of the current

trial from one cluster to another across a series of trials (Chow, Davids, Button, & Rein, 2008).

Artificial neural networks are another, somewhat underutilised, computational tool that

can quantify whole system (Schmidt, 2012). These techniques use unsupervised machine learning

to take many variables from a high dimensional space and project them onto a low dimensional

(often 2D) network (Davids et al., 2006). This projection forms a trajectory that moves across the

nodes of the network over the time course of the movement. Across trials, the trajectories can

then be compared as a quantitative assessment of whole system variability. A second, lower level

network, can then be derived from these trajectories to provide even further information on

individual variability (Schmidt, 2012). However, these computations often require sophisticated

statistical packages, perhaps resulting in their underutilisation (see Table 2.3). Furthermore, the

usefulness of these techniques in an applied setting may be limited by the at times complex nature

of result interpretation, further reducing their utilisation. By addressing these issues and through

further development of the techniques though they provide a potentially fruitful tool for future

research and application.

Making a selection from the presented methods to assess variability depends on many

factors including research question, data format and application. In terms of their application, the

methods are capable of producing large amounts of information. However, a less-is-more

approach often prevails in the applied settings which characterised many of the studies in this

review. For example, athletes and coaches will often want simplified and intuitive, as opposed to

complex and theoretical, values particularly for tracking elements over time. In this sense, the role

of the researcher is to balance these needs and make the appropriate selections of tools when

analysing variability.

2.6 General Discussion

The inclusion criteria for this review required that studies had implemented a design

wherein variability was quantified within subject across multiple same session trials, even if

subsequently these measures were collapsed across groups for comparative purposes. The

included studies (n = 66) represent a body of literature which reflects the potential importance

and implications of intra-individual discrete movement variability. Within the applied focus of this

review, it also seemed to accept the notion that it is impossible to have a single invariant

representative, optimal or normal pattern for any movement (Bartlett et al., 2007; Preatoni et al.,

2013). Unlike cyclical movements, where the movement pattern itself often determines the

success of the movement, within many applied discrete tasks, and in many sports not assessed in

this review, it is the outcome (goals scored, distances jumped, etc.) which ultimately determines

the success of a movement. As such it is not consistency in movement patterns, but rather

movement outcome, which is desirable.

The ability to consistently produce successful movement outcomes is indicative of skilled

performance. Movement variability was consistently reported to be present in the movement

profiles of such skilled performers within the sampled literature. For example, the phenomena of

successful outcome and movement variability coexisting was identified in diving (Barris et al.,

2013, 2014; Slobounov et al., 1997), table tennis (Bootsma & van Wieringen, 1990), basketball

(Button et al., 2003; Mullineaux & Uhl, 2010), soccer (Chow et al., 2005), baseball (Fleisig et al.,

2009) and water polo (Taylor et al., 2014). However, it was not only in the final determinant of

success (e.g., accuracy scores, shots made) that increased consistency was noted. There is

considerable evidence that constraint of variability in technical elements could be key to

successful movement outcome (Armour Smith et al., 2012; Bradshaw et al., 2009; Farana et al.,

2015; Hiley et al., 2013; Whiteside et al., 2015). For example, skilled performers have lower

variability at key points (address and top of backswing) of the golf swing (Bradshaw et al., 2009),

gymnasts show more consistent movement in mechanically important facets of skills such as high

bar swings and round offs (Farana et al., 2015; Hiley et al., 2013) and tennis players constrain

postural stability at the point of take-off during the serve (Whiteside et al., 2015). This behaviour

was more commonly observed in golf (Horan et al., 2011; Langdown et al., 2013), basketball

(Mullineaux & Uhl, 2010) and water polo (Taylor et al., 2014) as movement progressed to the

point of release or impact for ballistic skills. Similarly Bootsma and van Wieringen (1990) have

identified the phenomena of 'funnelling' in table tennis which show the constraining of variability

toward the point of impact. Moreover, as may be expected, some of the lowest values of

variability are reported in factors such as release/impact height, velocity and angle (Bradshaw et

al., 2009; Button et al., 2003; Chow et al., 2005; Knudson & Blackwell, 2005; Sheppard & Li, 2007;

Taylor et al., 2014), which are the final determinants of projectile trajectory and end point

location. It may be pertinent to consider release variables or similar to be movement outcomes in

such discrete ballistic skills due to their highly consistent nature in skilled performance. There

were exceptions to decreases in variability at critical points, which are often seen in those

elements that could act as a highly sensitive final effector to the release variables such as

orientation of club and bat face (Betzler et al., 2012; Sheppard & Li, 2007) and kinematic variables

of the wrist (McDonald et al., 1989; Robins et al., 2006; Taylor et al., 2014; Tucker et al., 2013;

Whiteside et al., 2015). The question remains as to what the role of variability is which exists up to

and including these points within successful movement.

A third of studies included in this review supported the idea that variability has a

functional role in movement, which concurs with other reviews (Bartlett et al., 2007; Preatoni et

al., 2013). Bartlett (2008) provided a helpful summary on what could be considered the three

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functional roles of movement variability: 1) reducing the risk of injury; 2) enabling coordination change; and 3) facilitating adaptation to varying task or environmental constraints. These three elements also find considerable support in the literature sampled in this review which is worth summarising herein, starting with a discussion of injury prevention.

Variability in movement may be a protective factor for injury since variable patterns of movement can spread loads over a greater area of tissue, whereas lack of variance in movement patterns can continually stress the same area in biological structures (Bartlett et al., 2007). Much of the support for this hypothesis comes from the investigation of continuous skill such as running or walking (Heiderscheit, Hamill, & van Emmerik, 2002; James, Dufek, & Bates, 2000) where the repetition of loading can be many more times higher than in a discrete task of the same duration. In discrete tasks, Farana et al. (2015) reported decreased hand position variability is prone to greater injury risk when coupled with increased ground reaction force values in a gymnastics round off technique. However, other evidence is less conclusive and there is weaker support for the role of discrete movement variability in injury prevention within the sampled research of this review. Depending on the variable, for example, both increased and decreased variability during sidestep cutting in a fatigued state is thought to increase the risk of injury (Cortes et al., 2014). McLean et al. (1999) found that females, a population more susceptible to non-contact ACL injury, had higher variability in axial rotation of the knee than males during sidestep cutting yet concluded that this is unlikely to be the root of higher injury incidence. Females have also displayed increased varus-valgus variability in the same task (McLean et al., 2004). Yet again, reasons of higher incidence of ACL injury in this population were thought more likely to stem from experience or conditioning levels and not from gender differences in variability for these joint rotations (McLean et al., 2004). When coordination is assessed in sidestep cutting, females display reduced variability in coupling of lower limb segments compared to males (Pollard et al., 2005)

while populations with knee reconstruction surgery exhibit increased variability in lower limb

coordination (Pollard et al., 2015). This suggests different neuromuscular strategies may be

employed across genders and injury status, changing the stress on tissues and altering the

adaptability to potentially injurious conditions. While a sidestep is a discrete skill, it is heavily

related to gait, and thus the evidence provides a far from clear picture about the role of variability

in injury in discrete tasks. As such, there remains much work to be done to understand the

interaction between discrete movement variability and injury. This question will begin to be

answered perhaps through adoption of longitudinal prospective research designs that examine

variability across several different tasks.

Another functional role of variability suggested in the literature is to facilitate changes in

coordination. An example often supplied for this hypothesis is during transition phases, such as

walk-to-run, which are less common in discrete skills. As such the role of variability in transitioning

phases may be of less importance for discrete tasks. Nevertheless, there were a few studies to

support this hypothesis, isolated to discrete skills which had distinct phases. For example,

increased variability was observed for segments responsible for the transition from backswing to

downswing in golf (Langdown et al., 2013), and peaks in variability were noted at the transition

from flight to landing phase during sauté jumps in dancers (Armour Smith et al., 2012). However,

as both of the studies measured variability in coordination, results might not be directly relevant

to the hypothesis where joint/segment angular variability is assumed. Perhaps, as suggested by

Bartlett (2008), a more pertinent role of variability in discrete skills is to facilitate coordination

changes during motor learning, increasing adaptability. As mentioned in section 2.5.1.5, variability

in the first layer of variables (joint and segment angles, etc.) could enable variability in functional

coordination. An increase in the number of variably coordinated couplings may subsequently

result in greater variability across a whole system. Whole system variability in turn could influence

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adaptability - i.e., many movement patterns are able to produce the same, successful outcome within changing task and environmental constraints.

When variability is associated with adaptability, the mechanism which produces this variability may be compensatory coordination, which can be manifested by perturbations in one variable being compensated by fluctuations in another, facilitating the adaptation to the original perturbation. Evidence of compensatory coordination was reported in table tennis (Bootsma et al., 1991; Bootsma & van Wieringen, 1990; Sheppard & Li, 2007), basketball (Button et al., 2003; Mullineaux & Uhl, 2010; Robins et al., 2006; Schmidt, 2012), throwing (Kudo et al., 2000), darts (McDonald et al., 1989), handball (Wagner et al., 2012) and triple jump (Wilson et al., 2008), providing good support for the link between functional variability and adaptability. Perhaps the strongest evidence came from studies which implemented a longitudinal design. Barris et al. (2014) trained experienced springboard divers to avoid baulking (i.e., aborting dive take off) over a 12-week period. They found that while overall coordination patterns did not change over time, as evidenced by consistent topography of angle-angle plots, normalised root mean square (NoRMS) indices rose indicating coordination variability increased across training. By the end of training, athletes were able to successfully complete dives and maintain pre-intervention scores in instances where they previously would have baulked. This result indicates that the athletes were able to adapt to conditions that had formerly caused them to abort. In a similarly longitudinal study, participants were trained to perform the soccer chip kick over a barrier to several target locations (Chow, Davids, Button, & Rein, 2008). As evidenced by number of retained clusters from cluster analysis of hip, knee ankle and trunk angles, the participant who explored the least movement patterns during the 4-week program scored the lowest during post training testing. Conversely, the participants who explored the most patterns had the highest post training scores. As the post-test task conditions had barrier heights which were different to those experienced

during practice, this result indicates that those who had the largest coordination variability, as expressed by greater number of movement patterns/clusters, had the better ability to adapt to the changed task constraints. These two studies highlight the following important factors: 1) movement variability appears to be linked to our ability to adapt to changing task and environmental constraints; 2) the phenomenon can be well explored by longitudinal study designs; and 3) functional variability, which facilitates adaptability and is more effective amongst the better skilled, may emerge during motor learning.

Wilson et al. (2008) presented the 'U-shaped' curve hypothesis which models the variability in coordination across learning as U-shaped such that both novice and advanced movers display higher levels of variability while those in the intermediate stages display reduced levels. This may explain, as originally posited by Bernstein (1967), how patterns of variability relate to the changes in degrees of freedom across different skill levels. He proposed that early motor learners have high initial variability in movement patterns as they search for an optimal movement solution for the task at hand. This is quickly followed by constraining of degrees of freedom as they settle on a movement pattern and look to attain effective coordination and outcome consistency. Once the individual moves towards mastery of a task, they begin to release degrees of freedom and display increased variability, this time in the presence of improved outcome success and consistency. The U-shaped curve may also characterise the relationship of variability to the 'coordination, control and skill' model of motor learning proposed by Newell (1985). According to Newell (1985) this model states that at the 'coordination' stage an individual attempts to develop rudimentary couplings between motor components with motion, which often appear stiff and stilted. The 'control' stage is relatively short in duration and sees attainment of control over derivatives of motion such as velocity and acceleration. In this stage dysfunctional variability will decline along with increased consistency in movement and performance outcome. In the 'skill'

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stage the mover is able to optimise all elements responsible for motor output. Similarities

between Newell and Bernstein's models exist, yet, while Newell's model did not receive much

attention in the included literature, evidence corroborating the degrees of freedom problem was

present. In learning a soccer chip, Chow, Davids, Button, and Koh (2008) reported early increased

degrees of freedom, followed by constraint and subsequent re-release of lower limb movements

among participants. Similar observations were reported in studies looking at soccer chipping

(Hodges et al., 2005), dart throwing (McDonald et al., 1989), basketball (Schmidt, 2012) and tennis

(Whiteside et al., 2015).

When considering whether any U-shaped relationship exists in the first layer of variability,

such as kinematics of markers, joints, segments or implements, there was a dearth of studies

which included three or more skill levels (e.g., Wilson et al. [2008]). In studies comparing only two

groups of skill levels, the consistent trend was for the lower skilled participants to display greater

variability than those who were more skilled (Betzler et al., 2012; Bradshaw et al., 2009; Hiley et

al., 2013). Similarly, in studies with multiple skill levels, there was a trend of decreasing variability

as skill level increased (Button et al., 2003; Fleisig et al., 2009). Evidence for a U-shaped curve at

this first layer of variability was also available, though not conclusive. As the original U-shaped

hypothesis was founded on coordination variability, it may not effectively describe variability of

individual variables such as joints, segments, release/impact parameters or implement measures.

For example, results across three skill levels (beginner, intermediate and skilled) in soccer chipping

identified a U-shaped relationship for foot velocity when kicking to two of three targets (Chow et

al., 2007). Yet, the profile for the same variable to one particular target showed an inverted U-

shape.

Chow et al. (2007) evaluated coordination variability of hip/knee and knee/ankle couplings using NoRMS indices in soccer chipping. The knee/ankle coupling displayed a U-shaped profile although degree of variability in skilled movers was not as high as that of the novice. For the hip/knee coupling, however, NoRMS indices showed a more linear increase from low to high skilled participants. In another study on soccer chipping, the NoRMS indices of the hip/knee coupling displayed a U-shaped pattern across skill levels which were ranked based on outcome score after following a 12-week training program (Chow, Davids, Button, & Koh, 2008). The knee/ankle coupling showed an increase in NoRMS index from the lowest to the next lowest scorer before displaying a U-shape pattern across the remaining participants. However, the investigations discussed herein had a small number of participants (4-5), and thus it may be difficult to take much support for the U-shape hypothesis from these studies. Furthermore, other research has reported a decreasing trend of coordination variability with increased skill in dancers and controls (Jarvis et al., 2014) and in handballers (Wagner et al., 2012). In tennis, there were several mixed patterns - U-shaped, inverted U, linear increase and decrease - for coordination variability using the coefficient of correspondence from vector coding (Whiteside et al., 2015). Perhaps the U-shaped curve is task-dependent, in which case a broad range of studies assessing different skills might be necessary to depict a variety of relationships between functional variability, adaptability and motor learning. How task dependence relates to or reflects the learning theories of Bernstein, Newell etc. would then also need to be investigated. Perhaps the changes in variability hypothesised by these theories present across different time frames depending on the task which could have resulted in some of the differences in curve shape reported. Furthermore, as the U-shaped hypothesis seems to have its explanatory power limited to coordination variability, it might be beneficial to model motor learning with other layers of variability.

In the context of motor learning, it appears that variability in the early stage of learning is non-functional in so much as it does not facilitate effective coordination of movement. In line with the U-shaped curve hypothesis, coordination variability may also be high at this stage of motor learning, with its level being associated with reduced performance outcomes. As such, the variability associated with early learning stages may be indicative of the search for effective movement patterns without acquiring better performance. On the other hand, variability of individual elements (e.g., segments, joints, implements, etc.) is shown to decrease with increased skill. Moreover, it appears that effective coordination, which compensates for the variability of individual elements, emerges as evidence by increased consistency in outcome measures. Coordination variability may also be constrained at this point in line with the U-shaped curve hypothesis. In later stages, as compensatory coordination continues to be attained, coordination variability may again rise along with an increase in consistency and performance in outcome measures. It is not clear what individual first level variability profiles will resemble at this stage, but it is possible that there is an optimal level which facilitates the compensatory coordination. Whole system variability is hypothesised to increase at this stage as movers should now have acquired multiple global movement patterns capable of producing the desired movement outcome within a given set of task and environmental constraints.

2.7 Conclusion

This review sampled a considerable body of work on discrete movement variability in sports-derived tasks. Regarding the role of variability in injury prevention, the evidence for discrete movement is not as strong as it is for continuous movements. Yet, there still remains a large scope for investigation into the functional role of variability in motor learning and adaptation, which in itself is still developing. The keys for effective investigation of variability are

described, especially with an emphasis on longitudinal studies capable of tracking changes in variability and injury incidence, learning and adaptation. Longitudinal studies provide better scope for assessing performance pre, post or throughout intervention, including a transfer test, wherein contextual interference designs may be useful. Selection of a sensitive measure for movement outcome/performance is recommended to ensure effective detection of meaningful changes that occur with practice. Three levels of variability have been proposed to seek a fuller understanding of its functional role: 1) variability in discrete and continuous measures of variables such as joints and segments, release/impact parameters and implement kinematics; 2) coordination variability; and 3) whole system variability. For future investigations, application of the recommended methods along with the assessment of all three levels holds the best chance of further understanding the phenomenon of discrete movement variability.

Chapter 3. Determining Optimal Trial Size Using Sequential Analysis (Study 2)

3.1 Preface

A methodological consideration raised by the preceding systematic review concerned the selection of appropriate trial size. The review identified that justification of trial size, i.e., the number of trials from which variability was assessed, was rarely reported in the literature. Considering that variability emerges as a family of trials are collected, it was considered important to ascertain empirically the optimum number of trials required to provide a true representation of this variance. The literature was searched and sequential estimation was identified as a potentially useful tool to address this need.

Sequential analysis provides a systematic way of determining how many trials are required to establish mean stability. The thought was that if a mean is stable, then the variance of scores around it are no longer affecting it. Therefore, as well as ensuring a representative mean, representative variability may also be assumed. While the application of this technique to human kinematic data had been limited, its use with kinetic data indicated the process could be similarly and easily employed with kinematic data. However, initial use of the process with pilot data indicated that results were affected by the number of trials to which it was applied. Yet, the technique still held potential as a viable means of determining trial size. Hence an experimental study was conducted with the aims of 1) determining the number of trials required for use with sequential analysis to yield valid variable stability results; and 2) determining the trial size for the further experimental studies of this thesis.

This chapter details the experimental study designed to address these aims. Preliminary data from this investigation was presented as an oral report at the 31st International Conference

on Biomechanics in Sports, Taipei, Taiwan in 2013. It was submitted to the Journal of Sports Science on the 24th of June 2013. The manuscript was returned on the 12th of October and following further revision and review was accepted for publication on the 30th of June 2014. Publication occurred online on the 1st of August 2014 and in print January 2015. This manuscript is presented in author accepted form, with minor proof edits, formatted to be consistent with the remainder of the thesis.

3.2 Abstract

When characterising typical human movement profiles, the optimal number of trials analysed for each participant should ensure a stable mean. Sequential analysis is one method able to establish the number of trials to stability by assessing a moving point mean against a set bandwidth. As the total trial number determining this bandwidth is selected arbitrarily, the effect of applying different total trial numbers on the results of sequential analysis was investigated. Twenty participants performed 30 trials of overarm throwing and sequential analyses were applied to three dimensional (3D) kinematic data over 10, 20, and 30 trial numbers. We found a total of 20 to be the preferred trial number for sequential analyses. Erroneous results were produced consistently by 10 trial number groups, while moving point means were statistically unchanged after the 10th trial. Subsequently, sequential analyses were applied to 20 trials to establish trials to stability in discrete and time series elements of the 3D kinematic data. The results suggest that a trial size between 13 and 17 provides stable means for overarm throwing kinematics.

KEY WORDS: Sequential analysis; Mean stability; Trial size; Overarm throw; Kinematic profile

3.3 Introduction

In human movement research, reported values of movement profiles should be as representative as possible. As Mullineaux and colleagues (2001) noted, values from the single best trial are often reported. However, when the typical performance is investigated, values obtained from a single trial may be considered inadequate. As a result, the number of trials from which a representative mean is calculated must be determined involving several considerations including power and reliability (Mullineaux et al., 2001). It has been suggested that for sample sizes of 20, 10 and 5, trial sizes of 3, 5 and 10 respectively provide sufficient statistical power (Bates et al., 1992). Similarly, increases in trial size enhance reliability (Salo, Grimshaw, & Viitasalo, 1997). Yet, even after these factors have been addressed, an insufficient trial size may result in unstable means, compromising the reliable representation of the true performance. Perhaps due to this reason, justification of trial size is rarely reported in human movement literature.

One approach to resolve this issue is to implement sequential analysis which can determine the minimum number of samples required from an individual to provide an acceptable estimate of stability in the mean. The sequential analysis technique uses a moving point mean coupled with a criterion against which trials to stability is determined (Wald, 1947). This criterion is a bandwidth, established by the mean and standard deviation (SD) of total trials (commonly mean ± 0.25 SD). Due to the arbitrary selection of the number of trials used to determine the criterion for sequential analysis, it is important to understand the effect of using different trial numbers when employing this technique. As such, the first aim of this study was to investigate the effect of using different trial numbers on the results of sequential analysis.

The sequential analysis technique has been used to determine trials to stability in a number of biomechanical measures including ground reaction forces during running (Bates,

Osternig, Sawhill, & James, 1983), walking (Hamill & McNiven, 1990), landing (James et al., 2007), jumping (Racic et al., 2009), cricket bowling (Stuelcken & Sinclair, 2009), joint power and moment during vertical jumping (Rodano & Squadrone, 2002) and time to postural stability (Colby, Hintermeister, Torry, & Steadman, 1999). Most research has concentrated on discrete kinetic variables from lower limb movements, while kinematic variable stability has only been addressed in one study (Amiri-Khorasani, Osman, & Yusof, 2010). Use of sequential analysis for upper limb kinematics is under-reported and stability in complete time series kinematic data has not been quantified. Yet, the technique provides an easily applied method for determining trial size within these data. Hence, the second aim of this study was to employ sequential analysis to establish the number of trials to stability in discrete and time series kinematic data from an overarm throwing task.

3.4 Method

3.4.1 Participants

Ten male [20.7 (2.1) years; 175.9 (9.2) cm; 72.2 (10.2) kg] and ten female [22.2 (3.0) years; 165.7 (7.8) cm; 62.8 (10.2) kg] participants provided informed consent and had their data included in this study. Throwing experience ranged from novice to semi-experienced. All methods and procedures were approved by the Human Research Ethics Committee of the University.

3.4.2 Equipment

Three dimensional (3D) motion capture, sampling at 400 Hz, was performed using 10 Vicon cameras (6 MX and 4 T-Series), Vicon Nexus software and the unilateral Vicon Upper Limb Model plug-in (Oxford Metrics, Oxford, UK). Two dimensional (2D) data of the ball trajectory in the sagittal plane were captured using a Basler A602fc camera (Basler AG, Germany), synchronised

with the 3D motion capture, sampling at 100Hz. Participant preparation, including marker

placement (13 markers across trunk and throwing arm), was performed as outlined in the Vicon

Upper Limb Model product guide (Taylor et al., 2014; Vicon Motion Systems, 2007).

3.4.3 Laboratory configuration

An image of a round target consisting of 5 equally spaced concentric circles (radius

increasing by 7 cm per circle to a maximum of 70 cm) was displayed via a beam projector (Dell Inc.,

Round Rock, Texas) on a cloth screen (5 m x 3 m) suspended from the ceiling. The vertical position

of the projected target centre was located 2 m from the ground. An adjustable piano stool was

placed square to the cloth screen at a distance of 7 m in line with the target centre.

3.4.4 Procedure

Participants performed 30 overarm throws seated on the piano stool. They maintained 90°

flexion at the hip, knee and ankle joints and began each throw with their frontal plane aligned

parallel to the projection screen. Participants were instructed to throw a regulation tennis ball as

accurately as possible toward the centre of the target using the hand of their choice. The chosen

hand was used for all trials. Participants were asked to begin each throw with their hands placed

on their knees. No other directions regarding throwing technique were provided though all

participants performed the throw with one of two general techniques. These included a more

developed technique where the humerus was held in the frontal plane, and ball velocity was

produced primarily by both elbow extension and internal rotation of the shoulder, equivalent with

stage 3 throwing development or higher (Gallahue, Ozmun, & Goodway, 2012). The second

technique was "front on" where degrees of freedom were more constrained. The humerus was

held in the sagittal plane, and elbow extension was the primary joint rotation contributing to ball

velocity. This technique was equivalent to a stage 1 throwing development (Gallahue et al., 2012).

Most participants maintained their chosen technique throughout testing with little deviation/experimentation noted. Participants familiarised themselves with the task until they were ready to proceed (2–3 minutes). Time between throws was self-determined. Once the ball was returned, participants were notified when data collection had begun and were instructed that they were free to throw at any point following this cue. Most participants performed three or four throws per minute during testing. All participant trials were included in analyses regardless of movement outcome and accuracy.

3.4.5 Data analysis

To represent 3D displacement values in three axes (X, Y, and Z) across proximal, distal, bony and fleshy locations and where large and small movement was expected, four anatomical markers were chosen for analyses: T10 (10th thoracic vertebra), Upper Arm (over the muscle belly of triceps), Elbow (lateral epicondyle) and Finger (distal end of the 3rd metacarpal bone) of the throwing arm. Three joint angles - shoulder internal/external rotation and flexion/extension at the elbow and wrist - from the kinematic model (Vicon Motion Systems, 2007) were chosen for their role in producing ball velocity (van den Tillaar & Ettema, 2004). Discrete values of the final determinants of ball trajectory (ball release angle, height and velocity) were also included from 2D data.

Following analyses of the frequency content and residuals of the power spectra (Winter, 2005) of the displacements of two distal markers (Finger and radial styloid process) of all participants, a cut-off frequency of 12 Hz was employed in a low pass, 4th order, dual Butterworth filter on the kinematic time series data. The start of the movement was determined as the beginning of elbow flexion during wind up. The end of the movement was ball release. Filtered data were trimmed to these instants and time-normalised to 101 data points.

3.4.6 Sequential analysis

The sequential analysis technique was employed to determine the point of mean stability (i.e., trial size). This technique is illustrated in Figure 3.1 using mock data. The dashed grey line represents the Nth trial mean taken from all (1 to N) trials and two solid grey lines labelled +0.25 SD and -0.25 SD represent a 'bandwidth' based on SD calculated from all trials. These elements form the criterion against which stability is assessed. For example, for a 20 trial condition the Nth trial mean is the mean of all trials up to and including the 20th. The value of one SD about this mean is then multiplied by +0.25 and -0.25 to create the upper and lower bounds of the bandwidth. Once the bandwidth is established, the technique requires the calculation of a moving point mean (solid black line), starting with the mean of the first two values and moving through the first three, first four etc., until reaching the Nth trial. Stability is determined when the moving point mean rests within the SD bandwidth and stays within for all remaining trials as indicated by A in Figure 3.1. It is worth noting that while points B and C also rest within the bandwidth in this example, they do not represent the point of stability as there are excursions of the moving point mean outside of the SD bandwidth between B and A or C and A.
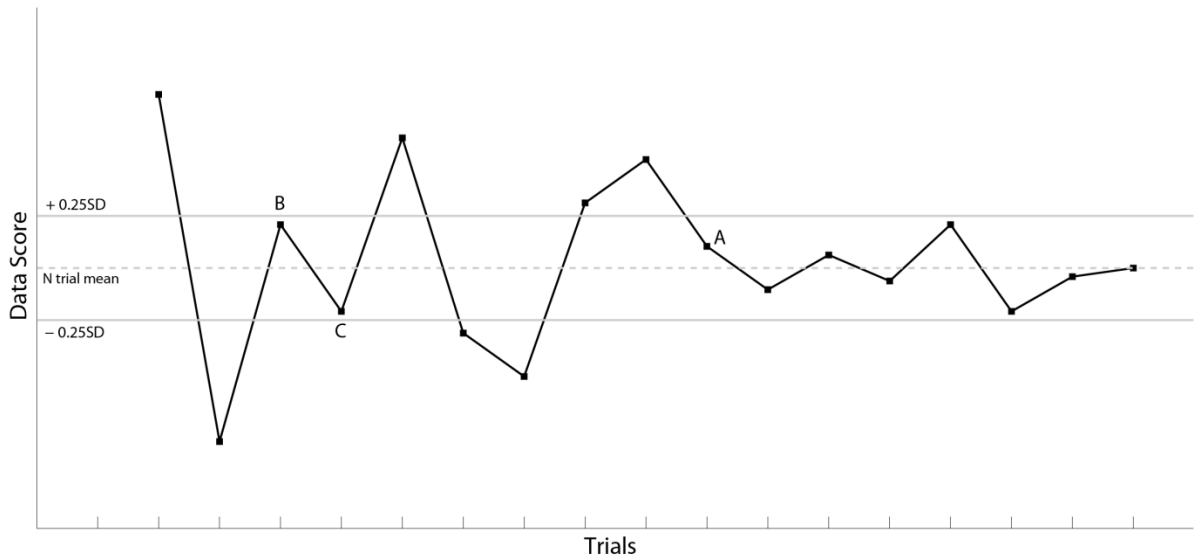
Figure 3.1. Example of sequential analysis technique applied to a trial size of N. Illustrated are the criterion elements of the total (trials 1 to N) mean (dashed grey line) and the ±0.25 SD bandwidth (two solid grey lines). Assessed against this criterion is the moving point mean, starting at trial two (black line). The point of stability is represented by the letter A. Points B and C do not represent stability as the mean deviates outside the bandwidth between these points and point A.

The sequential analysis technique was employed on both discrete and time series kinematic data (Table 3.1). To perform sequential analysis on 3D marker displacement and joint angle time series data, each of the 101 sample points were treated as a discrete point, providing trials to stability for each sample point along the entire time series. To determine the effect of using different trial numbers on sequential analysis score, three main conditions - first 10 (1st to 10th trial), first 20 (1st to 20th trial) and first 30 (1st to 30th trial) trials - were assessed with the criterion mean and 0.25 SD bandwidth calculated using all trials included in each condition. Similarly, mid 10 (11th to 20th trial), last 10 (21st to 30th trial) and mid 20 (6th to 25th trial) conditions were compared to establish if results were dependent on where in the sequence of throws a sample was extracted.

Table 3.1.

Discrete and time series variables included in sequential analysis.

Marker Variables	Joint Angle Variables	Ball Release Variables
Maximum value	Peak angle value	Release height
Minimum value	Time of peak angle value	Release velocity
Value at release	Value at release	Release angle
Normalised time series	Normalised time series	

Note: Peak angle value represents relevant maximum or minimum value, occurring near wind up completion. Joint angles were shoulder external/internal rotation, elbow and wrist flexion/extension. Marker data was analysed in X, Y and Z axes.

3.4.7 Comparing trial number conditions

To qualitatively assess the behaviour of the sequential analysis elements, the moving point mean for all discrete variables from the 30 trial condition was plotted against the criterion bandwidth from that condition and viewed for each participant (see Figure 3.3). While this bandwidth was specific to the 30 trial condition, the moving point mean is the same for each condition, up to the total trial number of that condition (for first 10, 20 and 30 conditions only).

For further determination of the condition from which to report sequential analysis values, two scores were submitted to statistical analyses, the sequential analysis score (trials to stability) and a relative sequential analysis score. The relative sequential analysis score is novel to this investigation and is calculated by dividing the sequential analysis score by the total trial number of the condition from which it was taken. This relative score can highlight differences in the behaviour of the sequential analysis technique between conditions in respect to the percentage of maximum possible trials taken to achieve mean stability.

The sequential analysis score for all time series variables were compared using a 4 x 101 (first 10, first and mid 20 and first 30 conditions x 101 time series samples) two way repeated measures analysis of variance (ANOVA) and a 3 x 101 (first, mid and last 10 x 101 time series samples) two way repeated measures ANOVA with Fisher's least significant difference post hoc tests. The time series ANOVA outcomes were considered as the primary results from which a determination would be made as all discrete variables were contained within the time series. To confirm any patterns observed within time series, group mean sequential analysis scores for the discrete marker variables taken from individual participant time series data were also compared across trial number conditions (first, mid and last 10, first and mid 20 and 30 trials) using a 6 x 1 one way repeated measures ANOVA with Fisher's least significant difference post hoc test. Discrete marker variables were analysed in this manner as they provided 12 cases (4 markers x 3 axes) per condition (minimum, maximum and release), whereas joint angle and ball release variables only provided 3 cases per condition and thus were not included in the analyses. Relative sequential analysis scores were compared across conditions in the same manner as the sequential analysis score.

To determine if any statistical differences existed between the 10th, 20th and 30th trial means of time series and discrete marker values, these elements were also compared in a similar manner to sequential analysis score and relative sequential analysis score. This comparison consisted of a 3 x 101 two way repeated measures ANOVA for time series variables and a 3 x 1 one way repeated measures ANOVA for group mean discrete marker values.

For repeated measures ANOVA testing an alpha level of 0.05 was taken to indicate significance. Fisher's least significant difference post hoc test significance was assessed against the relevant Bonferroni adjusted p-value in each instance. Discrete variable testing was conducted

using IBM SPSS Statistics, version 19 (SPSS Inc, Chicago, Illinois). Due to the need to analyse 101

data points per participant, time series analyses were conducted using Statistica 7 (StatSoft Inc,

Tulsa, Oklahoma).

3.4.8 Reporting sequential analysis results

To guide trial size selection, discrete variable sequential analysis results were reported

from the chosen condition - first 20 (see results and discussion for reasoning) - as group mean and

95% confidence interval (95% CI) values. A 101 x 1 one way repeated measures ANOVA was

conducted on all time series sequential analysis results. Fisher's least significant difference post

hoc test was used to determine whether differences existed across the 101 points. Where upon no

differences were found, the point (out of the 101 time normalised points) displaying the greatest

group mean sequential analysis result (95% CI) was extracted and reported to guide trial size

selection for time series analyses.

3.5 Results

3.5.1 Comparing trial number conditions

The sequential analysis scores were significantly different across all time series variables,

$F(3, 57) \geq 48.51$, $p < 0.01$, $\eta^2 \geq 0.72$. Pairwise comparisons displayed significant differences

between all conditions of different sizes while same sized conditions formed homogenous groups.

This result was mirrored within the discrete marker group mean variables $F(1, 11) \geq 2367.84$, $p <$

0.05, $\eta^2 \geq 0.99$ (Figure 3.2).
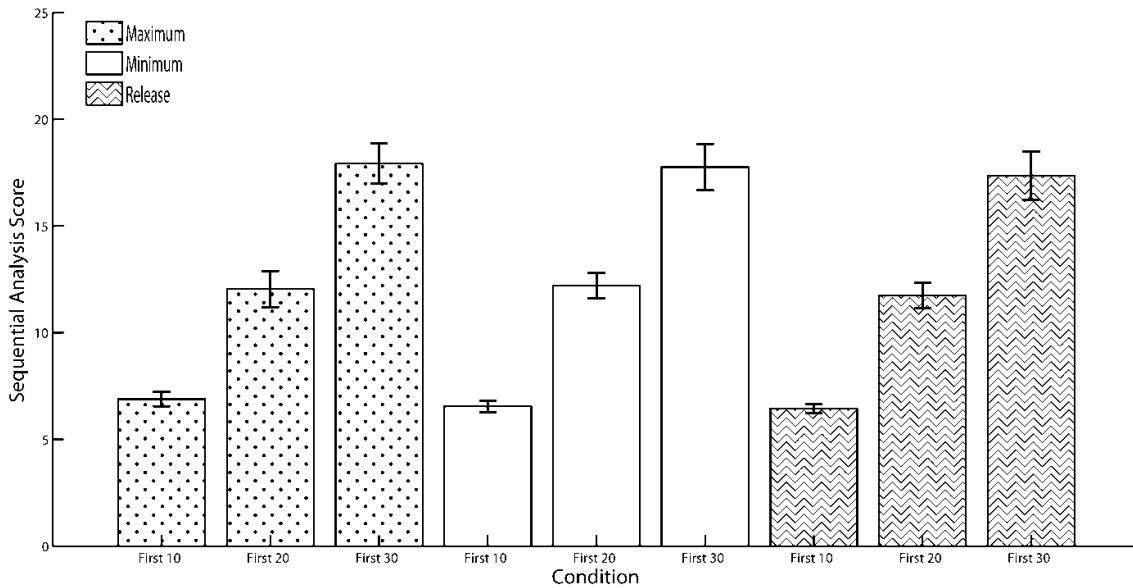
Figure 3.2. Comparison of the three main condition group mean sequential analysis scores for marker maximum, minimum and release values. All conditions were significantly different (p < 0.05) from other conditions within their marker variable.

Figure 3.3 shows a sample plot of the sequential analysis (Finger marker in X axis) from one participant, illustrating the most frequent pattern observed amongst the discrete variables, across all participants, in the 30 trial condition (54%; 523 out of 960 plots viewed). It can be seen that the moving point mean (solid black line) undergoes a 'transition phase', most commonly occurring during the first 10 trials, moving up or down toward the criterion bandwidth (dashed grey line). While this was the most frequent pattern, other transition patterns within the first ten trials were also common. These included the moving point mean lines that began on one side of the bandwidth prior to transitioning across to the other side before stabilising as well as those that began within the bandwidth before moving to either side then stabilising. While the patterns did vary, the consistent element was that the magnitude of the transition (slope of the curve) was greatest in the early trials and around the 10th trial fluctuations in the moving point mean generally became less severe. After the point of stability (trial 15 in this example), and even slightly

before, the mean tended to be robust to fluctuations in raw data (dash-dot grey line), illustrating

the concept of sequential analysis score and mean stability.
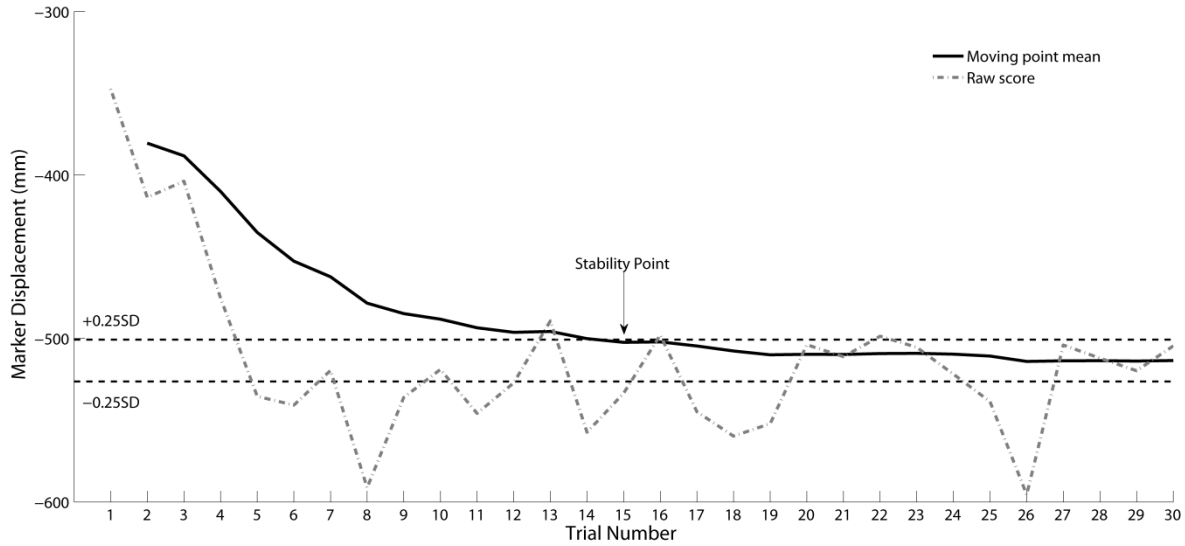
Figure 3.3. Example of sequential analysis of a finger marker (X axis) minimum value in 30 trial condition from one participant showing the relationship between raw kinematic data (dash-dot grey), moving point mean (solid black) and 0.25 standard deviation (SD) bandwidth (dash grey). Stability point (sequential analysis score = trial 15) is indicated by an arrow.

Of the 15 relative sequential analysis scores of time series variable ANOVAs, 12 (excluding T10 in X and Y axes, Finger in Y axis) displayed significance, $F(3, 57) \geq 4.78$, $p < 0.05$, $\eta^2 \geq 0.20$. In 11 of 12 significant time series variables, the first 10 condition was significantly greater than the other main conditions. Same sized conditions formed homogenous groups based on sample size. Results for discrete relative sequential analysis score group mean marker variables displayed significance, $F(1, 11) \geq 3304.52$, $p < 0.05$, $\eta^2 \geq 0.99$. Group mean discrete variable relative sequential analysis scores between the three main conditions can be seen in Figure 3.4.
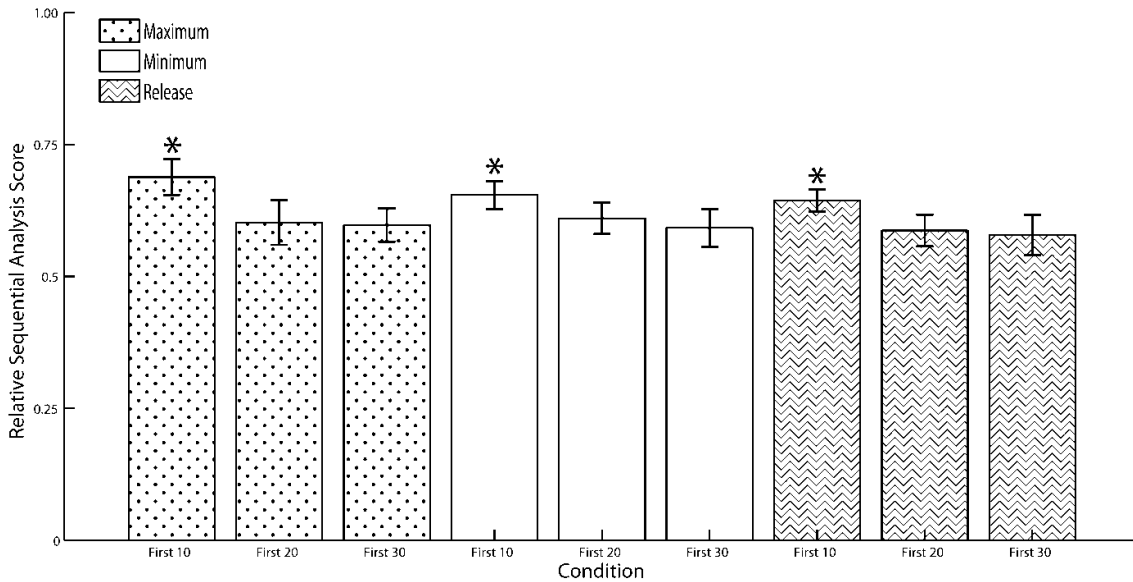
Figure 3.4. Comparison of the three main condition group mean relative sequential analysis scores for marker maximum, minimum and release values. Asterisk (*) indicates significant difference (p < 0.05) from the first 20 and first 30 conditions.

Comparisons of the criterion mean values showed no significant difference in 12 of the 15 variables, $F(2, 38) \leq 2.35$, $p > 0.05$, $\eta^2 \leq 0.11$. Of the three significant time series comparisons (T10 in Z axis, Upper Arm in X axis and Finger in Y axis), $F(2, 38) \geq 3.56$, $p < 0.05$, $\eta^2 \geq 0.16$ post hoc tests showed the first 10 condition to be different from the first 20 and 30 conditions for Upper Arm in X axis and different to the first 30 condition for T10 in Z axis and Finger in Y axis. Discrete group mean marker results reflected the time series results with non-significant ANOVA results for marker minimum and release values, $F(1, 11) \leq 2.94$, $p > 0.05$, $\eta^2 \leq 0.21$. While the ANOVA for marker maximum displayed significance, $F(1, 11) = 15.55$, $p < 0.05$, $\eta^2 = 0.59$ post hoc analyses showed no difference between conditions.

3.5.2 Sequential analysis results

Group mean sequential analysis scores (95% CI), of the first 20 condition, for discrete marker variables and for maximum group mean (95% CI) time series marker variables are reported in Tables 2 and 3 respectively. Repeated measures ANOVA results on first 20 time series were

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significant for Upper Arm, Elbow and Finger markers (in Z axes), $F(100, 1900) \geq 1.33$ $p \leq 0.02$, $\eta^2 =$ 0.07. However, post hoc analyses revealed no recurring pattern of results across time series and a consistent trend of all 101 points forming one homogenous group. As a result, it was determined that a single group mean value and associated confidence interval should be reported for all time series results. The maximum group mean value was therefore selected for this purpose as a decision based on this value would ensure that all points along the time series were accounted for. Group mean (95% CI) data for discrete joint angle variables and maximum group mean (95% CI) data for time series joint angle variables are reported in Table 3.4. Group mean (95% CI) results for release height, velocity and angle were 11.5 (1.8), 12.7 (1.9) and 10.5 (2.0) respectively.

Table 3.2.
Group mean (95% CI) sequential analysis results for marker maximum, minimum and release values.

	Maxima			Minima			Release		
	X	Y	Z	X	Y	Z	X	Y	Z
T10	13.9 (1.7)	13.2 (1.8)	10.0 (1.8)	13.4 (1.6)	13.5 (1.2)	12.7 (1.5)	13.1 (2.0)	13.1 (1.4)	11.5 (1.7)
UPA	13.2 (1.8)	12.9 (1.6)	9.3 (2.0)	12.6 (1.5)	11.7 (1.8)	11.2 (2.0)	12.0 (1.7)	12.2 (1.3)	9.9 (1.9)
ELB	12.6 (1.6)	11.8 (2.1)	12.2 (1.7)	13.3 (1.6)	12.0 (1.5)	10.8 (1.6)	11.4 (1.7)	12.0 (1.5)	11.9 (1.8)
FIN	12.1 (1.9)	11.3 (1.9)	12.2 (1.8)	12.6 (1.7)	11.1 (2.3)	11.8 (1.7)	11.0 (2.0)	10.6 (1.9)	12.3 (1.8)

Note: Markers were T10 (10th thoracic vertebra), Upper Arm (UPA), Elbow (ELB) and Finger (FIN).

Table 3.3.
Group mean (95% CI) sequential analysis results for marker time series.

	X	Y	Z
T10	14.5 (1.6)	14.0 (1.4)	13.1 (2.1)
UPA	14.1 (1.3)	12.9 (1.2)	14.3 (1.5)
ELB	13.4 (1.5)	13.6 (1.3)	13.8 (1.7)
FIN	13.7 (1.5)	13.0 (1.5)	13.3 (1.4)

Note: Markers were T10 (10th thoracic vertebra), Upper Arm (UPA), Elbow (ELB) and Finger (FIN).

Table 3.4.
Group mean (95% CI) sequential analysis results for discrete and time series (maximum group mean)
joint angle variables.

	Peak	Release	Time of Peak	Time Series
Shoulder	12.1 (2.2)	10.1 (2.2)	9.6 (2.1)	13.0 (1.9)
Elbow	12.2 (1.6)	11.3 (1.9)	11.3 (2.0)	12.4 (1.6)
Wrist	12.1 (1.5)	10.2 (1.8)	10.2 (1.7)	12.5 (2.1)

Note: Joint angles were shoulder internal/external rotation, elbow and wrist flexion/extension.

3.6 Discussion

Sequential analysis score results showed that the outcome of this technique is affected by the total trial number from which criterion mean and SD values are drawn (Figure 3.2 and Figure 3.4). Yet, results were not dependent on the position in the total sample where the subsample was drawn (e.g., first, mid or last 10). Qualitative assessment of the sequential analysis plots suggests that the results from the first 10 condition are affected by the 'transition' phase of the moving point mean (Figure 3.3). This transition appeared most commonly due to the mean of the first two trials lying above or below the criterion bandwidth as in the most regular pattern illustrated in Figure 3.3. There were of course instances where the transition phase did not exist and these data generally resulted in low sequential analysis scores. That the transition phase still existed in data from the mid 10 and last 10 conditions indicate it is not related to any warm up decrement or familiarisation with the task. Results of relative sequential analysis scores support the qualitative assessment (Figure 3.4), showing that the first 10 condition often produces a relative score higher (65.6%) than the first 20 and 30 conditions (59.0% and 56.9% respectively). Similar differences in relative sequential analysis scores can be calculated from the data reported by James et al. (2007) when comparing their 10 (72%) and 20 (58%) trial conditions. These results are sufficient to exclude the first 10 condition as a supply of valid sequential analysis results to determine the number of trials to stable means.

With the first 10 condition excluded, it must also be considered whether to accept sequential analysis values from either the first 20 or 30 trial number conditions. Despite the

evidence showing the different behaviour of the first 10 trials (mean 'transition' and higher

relative sequential analysis score) analyses showed that there were few differences (5 of 36

pairwise time series comparisons) between the criterion mean values derived at the 10th, 20th and

30th trial. As the kinematic mean does not vary statistically from the 10th trial to 20th and 30th, nor

are relative sequential analysis scores consistently different between the 20th to 30th trial

conditions, collecting 20 trials appears sufficient to estimate stable means. This will ensure that

the mean has passed the 'transition' phase illustrated in Figure 3.3 and avoided the different

relative sequential analysis score behaviour of the first 10 condition. It is worth noting that this is

the recommendation for the current population and task based on the process determining the

optimal condition from which to report sequential analysis results described previously and

summarised in Figure 3.5. Limitations such as time, budget or technological factors, learning

and/or fatigue may stipulate modification of this process within other research projects or applied

settings. Qualitatively, change in some participants' throwing technique was noted, perhaps

attributable to fatigue or learning, within the final ten throws of this study. These perceived

changes included decreased ball velocity, wrist and humerus height at release and changes in the

release angle, altering the path of the ball in flight. In the present investigation this provided

further justification for the use of the 20 trials condition, however, it is possible that the 30 trials

condition may be more appropriate for estimating stable mean values in other tasks and

populations.
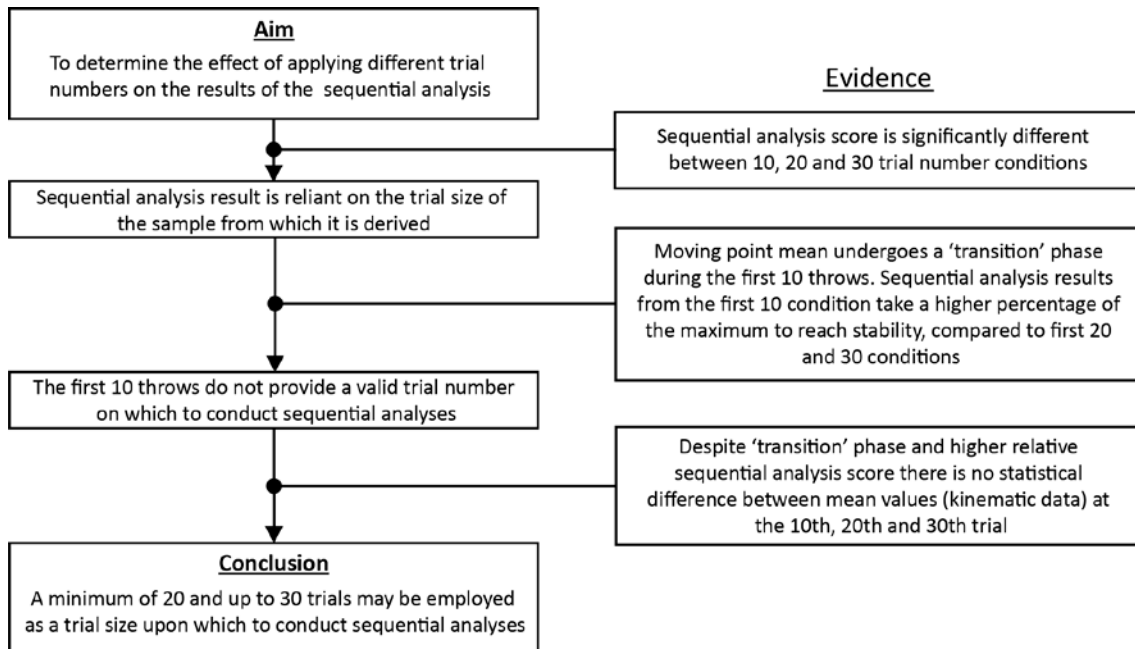
Figure 3.5. Flowchart of the aim, evidence and subsequent decisions/conclusion on which condition to report sequential analysis results from.

The reported sequential analysis results of marker displacement, joint angle data (Tables 3–4 and ball release data allow guidance in the determination of trial size for other studies of the same or similar design. While ball release and joint angle results may be of more impact in an applied setting than that of marker displacement , these data have been included as they are the direct measure of body movement, and all joint angle data are derived from these. When applying these results readers may choose to employ either the mean or the upper bound of the confidence interval, depending on how conservative they wish to be with this decision. While values are reported to one decimal place in order to provide a degree of precision, it is recommended that these values be rounded up when determining trials sizes from them. If discrete marker displacement data were to be analysed alone the reported results suggest that a trial size of 14–16 throws should provide mean stability in the selected variables. If discrete joint angle or ball release data are the only consideration then a trial size in the range of 13–15 is advised. From the results, the recommended trials sizes for analysing only complete marker or

joint angle time series are 15–17 and 13–15 throws respectively. However, as these values were derived from the maximum group mean across all 101 time series data points, there is an element of conservativeness about the results which researchers and practitioners may wish to consider when utilising them.

This study has attempted to address the selection of trial number condition size by comparing results across different conditions. The selection of an arbitrary size for the SD bandwidth (0.25 SD) allows for the creation of a conservative test which is a strength of the sequential analysis technique. Yet the inherent subjectivity makes it less objective than other tests such as intraclass correlation (ICC) which has also been used for the same purpose (James et al., 2007; Racic et al., 2009). Stability results from ICC analysis from these studies, admittedly addressing different variables, are however lower (4 trials). Results from this study show that a trial size of four risks reporting mean values from within the 'transition' phase which have not yet achieved stability as determined using the sequential analysis technique. As such, ICC may risk underestimation of a trial size which approximates stability in the mean compared to sequential analysis applied conservatively as in the current study, despite its objectivity. However, as James et al. (2007) reported, widening the SD bandwidth used in sequential analysis can yield similar results to ICC analyses. Researchers and practitioners should be aware of the strengths and weaknesses of the two techniques when choosing to use one over the other.

While differences exist between results from this study and from ICC analysis in other research, the current trial size recommendations are closer to those reported elsewhere based on sequential analysis. This includes 11 trials for continuous jumping (Racic et al., 2009) and 12 trials for drop landing, vertical jumps and cricket bowling (James et al., 2007; Rodano & Squadrone, 2002; Stuelcken & Sinclair, 2009). The higher results from this current study may be due to the

different task, different data types (kinematic versus kinetic) or associated differences in data

collection; it may also be related to the practice of using a range between the (rounded up) group

mean and 95% confidence interval employed in the current study.

3.7 Conclusion

The aims of this research were to investigate the effect of applying different trial numbers

on the results of sequential analysis applied to kinematic data of an overarm throwing task, in

order to determine the optimal trial number for conducting sequential analysis, and to report trial

size recomendations from this sample for future research. Based on the results, performing

sequential analysis on a sample of 20 trials or more to ascertain an acceptable estimate of mean

stability in kinematic data from an overarm throwing task is recommended. Furthermore, the use

of similar methods presented here to determine the required trial number for sequential analysis

in other populations and tasks are suggested. Researchers may choose to implement this method

on pilot samples of the target population to guide data collection and trial size decisions in studies

with larger samples. Practitioners may be able to use the technique to justify the number of trials

collected during regular testing and/or servicing of athletes. Depending on the data type, the

sequential analysis results suggest that collecting between 13 and 17 trials will provide stability in

the mean of the targeted variables from the overarm throwing task.

Chapter 4. A Surrogate Technique for Investigating Deterministic Dynamics in Discrete Human Movement (Study 3)

4.1 Preface

The results and conclusions taken from Study 2 allowed finalisation of the research design for the main intervention experiment of this thesis (see Study 4). Once data collection was complete the battery of statistical techniques to be used to assess variability was determined. Based on findings from Study 1 and further reading sample entropy was chosen as the technique to quantify changes in movement regularity. However, as entropy measures can quantify complexity in signals which are either stochastic or deterministic, a method which could show that the collected data were deterministic in nature was required. Surrogate methods were identified as a technique capable of fulfilling this requirement.

Investigation of the available methods identified that many surrogate techniques exist for different applications. The pseudo-periodic Surrogate method had previously been used similarly to the intended use in the present data. However, after gaining further insight into the time delay embedding method used by this technique, it was realised it was not valid for the intended use. Further searching revealed no surrogate method existed to adequately address the discontinuities existing between the end of one discrete movement time series and the beginning of the next. Hence, it was decided to develop such a method making use of a valid and effective embedding technique and to test its reliability within the intended application.

Study 3 documents the development of this novel surrogate technique. Preliminary data from this investigation was presented as a poster at the 33rd International Conference on Biomechanics in Sports, Poitiers, France in 2015. It was submitted to Motor Control on the 5th of

June 2015. The manuscript was returned for revision on the 10th of September and following

further revision and review it was accepted for publication on the 7th of October 2015. This

manuscript is presented in author accepted form formatted to be consistent with the remainder of

the thesis.

4.2 Abstract

Entropy is an effective tool for investigation of human movement variability. However,

before applying entropy, it can be beneficial to employ analyses to confirm that observed data is

not solely the result of stochastic processes. This can be achieved by contrasting observed data

with that produced using surrogate methods. Unlike continuous movement, no appropriate

method has been applied to discrete human movement. This article proposes a novel surrogate

method for discrete movement data, outlining the processes for determining its critical values.

The proposed technique reliably generated surrogates for discrete joint angle time series,

destroying fine-scale dynamics of the observed signal, while maintaining macro structural

characteristics. Comparison of entropy estimates indicated observed signals had greater regularity

than surrogates and were not only the result of stochastic but also deterministic processes. The

proposed surrogate method is both a valid and reliable technique to investigate determinism in

other discrete human movement time series.

4.3 Introduction

Human movement variability has received increasing attention over the last 30 years and

has historically been attributed to noisiness within the neuromuscular system (Newell et al., 2006).

Contemporary investigations hypothesise that variability is not representative of purely stochastic

processes but rather manifestation of intrinsic, deterministic, dynamical systems (Newell &

Corcos, 1993a), which can facilitate motor learning, improve performance and prevent injury

(Bartlett et al., 2007; Davids et al., 2003; Preatoni et al., 2013). Sample entropy is an effective tool for investigating movement variability (Preatoni et al., 2010). Sample entropy can quantify the regularity of a signal allowing inference to the complexity of the organism or system producing the signal (Lake, Richman, Griffin, & Moorman, 2002; Preatoni et al., 2010; Richman & Moorman, 2000). However, as entropy quantifies the regularity of signals that are stochastic, deterministic or a combination of both, a method which can demonstrate that a biological signal is not solely stochastic in nature is beneficial. If a signal can be shown to contain deterministic dynamics then it may provide evidence against the null, variability as noise, hypothesis. Furthermore, it provides confidence that inferences made about observed changes or differences in regularity are the result of purposeful rather than random processes. This outcome can be achieved by contrasting observed data with data generated from surrogate methods (Small et al., 2007; Theiler, Eubank, Longtin, Galdrikian, & Doyne Farmer, 1992). Surrogate methods can produce time series which resemble observed data yet present properties consistent with a non-deterministic signal.

Various surrogate techniques exist for different applications (Small et al., 2007). Many of these techniques deal with intrinsically stochastic signals. These methods may be applied to deterministic data by pre-filtering the observed signal to remove the deterministic component. However, segmentation of data into noise and deterministic components can result in spurious effects (Theiler & Eubank, 1993). When dealing with human movement data, surrogate methods designed for use with deterministic signals need to be considered. Due to its cyclical nature, human gait has previously been investigated using a pseudo-periodic surrogate method (Miller, Stergiou, & Kurz, 2006; Preatoni et al., 2010). This method derives a noise contaminated signal from a reconstruction of the underlying deterministic dynamic (a phase space created via time delay embedding consistent with Takens (1981) theorem). However, this method is inappropriate for discrete movements. This is due to the data consisting of *N* short time series rather than the

type of continuous and repetitive time series which facilitate time delay embedding. That is, despite resembling a continuous and periodic variable when concatenated together, the final value of one trial/cycle is not a neighbour to the initial value of the next, excluding the pseudo-periodic surrogate and other surrogate methods which employ time delay embedding. Therefore, the purpose of this article is to propose a generalisation of the pseudo-periodic surrogate method, without time delay embedding, which can be applied to discrete movement data. It is expected that this technique will produce outcomes similar to those of the Small shuffled surrogate method (Nakamura & Small, 2005, 2006), whereby the sequence of data is shuffled on a fine scale, destroying the micro structure of the original data (relationship between each datum and those immediately surrounding it), while the macro structural elements of the data (mean, variance, length) are maintained. The use of the proposed technique, quantification of critical values and the implementation of sample entropy to test for deterministic dynamics within discrete human movement will then be outlined.

4.4 Method

4.4.1 Participants

This project was approved by the Australian Catholic University Human Research Ethics Committee. Ten male participants [24.1 (3.3) years; 176.6 (5.9) cm; 76.4 (7.8) kg] provided informed consent and had their data included in this study. The task chosen to demonstrate surrogate generation was an overarm throw toward a target. Participants were seated on an adjustable piano stool with knee and ankle angles approximating 90° and anatomical orientation respectively. The piano stool was placed 7 m from a projection screen (5 m x 3 m) upon which a 70 cm round target consisting of 5 concentric circles was projected with the target centre being at a height of 2 m. Participants were seated such that their frontal plane was oriented perpendicular to

a line projected from the centre of the target to the piano stool. Participants attended two

sessions where they performed two blocks of trials with 16 throws per block. The choice of 16

throws per block was based on previous work (Taylor et al., 2015). Kinematic data were collected

using a 10 camera (6 MX and 4 T-series) Vicon (Oxford Metrics, Oxford, UK) motion capture

system, operating at 400 Hz. A Basler A602fc camera (Basler AG, Germany) recording at 100 Hz

was used to capture ball release for later data cropping. Following data collection, three-

dimensional joint angles – shoulder internal/external rotation and flexion/extension at the elbow

and wrist – were calculated. All angle data were cropped from the first target-directed motion of

the finger marker through to ball release. Following investigation of the residuals (Winter, 2005)

and frequency content of the data, all time series were filtered at 12 Hz using a 4th order

Butterworth filter.

4.4.2 Surrogate technique

The following details the surrogate generation method.

1. Let x_{ij} and y_{ij} be the jth scalar time point from the ith trial of observed joint angle time series

    (e.g., where x_{ij} is elbow angular displacement and y_{ij} is the same for the shoulder). Let the

    concatenated time series X and Y be;

    $$X = (x_{ij})_{\substack{i=1,\dots,N \\ j=1,\dots,T_i}}$$

    $$Y = (y_{ij})_{\substack{i=1,\dots,N \\ j=1,\dots,T_i}}$$

    where N is the total number of trials collected, T_i is the total number of data

    points in the ith trial and X and Y are matrices with dimensions $\sum_{i=1}^{N} T_i$.

2. Then the concatenated time series X and Y are combined to form a phase space, P, where P is a matrix with dimensions $2 * \sum_{i=1}^{N} T_i$;

$$P = (X_{ij}, Y_{ij})_{\substack{i=1,\ldots,N \\ j=1,\ldots,T_i}}$$

3. Initial (A) and final (B) conditions of individual trials within P are extracted where A and B are both *2 x N* matrices;

$$A = (x_{i1}, y_{i1})_{i=1,\ldots,N}$$

$$B = (x_{iT_i}, y_{iT_i})_{i=1,\ldots,N}$$

4. Elements of P are then shuffled, with no new entries (randomly resampled with replacement), to form the surrogate P_s. First an initial current state $P_{s(i,t)}$ is selected at random from A. Set t = 1.

5. To select the next state of P_s first noise is added to the current state creating C;

$$C = P_{s(i,t)} + \rho g P_{s(i,t)}$$

where ρ is a constant and g is Gaussian noise;

$$g \sim N(0,1)$$

6. The state in P which is closest to the noisy current state C created above is identified as $k_{m,n}$ using the least root mean square difference between C and each column of the matrix P. Then the next state of P_s is defined as the successor;

$$P_{s(i,1+t)} = k_{m+1,n+1}$$

7. The state $P_{s(i,1+t)}$ is now the current state of P_s. Increment t. The next state of P_s is selected by repeating steps 5–6. The process of incrementing t and selecting the next state continues until the current state of P_s is equal to one of the sets in B.

8. The value i can then be incremented and steps 4–7 repeated to obtain the next surrogate.

This method is documented here using two concatenated input variables (X and Y in step 1). Researchers should use the knowledge of their own data to ensure there is a suitable level of appropriateness when selecting these input variables, avoiding the use of unrelated or irrelevant combinations. However, as long as this level of appropriateness is maintained there is no theoretical limit to the number of input variables that are used to form the phase space P at step 2. As such the matrix P could be defined such that its dimensions are $V * \sum_{i=1}^{N} T_i$ where V is equal to the number of input variables. Matrices A and B would then be $V \times N$ in dimension.

4.4.3 Determining ρ

An optimal value for ρ elicits the greatest number of small segments within the surrogated time series (Small, Yu, & Harrison, 2001), providing an optimal balance between effectively destroying the fine-scale dynamics of the signal and maintaining its macro structure. A small segment is defined as any run of surrogate data of length between 2 and the total length of the surrogate, identical to one existing at any point within the original data set. The segment is created when a switch in the sequence of data in P, currently being sampled to provide the next state of P_s, occurs. When ρ is very small (at or approaching zero) the number of small segments will be zero as original data and surrogate will be identical. As ρ increases, so too will the number of small segments, towards a maximum, before returning toward zero (as $\rho \to \infty$). A large range of values for ρ (0–5; increments of 0.1) were tested 100 times using a block of data of one participant

(Figure 4.1a). This identified the probable range (0.1 – 0.9 and 0.1 – 2.0 for two and three

dimensional phase spaces respectively) over which to test for individual peaks in small segments

(Figure 4.1b). Each participant's data were then tested over this range five times, and the ρ value

associated with the highest mean number of small segments was selected (e.g., Figure 4.1c). This

resulted in an individualised value for ρ to be used for surrogate generation for each block of 16

throws for each participant.
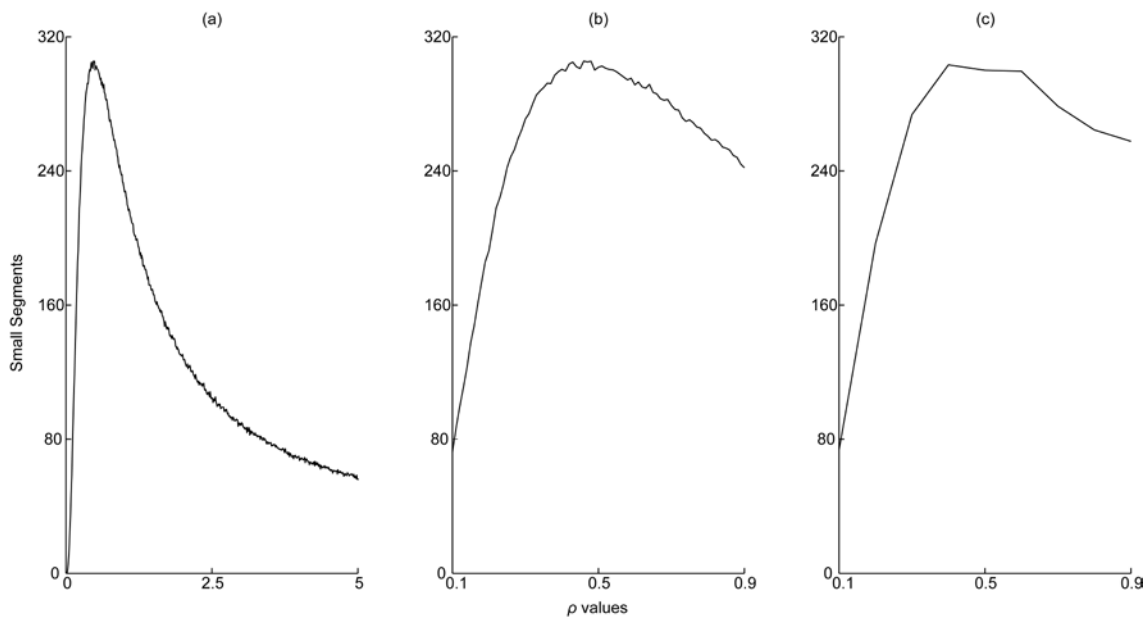
Figure 4.1. Results of testing over a large range of ρ values (a), probable range for individual values of ρ (b) and results of testing over this range for a single participant (c).

4.4.4 Discrete data surrogate generation

To demonstrate the use of the technique with different multiples of input variables, two

different surrogate generations were conducted. First, elbow and shoulder time series were

concatenated and combined to form a two dimensional phase space from which the respective

surrogates were drawn. Next, wrist time series were included to form a three dimensional phase

space and the process was repeated. The number of surrogates generated matched the number of

throws in the observed data for each block. Surrogates with similar length (± 1SD) as the mean length in the original data were accepted to maintain comparability. If this criterion was not met, the surrogate was rejected and the process repeated. This process resulted in two elbow and two shoulder surrogate time series, from the two and three dimensional phase space generation, being produced for each observed throw included in the study. In addition, one wrist surrogate was produced via the three dimensional phase space for each observed throw.

4.4.5 Validity and reliability

The biomechanical data used in this investigation was filtered, as is convention, to remove any systematic noise introduced by the data collection equipment. However, since surrogate data can appear similar to unfiltered/raw data, the surrogate generation process was also carried out on the raw movement data in addition to the filtered data. This analysis ensured that any observed differences in regularity between the data and its surrogate was the result of the methodology and not due to increased regularity introduced to the signal via the post collection smoothing. That is, if the raw data and its surrogate, as well as the filtered data and its surrogate, are both significantly different in regularity, this can be attributed to the surrogate method and not to any other conditioning of the observed data.

To demonstrate the ability of the technique to produce surrogates which approximate the macro structure of the original data, surrogate mean, SD and data length were compared to that of observed signals using Mann-Whitney U tests. Furthermore, the ability for these values to be produced reliably was tested by repeating the surrogate generation process 6 times for each included block of throws. The mean, SD and length of the resultant data were assessed for reliability using intraclass correlation and standardised typical error tests (Hopkins, 2000, 2011). This was performed for surrogates produced both via two and three dimensional phase space.

4.4.6 Comparing real and surrogate data

Sample entropy values quantify the regularity of a signal by assessing the probability that two sequences of points extracted from a time series of length N, which are similar for a period of m points within a tolerance r, will remain similar for a period of $m + 1$ points excluding self matches (Lake et al., 2002; Richman & Moorman, 2000). The sample entropy estimates of the observed and surrogate data were used for statistical inference. It was hypothesised that the observed time series would return lower sample entropy estimates than surrogates as they are not solely the result of noisy, random processes, but contain some element of deterministic dynamics. The lower entropy estimate of the observed data would reflect the increased regularity of a signal under the control of the neuromuscular system as opposed to the random, stochastic process producing the surrogate.

The choice of values for the parameters m and r will affect the outcome of the entropy estimate, and consistency between parameters used for real and surrogate data comparison is the key concern. Still, values of $m = 2$ and $m = 3$ as well as a range of r values (0.1 – 0.3) were tested as recommended (Yentes et al., 2013) to determine these values. As a result, the parameters of $m = 2$ and $r = 0.1$ were employed. Sample entropy estimated for the concatenated real and surrogate time series of the three joint angles for all blocks of throws. These estimates were compared using the Mann-Whitney U test. Non parametric statistics were employed as data did not display normality (Peat & Barton, 2005).

4.5 Results

Surrogate generation was successfully conducted via the documented algorithm using both two and three dimensional phase spaces. An example of concatenated real and surrogate data as well as a single real and surrogate throw can be seen in Figure 4.2 (two dimensional phase space).
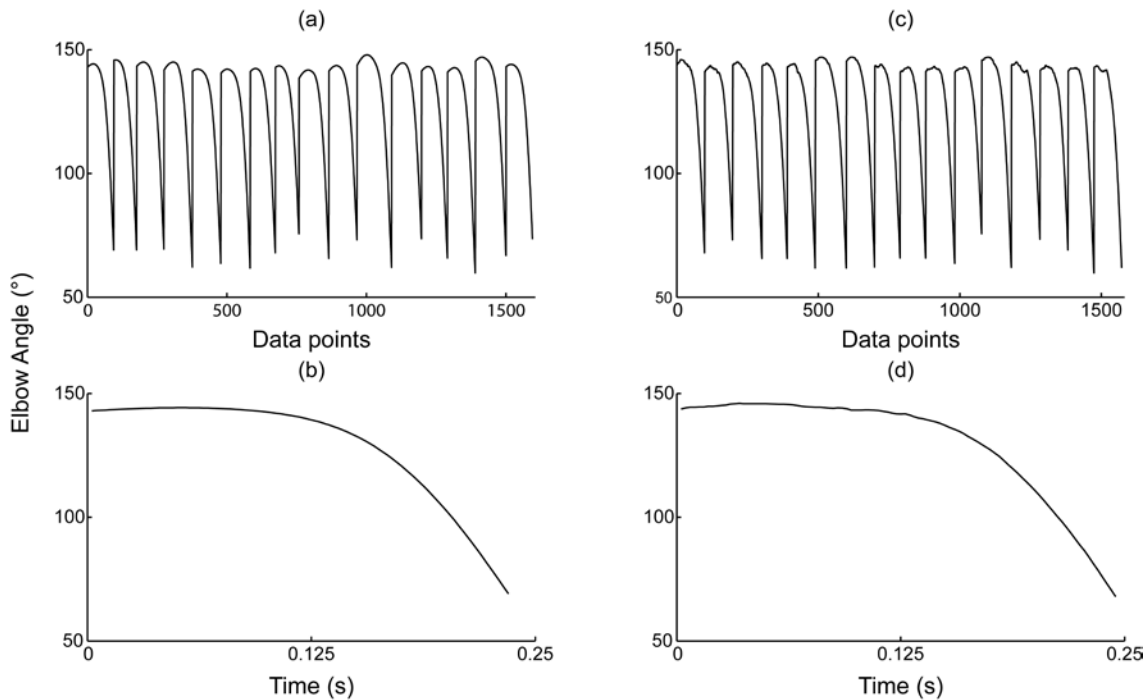
Figure 4.2. All throws concatenated and a single throw for observed (a & b) and surrogate (c & d) data.

The comparison of macro characteristics (mean, SD and length) showed no significant differences between the real and surrogate throws ($p \geq 0.68$). There were also no significant differences between the mean, length and SD of elbow and shoulder surrogates produced via two and three dimensional phase space ($p \geq 0.61$). The group mean value of ρ was significantly higher for the three dimensional phase space surrogate generation ($p < 0.01$). However, the number of short segments produced by this increased ρ value was no different ($p = 0.55$) between two and three dimensional applications. Reliability analysis indicated that the surrogate generation

algorithm was able to consistently produce this output as indicated by an ICC ≥ 0.99 and a small standardised typical error of ≤ 0.1 (Hopkins, 2000, 2011).

Comparison between the sample entropy estimate of real and surrogated data for elbow, shoulder and wrist angles can be seen in Figure 4.3. Results of the Mann Whitney U tests indicated that observed time series had significantly lower sample entropy (p ≤ 0.05) than their respective surrogate for all joint angles across both two and three dimensional phase space generation. This was observed for both the filtered and unfiltered/raw data. There was no significant difference between the entropy estimates of the elbow and shoulder surrogates produced via the two and three dimensional phase space (p ≥ 0.08).
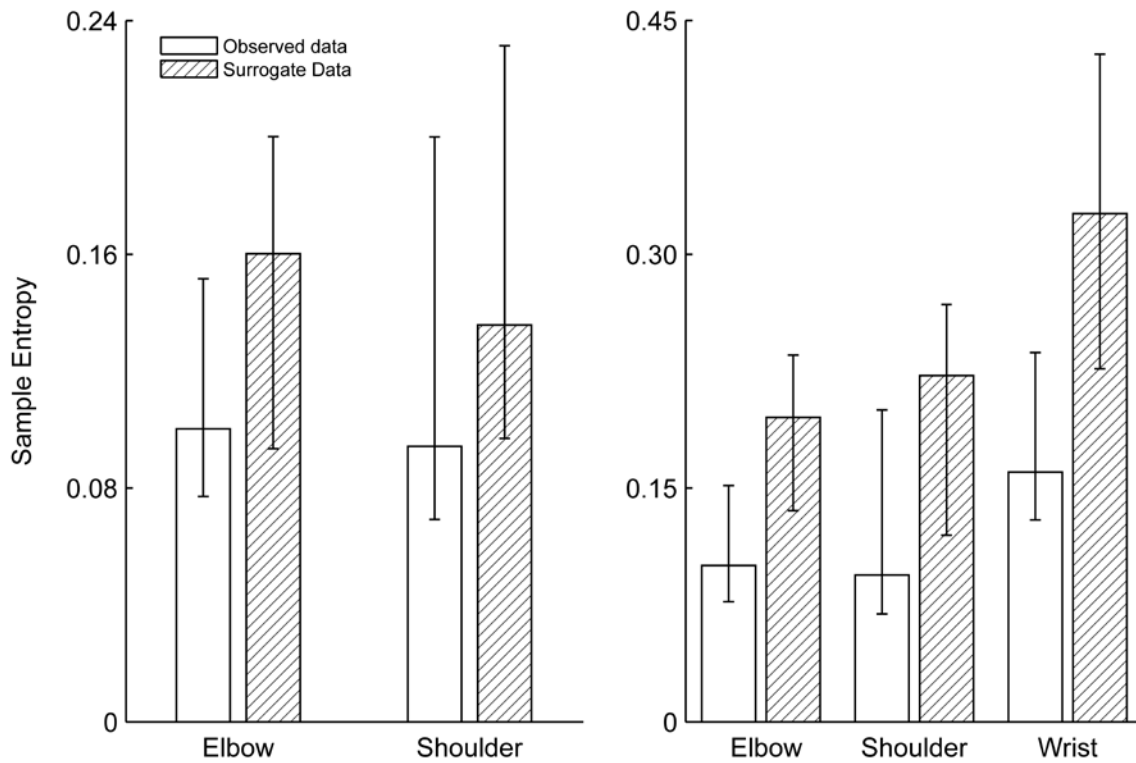
Figure 4.3. Median (± inter-quartile range) sample entropy estimate for observed and surrogate data across the three included joint rotations. All surrogate data sample entropy estimates were significantly greater than their respective observed data estimate (p < 0.05).

4.6 Discussion

The purpose of this paper was to propose a surrogate generation method for discrete movement data and to illustrate its use - i.e., to demonstrate that these data were not solely the result of stochastic processes. Shoulder, elbow and wrist joint angle time series were taken from an overarm throwing task and appropriate surrogates generated. Reliability analyses suggest that this method can be depended upon to consistently produce the expected outcomes. All surrogate time series effectively maintained the overall trends in the observed data (Figure 4.2), as confirmed by the Mann Whitney U results showing no significant difference in the mean, SD and length between real and surrogate data. While the macro characteristics of the observed data were maintained, comparison of the sample entropy estimate for both real and surrogate data (Figure 4.3) showed that the observed discrete human movement is not solely the product of non-deterministic 'noisy' processes. Furthermore, repeating the process using unfiltered/raw data produced the same results indicating that the differences between observed and surrogate data is the result of the surrogate method and not from any post-processing (increased regularity due to filtering) of the data.

The documented method is theoretically capable of producing surrogates using any number of input variables, greater than or equal to two, by creating an equally dimensioned phase space. To demonstrate this, two and three variables were used to form two and three dimensional phase spaces respectively. Results showed that surrogates were effectively created using both approaches. However, despite no significant differences in the macro characteristics, the entropy estimates or in the number of short segments created, the selected values for ρ were significantly higher for each participant in the three dimensional phase space approach. This can be attributed to the requirement of a greater noise radius to effectively select the nearest noisy neighbour due

to the increased distance between trajectories that exist in a higher dimensional phase space. Qualitatively, it did appear that the increased ρ resulted in 'noisier' surrogates being produced via the three dimensional phase space, supported by the p values of the compared surrogates appearing to approach significance (p ~ 0.08). In addition to determining whether the variables being combined to form the phase space in this method are appropriate for the task, researchers should also ensure that the dimensions employed have the desired effect on surrogate outcomes.

This study is not the first to investigate the use of surrogate techniques with human movement data. Previous work using a pseudo-periodic surrogate with normal walking and race walking (Miller et al., 2006; Preatoni et al., 2010) successfully displayed the presence of deterministic dynamics within the time series taken from these tasks. While the discrete data used in this study can appear cyclical when concatenated (Figure 4.2a), discontinuities are present which do not exist in cyclical data. Hence, the discrete, separate trajectories of the current data required a new method capable of producing multiple surrogates with multiple random walks from a single phase space formed by embedding multiple observed time series as opposed to one created by time delay embedding (Takens, 1981) such as with pseudo-periodic surrogates. Hence, the concatenated data of two or more joint rotations (step 1 in Surrogate Technique) are brought together to form the phase space (step 2 in Surrogate Technique) which maintained the biomechanical relationship between variables.

In conclusion, the proposed method effectively produced surrogates for comparison with collected discrete movement data. This comparison identified that the observed signal is not solely the result of stochastic processes suggesting the presence of deterministic dynamics. Coupled with the ability of the algorithm to consistently produce the expected outcome, the modified small

shuffle surrogate method is both a valid and reliable technique to investigate the stated

hypotheses in other discrete human movement time series.

4.7 Acknowledgements

Chapter 5. Changes in Variability and Adaptability during the Learning of a Novel Discrete Task (Study 4)

5.1 Preface

Studies 1, 2 and 3 laid the theoretical and method-related foundation to begin answering questions regarding the possible functional role of discrete movement variability in facilitating adaptability and to understand any interaction with learning. Study 4 documents the implementation of a longitudinal research design and the use of the contextual interference affect to this end, both recommendations from Study 1. Results from Study 2 guided the selection of trial size in this study. The novel surrogate method developed in Study 3 was implemented to strengthen the use of sample entropy in quantifying movement complexity (variability) in the collected time series. Preliminary data from this investigation was presented as an oral report at the 33rd International Conference on Biomechanics in Sports, Poitiers, France in 2015.

5.2 Abstract

Variability is an ever present and functional element of human movement which may facilitate adaptation to changing constraints. Adaptability may emerge throughout motor learning and be related to the variability profiles of an individual during this process. This study aimed to employ a longitudinal design and contextual interference to investigate changes in movement variability while learning a novel discrete task. It was hypothesised that those exposed to high contextual interference (task variability) during skill acquisition would outperform those exposed to low contextual interference. Furthermore, that improved performance by the high contextual interference group in a transfer task would provide evidence of adaptability. Twenty participants were randomised into one of two experimental groups and attended nine training sessions where

they practiced overarm throwing with their non-dominant hand. Surrogate methods and sample entropy were used to assess changes in movement variability at the first (joint) level while learning this novel discrete task. The results indicated the presence of the contextual interference effect which enhanced adaptability in the high contextual interference group. Surrogate techniques effectively demonstrated the presence of deterministic dynamics. Movement variability was not significantly different between the high and low contextual interference groups though several trends corroborated evidence reported from previous research. While inconclusive, the combination of longitudinal design, contextual interference and measurement of variability allowed speculation on several hypotheses to guide work on furthering our understanding of the functional role of variability in motor learning and adaption.

5.3 Introduction

Variability is considered an ever present and functional element of human movement within a dynamical systems approach (Newell & Corcos, 1993a). One of the functions attributed to movement variability is facilitation of adaptability of an organism to changing environmental and task constraints (Bartlett et al., 2007). In discrete movements this variability is different to undesired variability in the endpoint or outcome of the movement (e.g., the number of targets hit). Functional movement variability is considered to be a characteristic of highly skilled movers (Button et al., 2003; Wilson et al., 2008) and an individual's variability profile is thought to change during task learning. For example, a U-shaped curve has been hypothesised to characterise coordination variability across skills, where the highest and lowest skilled display increased variability while those in intermediate stages have their variance constrained (Wilson et al., 2008). This pattern correlates well with the changes in degrees of freedom proffered by Bernstein (1967) with supporting evidence to be found in practice of soccer chipping (Chow et al., 2007; Chow,

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Davids, Button, & Koh, 2008). In this sense, the later variability is considered functional as it exists alongside successful movement outcome. It is therefore different to the high variability displayed in early stages of motor learning, associated with searching for effective movement patterns, and the more stereotyped movement of middle stages (Bernstein, 1967).

However, variability does not just exist within coordination and can manifest at different levels within an individual's kinematic profile. One level consists of fluctuations in individual elements such as joints and segments. Another perhaps is whole system variability, where several coordinated elements combine to produce an overall movement pattern. At the first level, there is consistent evidence that variability decreases when skill increases (Betzler et al., 2012; Bradshaw et al., 2009; Button et al., 2003; Fleisig et al., 2009; Hiley et al., 2013). It could be hypothesised that higher variability in the lower skilled at this level is reflective of searching for effective movement patterns in line with the degrees of freedom and U-shaped curve hypotheses. However, the consistent decrease in individual variability as skill rises may be evidence of the need to constrain variability to facilitate optimal coordination and allow functional coordination variability to emerge. Understanding the change in variability profile at each level, in particular during any interaction with motor learning and/or adaptation, could provide insight into how any functional role of variability emerges.

Retention and transfer tests are key methodologies in evaluation of motor learning. Retention tests assess the level of performance retained or present at the cessation of practice. Transfer tests determine the level of proficiency in a task which is related, yet novel, to the acquisition task. Concerning adaptability in motor learning, contextual interference effect describes the relatively superior performance on retention and transfer tasks of individuals who practice within a randomised sequence (high contextual interference) in contrast to the poorer

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performance of those who practice a single task under blocked conditions (Brady, 2004). In

particular, the improved performance on transfer tasks of those who learn under high contextual

interference is considered evidence of greater levels of adaptability to changed task constraints

(Magill & Hall, 1990). Contextual interference effect, which is supported by a large body of

literature (Brady, 2004), provides a tool to observe differentials in adaptability, and hence tracking

the changes and differences in movement variability of those learning a task under high and low

contextual interference may yield useful indications about any relationship between variability

and adaptability.

In order to detect changes effectively over a period of learning, it is important to select an

appropriate measure to quantify variability. Despite the fact that human movement data is almost

always obtained in the form of time series sampled at a reasonably high sampling rate, much of

the variability literature has relied on temporally discrete values extracted from time series, such

as minima and maxima, which are often quantified using standard deviation and/or coefficients of

variation (Bartlett, 2008). These discrete measures may fail to reflect the patterns or irregularities

of the time-domain information obtained during data collection. More recent investigations have

advocated the use of sample entropy measures which analyse the pattern of regularity in entire

time series or groups of time series (Preatoni et al., 2010; Preatoni et al., 2013; Richman &

Moorman, 2000). However, as measures of entropy quantify the regularity in signals of both

deterministic and stochastic origin, it is important to first indicate that any captured signal is

deterministic in nature to confirm that any detected variability is the result of deliberate neuro-

motor control as opposed to that of stochastic noise. This validation can be achieved by comparing

observed data to that of a known stochastic origin derived using surrogate methods (Small et al.,

2007; Taylor et al., in press).

The aim of this investigation therefore is to examine the changes in movement variability during the learning of a novel discrete task under high and low contextual interference conditions using a surrogate method and sample entropy measures. The study intends to determine variability at the first (joint) level of the chosen activity as an initial step to understanding any relationship amongst variability, adaptability and learning. It is expected that those exposed to high contextual interference (task variability) during skill acquisition will outperform those exposed to low contextual interference in both retention and transfer tasks. Furthermore, that superior performance in the transfer task will provide evidence of adaptability in the high contextual interference group which will also display reduced movement variability at the first (joint) level. However, it will be interesting to ascertain whether the use of sample entropy, thereby assessing the entire time series, produces any contrary results.

5.4 Method

5.4.1 Participants

Twenty healthy adult males [22.2 (3.3) years; 179.4 (6.5) cm; 78.1 (9.1) kg] were recruited and provided informed consent to participate in this study which was approved by the University Human Research Ethics Committee. Each participant completed a questionnaire to determine their dominant and non-dominant arm (Oldfield, 1971). To avoid any bi-lateral skill transfer, participants were not currently, or in the previous 5 years, participating in any task requiring overarm throwing for accuracy (e.g., cricket).

5.4.2 Intervention design

Each participant was randomised into one of two groups to practice the novel task of overarm throwing with their non-dominant hand. All throwing tasks took place in a laboratory and

consisted of throwing a regulation tennis ball at a target projected on a cloth screen (5 m x 3 m).

One target was projected at a time at one of the nine locations indicated in Figure 5.1. The

projection volume was set up such that the centre of the central target (2B in Figure 5.1) was at a

height of two metres above the ground. Participants were seated on an adjustable stool, with their

frontal plane square to and seven metres from the projection screen, their sagittal plane

perpendicular to a line intersecting the centres of targets 1B-2B-3B (Figure 5.1), their feet flat on

the ground and ankle and knee joints each approximating 90° flexion. Participants were asked to

start each throw with hands resting on their knee, to throw overarm, as accurately as possible

toward the centre of the projected target.
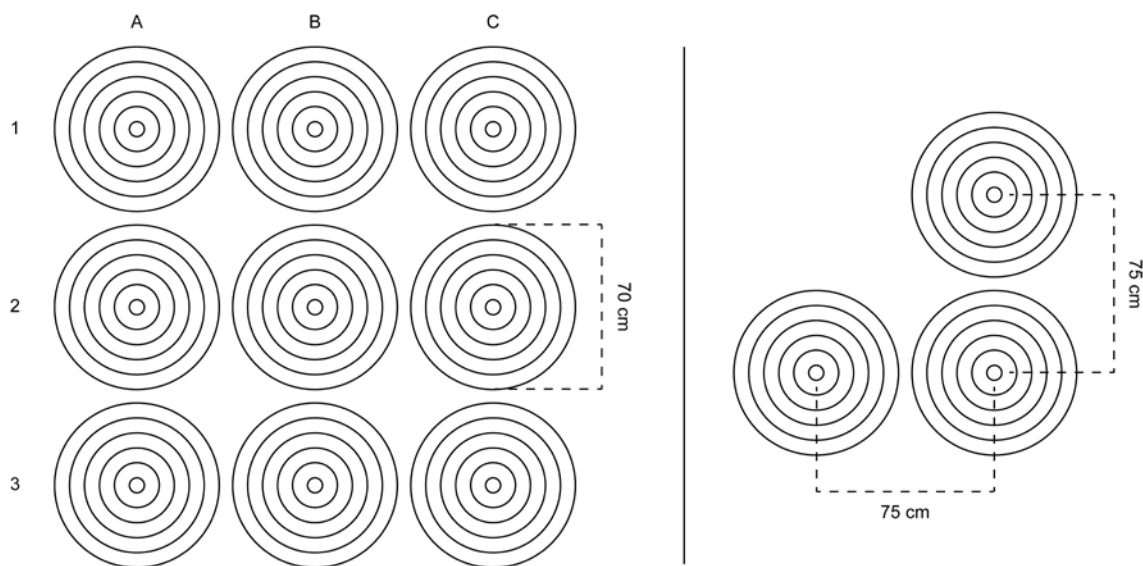
*Figure 5.1. Layout and size of the nine targets used in this investigation (left panel) and separation
measurements (right panel). Only one target was visible during each throw.*

A contextual interference design was implemented which would see one group (Low CI)

practicing under low contextual interference conditions and another (High CI) practicing under

high contextual interference conditions. Each participant attended nine sessions. There was a

minimum of 24 hours and a maximum of 72 hours between sessions. Each session consisted of a

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pre-test, four blocks of practice throws and a post-test. In addition session nine included a transfer

test where participants performed throws to novel targets. The pre-test of session one and the

post-test of session nine acted as the pre and post tests for the entire experiment. The task flow

for each session for each group can be seen in Table 5.1. Kinematic data were collected for all pre-

and post-tests while ball impact/accuracy data was collected for all pre-, post- and transfer-tests.

The number of throws performed in pre- and post-tests was based on previous work (Taylor et al.,

2015). For this investigation the data of interest comes from the pre-test of session one and the

post- and transfer-tests of session nine.

Table 5.1.
Task flow for each group for session one through nine.

	Low CI	**High CI**
Warm up	Self-selected number of throws ~2 mins	Self-selected number of throws ~2 mins
Pre-test	16 throws at target 2B	16 throws at target 2B
Rest	3 minutes	3 minutes
Practice blocks	4 blocks of 10 throws at target 2B (1 min rest between blocks)	4 blocks of 10 randomised throws at targets 1B, 2A, 2C, 3B (1 min rest between blocks)
Rest	3 minutes	3 minutes
Post-test	16 throws at target 2B	16 throws at target 2B
Rest	5 minutes (session 9 only)	5 minutes (session 9 only)
Transfer-Test	4 x 4 throws at randomised novel targets 1A, 1C, 3A, and 3C (session 9 only)	4 x 4 throws at randomised novel targets 1A, 1C, 3A, and 3C (session 9 only)

Note: Target locations (e.g., 2B) refer to grid positions in Figure 5.1.

5.4.3 Equipment

Three dimensional (3D) motion capture and analysis were carried out using a 10 camera (6

MX and 4 T-series) Vicon system operating at 400 Hz paired with Vicon Nexus software and the

unilateral Vicon Upper Limb Model plug-in (Oxford Metrics, Oxford, UK). A Basler A602fc camera

(Basler AG, Germany), synchronised with the Vicon system and recording at 100 Hz (every frame

synchronised with every 4th frame of the 3D data) was mounted perpendicular to the sagittal plane

to capture ball release for later data cropping. All system set-up, including participant preparation and post processing, was performed as per the Vicon Upper Limb Model product guide (Vicon Motion Systems, 2007). Ball impact with the target screen was captured at 120 Hz using a Casio EX-ZR1000 digital camera (Casio Computer Co., Tokyo, Japan) mounted behind the participant at the height of the central target (2B in Figure 5.1) with the focal axis aligned perpendicular to the projection screen.

5.4.4 Analysis

Due to the similarity of the data, the justification for and filtering method came from a previous investigation (Taylor et al., in press). All kinematic data were filtered within Nexus using a 4th order low pass Butterworth filter with a cut-off frequency of 12 Hz. Elbow flexion/extension, shoulder internal/external rotation and wrist flexion/extension were extracted from the model outputs. These variables were chosen because of their key contribution to ball release velocity (van den Tillaar & Ettema, 2004). Data were cropped such that the beginning of the movement was the first positive (toward the target) motion of the finger marker, coinciding with the completion of wind up. The point of ball release, ascertained from the Basler camera data, indicated the end of the movement.

Throw accuracy was determined by manually digitising the centre of the target and the ball, one frame before impact. Pixel distance between these two points was calculated and divided by the radius of the target in pixels to create a radial error 'score' such that the lower the score, the more accurate the throw is. A custom MATLAB script (The MathWorks Inc., Natick, MA, USA) was used to digitise the image and calculate radial error score, and digitisation was performed by one investigator and intra-individual reliability was high as indicated by an ICC > 0.99 and a small standardised typical error (≤ 0.03) (Hopkins, 2000, 2011).

To test for the presence of deterministic dynamics in the observed signals, data were compared to those produced using surrogate methods. Surrogate methods produce a time series which mimics the observed signal in macro characteristics such as shape, length, mean and variance but have its micro structure altered. In particular the method changes the relationship between one data point and its neighbours where determinism is stored (Theiler et al., 1992). With the relationship between consecutive values destroyed, the resultant time series is stochastic in nature compare to observed time series. Surrogate data were produced by a generalisation of the pseudo-periodic time series (Small et al., 2001) which produces outcomes similar to the Small shuffled surrogate method (Nakamura & Small, 2005, 2006) and has been shown to be valid and reliable to be applied to discrete human movement data (Taylor et al., in press). The number of surrogates generated matched the number of collected throws (i.e., 16 pre-test throws/observed time series) for each joint angle per participant. To ascertain determinism of the observed time series, observed and surrogate time series of each participant were concatented and then compared using sample entropy(m,r,N) (Richman & Moorman, 2000). If the observed signals return a lower entropy estimate than the respective surrogate, then it can be stated that the observed signal contains information that is deterministic in nature (Taylor et al., in press). Sample entropy(m,r,N) was estimated for the observed pre-test time series, where N was the length of the concatenated time series and $m = 2$ and $r = 0.1$ as determined via testing advocated by Yentes et al. (2013). This process was repeated for the 16 throws of each participant for each joint angle from the post-test. Thus, each participant had two sample entropy values calculated as measures of intra-individual variability, one each for the pre- and post-test for each joint angle.

Entropy content of observed data and their respective surrogates were screened for normality and changes in entropy content of included time series (pre- to post-test) within and between groups were analysed using Wilcoxon Signed Rank and Mann Whitney U tests

respectively. Significance level was set at p < 0.05 and appropriate effect size measures were

calculated for the parametric and non-parametric statistics (Cohens *d* and *r* respectively

where $r = \frac{Z_{score}}{\sqrt{N}}$). Radial error scores (pre-, post- and transfer-test) were screened for normality

and changes in radial error score (pre- to post-test) within and between groups were analysed

using dependent and independent t-tests, respectively. The relationship between individual pre-

and post-test radial error score and entropy values as well as change in score and entropy across

training was assessed using Spearman's rho. All statistical analysis was completed using MATLAB

(The MathWorks Inc., Natick, MA, USA) or IBM SPSS (IBM, Armonk, BY, USA).

5.5 Results

Both Low CI (p < 0.05, *d* = 0.73) and High CI (p < 0.01, *d* = 1.44; Figure 5.2) groups

significantly improved their radial error score from pre- to post-test. Significant improvement from

pre- to transfer-test was also noted for the High CI group (p < 0.01, *d* = 1.39) while Low CI (p =

0.70, *d* = 0.20) showed no statistical difference for the same comparison. Throwing performance

of High CI was significantly better than Low CI at post- (p = 0.03, *d* = 0.96) and transfer-tests (p <

0.01, *d* = 1.36). No statistical differences existed between groups in their throwing performance at

the pre-test (p = 0.51, *d* = 0.31; Figure 5.2).
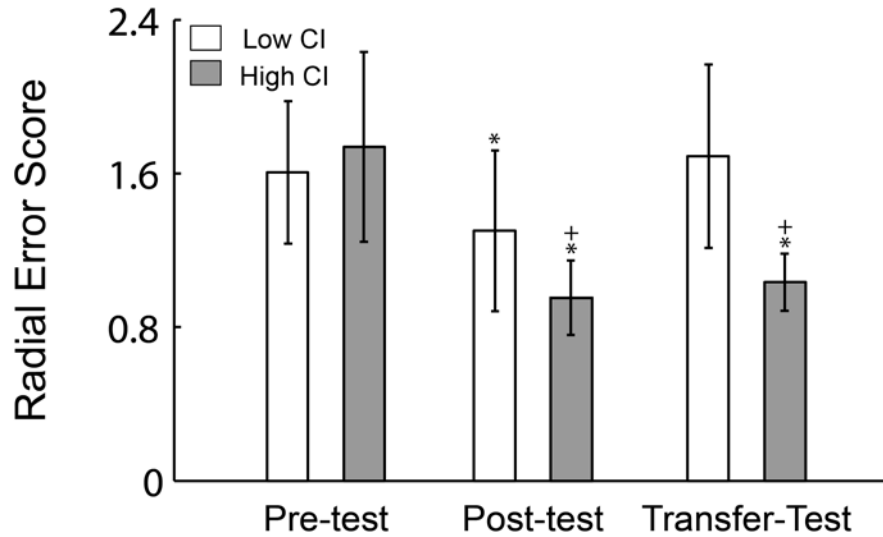
*Figure 5.2. Results of radial error score (± SD) for pre-, post- and transfer-tests. * Significantly different (p < 0.05) from the pre-test score of the same group. + Significantly different (p < 0.05) from the corresponding Low CI score.*

Sample entropy estimates of observed data were all significantly lower than that of their respective surrogates (p < 0.01, r ≥ 0.63; Figure 5.3). There were no significant differences within or between groups for the sample entropy estimates of observed elbow, shoulder and wrist joint rotation data (p ≥ 0.06; Figure 5.4). There were several trends in the data which were associated with small, medium or large effects with practice. The increase in entropy estimate of the Low CI group, pre- to post-test, for elbow and shoulder returned medium ($r = 0.40$), large ($r = 0.60$) and small ($r = 0.21$) effects for elbow, shoulder and wrist respectively. The High CI group displayed a trend of decreasing entropy estimate with practice associated with a medium ($r = 0.47$) and large ($r = 0.53$) effect for the shoulder and wrist, respectively. The entropy estimate for the elbow of the High CI group had an insignificant increase with associated small effect size ($r = 0.21$). At post-test the High CI group displayed lower variability than Low CI at the shoulder and wrist showing small effects ($r ≤ 0.24$). There was very little difference between groups in elbow variability at post-test ($r = 0.07$).
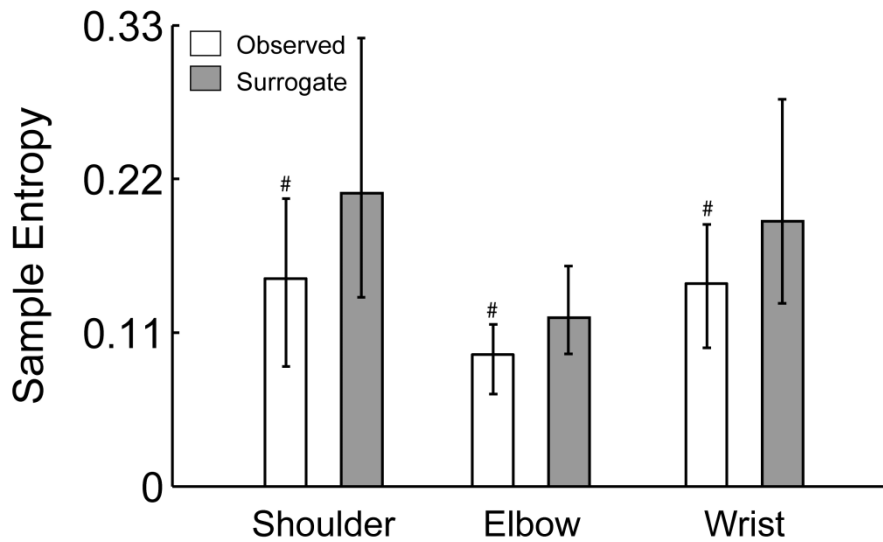
Figure 5.3. Results of entropy content (± interquartile range) comparisons between observed and surrogate data. # significantly lower (p < 0.05) than the corresponding surrogate.
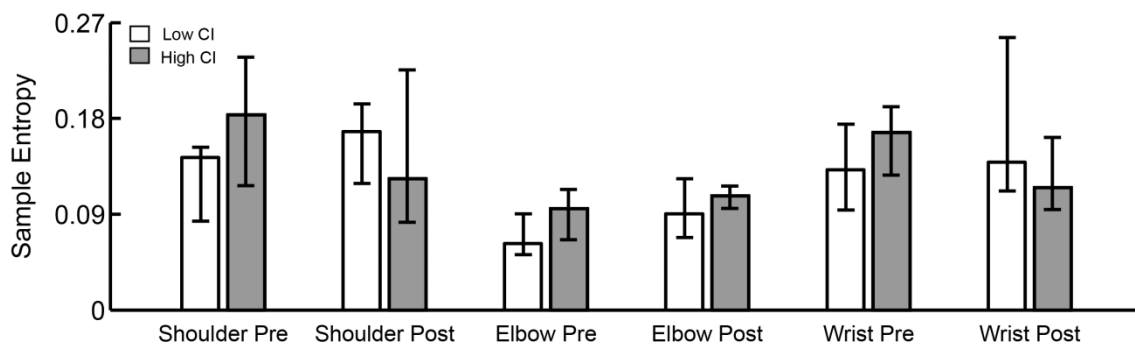
Figure 5.4. Results of entropy content (± interquartile range) comparisons between groups for all joint rotations.

There was significant moderate positive correlation between change in radial error score and change in entropy pre- to post-test for the shoulder (rho = 0.46, p = 0.04) while shoulder and wrist joint showed insignificant and small positive correlations for the same comparison (rho ≤ 0.21, p ≥ 0.37; Figure 5.5). The relationships between pre-test radial error score and entropy estimates were insignificant (p ≥ 0.13) and negative (Figure 5.6) with small rho (- 0.06 and - 0.07) for shoulder and wrist and medium rho for elbow (- 0.35). Conversely, the relationships between

post-test radial error score and entropy estimates were (Figure 5.7). Again these correlations were

weak (rho ≤ 0.18) and insignificant (p ≥ 0.45).
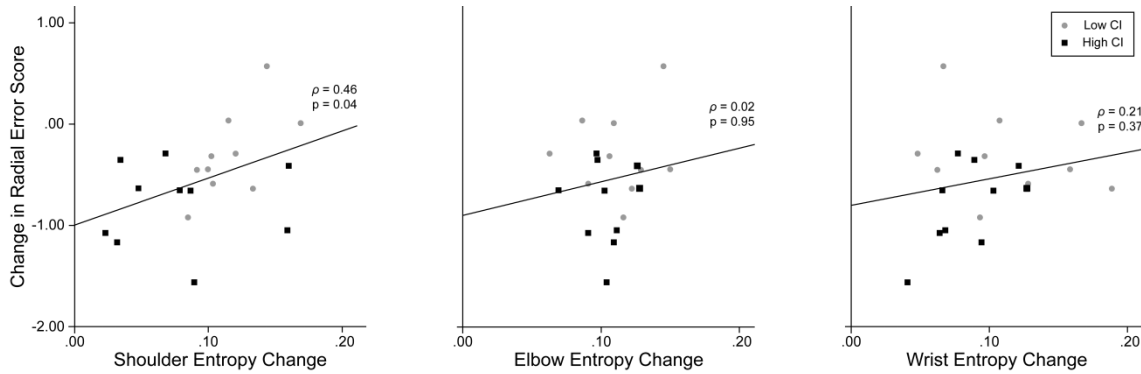
Figure 5.5. Relationship between change in radial error score from pre- to post-test and change in entropy over the same period. Correlation between change in radial error and shoulder entropy estimate was significant (rho = 0.46, p = 0.04).
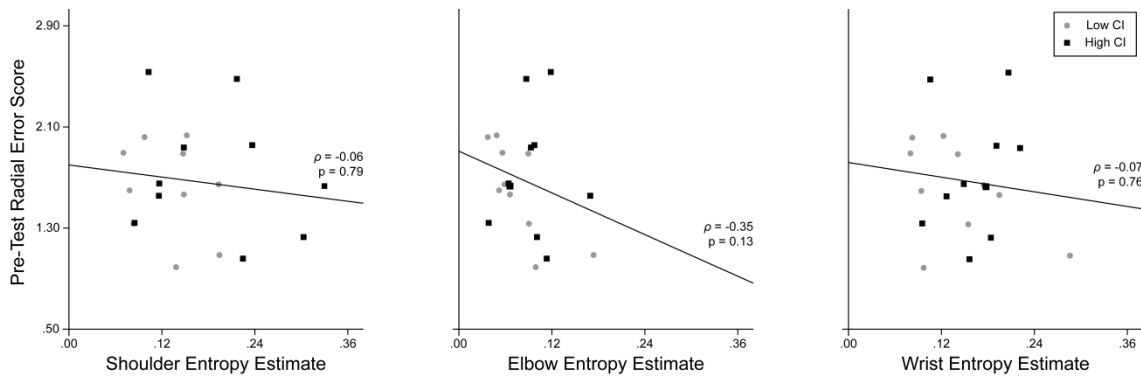
Figure 5.6. Correlation between pre-test radial error score and elbow entropy estimate.
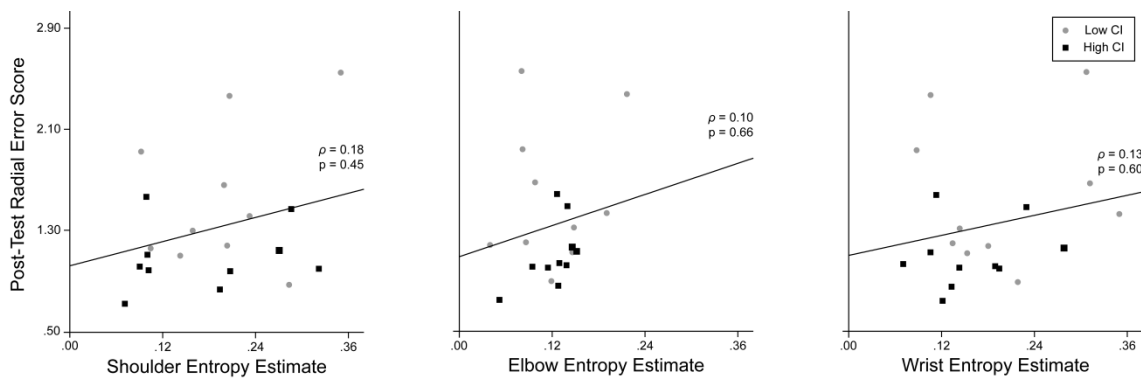
Figure 5.7. Correlation between post-test radial error score and elbow entropy estimate.

5.6 Discussion

The contextual interference hypothesis was confirmed as throwing accuracy was superior in the High CI compared to Low CI group for both the post-test and transfer-test, despite the significant improvement which occurred with practice for both groups. The results comply with a large body of research using analogous methods (Brady, 2004). The better performance of the High CI group at the post-test indicates that the mode of practice undertaken facilitated enhanced retention and progression of skill acquisition in this group. Furthermore, and of more importance to this investigation, the improved performance on the transfer-test suggests that High CI were better able to adapt movement patterns acquired during practice to changed task constraints.

The entropy content of the surrogate data was significantly greater than that of the observed data. This signifies that deterministic dynamics in the observed data, as manifested in the relationship between consecutive data points, are destroyed during surrogate generation (Taylor et al., in press). This provides confidence that the variability in observed kinematic signals is the result of direct neuromuscular control, rather than from random noise, and any observed changes in variability can be considered the result of adjustment in the neuromuscular organisation or control of the individuals tested. Furthermore, the result allows inference to be made when changes in regularity are identified over time, such as the period of learning in this investigation.

Despite the detected differences in throwing accuracy, within or between groups with practice, there were no significant differences found for the sample entropy estimates of joint rotations. However, associated effect sizes suggested there were trends in data which may warrant further consideration. Post practice the better skilled (High CI) group displayed a trend of having lower variability than lower skilled participants (Low CI) for shoulder and wrist joints.

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Across training, the High CI group tended to decrease their variability, while Low CI showed the opposite. These patterns of results corroborate other research evidence which has shown lower variability at the joint/segment level for higher skilled compared to lower skilled participants (Betzler et al., 2012; Bradshaw et al., 2009; Button et al., 2003; Fleisig et al., 2009; Hiley et al., 2013). The elbow behaved differently, displaying the lowest level of variability which increased for both groups over training. Although the results were non-significant and had small effect sizes, the lower variability at this joint may be explained by anatomical factors. The elbow has fewer degrees of freedom compared to the shoulder and wrist, and often travels across nearly its full range of motion ($130° \pm 15°$ - $43° \pm 13°$) in the sagittal plane during throwing. Thus, assessing the time series via entropy and not just a discrete extraction, such as value at release, may result in decreased variability as maxima, minima and acceleration at the extremes of range of motion may be mediated by anatomical constraints. Furthermore, the increase in variability at the elbow pre- to post-test for both groups could be indicative of an improvement in developmental level of throwing over training. It was noted from observation that some participants changed from a more front on technique where degrees of freedom were more constrained similar to stage 1 development (Gallahue et al., 2012), to a more developed movement comparable to stage 3 throwing development or higher (Gallahue et al., 2012) with greater contribution from the shoulder.

Correlations between pre- and post-test scores and their relevant entropy estimate were not significant. Perhaps of most interest is the reversal of slopes describing the relationship with practice (as shown in Figure 5.6 and Figure 5.7) where better scores became mildly more related to lower variability at post-test. This is supported by the stronger and significant result for the shoulder joint, wherein a relationship between improvement in accuracy with practice and decrease in entropy were shown (Figure 5.5).

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It is important to consider how these variability results relate to the demonstrated improved performance and adaptability of the High CI compared to Low CI group. Superior performance on the transfer task of the High CI group could indicate that this cohort made better use of compensatory coordination to enhance adaptability, whereby perturbations in one element of a coordinated system compensated for by the other element(s). This phenomenon has been identified in many discrete sporting tasks (Bootsma & van Wieringen, 1990; Button et al., 2003; Kudo et al., 2000; McDonald et al., 1989; Mullineaux & Uhl, 2010; Schmidt, 2012; Wilson et al., 2008). Furthermore, one of the functional roles credited to variability is the ability to facilitate changes in coordination (Bartlett, 2008; Bartlett et al., 2007). Taken together, it appears the trend in reduced variability of High CI at the level measured in this investigation could be at a magnitude which allowed this compensatory coordination to occur. The increased variability levels in Low CI might indicate that either they do not allow compensatory coordination, or, that this ability has not yet been attained by this group. These observations are strengthened by the trend in individual correlation results which indicated a relationship between decreased variability and improved performance (Figure 5.5).

In order to strengthen these hypotheses coordination variability will need to be quantified over a similar period of motor learning. Furthermore, a full description of how the variability profiles at this first level change over the course of skill acquisition, and not just their respective values at pre- and post-test, will also provide further insight into the interaction between variability, adaptation and learning. Another consideration is the structure of the variability present. While entropy offers many strengths, such as the ability to reduce data without losing information, it only quantifies the magnitude of variability. Adoption of other methodologies such as functional principal component analysis could reveal differences in the way variability is structured between more and less skilled groups which could further enhance our understanding.

5.7 Conclusion

The contextual interference effect was observed in the current population for an applied discrete task, confirming enhanced adaptability in the group experiencing greater contextual interference. Results from the surrogate technique highlighted the deterministic nature of the collected time series, and subsequently the variability of three joint angles of the upper limb were quantified using sample entropy. Several trends in variability changes followed those reported in previous research that examined the interaction of variability, adaptability and learning. The combination of adopting a contextual interference design and measurement of variability allowed several hypotheses to be formed which could enhance our understanding of the functional role of variability in motor learning and adaption.

Chapter 6. Extended Method

Throughout this extended method several computer software packages and applications are repeatedly referred to. For brevity in the ensuing paragraphs the relevant full name, description, version and manufacturer information for these items are outlined in the Table 6.1. Subsequently, reference to these elements will use simplified names/descriptions.

Table 6.1.
Software programs used.

Item	Description	Manufacturer	Versions Used
Vicon Nexus	Used for control of the Vicon motion capture system and post processing of collected data	Oxford Metrics, Oxford, UK	1.8.1 to 1.8.9
Vicon Motus	For manual digitisation purposes	Oxford Metrics, Oxford, UK	8
Matlab	Used for the majority of data analyses using included and custom scripts/functions	The MathWorks, Natick MA, USA	R2012b – R2015a
Microsoft Excel	Used for organisation and cross-checking of data and for interfacing with the Matlab software	Microsoft Corporation, Redmond, WA, USA	2007 - 2013
Microsoft PowerPoint	Used for projection of the targets onto the projection screen.	Microsoft Corporation, Redmond, WA, USA	2007 - 2013
SportsCode	Used to identify, and export in image format, key frames from ball impact footage.	Sportstec, Sydney, Australia	Version 10
IBM SPSS	Statistical testing	IBM, Armonk, NY, USA	19 - 21
Statistica	Statistical testing	Dell, Tound Rock, TX, USA	7
EndNote	Bibliography management software used to manage the results of the systematic review search (Study 1)	Thompson Reuters, New York, NY	X3 – X7

6.1 Discrete Movement Variability in Sports and Sports Derived Tasks: A Systematic

Review (Study 1)

6.1.1 Search criteria development

6.1.1.1 Early approaches

Early approaches to develop the search criteria attempted to implement the 'subject

terms', 'headings', 'MeSH' and 'sports thesaurus' of the Academic Search Complete, CINAHL,

MEDLINE and SPORTDiscus academic databases respectively. Time was spent selecting all relevant

terms from these database tools. This was attempted to achieve the dual goals of including all

relevant articles whilst minimising the number of results returned to reduce the manual search

time. However, several key articles were not included in the initial search results. As such this

approach was abandoned in favour of the method reported in Study 1.

6.1.2 Manual search method

6.1.2.1 Use of EndNote

Following the conducting of the search (sections 2.3.2 and 2.3.3), results were imported

into the bibliographic management software EndNote for title and abstract inclusion/exclusion.

Due to the large number of results several techniques were implemented to attempt to quickly

identify articles which obviously were outside of the inclusion criteria. Firstly the EndNote search

function was used to identify common terms associated with excluded content. These included

physiological terms such as "heart rate" and "blood pressure" for which variability studies are

common. Following the exhaustion of relevant search terms results were sorted by author name

and a line-by-line consideration of title and/or abstract was implemented until the 66 articles

reported in the method of Chapter 2 remained and the second stage of inclusion/exclusion

assessment commenced.

6.2 Determining Optimal Trial Size Using Sequential Analysis (Study 2)

6.2.1 Participants

Participants for this study were drawn predominantly from a convenient sample consisting

of staff and students of the University. The main methods of recruitment consisted of posting the

appended flyer on campus (see section 9.6), emailing the same flyer to interested staff, and by

calls for participant's given by staff during lecture presentations. In accordance with ethical

clearance, no students were directly recruited by the research team.

A total of 10 female and 13 male participants were recruited for the study. Of the 13

males recruited, 3 were removed due to their age ($\geq$ 32) in order to provide a more homogenous

sample. All participants were engaged in regular physical activity and throwing experience ranged

from novice to semi-experienced. Preferred throwing arm was self-reported. Participant data can

be seen in Table 6.2.

Table 6.2.
Participant data for Study 2.

Participant #	Sex	Age (yrs)	Height (cm)	Weight (kg)	Preferred Arm
001	F	23	174.9	70.95	R
004	F	27	171.5	74.00	R
006	M	20	178.6	62.55	R
007	M	21	180.4	82.40	R
008	M	20	160.1	69.55	R
009	M	20	179.6	67.20	R
010	M	20	160.6	60.40	R
011	M	20	182.5	90.40	R
012	F	20	160.9	55.30	R
013	F	20	159.0	56.15	R
014	M	26	182.1	72.05	R
015	F	21	161.1	51.25	L
016	F	20	171.8	58.35	L
017	M	21	175.3	70.35	R
018	F	18	178.3	77.25	L
019	M	18	187.4	72.65	R
020	F	23	156.1	75.35	L
021	F	28	158.3	55.55	R
022	F	23	165.1	54.25	R
023	M	21	172.0	73.90	R

6.2.2 Data collection equipment

A Vicon (Oxford Metrics, Oxford, UK) motion capture system was used to acquire kinematic data. The system consisted of 10 cameras of which 6 were MX models and 4 were T-series models, Vicon Ultranet and Giganet control modules and a compatible computer system. The cameras were configured to capture at 400 Hz, with exposure adjusted to maximise image clarity.

Two dimensional (2D) data of the ball trajectory in the sagittal plane were captured using a Basler A602fc camera (Basler AG, Germany), synchronised with the 3D motion capture using a Vicon sync cable. This camera had a capture frequency of 100 Hz and as such each frame captured

was synchronised with every 4th frame collected by the Vicon system. The camera was placed

perpendicular to the sagittal plane of the participant on the side of the throwing arm.

6.2.3 Laboratory configuration

Configuration of the laboratory, including participant position, location of Vicon Cameras,

Basler Camera and configuration dimensions can be seen in Figure 6.1.
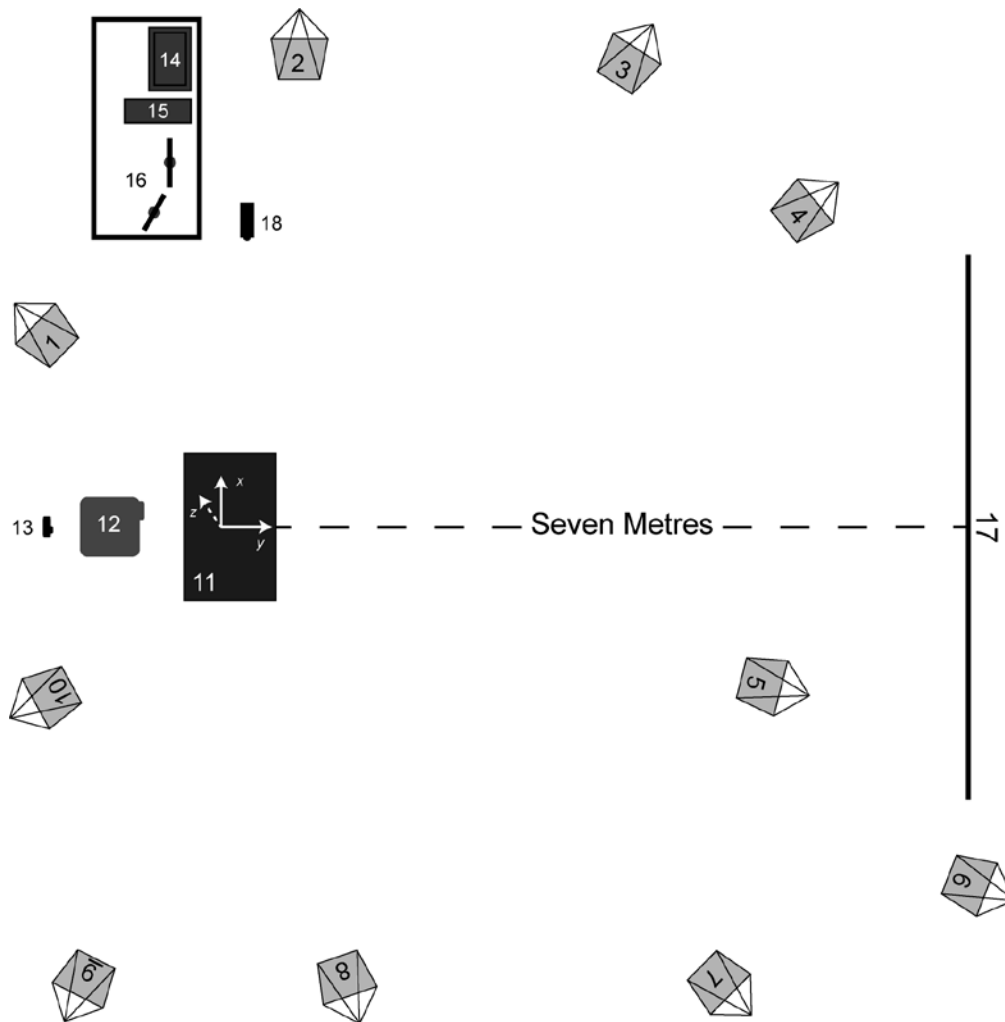
KEY: 1 – 10 Vicon Cameras. 11 Stool (with capture volume origin and axes). 12 Projector. 13 Casio camera. 14 Vicon Giganet and Ultranet. 12 PC. 16 Monitors. 17 Projection screen. 18 Basler camera.
CAMERA LENS HEIGHTS: 1, 6, 7, 8 (~2 m). 2 & 3 (~ 2.2 m). 4, 9 & 10 (~1.8 m). 5 (~0.4 m). 13 (2 m – aligned with target centre). 18 (approximately ball release height).

Figure 6.1. Laboratory configuration.

An image of a round target consisting of 5 equally spaced coloured concentric circles, radius increasing by 7 cm per circle to a maximum of 70 cm (Figure 6.2) was displayed via a beam projector (Dell Inc., Round Rock, Texas) on a cloth screen (5 m x 3 m) suspended from the ceiling. The vertical position of the projected target centre was located 2 m from the ground.
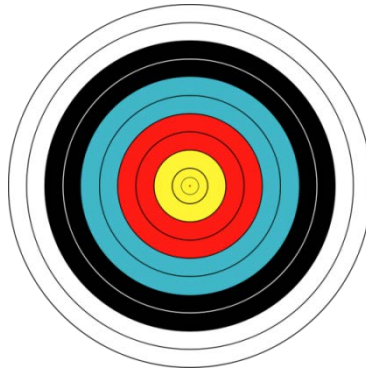
Figure 6.2. Target for Study 2.

An adjustable piano stool (to facilitate consistent ankle and knee posture across participants of different stature) was placed square to the cloth screen at a distance of 7 m in line with the target centre. A capture volume was created by aligning the cameras to the piano stool as illustrated in Figure 6.1). This arrangement of the cameras was settled on after extensive trial and error testing of many configurations and enabled the most consistent tracking of each of the passive markers by three or more cameras throughout the throwing motion. This capture volume was dynamically calibrated using a 5 marker Vicon T-shaped calibration wand in accordance with the manufacturers' recommendations before each new participant. Volume system origin was then set such that the x-axis represented medial – lateral movement, y-axis represented anterior – posterior movement and the z-axis represented vertical movement with the central (0,0,0) point located at the centre of the piano stool at sitting height (Figure 6.1).

6.2.4 Participant preparation

Upon arrival participants were asked to change into the attire they were requested to bring. Male participants undertook testing shirtless while female participants were asked to wear a crop top, sports bra or similar. Once attired, participant height and weight was recorded using a stadiometer (accurate to 0.1 cm) and scales (accurate to 0.05 kg) in accordance with ISAK guidelines. Participants then had 14 retro-reflective 14 mm markers attached to the torso and throwing arm at appropriate landmarks using double sided tape (3M, Maplewood, MN). Fixomull (BSN Medical, Luxembourg) hypoallergenic flexible cloth tape was then placed over the marker base to further secure the marker and avoid any unwanted movement. The marker locations were placed in accordance with the Vicon Upper Limb Model product guide (Vicon Motion Systems, 2007). Marker locations can be seen in Figure 6.3. Definition of marker locations can be seen in Table 6.3.

Table 6.3.
Definition of marker locations.

#	Name	Definition
1.	Clavicle	Jugular notch at the meeting of the clavicles
2.	Sternum	Xiphoid process
3.	C7	7th cervical vertebra
4.	T10	10th thoracic vertebra
5.	Shoulder	Acromioclavicular joint
6.	Upper Arm A	Lateral aspect of the upper (throwing) arm (forming a triangular cluster with upper arm B and C markers)
7.	Upper Arm B	Lateral aspect of the upper (throwing) arm (forming a triangular cluster with upper arm A and C markers)
8.	Upper Arm C	Lateral aspect of the upper (throwing) arm (forming a triangular cluster with upper arm A and B markers)
9.	Elbow	Lateral epicondyle of the elbow
10.	MEP	Medial epicondyle of the elbow (calibration only)
11.	Wrist A	Thumb side of the wrist
12.	Wrist B	5th phalange side of the wrist
13.	Forearm	Postero-lateral aspect of the forearm (forming a triangular cluster with the wrist markers)
14.	Finger	Head of the 3rd metacarpal
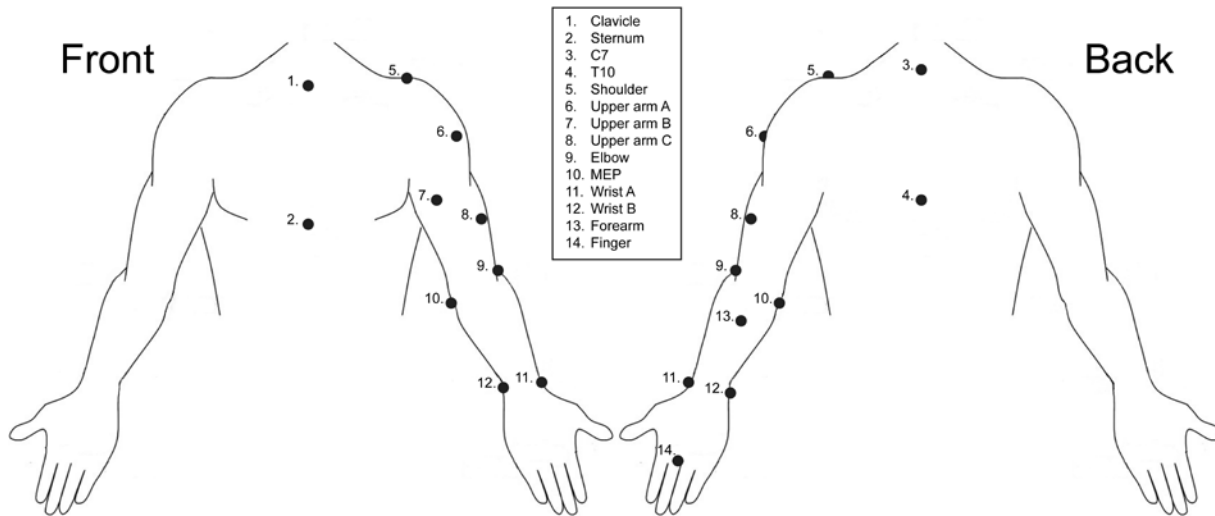
Figure 6.3. Retro-reflective marker locations.

6.2.5 Procedure

Following placement of the markers, participants were seated on the piano stool within the capture volume. The stool was adjusted such that hip and knee angles approximated 90° flexion and the ankle joint was at anatomical position (0° plantar/dorsiflexion). Participants were then asked to orient the upper body into anatomical position and a static trial was collected. This trial was used to perform a static calibration where the model was fitted to the individuals' anthropometry. Participants were then instructed of the task. They were asked to throw a regulation tennis ball, as accurately as possible, toward the centre of the target using their chosen dominant arm. Participants were asked to begin each throw with their hands placed on their knees and their frontal plane aligned parallel to the projection screen. Participants familiarised themselves with the task until they were ready to proceed (~2–3 minutes). Participants then performed 30 throws which were included in the analyses. Time between throws was self-determined. Once the ball was returned, participants were notified when data collection had begun and were instructed that they were free to throw at any point following this cue. Most

participants performed three or four throws per minute during testing. All participant trials were included in analyses regardless of movement outcome and accuracy.

6.2.6 Post processing

Following data collection three dimensional data were post processed using Vicon Nexus software. Marker trajectories were reconstructed and labelled. The moment of ball release, the last frame where the finger(s) were in contact with the ball, was identified from the synchronised video data and served as the end point of the trial. Data after this point were cropped and discarded. Data were inspected for any discontinuities or erroneous data (marker drop outs, flipping etc.) and filled/corrected where necessary. Trajectories were then filtered using a 4th order Butterworth low pass filter implementing a cut-off frequency of 12 Hz (information on the selection of cut-off frequency can be found in section 0). Once filtered these trajectories were submitted to the Vicon Upper Limb Model which produced angular displacement histories detailed in Table 6.4. These model outputs were then filtered using a 4th order Butterworth low pass filter implementing a cut-off frequency of 12 Hz. Marker trajectory and model output data were then exported from the Vicon Nexus program in ASCII format for further analyses.

Table 6.4.
Angular displacement histories output by the Vicon Upper Limb Model.

Location	Rotation
Shoulder	Abduction – adduction
	Flexion – extension
	Horizontal abduction – adduction
	Internal – external rotation
Elbow	Flexion – extension
Forearm	Pronation – supination
Wrist	Flexion – extension
	Radial – ulnar deviation

6.2.7 Ball release variables

Footage from the Basler camera was exported from the Vicon Nexus software and imported into Vicon Motus to determine ball release height, angle and velocity. This camera was calibrated prior to each participants capture using a calibration rod of known length (0.52 m). The ball centroid was digitised using a circular mask and data exported. All manual digitising was performed by one person who had previously demonstrated high intra-tester reliability in this task (Taylor et al., 2014). Ball release variables were calculated using a custom script in Matlab. Release height was the positive displacement in the y-axis of the ball centroid at the point of release. This was calculated by determining the difference in height (y-axis displacement) between the ball centroid and the wrist marker in millimetres from the ball release video and adding this value to the y-axis displacement of the wrist marker at release from the Vicon data. Release velocity was calculated at the point of release using the first central difference method. Release angle was calculated as the angle to the horizontal of a 2D segment defined by the ball centroid position at release and one frame after release.

6.2.8 Data selection

The following variables were chosen as they represent either commonly employed dependent variables in biomechanics research or the raw coordinates from which they are calculated. Furthermore, the landmarks chosen for these 3D displacement variables were selected to represent different anatomical locations (proximal/distal), sites more and less susceptible to skin artefact and where low and high frequency movement would occur. The four anatomical markers chosen for analyses: T10 (10th thoracic vertebra), Upper Arm (over the muscle belly of triceps), Elbow (lateral epicondyle) and Finger (distal end of the 3rd metacarpal bone) of the throwing arm. Three joint angles - shoulder internal/external rotation and flexion/extension at the

elbow and wrist - from the kinematic model were chosen for their role in producing ball velocity (van den Tillaar & Ettema, 2004). Selected time series data were time normalised to 101 points using cubic spline interpolation. Discrete values of the final determinants of ball trajectory (ball release angle, height and velocity) were also included from 2D data.

6.2.9 Sequential analysis

The aim of this study was to determine optimal trial size for overarm throwing and similar movements by determining the point at which the mean of target variables becomes stable. The sequential analysis technique was employed to determine the point of mean stability (i.e., trial size). This technique is illustrated in Figure 3.1 using mock data. The dashed grey line represents the Nth trial mean taken from all (1 to N) trials and two solid grey lines labelled +0.25 SD and -0.25 SD represent a 'bandwidth' based on SD calculated from all trials. The selection of ±0.25 for the bandwidth was based on it being the most commonly reported value from the sampled sequential estimation literature (see Table 9.1 in section 9.7 for information on previous sequential estimation studies).

The Nth trial mean and SD bandwidth form the criterion against which stability is assessed. For example, for a 20 trial condition the Nth trial mean is the mean of all trials up to and including the 20th. The value of one SD about this mean is then multiplied by +0.25 and -0.25 to create the upper and lower bounds of the bandwidth. Once the bandwidth is established, the technique requires the calculation of a moving point mean (solid black line), starting with the mean of the first two values and moving through the first three, first four etc., until reaching the Nth trial. Stability is determined when the moving point mean rests within the SD bandwidth and stays within for all remaining trials as indicated by A in Figure 6.4. It is worth noting that while points B and C also rest within the bandwidth in this example, they do not represent the point of stability

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as there are excursions of the moving point mean outside of the SD bandwidth between B and A

as well as between C and A.
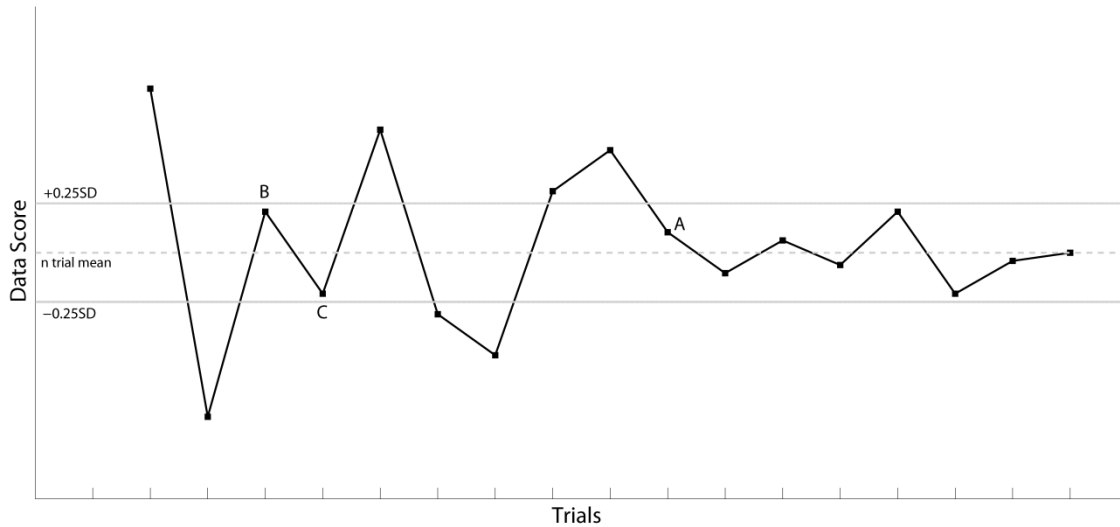
Figure 6.4. Example of sequential analysis technique applied to a trial size of N. The criterion bandwidth is illustrated by the solid grey lines indicating a distance of ±0.25 SD from the N trial mean (dashed grey line). Assessed against this criterion bandwidth is the moving point mean (black line), starting at trial two. The point of stability is represented by the letter A. Points B and C do not represent stability as the mean deviates outside the bandwidth between these points and point A.

The sequential analysis technique was employed on both discrete and time series

kinematic data (Table 6.5). To perform sequential analysis on 3D marker displacement and joint

angle time series data, each of the 101 sample points were treated as a discrete point, providing

trials to stability for each sample point along the entire time series. To determine the effect of

using different trial numbers on sequential analysis score, three main conditions - first 10 (1st to

10th trial), first 20 (1st to 20th trial) and first 30 (1st to 30th trial) trials - were assessed with the

criterion mean and 0.25 SD bandwidth calculated using all trials included in each condition.

Similarly, mid 10 (11th to 20th trial), last 10 (21st to 30th trial) and mid 20 (6th to 25th trial)

conditions were compared to establish if results were dependent on where in the sequence of

throws a sample was extracted.

Table 6.5.

Discrete and time series variables included in sequential analysis.

Marker Variables	Joint Angle Variables	Ball Release Variables
Maximum value	Peak angle value	Release height
Minimum value	Time of peak angle value	Release velocity
Value at release	Value at release	Release angle
Normalised time series	Normalised time series	

Note: Peak angle value represents relevant maximum or minimum value, occurring near wind up completion. Joint angles were shoulder external/internal rotation, elbow and wrist flexion/extension. Marker data was analysed in X, Y and Z axes.

6.2.10 Comparing trial number conditions

To qualitatively assess the behaviour of the sequential analysis elements, the moving point mean for all discrete variables from the 30 trial condition was plotted against the criterion bandwidth from that condition and viewed for each participant (see Figure 6.5). While this bandwidth was specific to the 30 trial condition, the moving point mean is the same for each condition, up to the total trial number of that condition (for first 10, 20 and 30 conditions only).
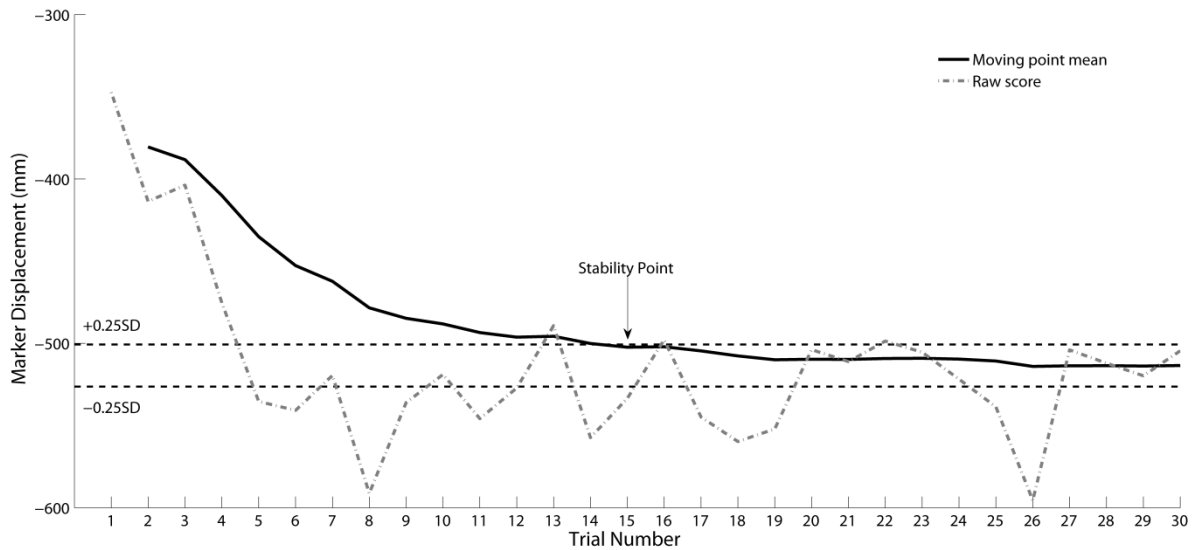
Figure 6.5. Example of sequential analysis of a finger marker (X axis) minimum value in 30 trial condition from one participant showing the relationship between raw kinematic data (dash-dot grey), moving point mean (solid black) and 0.25 standard deviation (SD) bandwidth (dash grey). Stability point (sequential analysis score = trial 15) is indicated by an arrow.

For further determination of the condition from which to report sequential analysis values, two scores were submitted to statistical analyses, the sequential analysis score (trials to stability) and a relative sequential analysis score. The relative sequential analysis score is novel to this investigation and is calculated by dividing the sequential analysis score by the total trial number of the condition from which it was taken. This relative score can highlight differences in the behaviour of the sequential analysis technique between conditions in respect to the percentage of maximum possible trials taken to achieve mean stability. Calculation of all sequential analysis results and generation of all relevant plots were performed using custom scripts in Matlab.

The sequential analysis score for all time series variables were compared using a 4 x 101 (first 10, first and mid 20 and first 30 conditions x 101 time series samples) two way repeated measures analysis of variance (ANOVA) and a 3 x 101 (first, mid and last 10 x 101 time series samples) two way repeated measures ANOVA with Fisher's least significant difference post hoc

tests. The time series ANOVA outcomes were considered as the primary results from which a determination would be made as all discrete variables were contained within the time series. To confirm any patterns observed within time series, group mean sequential analysis scores for the discrete marker variables taken from individual participant time series data were also compared across trial number conditions (first, mid and last 10, first and mid 20 and 30 trials) using a 6 x 1 one way repeated measures ANOVA with Fisher's least significant difference post hoc test. Discrete marker variables were analysed in this manner as they provided 12 cases (4 markers x 3 axes) per condition (minimum, maximum and release), whereas joint angle and ball release variables only provided 3 cases per condition and thus were not included in the analyses. Relative sequential analysis scores were compared across conditions in the same manner as the sequential analysis score.

To determine if any statistical differences existed between the 10th, 20th and 30th trial means of time series and discrete marker values, these elements were also compared in a similar manner to sequential analysis score and relative sequential analysis score. This comparison consisted of a 3 x 101 two way repeated measures ANOVA for time series variables and a 3 x 1 one way repeated measures ANOVA for group mean discrete marker values.

For repeated measures ANOVA testing an alpha level of 0.05 was taken to indicate significance. Fisher's least significant difference post hoc test significance was assessed against the relevant Bonferroni adjusted p-value in each instance. Discrete variable testing was conducted using IBM SPSS. Due to the need to analyse 101 data points per participant, time series analyses were conducted using Statistica.

6.2.11 Reporting sequential analysis results

To guide trial size selection, discrete variable sequential analysis results were reported from the chosen condition - first 20 (see results and discussion for reasoning) - as group mean and 95% confidence interval (95% CI) values. A 101 x 1 one way repeated measures ANOVA was conducted on all time series sequential analysis results. Fisher's least significant difference post hoc test was used to determine whether differences existed across the 101 points. Where upon no differences were found, the point (out of the 101 time normalised points) displaying the greatest group mean sequential analysis result (95% CI) was extracted and reported to guide trial size selection for time series analyses.

6.3 A Surrogate Technique for Investigating Deterministic Dynamics in Discrete Human Movement (Study 3)

6.3.1 Participants

Participants were recruited for this study in the same manner as for Study 2. See section 6.2.1 for further information. A total of 10 male participants [24.1 (3.3) years; 176.6 (5.9) cm; 76.4 (7.8) kg] had their data included in this study. As this represented a sub-sample from the total group recruited for the overall project (see section 6.4.1), the group was counterbalanced to ensure equal representation from the two experimental groups. A sub-sample was used so as to begin work developing the surrogate method before the collection and post processing of all data had been completed. Pre- and Post-test data was used to ensure that the technique was effective on the range of data that was to be expected, i.e., that it could be used on time series from novice and more skilled throwers. Participant data for this sub sample can be seen in Table 6.6.

Table 6.6.
Participant data for Study 3.

Participant #	Group	Age (yrs)	Height (cm)	Weight (kg)	Preferred Arm
001	1	21	179.3	64.95	R
002	2	23	177.2	83.30	R
003	2	27	169.9	73.35	R
004	2	27	169.9	63.85	R
005	1	27	177.8	86.30	R
006	1	23	180.4	83.75	R
007	2	19	182.9	79.50	R
009	1	27	184.3	81.05	R
010	1	20	166.8	71.35	R

6.3.2 Data collection equipment and laboratory configuration

The data collection equipment and configuration of the laboratory are predominantly the same as those reported in sections 6.2.2 and 6.2.3 respectively. The only difference being the use of a different, greyscale, target which consisted of six equally spaced concentric circles (Figure 6.6). This target provided better contrast for post processing analyses than the coloured target (Figure 6.2) and was projected as reported in section 6.2.3 such that it had a diameter of 70 cm.
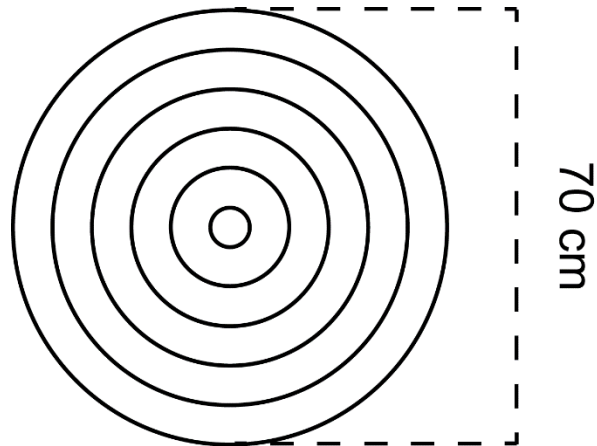
Figure 6.6. Target for Study 3.

6.3.3 Participant preparation

Participant preparation was the same as that reported for the male participants in section 6.2.4.

6.3.4 Procedure

Participants attended two sessions where they performed two blocks of trials with sixteen throws per block (total of 4 blocks; 64 throws). The choice of 16 throws per block was based on previous research (Taylor et al., 2015). Following being marked up, participants were seated on the piano stool within the capture volume. The stool was adjusted such that hip and knee angles approximated 90° flexion and the ankle joint was at anatomical position (0° plantar/dorsiflexion). Participants were then asked to orient the upper body into anatomical position and a static trial was collected. This trial was used to perform a static calibration where the model was fitted to the individuals' anthropometry. Participants were then instructed of the task. They were asked to throw a regulation tennis ball, as accurately as possible, toward the centre of the target using their non-dominant hand. The non-dominant hand was used as data from this study were taken from the larger, overall project sample. Handedness was determined using an Edinburgh Handedness Scale (Oldfield, 1971) questionnaire (see section 9.9). Participants were asked to begin each throw with their hands placed on their knees and their frontal plane aligned parallel to the projection screen. No other directions regarding throwing technique were given. Time between throws was self-determined. Once the ball was returned, participants were notified when data collection had begun for the next trial and were instructed that they were free to throw at any point following this cue. Most participants performed three or four throws per minute during testing. All participant trials were included in analyses regardless of movement outcome and accuracy (4 blocks x 16 throws totalling 64 throws).

6.3.5 Post processing

Post processing was performed as reported in section 6.2.6.

6.3.6 Selection of variables

All marker displacement and model output time series were exported in ASCII format. These files were then imported into Matlab. The start of the movement was defined as the first positive movement of the most distal (finger) marker in the anterior/posterior (y) axis (i.e., first movement towards the target). A custom script identified this point and cropped all data to this moment. Based on their contribution to throw velocity (van den Tillaar & Ettema, 2004), three joint rotations were extracted from the model outputs for the further use in this investigation. These were; shoulder internal/external rotation, elbow flexion/extension and wrist flexion/extension.

6.3.7 Surrogate technique

A surrogate technique for use with discrete human movement data was developed in line with the aims of the study. This technique is a generalisation of the pseudo-periodic surrogate method (Small et al., 2001) which was inappropriate for the intended application because of its us of time delay embedding. Time delay embedding creates a representation of a multi-dimensional state space formed by the interaction of multiple independent yet related variables using just one of those variables (Takens, 1981). This method employs a single variable as the first dimension and then all subsequent dimensions are time delayed versions of the original variable where the delays are multiples of tau. While very effective in creating surrogates this method requires data to be continuous in nature. As such the novel technique in this study was defined such as to effectively account for the discontinuities that exist between the end of one trial and the beginning of the

next when discrete movement data is concatenated. These discontinuities do not exist in periodic or pseudo-periodic data. The method is documented formulaically in Chapter 4. To implement this algorithm a custom function was written in Matlab (section 0). This served as the key function in several subsequent scripts derived to implement the analyses and testing documented below.

6.3.8 Determining rho (ρ)

Rho (ρ) is a critical value in the novel technique due to its role in determining the distance between the current state of the surrogate and the next state. However, as it is arbitrarily set a method and rationale for optimising the value chosen is important. An optimal value for ρ elicits the greatest number of small segments within the surrogated time series (Small et al., 2001), providing an ideal balance between effectively destroying the fine-scale dynamics of the signal and maintaining its macro structure. A small segment is defined as any run of surrogate data of length between 2 and the total length of the surrogate, identical to one existing at any point within the original data set. The segment is created when a switch in the sequence of data in P, currently being sampled to provide the next state of Ps, occurs. When ρ is very small (at or approaching zero) the number of small segments will be zero as original data and surrogate will be identical. As ρ increases, so too will the number of small segments, towards a maximum, before returning toward zero (as $\rho \rightarrow \infty$). A large range of values for ρ (0–5; increments of 0.1) were tested 100 times using a block of data (16 throws) of one participant (Figure 6.7a). This identified the probable range (0.1 – 0.9 and 0.1 – 2.0 for 2D and 3D phase spaces respectively) over which to test for individual peaks in small segments (Figure 6.7b). Each participant's data were then tested over this range five times, and the ρ value associated with the highest mean number of small segments was selected (e.g., Figure 6.7). This resulted in an individualised value for ρ to be used for surrogate generation for each block of 16 throws for each participant.
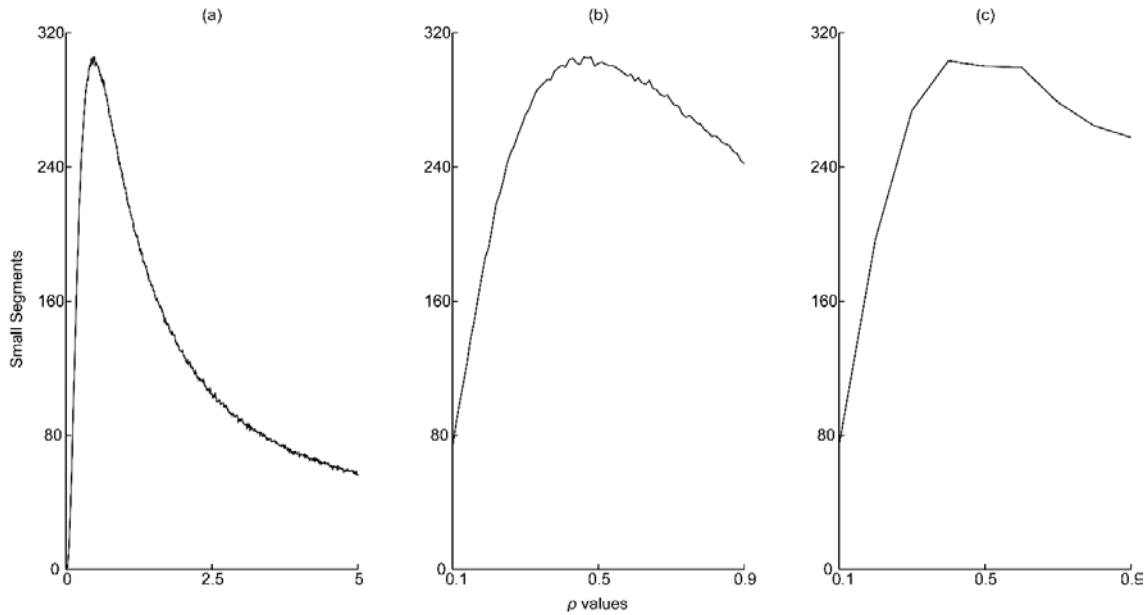
Figure 6.7. Results of testing over a large range of ρ values (a), probable range for individual values of ρ (b) and results of testing over this range for a single participant (c).

6.3.9 Discrete data surrogate generation

To demonstrate the use of the technique with different multiples of input variables, two different surrogate generations were conducted. First, elbow and shoulder time series were concatenated and combined to form a 2D phase space from which the respective surrogates were drawn. Next, wrist time series were included to form a three dimensional phase space and the process was repeated. The number of surrogates generated matched the number of throws in the observed data for each block. Surrogates with similar length (± 1 SD) as the mean length in the original data were accepted to maintain comparability. If this criterion was not met, the surrogate was rejected and the process repeated. This process resulted in two elbow and two shoulder surrogate time series, from the 2D and 3D phase space generation, being produced for each observed throw included in the study. In addition, one wrist surrogate was produced via the three dimensional phase space for each observed throw.

6.3.10 Validity and reliability

The biomechanical data used in this investigation was filtered, as is convention, to remove any systematic noise introduced by the data collection equipment. However, since surrogate data can appear similar to unfiltered/raw data, the surrogate generation process was also carried out on the raw movement data in addition to the filtered data. This analysis ensured that any observed differences in regularity between the data and its surrogate was the result of the method and not due to increased regularity introduced to the signal via the post collection smoothing. That is, if the raw data and its surrogate, as well as the filtered data and its surrogate, are both significantly different in regularity, this can be attributed to the surrogate method and not to any other conditioning of the observed data. To achieve this, captured data was post processed as outlined in section 6.2.6, with the exception that neither the trajectories nor model outputs were filtered. Raw data were then exported and cropped as detailed in section 6.3.6. Surrogates were then generated as stated in section 6.3.9.

To demonstrate the ability of the technique to produce surrogates which approximate the macro structure of the original data, surrogate mean, SD and data length were compared to that of observed signals using Mann-Whitney U tests.

The ability for these macro characteristics to be produced reliably was tested by repeating the surrogate generation process six times for each included block of throws. The mean, SD and length of the resultant data were assessed for reliability using intraclass correlation and standardised typical error tests (Hopkins, 2000, 2011). This was performed for surrogates produced both via two and three dimensional phase space. The reliability calculations were carried out using Microsoft Excel spreadsheets (Hopkins, 2000, 2011).

6.3.11 Comparing real and surrogate data

Sample entropy values quantify the regularity of a signal by assessing the probability that two sequences of points extracted from a time series of length *N,* which are similar for a period of *m* points within a tolerance *r*, will remain similar for a period of *m + 1* points excluding self matches (Lake et al., 2002; Richman & Moorman, 2000). The sample entropy estimates of the observed and surrogate data were used for statistical inference. It was hypothesised that the observed time series would return lower sample entropy estimates than surrogates as they are not solely the result of noisy, random processes, but contain some element of deterministic dynamics. The lower entropy estimate of the observed data would reflect the increased regularity of a signal under the control of the neuromuscular system as opposed to the random, stochastic process producing the surrogate. Sample entropy was estimated for the concatenated real and surrogate time series of the three joint angles for all blocks of throws. These estimates were compared using the Mann-Whitney U test. Non parametric statistics were employed as data did not display normality (Peat & Barton, 2005).

6.3.12 Selection of critical values for sample entropy

The choice of values for the parameters *m* and *r* will affect the outcome of the entropy estimate. What is most important, when using entropy estimates for comparisons within or between condition, individuals etc., is consistency in the selection of these critical values. Of course, optimising validity as much as possible is still important. As such values of *m* = 2 and *m* = 3 as well as a range of r values (0.1 – 0.3) were tested as recommended by Yentes et al. (2013) to determine these values. Minimal difference was noted between the use of *m* = 2 and *m* = 3 and as such a value of *m* = 2 was used in line with the recommendation of Yentes et al. (2013) for short data sets. All participant mean sample entropy estimate results for the range of *r* values (0.1 – 0.3)

indicated a consistent decrease in entropy as *r* values increased (Figure 6.8). This indicates that as

the test becomes more liberal, through an increase in r which increases the threshold within which

two segments of a time series can be considered similar, the signal is considered less variable. As

such it was decided to employ *r* = 0.1 as this makes the test more conservative. Furthermore, this

value has been employed previously in human movement (Preatoni et al., 2010).
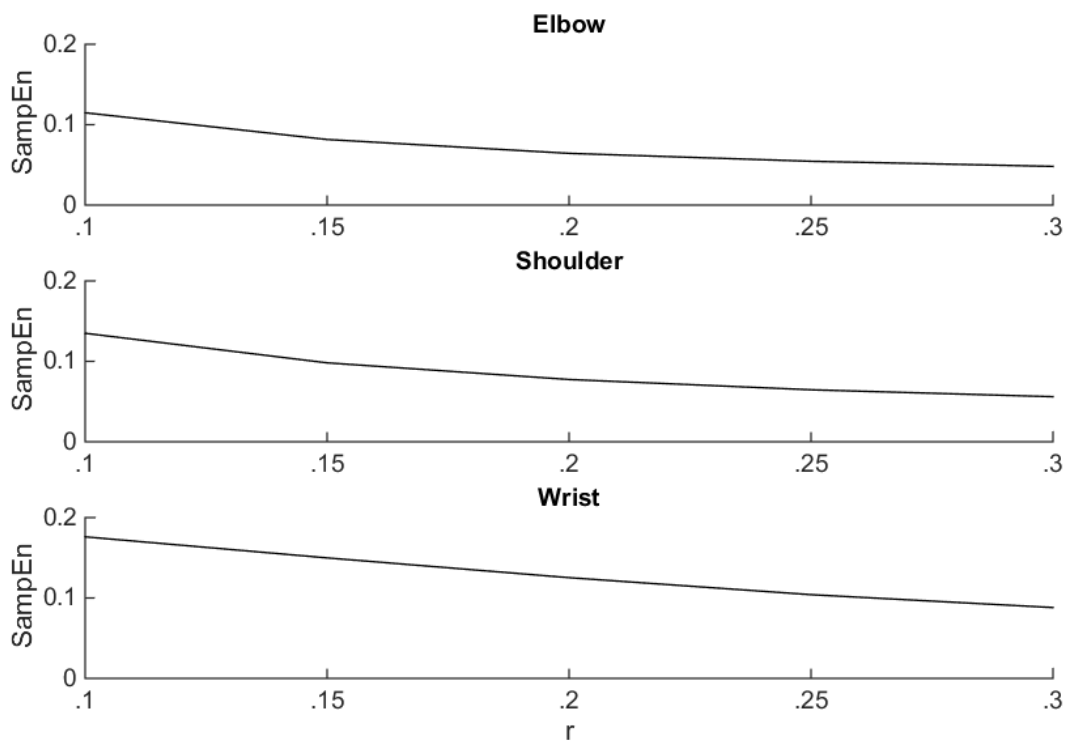
Figure 6.8 Mean sample entropy (SampEn) estimates for all participants when employing different values for r on elbow, shoulder and wrist time series.

6.4 Changes in Variability and Adaptability during the Learning of a Novel Discrete Task (Study 4)

6.4.1 Participants

Twenty adult males [22.2 (3.3) years; 179.4 (6.5) cm; 78.1 (9.1) kg] free of injury and illness had their data included in this study. In total 21 participants were recruited into the study. However, one participant received a back injury (not during testing) during their participation period. Due to concerns over altered biomechanics and the effect of that on variability measures they were excluded from further participation. Handedness was determined for each participant using an Edinburgh Handedness Scale (Oldfield, 1971) questionnaire (section 9.9). To avoid any bi-lateral skill transfer, participants were not currently, or in the previous 5 years, participating in any task requiring overarm throwing for accuracy (e.g., cricket). Participant data for this study can be seen in Table 6.7.

Table 6.7.
Participant data for Study 4.

Participant #	Group	Age	Height	Weight	Arm	Sport?
001	Low CI	21	179.3	64.95	R	Soccer
002	High CI	23	177.2	83.30	R	Touch
003	High CI	27	169.9	73.35	R	Personal Fitness
004	High CI	27	169.9	63.85	R	Personal Fitness
005	Low CI	27	177.8	86.30	R	Crossfit
006	Low CI	23	180.4	83.75	R	Olympic Lifting
007	High CI	19	182.9	79.50	R	Oz Tag
008	Low CI	27	184.3	81.05	R	Personal Fitness
009	Low CI	20	166.8	71.35	R	Soccer
010	Low CI	19	180.5	90.05	R	Soccer
011	Low CI	19	184.4	82.80	L	Rugby Union
012	Low CI	19	185.4	80.50	R	Cycling
013	High CI	27	177.2	76.10	R	Personal Fitness
014	High CI	19	183.0	75.60	R	Soccer
015	High CI	20	183.1	84.20	L	Personal Fitness
016	Low CI	20	189.1	70.35	R	Endurance events
017	Low CI	19	173.4	66.15	R	Futsal
018	High CI	26	188.3	100.80	R	Thai Boxing
019	High CI	21	179.3	81.15	R	Swimming
020	High CI	23	185.8	78.05	R	Soccer

High CI = High contextual interference; Low CI = Low contextual interference.

6.4.2 Data collection equipment and laboratory configuration

The data collection equipment and configuration of the laboratory are predominantly the same as those reported in sections 6.2.2 and 6.2.3 respectively. In addition to the data collection equipment outlined in these sections ball impact with the target screen was captured at 120 Hz using a Casio EX-ZR1000 digital camera (Casio Computer Co., Tokyo, Japan). Differences also existed in the projection of the target/s to facilitate the experimental design. The target used was the same as that reported in section 6.3.2. This target was projected, one at a time, at one of the nine locations indicated in Figure 6.9. The projection volume was set up such that the centre of the

central target (2B in Figure 6.9) was at a height of two metres above the ground and space

between targets was as indicated in the right hand panel of Figure 6.9.
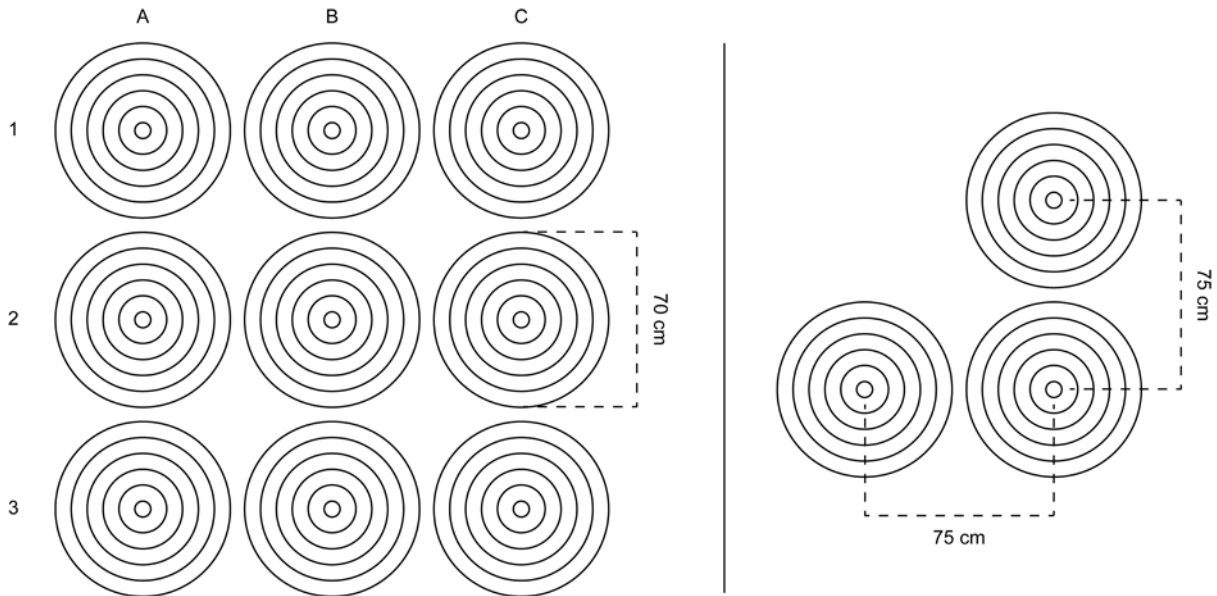
Figure 6.9. Layout and size of the nine targets used in this investigation (left panel) and separation measurements (right panel). Only one target was visible during each throw.

6.4.3 Experimental design

Each participant was randomised into one of two groups to practice the novel task of

overarm throwing with their non-dominant hand. Group assignment can be seen in Table 6.7. A

contextual interference design was implemented which would see on group practicing under low

contextual interference conditions (Low CI) and another practicing under high contextual

interference conditions (High CI). Each participant attended nine sessions (see Table 6.8). There

was a minimum of 24 hours and a maximum of 72 hours between sessions. Each session consisted

of a pre-test, four blocks of practice throws and a post-test. In addition session nine included a

transfer test where participants performed throws to novel targets. The pre-test of session one

and the post-test of session nine acted as the pre and post tests for the entire experiment. The

task flow for each session for each group can be seen in Table 6.8. Kinematic data were collected

for all pre- and post-tests while ball impact/accuracy data was collected for all pre-, post- and transfer-tests. The number of throws performed in pre- and post-tests was based on previous work (Taylor et al., 2015). For Study 4 the data of interest came from the pre-test of session one and the post- and transfer-tests of session nine.

Table 6.8.
Task flow for each group for session one through nine.

	Low CI	High CI
Warm up	Self-selected number of throws ~2 mins	Self-selected number of throws ~2 mins
Pre-test	16 throws at target 2B	16 throws at target 2B
Rest	3 minutes	3 minutes
Practice blocks	4 blocks of 10 throws at target 2B (1 min rest between blocks)	4 blocks of 10 randomised throws at targets 1B, 2A, 2C, 3B (1 min rest between blocks)
Rest	3 minutes	3 minutes
Post-test	16 throws at target 2B	16 throws at target 2B
Rest	5 minutes (session 9 only)	5 minutes (session 9 only)
Transfer-Test	4 x 4 throws at randomised novel targets 1A, 1C, 3A, and 3C (session 9 only)	4 x 4 throws at randomised novel targets 1A, 1C, 3A, and 3C (session 9 only)

Note: Target locations (e.g., 2B) refer to grid positions in Figure 6.9.

6.4.4 Participant preparation

Participant preparation for each session was the same as that reported for the male participants in section 6.2.4 with the exception that height and weight were only recorded before session one.

6.4.5 Procedure

Participants performed their throws seated on an adjustable stool, with their frontal plane square to and seven metres from the projection screen, their sagittal plane perpendicular to a line intersecting the centres of targets 1B-2B-3B (Figure 6.9). The stool was adjusted such that hip and knee angles approximated 90° flexion and the ankle joint was at anatomical position (0°

137

plantar/dorsiflexion). Participants were asked to start each throw with hands resting on their knee, to throw overarm, as accurately as possible toward the centre of the projected target. The object thrown was a regulation tennis ball which had been dyed black in order to provide contrast against the projected target during digitisation.

A session specific PowerPoint file was created for each participant containing the target images to be projected for that session. For participants in the Low CI group this consisted of just the central target image separated by slides indicating the current participant, session and test/practice block. Targets for the practice blocks of the High CI group included 10 instances of each of targets 1B, 2A, 2C, 3B (Figure 6.9). The order that these were presented across the 4 training blocks per session was randomised so that each participant from the High CI group experienced a unique sequence of training throws across the 9 sessions. Hence, the High CI group PowerPoints consisted of the central target for pre- and post-tests and the 10 instances of the 4 practice targets, again separated by slides indicating the current participant, session and test/practice block. PowerPoints for each participants transfer task included 4 instances each of the novel targets 1A, 1C, 3A, and 3C (Figure 6.9). The order of these were again randomised.

For the pre- and post-test, participants were notified when data collection had begun and instructed they could begin the throw any time after that. When each throw was completed they selected a new ball from those placed beside them, adopted the ready position and awaited notification that data collection had begun again. This process was repeated until all 16 balls had been thrown. Most participants completed three to four throws per minute during testing.

For the training blocks and transfer-test, no movement data collection was captured, only ball impact data. For the training blocks 10 balls were provided. Participants were again instructed to throw as accurately toward the centre of the target as possible and to begin the throw with

hands on their knees. The timing of the throws was determined by the participant but each training block usually lasted 60 – 90 seconds. The only difference in training block procedure between groups was that the High CI participants had to wait until the new target was displayed before proceeding with their next throw. This did not alter the flow of the training blocks substantially compared to the Low CI group.

During the rest periods between test and practice blocks, the tennis balls were collected and returned to the position beside the stool. During this time participants were free to move around the laboratory or remain seated as they preferred.

6.4.6 Post processing

Post processing of motion capture data from the pre- and post-tests was the same as reported in section 6.2.6.

6.4.7 Selection of variables

Movement trajectories and model outputs were exported, cropped and variables extracted as reported in section 6.3.6.

6.4.8 Throw accuracy data

Video files containing ball impact footage from each session's pre-test and post-test as well as the transfer test were exported in .avi format. These files were imported into SportsCode where the frame before impact with the cloth screen for each throw was identified. This frame was then exported as a .jpeg image file. This image file was then imported into Matlab. Within Matlab, three points on the circumference of the target and the centre of the ball were manually digitised. Digitising was performed by one investigator and intra-individual reliability was high as

indicated by an ICC > 0.99 and a small standardised typical error (≤ 0.03) (Hopkins, 2000, 2011). This reliability was calculated using the same spreadsheet as reported in section 6.3.10.

Using custom Matlab scripts coordinates of the centre of the target were identified and its radius and circumference calculated in pixels. The distance of the ball centre from the target centre, in pixels, was then calculated. This distance was then divided by the radius of the circle in pixels to produce a radial error score. This resulted in a score where the lower the value, the more accurate the throw. Further, scores ≤ 1 represent an instance where the ball struck within the circumference of the target while scored > 1 struck outside of the target circumference.

6.4.9 Testing for determinism

Joint rotation data (elbow, shoulder and wrist) were compared to surrogate data to test for the presence of determinism. This was conducted by using the methods outlined in section 6.3 including surrogate generation and comparison to observed data using sample entropy.

6.4.10 Analysis

Once determinism of the observed time series was ascertained the 16 throws of each participant during the pre-test were concatenated and sample entropy(m,r,N) calculated where m = 2, r = 0.1 and N was the length of the concatenated time series. This was repeated for the 16 throws of each participant from the post-test. Thus, each participant had two sample entropy values calculated as measures of intra-individual variability, one each for the pre- and post-test. The dependent variables, radial error score (pre-, post- and transfer-test) and entropy estimates of the included time series (pre- and post-test) were screened for normality and submitted to appropriate inferential tests. Changes in radial error score (pre- to post-test) within and between groups were analysed using dependent and independent t-tests, respectively. Changes in entropy

content of included time series (pre- to post-test) within and between groups were analysed using

Wilcoxon Signed Rank and Mann Whitney U tests, respectively. Significance level was set at p <

0.05 and appropriate effect size measures were calculated for the parametric and non-parametric

statistics (Cohens *d* and *r* respectively where $r = \frac{Z}{\sqrt{N}}$).

Chapter 7. Summary

7.1 Overview

The aim of this thesis was to contribute new knowledge to the understanding of any functional role of variability in discrete movement and, in particular, its interaction with adaptation and motor learning. Four primary studies (Study 1 through 4) form the basis of this work and provide an account of the systematic approach to ensure this aim was achieved with due understanding of what had been done previously and via the use of valid methodologies. Study 1 documented a systematic review of the literature and provided collation of the previously published evidence supporting the concept of a functional role for movement variability. It facilitated further development of hypotheses and provided guidance on research questions concerning the phenomenon of discrete movement variability. The review also documented the previous methods used to investigate movement variability and allowed discussion of the contemporary techniques which are, or may be, employed in the field. Furthermore, it highlighted areas of research design and method which need to be in place to enable effective and valid study of discrete movement variability.

Two method-related factors raised in Study 1, regarding trial size and the use of surrogate techniques, resulted in Studies 2 and 3. Specifically, the review identified the need to adequately determine the number of trials required for variability quantification. To determine the optimal trials size, Study 2 presented the results of the work to ensure a valid employment of the sequential analysis technique. The review also outlined the potential benefits of adopting surrogate techniques within variability investigations. Unfortunately, no suitable surrogate

method existed for discrete movement. Study 3 outlined the development of such a technique and the testing of its validity and reliability for the role.

With the completion of Studies 1, 2 and 3 the overarching aim of the thesis could be addressed. By coupling the developed methods with the knowledge and techniques drawn from the review an experimental study (Study 4) was designed to monitor and quantify variability during motor learning and to detect any evidence of adaptability. It is acknowledged that this study provides only the first step in beginning to better understand these relationships. However, coupled with theoretical understanding provided by Study 1 and the rigorous method provided by Studies 2 and 3, this thesis provides important knowledge to variability research and a solid platform for future work.

7.2 Summary of Aims, Hypotheses and Findings

7.2.1 Discrete Movement Variability in Sports and Sports Derived Tasks: A Systematic Review (Study 1)

The aim of Study 1 was to provide a systematic review of the design, methods and analyses of research into discrete movement variability in sport or sports derived tasks. A second aim was to review the findings and conclusions of the systematically sourced studies to ascertain what was known and unknown about the role of variability in discrete sporting movements, particularly related to any functional role for variability in discrete movement. The assembled literature represented a considerable body of work within the field and provided valuable information on method-related and theoretical considerations, and understanding within this research area.

The number of studies included is indicative of an appreciation of the importance of intra-individual studies of discrete movement variability. Predominantly driven by a dynamical systems perspective of human movement, these researchers saw value and importance in investigating discrete movement variability. There was an acceptance that variability is omnipresent and evidence that it can exist alongside consistent and successful movement outcomes. However, the key findings of this review relate to the hypothesised functional roles of variability in movement: 1) reduction of injury risk; 2) enabling coordination change; and 3) facilitating adaptation to varying task or environmental constraints.

Alongside facilitating adaptability, another functional role proffered for movement variability is injury prevention. However, a limitation of the review in relation to this is that studies documenting only injured participants were excluded. This was done so as to remove studies which may have methodologies governed by the capabilities of such a population rather than dictated by what was considered most rigorous, in particular relating to trials size. As such, the evidence in this review regarding injury and movement variability is far from comprehensive or convincing. That is not to say the evidence does not exist for this function in discrete movement as it does in continuous tasks, rather that it may have been excluded. Yet, this is a very important and potentially beneficial area for future work, one that aligns with a primary aim of sports biomechanics, injury prevention.

Concerning the role of variability in coordination change and adaptability, the evidence suggested that by assessing the phenomenon across different kinematic levels, during a process of skill acquisition, a greater understanding may be achieved. Those levels include 1) single elements such as joint, segment or implement kinematics; 2) coordination; and 3) whole system movement. In line with the assembled evidence, it may be expected that at the first level, movement

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variability would decrease as skill level increased. This reflects the possibility that variability at this level needs to be constrained to a certain extent to produce consistently successful movement outcomes, possibly to facilitate effective coordination. However, regarding coordination variability, the evidence was less conclusive. There was some support for the U-shaped curve hypothesis proffered by Wilson et al. (2008) while other studies showed different relationships between coordination variability and skill level leading to the consideration that it may be task dependent. It is also hypothesised that adaptability emerges in concert with coordination variability, perhaps as a function of compensatory coordination. This provides another avenue of investigation.

The tools to effectively investigate these theories and hypotheses were highlighted by the work on the first aim of this review. It was recommended that investigators adopt longitudinal research designs. While much useful information was provided by studies which had a single contact with participants, some of the strongest evidence came from those with multiple longitudinal data points. In particular, those that implemented some form of training intervention showed the greatest link between variability and adaptability. It was also deemed important to ensure a valid justification of trials size for the purposes of variability quantification. The benefits of adopting surrogate methods was explained, both to ensure the maintenance of biological determinism post data smoothing and to indicate that any detected variability was the outcome of neuromuscular control and not of random noise. Finally, contemporary issues surrounding the quantification of variability were discussed. In particular the shortcomings of SD and CV were explained and the use of emerging techniques that can assess entire time series, potentially expose variability structure or allow informative data reduction were advocated.

7.2.2 Determining Optimal Trial Size Using Sequential Analysis (Study 2)

One of the recommendations arising from the systematic review was the valid determination of trial size a priori. That is, to provide justification of the number of trials that an individual participant is asked to complete such that investigators or practitioners can be confident that the measured variability is reflective of the true variability. A statistical method, sequential analysis technique, was identified from the literature and deemed appropriate for this task. During pilot testing of the method however it was discovered that the technique responded differently depending on how many trials were used to calculate the criterion SD. As such, an exploratory study was designed with two main aims. The first aim was to determine the effect of using different numbers of trials from which to calculate the criterion SD on the result of the sequential analyses. The second aim was to determine the number of throws required to achieve mean stability in overarm throwing. The hypothesis behind the second aim was that, as variability is the fluctuation in scores around a mean, to obtain a true reflection of that variance requires the mean to be stable. While these aims are clearly relevant to the overall theme of this thesis, the technique and results of the article potentially have a broader impact beyond variability research and are reported as such.

The results showed that the outcome of the technique was affected by the total trial number from which criterion mean and SD values were drawn. The moving average plotted against the number of trials underwent a 'transition phase' early on which was evident in the qualitative analysis of the plots of each iteration of the technique. Significant differences were seen between 'relative' sequential analysis scores taken from trials where the criterion SD was calculated from a total of 10, compared to 20 or 30 trials. The mean took relatively longer to stabilise in 10-trial conditions and as such it was concluded that 20 or more trials should be used

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for the determination of the criterion SD. As there were few differences between results taken from 20- and 30-trial conditions, the decision was made to calculate trials to stability from the 20-trial conditions. This resulted in a recommendation of between 13 and 17 trials to ensure a stable mean in overarm throwing studies.

This study has several key strengths. It assessed multiple variables – e.g., marker trajectories, joint displacements and ball release variables – to ensure coverage of many relevant biomechanical factors. Furthermore, both discrete and time series variables were tested. The technique was assessed predominantly across the first 10, 20 and 30 trials from the 30 throws collected per individual. Furthermore, 10 throws from the middle of the 30, last 10 throws and the middle 20 throws were tested to ensure that the results achieved were determined by the number of trials and not by the position from wherein the sample they were taken. No differences were found between these sub samples and the first 10 or first 20 throws. To ensure that sufficient throws were suggested for future studies the testing carried out and the subsequent recommendations (mean trials to stability + 95% CI) were conservative yet results were still similar to previous kinetic studies.

Despite these stated strengths there were some limitations. The inclusion of sequential analysis of time series was novel to this investigation and was done due to the understanding that variability information is contained across entire waveforms. However, some limitations can be acknowledged since the time series were normalised and each of the 101 data points were treated separately. This presumes that each point is independent, which is against the assumption of determinism within biological systems linking each datum and its neighbours. Despite this limitation it was still considered worthwhile applying the technique to the normalised time series to gain some guidance on the number of trials required for valid future analysis of time series

data. An avenue for future work might be to combine other analyses, such as functional data analysis, with the concepts of sequential analysis to provide a more valid determination of trials to stability in time series data.

As the selection of number of trials and the criterion bandwidth (as a fraction of criterion SD) are arbitrarily determined, this technique is not as objective as others such as intra-class correlation, which is another limitation of sequential analysis. Other measures taken to mediate this limitation included the testing done on trial numbers as well as selecting the criterion bandwidth (± 0.25 SD) based on it being the most common application in the literature (Table 9.1 in section 9.7). Still, sequential analysis is more conservative than intraclass correlation which can perhaps compensate for its subjectivity (see section 3.6).

The sequential analysis technique was chosen to determine the number of trials required to be collected per session in the main data collection phase for this thesis. Due to potential limitations of the technique determined early, the method was subjected to rigorous testing, and interpreted conservatively, to ensure that the number of trials selected provided the opportunity to effectively quantify movement variability. Following the analyses, a trial size of 16 throws was determined to be used for the remaining investigations.

7.2.3 A Surrogate Technique for Investigating Deterministic Dynamics in Discrete Human Movement (Study 3)

As identified within Study 1, surrogate methods are potentially beneficial statistical techniques for use in human movement variability research. These methods have the ability to demonstrate that a collected biological signal is deterministic in nature and can provide evidence against the 'variability as noise' hypotheses of some motor control theories. Furthermore, they

may provide assurance that a filtered biological signal has retained its determinism post treatment. Another consideration relating to the use of surrogate methods lay in the application of entropy measures which was the intention in the final study of this thesis. As entropy quantifies variability in signals which are either deterministic or stochastic in nature, it is important to demonstrate the determinism present in observed data.

Many surrogate techniques exist for a variety of different applications. Continuous human motion, in the form of gait, had previously been investigated using a pseudo-periodic surrogate method. However, the embedding method used in this surrogate technique was rendered inappropriate by the discontinuities that exist from one trial to the next in discrete human movement such as overarm throwing. Searches revealed no appropriate method currently existed for such an application. Hence, the first aim of this study was to develop a surrogate method for discrete human movement and determine its validity and reliability. The second aim was to demonstrate the implementation of the technique including determination of critical values and the testing of surrogate output using sample entropy as a discriminating statistic.

The resultant technique made use of a phase space constituted by two or more biomechanically relevant variables from which the sampling occurred to create each surrogate. This phase space, when in 2D form, resembles an angle-angle plot and replaces that created by time delay embedding within the pseudo-periodic surrogate technique. In theory this space can contain as many dimensions as the investigator sees fit, as long as included variables remain relevant and related. In order to demonstrate as such, the technique was employed using both a 2D and 3D space. The selection of the critical value rho (ρ) was thoroughly explained and subsequently surrogates were generated. The statistical analysis of the resultant output indicated that the technique was able to validly produce surrogates of discrete human movement.

Surrogates resembled time series produced from the collected throws with statistically indifferent length, mean and variance. Sample entropy estimates confirmed that the surrogates had been stripped of their deterministic dynamics while this had been maintained in the observed data.

The strength of this study is that it has produced a surrogate technique, with evidenced validity, which has the potential for a broad range of applications. Furthermore, it serves the final aim of this thesis by providing a tool to support subsequent variability analyses. The method of this technique is comprehensively documented and all relevant information is provided to enable readers to implement it in their own investigation. A rigorous battery of reliability tests employed in this study ensures that researchers can be confident that the technique will consistently produce the expected output. A limitation of the study is that the technique has only been employed on kinematic data from overarm throwing. While care was taken to ensure wide applicability, it cannot be stated that the method would behave in the exact same manner across different discrete movements or for non-kinematic variables. As such, scope exists to further the testing of the technique by investigating other applications.

7.2.4 Changes in Variability and Adaptability during the Learning of a Novel Discrete Task (Study 4)

The final study of this thesis addressed the overarching focus of the entire work: to investigate the interaction of discrete movement variability, adaptation and learning. It sees the bringing together of factors suggested within Study 1, such as use of appropriate research design and quantification techniques, alongside the method-related elements determined or developed in Studies 2 and 3. The study employed a longitudinal design, contextual interference, surrogate methods and sample entropy to investigate changes in movement variability at the first (joint kinematic) level during learning of a novel discrete task. It was hypothesised that the contextual

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interference effect would be observed in line with previous works and that improved performance by the high contextual interference group in a transfer task would provide evidence of adaptability. At the beginning and end of a series of nine practice sessions, movement variability would be quantified at the first, joint kinematic, level where it was expected those that perform better would display lower variability in line with previous research. Finally, the use of the trial size determined in Study 2 and the surrogate technique developed in Study 3 would lend validity to the final results.

Results indicated the presence of the contextual interference. The group exposed to contextual interference, in the form of task variability during skill acquisition, outperformed those exposed to low contextual interference. Furthermore, the superior performance of this group in the transfer-test indicated their better ability to adapt to these novel task constraints. The use of the surrogate technique effectively demonstrated the presence of deterministic dynamics within the observed time series. This allowed further inference to be sought through the use of sample entropy. The entropy results were not statistically significant. However, several group and individual trends appeared to reflect previous works where variability at the first, joint kinematic, level was lower for those who performed better, and their superior adaptability was suggestive of effective compensatory coordination within these participants. Considered alongside their lower variability at the joint level, the result may indicate that a constraining of joint variance is required to facilitate functional coordination and coordination variability for enhancing adaptability. More work is required in quantifying coordination and coordination variability to enable further inference to be made on this hypothesis.

The strengths of this study lie in the bringing together of the work proceeding it in this thesis, the recommendations from Study 1 and the methodologies of Studies 2 and 3. There were

several limitations present in this study though which warrant discussion. The lack of significant results in the entropy comparisons and correlations could be indicative of several factors. First, the sample size may have left the study underpowered for the non-parametric analyses. The study had significant power for individual comparisons through the large trial sizes but this is not reflected in the inferential statistics. Alternatively, sample entropy may not be sensitive enough to elicit differences at this level. Perhaps, the differences do not lie in the magnitude of the variance but rather in its structure. In this case, other methods such as functional data analysis or functional principal component analysis may need to be explored. The hypotheses proffered regarding the relationship between joint variability, coordination variability and adaptability need to be treated cautiously. They could be strengthened had there been coordination data, or data from each of the nine sessions, available. Yet, as this was not the aim of the study, it simply provides clear direction for the next steps in the investigation of this phenomenon.

7.3 Future Research Directions

7.3.1 Applicability of sequential analysis to other movements

Study 2 documented the work carried out to validate and then apply the sequential analysis technique to determine the number of trials required for mean stability in overarm throwing. One of the key findings was a transition period for the moving point average that existed with the first 10 trials. It may be worthwhile to determine whether this exists within other discrete movements and to investigate whether the choice of using 20 trials from which to determine trials to stability has applicability beyond overarm throwing.

7.3.2 Application of sequential analysis to time series data

An acknowledged limitation of Study 2 was the way in which sequential analysis was applied to time series data. Specifically that each time normalised point was considered independent rather than being related to the data before and after it. This was mediated by taking a conservative approach to the interpretation of sequential analysis results of the time series. However, the studies in this thesis all advocate for the consideration of whole waveforms within the dynamical systems perspective regarding the determinism that exists between each datum and its neighbour. As such, if there is an intention to apply sequential analyses to time series data, it may be required to investigate a way which considers each waveform as a single, whole entity. In such case, an approach of functional data analysis and other related techniques may provide acceptable tools.

7.3.3 Applying surrogate methods to other discrete movement

The development and validation of the novel surrogate technique in Study 3 was applied only to overarm throwing data. The technique would be expected to behave very similarly with other discrete movement data but there is no empirical evidence to support such a position. Hence, application to other discrete movements would further the validation effort and strengthen the rationale for the wider use of the surrogate method.

7.3.4 Use of different quantification methods on first level data

Study 4 employed sample entropy to quantify the variability of first, joint kinematic, level data in pre- and post-intervention. This was to ensure the method used was able to assess all collected data by measuring the variability in entire time series and to confirm that the relationship between an individual datum and its neighbours was maintained. However, a

limitation of entropy measures is that they only quantify the magnitude of variability without consideration of its structure. Other methods that are able to quantify both magnitude and variability include functional principal component analysis as indicated within Study 1. Applying these techniques to data similar to that collected in Study 4 may allow insight into whether the high and low contextual variability groups have a different structure to their variability. For example, the question might be answered whether they manifest the variability in their signals in the same order of magnitude yet at different points across the time domain.

7.3.5 Assessment of coordination and whole system variability

A natural progression of the analyses contained in Study 4 is to assess the remaining two levels of variability, coordination and whole system, as identified in Study 1. This will facilitate a clearer picture of the interaction of movement variability, adaptation, learning and skill level as well as the interplay between the three levels of variability within contextual interference groups. Preliminary work may need to be done first to determine the optimal means of quantifying variability at these levels.

7.3.6 Assessment of variability across the entire span of learning

Study 4 presented data related to the learning of a novel task isolated to pre- and post-intervention testing. Much knowledge can be gained from assessing variability across all three levels - before, during and after motor learning. In this approach, we may understand whether expected phenomena, such as a U-shaped curve description of coordination variability, actually manifest.

7.4 Potential Application of Results

7.4.1 Use of sequential analysis in athlete monitoring

While sequential analysis was employed as a means to determine trial size for research applications in Study 2, the technique can be a potential tool for informing the data collection choices of those involved in athlete monitoring. Access to athletes can often be time-constrained and come with workload and injury concerns that need to be mediated. Sequential analysis may provide a means for justifying the number of trials a practitioner is requesting an athlete perform in order to provide valid feedback. Similarly, when the number of trials collected is reduced by external concerns, sequential analysis may allow the practitioner to understand any limitations regarding stability of the mean/variance of target variables when providing feedback and results of testing to coaches and athletes.

7.4.2 Use of entropy measures for athlete tracking

One of the major strengths of entropy measures is that they allow reduction of large amounts of data to a single variability value without loss of information by assessing all collected data points. Within the context of tracking and monitoring of athletes, the ability to share a single value can reduce the complexity of the interaction of practitioners with athletes and coaches. With further understanding from research, sample entropy may be employed as an easy means of tracking new skill acquisition or monitoring for any changes to variability profiles manifested by injury, illness, fatigue, etc.

7.4.3 Increasing task variability in training

Once well understood the relationship between contextual interference, variability and adaptability could provide reasoning for increasing variation of task constraints in athletic training.

In particular among team sports, where the movement of opposition players is constantly changing the task constraints, equipping athletes with the ability to vary movement patterns in order to maintain successful movement outcomes could be beneficial. However, any potential decrease in self-efficacy precipitated by the increased challenge and high probability of task failure often experienced during high contextual interference exposure, particularly in early phases, may need to be understood and managed.

7.5 Conclusion

This thesis details a body of work which adds important guidance, methods and results to movement variability research. The systematic review effectively collated evidence from previous work and in particular provided direction and hypotheses for future work related to the functional role of movement variability and its interaction with adaptation and learning. It also outlined some key method-related considerations for researchers within the field of movement variability.

As a response to this method guidance, two studies were conducted. The first sought to validly determine the number of trials required for the experimental studies in this thesis. The sequential analysis technique was chosen for this task and analyses conducted to ensure that this method was employed in a valid way. The second method study developed a valid and reliable surrogate technique for use in discrete human movement. As a result, the research area is now equipped with a tool which can be employed across many different analyses and contexts in the future.

Finally, all the previous work culminated in the resultant experimental study aiming to further investigate the functional role of movement variability and its interaction with adaptation and learning. The method-related and theoretical considerations from Study 1 and methods from

Studies 2 and 3 were employed to ensure this topic was rigorously assessed. However, much work remains to be done to further the methods employed and developed within this thesis and to fully understand roles and impact of movement variability in discrete movement. Several key areas for future research are proposed. When understood, these factors could provide many useful tools for the assessment of individuals during motor learning, a means for athlete tracking and a better understanding of the organisation of the human motor system.

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Chapter 9. Appendices

9.1 Ethics Approval

ACU
AUSTRALIAN CATHOLIC UNIVERSITY

Human Research Ethics Committee
Committee Approval Form

Principal Investigator/Supervisor: Dr David Greene   Sydney Campus

Co-Investigators: Dr Raul Landeo   Sydney Campus

Student Researcher: Mr Paul Taylor   Sydney Campus

Ethics approval has been granted for the following project:
Discrete Movement Variability - Interaction with Adaptation and Learning. (Discrete Movement Variability)

for the period: 7 April 2011 to 31 December 2012

Human Research Ethics Committee (HREC) Register Number: N2011 07

Special Condition/s of Approval

Prior to commencement of your research, the following permissions are required to be submitted to the ACU HREC:

N/A

The following standard conditions as stipulated in the *National Statement on Ethical Conduct in Research Involving Humans* (2007) apply:

(i)   that Principal Investigators / Supervisors provide, on the form supplied by the Human Research Ethics Committee, annual reports on matters such as:
  * security of records
  * compliance with approved consent procedures and documentation
  * compliance with special conditions, and

(ii)   that researchers report to the HREC immediately any matter that might affect the ethical acceptability of the protocol, such as:
  * proposed changes to the protocol
  * unforeseen circumstances or events
  * adverse effects on participants

The HREC will conduct an audit each year of all projects deemed to be of more than low risk. There will also be random audits of a sample of projects considered to be of negligible risk and low risk on all campuses each year.

Within one month of the conclusion of the project, researchers are required to complete a *Final Report Form* and submit it to the local Research Services Officer.

If the project continues for more than one year, researchers are required to complete an *Annual Progress Report Form* and submit it to the local Research Services Officer within one month of the anniversary date of the ethics approval.

K. Pashly.

Signed: ....Date: .... 07.04.2011.....
(Research Services Officer, McAuley Campus)

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9.2 Participant information letter for Study 2

Australian Catholic University Limited
ABN 15 050 192 660
School of Exercise Science
Strathfield Campus (Edward Clancy Building)
25a Barker Road
New South Wales 2135 Australia
Locked Bag 2002 Strathfield
New South Wales 2135 Australia
Telephone 61 2 9701 4319
Facsimile 61 2 9701 4290
www.acu.edu.au

School of Exercise Science

Discrete Movement Variability – Methodology Study

Dr David Greene, Dr Raul Landeo (supervisors) and Paul Taylor (student researcher)
Exercise Science

Dear Participant,

You are invited to participate in the above study which is being conducted as part of the requirements for a PhD degree. Movement variability describes the minor differences in actions from one trial to the next. The purpose of this study is to determine the best measures of movement variability. Participation in this study may enable you to improve your accuracy in over arm throwing.

In order to be a participant we require that you be currently free of injury and not currently taking any medication used to treat injury. You will be asked to attend a maximum of one (1) testing session during the course of your participation. On arrival you will be asked to provide body measures including height, weight and arm length and circumference. You well then have small markers attached which identify various anatomical landmarks for the data collection cameras. During the course of the data collection you will be asked to perform repeated trials, throwing a ball, over arm, toward targets as directed. Throws will not be at maximal power and you will be asked to throw for accuracy in outcome. The volume of throws should not cause fatigue. Each session should last no longer than one (1) hour and will be conducted in the biomechanics laboratory at the ACU Strathfield Campus (25a Barker Rd, Strathfield 2135) between 1/5/2011 and 1/10/2011. Testing will occur at a time determined via consultation with you, between 8am and 8pm, Monday to Friday..

The data collection techniques and the testing protocol used in this study are low risk. The markers used are attached via low allergy, low adhesive tape to the skin at various sites on the body. Removal of these is quick and easy and cause minor discomfort at worst. At times it may be necessary to shave a small area of the skin at the point of attachment to ensure proper adhesion. This will also reduce any discomfort as the marker is removed.

As a participant in research you have the right to refuse your consent to participate at any time. You are not obliged to notify the researchers of any reasoning for your decision. Procedures will be in

place to protect the privacy of your personal data. Any personal information or images collected during the study will be securely stored (in locked filing cabinets or password protected computers) and destroyed (shredding and erasing) appropriately upon completion of the study. Any data or information reported from the study will be done so that individuals cannot be identified.

Any questions regarding this project should be directed to the Principal Investigator (Supervisor) and/or the Student Researcher:

Supervisors	Student Researcher
Dr David Greene (9701 4377)	Paul Taylor
David.greene@acu.edu.au	0418 249 543
Dr Raul Landeo (9701 4295)	Exercise Science
Exercise Science	17a Lawson Street Sans Souci
Strathfield Campus (Mount St Mary)	NSW 2219 Australia
25A Barker Road Strathfield NSW 2135	

Upon completion the research team will honour any request for feedback as to study results and findings.

This study has been approved by the Human Research Ethics Committee at Australian Catholic University.

In the event that you have any complaint or concern about the way you have been treated during the study, or if you have any query that the Investigator or Supervisor and Student Researcher has (have) not been able to satisfy, you may write to the Chair of the Human Research Ethics Committee care of the nearest branch of the Research Services Office.

NSW and ACT: Chair, HREC
C/- Research Services
Australian Catholic University
Strathfield Campus
Locked Bag 2002
STRATHFIELD NSW 2135
Tel: 02 9701 4093
Fax: 02 9701 4350

Any complaint or concern will be treated in confidence, fully investigated and you will be informed of the outcome.

If you agree to participate in this project, you should sign both copies of the Consent Form, retain one copy for your records and return the other copy to the Supervisor or Student Researcher (details above).

Regards,

Dr David Greene   Dr Raul Landeo   Paul Taylor

9.3 Participant consent forms for Study 2

CONSENT FORM
Copy for Participant to Keep

Discrete Movement Variability – Methodology Study

Dr David Greene, Dr Raul Landeo (supervisors) and Paul Taylor (student researcher)
Exercise Science

I .... *(the participant)* have read *(or, where appropriate, have had read to me)* and understood the information provided in the Letter to Participants. Any questions I have asked have been answered to my satisfaction. I agree to participate in the allocated testing and training sessions and to undertake required protocols including;

- Attending one (1) testing session of approximately 1 hour
- Performing up to 70 over arm throws
- Measurement of height, weight and arm length and circumference
- Attachment of reflective markers
- Recording of my movements

I understand that I will be required to attend testing session at the biomechanics laboratory at the ACU Strathfield Campus (25a Barker Rd, Strathfield 2135) between 1/10/2011 and 1/6/2012. I acknowledge that testing will occur at a time determined via consultation between me and the researchers, between 8am and 8pm, Monday to Friday. I give my consent understanding that it can be withdrawn at any time without comment or consequence and on the understanding that my personal information and privacy will be protected at all times. I agree that research data collected for the study may be published or may be provided to other researchers in a form that does not identify me in any way.

NAME OF PARTICIPANT: ....

SIGNATURE ....   DATE

....

SIGNATURE OF SUPERVISOR: ....

DATE:.............................

SIGNATURE OF STUDENT RESEARCHER: ....

PhD Candidate, ACU School of Exercise Science)

DATE:........................…………

Discrete Movement Variability – Methodology Study

**Dr David Greene, Dr Raul Landeo (supervisors) and Paul Taylor (student researcher)
Exercise Science**

I .... *(the participant)* have read *(or, where appropriate, have had read to me)* and understood the information provided in the Letter to Participants. Any questions I have asked have been answered to my satisfaction. I agree to participate in the allocated testing and training sessions and to undertake required protocols including;

- Attending pre and post testing sessions
- Attending up to eight (8) training sessions
- Performing up to 70 over arm throws per session
- Measurement of height, weight and arm length and circumference
- Attachment of reflective markers
- Recording of my movements

I understand that I will be required to attend testing sessions at the biomechanics laboratory at the ACU Strathfield Campus (25a Barker Rd, Strathfield 2135) between 1/10/2011 and 1/6/2012. I acknowledge that testing will occur at a time determined via consultation between me and the researchers, between 8am and 8pm, Monday to Friday. I give my consent understanding that it can be withdrawn at any time without comment or consequence and on the understanding that my personal information and privacy will be protected at all times. I agree that research data collected for the study may be published or may be provided to other researchers in a form that does not identify me in any way.

NAME OF PARTICIPANT: ....

SIGNATURE .... DATE

....

SIGNATURE OF SUPERVISOR: ....

DATE:………………………..

SIGNATURE OF STUDENT RESEARCHER: ....

PhD Candidate, ACU School of Exercise Science)

DATE:…………………..……….

9.4 Participant information letter for Studies 3 and 4

Australian Catholic University Limited
ABN 15 050 192 660
School of Exercise Science
Strathfield Campus (Edward Clancy Building)
25a Barker Road
New South Wales 2135 Australia
Locked Bag 2002 Strathfield
New South Wales 2135 Australia
Telephone 61 2 9701 4319
Facsimile 61 2 9701 4290
www.acu.edu.au

School of Exercise Science

Discrete Movement Variability

Dr David Greene, Dr Raul Landeo (supervisors) and Paul Taylor (student researcher)
Exercise Science

Dear Participant,

You are invited to participate in the above study which is being conducted as part of the requirements for a PhD degree. Movement variability describes the minor differences in actions from one trial to the next. The purpose of this study is to investigate this movement variability in relation to over arm throwing. Participation in this study may enable you to improve your accuracy in over arm throwing and improve your skill acquisition ability.

In order to be a participant we require that you be currently free of injury and not currently taking any medication used to treat injury. Furthermore, depending on your inclusion group there may be a performance criteria set so that included participants are of a similar skill level. You will be randomly assigned into groups for the data collection. Depending on the group assigned you will be asked to attend a maximum of eight (8) testing session during the course of your participation. Each session should last no longer than one (1) hour and will be conducted in the biomechanics laboratory at the above address.

On arrival at each session you will be asked to provide body measures including height, weight and arm length and circumference. You well then have small markers attached to your skin which identify various anatomical landmarks for the data collection cameras. During the course of the data collection you will be asked to perform repeated trials, throwing a ball, over arm, toward targets as directed. Throws will not be at maximal power and you will be asked to throw for accuracy in outcome. The volume of throws should not cause fatigue. Each session should last no longer than one (1) hour and will be conducted in the biomechanics laboratory at the ACU Strathfield Campus (25a Barker Rd, Strathfield 2135) between 1/10/2011 and 1/6/2012. Testing will occur at a time determined via consultation with you, between 8am and 8pm, Monday to Friday.
The data collection techniques and the testing protocol used in this study are low risk. The markers used are attached via low allergy, low adhesive tape to the skin at various sites on the body. Removal

of these is quick and easy and cause minor discomfort at worst. At times it may be necessary to shave a small area of the skin at the point of attachment to ensure proper adhesion. This will also reduce any discomfort as the marker is removed.

As a participant in research you have the right to refuse your consent to participate at any time. You are not obliged to notify the researchers of any reasoning for your decision. Procedures will be in place to protect the privacy of your personal data. Any personal information or images collected during the study will be securely stored (in locked filing cabinets or password protected computers) and destroyed (shredding and erasing) appropriately upon completion of the study. Any data or information reported from the study will be done so that individuals cannot be identified.
Any questions regarding this project should be directed to the Principal Investigator (Supervisor):

Supervisors	Student Researcher
Dr David Greene (9701 4377)	Paul Taylor
David.greene@acu.edu.au	0418 249 543
Dr Raul Landeo (9701 4295)	Exercise Science
Exercise Science	17a Lawson Street Sans Souci
Strathfield Campus (Mount St Mary)	NSW 2219 Australia
25A Barker Road Strathfield NSW 2135	

Upon completion the research team will honour any request for feedback as to study results and findings.

This study has been approved by the Human Research Ethics Committee at Australian Catholic University.

In the event that you have any complaint or concern about the way you have been treated during the study, or if you have any query that the Investigator or Supervisor and Student Researcher has (have) not been able to satisfy, you may write to the Chair of the Human Research Ethics Committee care of the nearest branch of the Research Services Office.

NSW and ACT: Chair, HREC
C/- Research Services
Australian Catholic University
Strathfield Campus
Locked Bag 2002
STRATHFIELD NSW 2135
Tel: 02 9701 4093
Fax: 02 9701 4350

Any complaint or concern will be treated in confidence, fully investigated and you will be informed of the outcome.

If you agree to participate in this project, you should sign both copies of the Consent Form, retain one copy for your records and return the other copy to the Supervisor or Student Researcher (details above).

Regards,

Dr David Greene   Dr Raul Landeo   Paul Taylor

9.5 Participant consent forms for Studies 3 and 4

CONSENT FORM
Copy for Participant to Keep

Discrete Movement Variability

Dr David Greene, Dr Raul Landeo (supervisors) and Paul Taylor (student researcher)
Exercise Science

I .... *(the participant)* have read *(or, where appropriate, have had read to me)* and understood the information provided in the Letter to Participants. Any questions I have asked have been answered to my satisfaction. I agree to participate in the allocated testing and training sessions and to undertake required protocols including;

- Attending pre and post testing sessions
- Attending up to eight (8) training sessions
- Performing up to 70 over arm throws per session
- Measurement of height, weight and arm length and circumference
- Attachment of reflective markers
- Recording of my movements

I understand that I will be required to attend testing sessions at the biomechanics laboratory at the ACU Strathfield Campus (25a Barker Rd, Strathfield 2135) between 1/10/2011 and 1/6/2012. I acknowledge that testing will occur at a time determined via consultation between me and the researchers, between 8am and 8pm, Monday to Friday. I give my consent understanding that it can be withdrawn at any time without comment or consequence and on the understanding that my personal information and privacy will be protected at all times. I agree that research data collected for the study may be published or may be provided to other researchers in a form that does not identify me in any way.

NAME OF PARTICIPANT: ....

SIGNATURE .... DATE

....

SIGNATURE OF SUPERVISOR: ....

(PhD Candidate, ACU School of Exercise Science)

DATE:.............................

SIGNATURE OF STUDENT RESEARCHER: ....

DATE:.........................…………

CONSENT FORM
Copy for Researcher to Keep

Discrete Movement Variability

Dr David Greene, Dr Raul Landeo (supervisors) and Paul Taylor (student researcher)
Exercise Science

I .... *(the participant)* have read *(or, where appropriate, have had read to me)* and understood the information provided in the Letter to Participants. Any questions I have asked have been answered to my satisfaction. I agree to participate in the allocated testing and training sessions and to undertake required protocols including;

- Attending pre and post testing sessions
- Attending up to eight (8) training sessions
- Performing up to 70 over arm throws per session
- Measurement of height, weight and arm length and circumference
- Attachment of reflective markers
- Recording of my movements

I understand that I will be required to attend testing sessions at the biomechanics laboratory at the ACU Strathfield Campus (25a Barker Rd, Strathfield 2135) between 1/10/2011 and 1/6/2012. I acknowledge that testing will occur at a time determined via consultation between me and the researchers, between 8am and 8pm, Monday to Friday. I give my consent understanding that it can be withdrawn at any time without comment or consequence and on the understanding that my personal information and privacy will be protected at all times. I agree that research data collected for the study may be published or may be provided to other researchers in a form that does not identify me in any way.

NAME OF PARTICIPANT: ....

SIGNATURE .... DATE

....

SIGNATURE OF SUPERVISOR: ....

DATE:……………………….

SIGNATURE OF STUDENT RESEARCHER: ....

(PhD Candidate, ACU School of Exercise Science)

DATE:......................…………

Research Project Needs You!!

Are you??

- Male and

- Aged 18—30 years

- Not participating in activities where you have to throw accurately (cricket, baseball etc.)

- Free from injury

Do you want to??

- Complete ESSA or industry experience hours on campus (Exercise Science students)

- Take part in biomechanical research

Participation will require you to attend 9 1hr training/testing sessions, during which you have certain measures taken and your movements recorded using 3D motion analysis technology.

All testing will take place at the ACU (Strathfield) biomechanics lab. If you are interested please contact Paul Taylor via the email address below.

Throwing Study Contact: Paul.taylor@acu.edu.au
Throwing Study Contact: Paul.taylor@acu.edu.au
Throwing Study Contact: Paul.taylor@acu.edu.au
Throwing Study Contact: Paul.taylor@acu.edu.au
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9.7 Trials and criterion SD values for sequential estimation technique studies

Table 9.1.
Trials and criterion SD values used for sequential analysis in the literature.

Study	Sample Size	Number of Trials	SD Criterion
Bates et al. (1983)	N = 5	10	±0.25
Colby et al. (1999)	N = 49	NR	±0.25
Hamill and McNiven (1990)	N = 20	NR	±0.25
Rodano and Squadrone (2002)	N = 9	25	±0.30
Wikstrom, Tillman, and Borsa (2005)	N = 58	NR	±0.25
James et al. (2007)	N = 10	20	±0.25
Racic et al. (2009)	N = 12	20	±0.25
Stuelcken and Sinclair (2009)	N = 15	20	±0.25

NR = Not reported.

9.8 Determining the cut-off frequency for filtering

9.8.1 Introduction

Determining the cut-off frequency for low pass filtering is a common task for those dealing with biomechanical time series data. By selecting an appropriate cut-off frequency the researcher is attempting to have the filter of choice include all desirable signal content while excluding higher frequency systematic "noise" from the filtered signal. Two methods proposed for this are frequency spectrum analysis and residual analysis. Frequency spectrum presents the signal in the frequency domain through the use of a Fast Fourier transformation. This can give a visual indication of the frequency content of the signal and is particularly effective at highlighting any frequency concentrations outside of those expected. In terms of human movement this could be expected to occur above 50 Hz due to the general inability of the human body to produce voluntary high frequency movement. Residual analysis, as proposed by Winter (2005), sees the sum of the squared residuals between the raw signal and a signal filtered at several selected cut-off frequencies, plotted against those cut-off frequencies. A visual representation of this can be

seen in Figure 9.1. A power curve is fitted to the cut-off frequency vs. residual curve (solid grey line). A straight line is then fitted to the linear portion of the power curve and extended until it intercepts the *y* axis (dashed grey line). From this intercept a horizontal line is drawn across to the previously created power curve then vertically to the *x* axis (dash-dot black line). This *x* axis value is the suggested cut-off frequency. While the process of residual analysis can be carried out visually as below, the formulae of the power and linear lines can be used to derive the *y* and *x* intercept values. The strength of spectral analysis is in identifying the frequency range in which the signal lies, and any noise which must be excluded, and can provide an estimate of the cut-off frequency. However, residual analysis provides a more sensitive and specific estimation of the appropriate cut-off frequency. The purpose of this investigation was to determine the appropriate cut-off frequency for use when filtering the data collected from throwers throughout this thesis.
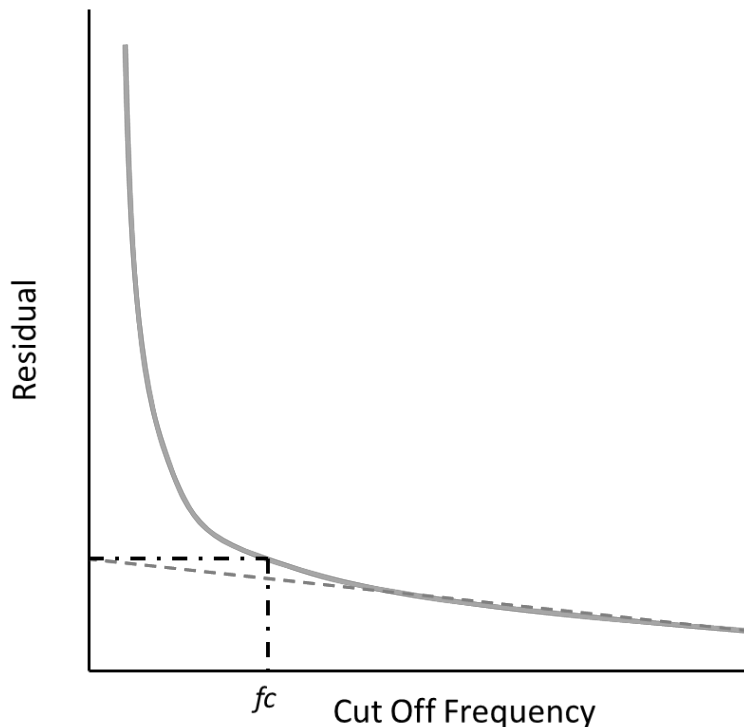

Figure 9.1. Residual analysis (fc = chosen cut-off frequency).

9.8.2 Method

Wrist and finger marker trajectories in three planes of movement (9 variables per trial) were analysed to determine cut-off frequency. These markers were chosen as they achieve the greatest velocity during the tested movement and therefore exhibit the greatest frequency. All data from each trial of each participant (5400 individual variables) were plotted in the frequency domain. A line representing the average frequency trace was then plotted over the composite plot. Residual analyses were then conducted on the same set of data. These were carried out using different numbers of cut-off frequencies ranging from 6 to 30 (6, 12, 18, 24 and 30). Goodness of fit of the power curve was determined by calculating r^2. For each variable a linear fit was applied to all plotted points (cut-off frequency vs. residual sum of squares) then consecutively to all points minus the first, second etc. (*n, n-1, n-2…..n-(n-1)*). The formulas of these lines were then used to determine the *y* intercept of that line. This *y* intercept was then inserted into the equation for the power curve to determine the corresponding *x* value which represented the estimated cut-off frequency. The estimated cut-off frequencies were then averaged across all trials of all participants. Testing *n* cut-off frequencies results in *n-1* cut-off frequency estimates. The goodness of each linear fit (r^2) was calculated to determine the point at which the values displayed acceptable linearity and aid in determining the correct cut-off frequency estimate to use. This was also averaged across all trials and participants. It was determined from the results of analyses conducted that including too many frequencies in a residual analysis falsely inflates the calculated cut-off frequencies with many frequencies exceeding the data capture frequency. As such it was decided to use cut-off frequencies estimated from an analysis that included 12 different cut-off frequencies.

9.8.3 Results

The mean r^2 (95% CI) value for all power curve fitments was 0.995 (± <0.001) suggesting

acceptable goodness of fit across all participants and trials. Figure 9.2 shows the frequency

spectrum trace of all trials for all participants. This figure illustrates the clustering of the frequency

content close to zero. Figure 9.3 is an enlarged section of the traces with the mean trace overlaid.

This clearly indicates that the vast majority of frequency content exists in the 0 – 20 Hz range.

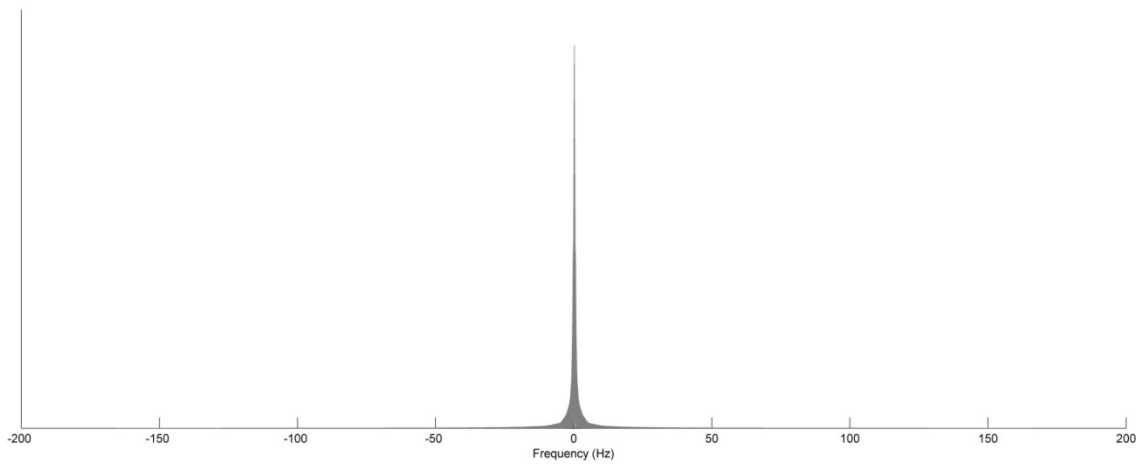There was no evidence of any frequency clusters outside this range.

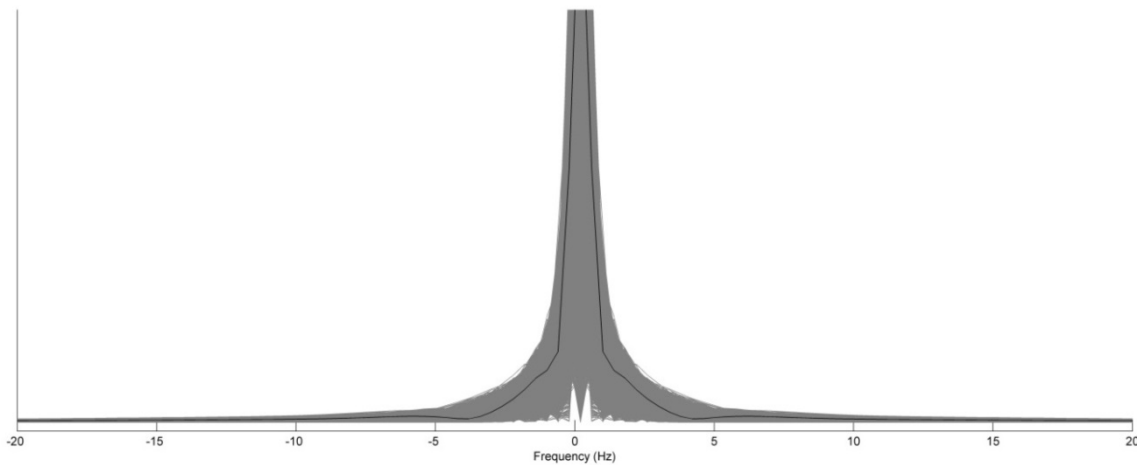*Figure 9.2. Results of frequency spectrum analysis.*

Figure 9.3. Enlarged results of frequency spectrum analysis with mean curve (solid black line).

The residual analysis results supported that of the frequency spectrum analysis and

provided a more specific estimation of an appropriate cut-off frequency. The mean estimated cut-

off frequencies and the corresponding r^2 values of the linear regression line used to calculate that

frequency can be seen in Table 9.2.

Table 9.2.
Points per line used to estimate linear portion of the power curve, goodness of fit and resulting
estimated cut-off frequency.

Points per Line	Goodness of Fit (r^2)	Cut-off Frequency (Hz)
12	0.291	1.654
11	0.362	2.751
10	0.407	4.091
9	0.462	5.904
8	0.511	8.307
7	0.526	11.613
6	0.719	19.221
5	0.824	27.485
4	0.903	36.409
3	0.961	46.171
2	1.000	56.758

While using a line derived from the last two points of the residual vs. cut-off frequency curve will obviously produce perfect linearity ($r^2 = 1.000$), it also tends to overestimate the appropriate cut-off frequency. As such it is important to balance the desire for linearity with realistic resultant cut-off frequency values. For the purpose of this investigation an r^2 value of greater than 0.5 was considered to represent acceptable linearity of the line used to estimate cut-off frequency. This corresponds to a correlation coefficient of greater than 0.7 for the relationship between actual and calculated values from the linear regression which is considered a large effect (Cohen, 1992). This linearity is demonstrated in Figure 9.4. From the results of the current residual analysis there are three values, corresponding to eight, seven and six points per line, that appear as possibly appropriate cut-off frequencies while being derived from lines displaying appropriate linearity ($r^2 > 0.5$). Keeping in mind the results from the frequency spectrum analysis (Figure 9.3) it can be suggested that the value derived from a line taken from the final 7 points (Figure 9.4) of the curve provided the most appropriate estimate of cut-off frequency (11.613 Hz). As such it has been decided to employ a cut-off frequency of 12 Hz for all low pass filtering of kinematic data during the course of this investigation.
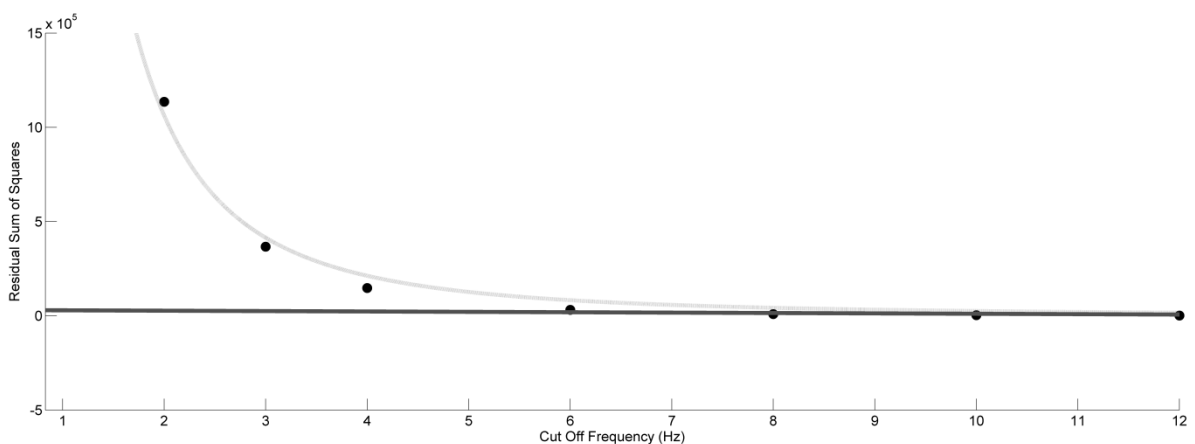

Figure 9.4.Example of the residual analysis resulting in adoption of a 12 Hz cut-off frequency. The black represents the linear regression of the final 7 points in the residual analysis. The y-intercept of this line was used in the calculation of the cut-off frequency estimate (11.613 Hz).

9.9 Handedness questionnaire

The Edinburgh Handedness Inventory (Oldfield, 1971) was formatted into an online form which each participant completed before attending their first training session for Study 4. Custom formulas in the results sheet automatically determined the handedness of the individual.

Throwing Training Participant Questionnaire

*Required

First Name *

[   ]

Surname *

[   ]

Date of birth *

DD/MM/YYYY

[|]

Sex *

[▼]

Were you one of twins or triplets at birth or were you single born?

[▼]

Have you competed in a sport requiring single hand throwing for accuracy (e.g. cricket, baseball, softball) in the last 5 years? *

[▼]

If you answered yes to the above question, which sport have you participated in, for how many full seasons, with how many training sessions per week?

For example; Cricket. 3 seasons. 1 Session per week.

[   ]

Please indicate which hand you habitually use for each of the following activities by selecting either Right, Left or Either.

Please indicate which hand you habitually use for each of the following activities by selecting either Right, Left or Either.

Which hand do you use to write a letter legibly? *

[▼]

Which hand do you use to throw a ball to hit a target? *

[▼]

Which hand do you use to hold a racket in tennis, squash or badminton? *

[▼]

Which hand do you use to hold a match whilst striking it? *

[▼]

Which hand do you use to cut with scissors? *

[▼]

Which hand do you use to guide a thread through the eye of a needle (or guide needle on to thread)? *

[▼]

Which hand do you use at the top of a broom while sweeping? *

[▼]

Which hand do you use at the top of a shovel when moving sand? *

[▼]

Which hand do you use to deal playing cards? *

[▼]

Which hand do you use to hammer a nail into wood? *

[▼]

Which hand do you use to hold a toothbrush while cleaning your teeth? *

[▼]

Which hand do you use to unscrew the lid of a jar? *

[dropdown ▾]

If you use the right hand for all of these actions, are there any one-handed actions for which you use the left hand? Please record them here.

[text box]

If you use the left hand for all of these actions, are there any one-handed actions for which you use the right hand? Please record them here.

[text box]

[Submit]

Never submit passwords through Google Forms.

9.10 MATLAB code for surrogate technique

```matlab
function [z,breakcounts]=newbowlPT_ncc(x,n,rho)

%Inputs:
%x - an array of k d-dimensional time series (of variable length)
%n - number of surrogate time series to be constructed
%rho - a constant used to determine the number of short segments in the
%created surrogates. For further infomration on the selection of rho see
% Taylor, P. G., Small, M., Lee, K.-Y., Landeo, R., O'Meara, D. M., &
% Millett, E. L. (in press). A surrogate technique for investigating
% deterministic dynamics in discrete human movement. Motor Control.
% doi:10.1123/mc.2015-0043
% and
% Small, M., Yu, D., & Harrison, R. G. (2001). Surrogate test for
% pseudoperiodic time series data. Physical Review Letters, 87(18),
188101.
% doi:10.1103/physrevlett.87.188101

%Outputs:
%z - surrogate time series
%breakcounts - number of small segments created during the generation of
%each of the n surrogates


% Given a cell array x of k d-dimensional time series (of variable
length)
% construct n surrogate time series by:
% choosing one of the k initial conditions in x, iterating forward (with
% random perturbations dictated by rho until reaching one of the final
% conditions of x

na=nargin;

if na<3,
    rho=[];
    if na<2,
        n=1;
    end;
end;

if isempty(rho),
    rho=1;
end;

for i=1:length(x); %collate lengths of original data trials
    lengths(i)=length(x{i});
end

a=ceil(mean(lengths)+std(lengths)); %create max acceptable surrogate
length
b=floor(mean(lengths)-std(lengths)); %create min acceptable surrogate
length
```

```
S1=[]; %list of current states
S2=[]; %list of next states
ic=[]; %iniitial conditions
en=[]; %final states

nx=length(x);
for i=1:nx, %populate S2, S2, ic and en from cell array
    xi=x{i};
    S1=[S1 xi(1:(end-1),:)'];   %concatenate 1st through 2nd last value
of x{i} into a single column vector
    S2=[S2 xi(2:end,:)'];        %concatenate 2nd through last value of
x{i} into a single column vector
    ic=[ic xi(1,:)'];            %results in a d by k row vector of
initial values of each ith trial
    en=[en length(S1)];          %results in a d by k row vector
containing the index of the ith trial endpoints in S1
end;

[d,ns]=size(S1);    %number of rows (d) and columns (ns) in the S1 vector

for i=1:n, % n surrogates
    loopcount=0;
    zi=[]; %ith surrogate created

    while length(zi)>a || length(zi)<b
        zi=ic(:,floor(rand*nx)+1); %choose a random initial condition
value from ic
        endpoint=0;
        xt=zi;
        breakcount=0;
        ti0=0; ti1=ti0; ti2=ti1;

        while ~endpoint,
            xt=xt+randn(d,1)*rho;  %add noise to the initial condition
            ti=findclosest(S1,xt); %find nearest neighbour to noisy state
            xt=S2(:,ti); %next state of noisy neighbour
            zi=[zi xt];
            endpoint=isendpoint(en,ti); %is the current time index (ti)
one of the endpoints of the original data

            ti0=ti1;
            ti1=ti2;
            ti2=ti;

            if ti0==0
                breakcount=breakcount+0;
                elseif ti1==ti0+1 && ti2~=ti1+1
                breakcount=breakcount+1;
            end

        loopcount=loopcount+1;
        %disp(num2str(loopcount))
        %uncomment the above line if you want a display of the number of
        %rejected surogates
```

```matlab
        end

        if length(zi)<=a || length(zi)>=b
            breakcounts(i)=breakcount;
        end
    end

    z{i}=zi;
end;


function ti=findclosest(S,x)

[ds,ns]=size(S); %number of rows (d) and columns (ns) in the S1 vector
d=rms(S-x*ones(1,ns)); %root mean square of difference beteen the initial
value with noise added (xt) from every value of S1
[~,ti]=min(d); %ti is the min rms value and the time index of the nearest
noisy neighbour

function b=isendpoint(en,ti)
ti;
b=any(ti==en);

function d=rms(x)

d=sqrt(mean(x.^2));
```