THE VALIDATION OF BIOMECHANICAL METHODS FOR AGEING AND SEX: FORCE STEADINESS AND BODY SEGMENT INERTIAL PARAMETERS

A thesis submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy in Biomechanics

by

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The thesis of Sarah Forrest is approved.
This thesis is dedicated to Mr. Toby Trugeon-Smith. Coach, taxi driver, ear, shoulder, flatmate and above all a true friend.
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Abstract of the Thesis

The Validation of Biomechanical Methods for Ageing and Sex: Force Steadiness and Body Segment Inertial Parameters

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One of the aims of this body of work was to validate different data collection and modelling techniques on older adults and females. Part I also investigates the differences in the structure of isometric force signal between elderly and younger adults and the consequences of these differences. Part II was aimed at validating a new geometric model in order to determine body segment inertial parameters of females.

Part I

Study 1: Effect of Sample Frequency and Filter Frequency on the Approximate Entropy Values for Isometric Force Records

ApEn has been used to quantify signal complexity in isometric contractions and distinguish between patient groups. Sampling frequencies, ‘r’ values (a parameter needed in the ApEn algorithm which essentially accounts for the noise in the signal (Pincus 1991) and filters may affect signal characteristics reflected in an alteration in ApEn values and subsequent patterns of results. However, there is little standardisation of such procedures for this measure. While the ‘true’ ApEn value cannot be known the
approach taken here was to start with the highest resolution signal and to identify the pattern of ApEn results across different percentages of maximum voluntary contraction and then assess the effect of the post-processing changes on this pattern. Isometric contractions of the first dorsal interosseus for 10 seconds at 5, 10, 25, 50, and 75% of maximum voluntary contraction (MVC) were collected at 1200 Hz. Signals were post processed to determine the effect of different filter cutoff frequencies, ‘r’ values, sample rates (by resampling) and lengths of data series. Resampling of the data changed the pattern of ApEn results across the percentages of MVC range dramatically, whereas shortening the length of the time series had no effect on this pattern. This suggests that it is the sample rate but not the number of samples that affects the pattern of ApEn results across the percentages of MVC range. ‘r’ values representing the noise in the signal that were scaled using the SD of each force record flattened the pattern of ApEn values across the percentage of MVC range, whereas ‘r’ values derived from the transducer noise led to a generally monotonic trend across the %MVC range. The filter cutoff frequency did not alter the pattern of ApEn values across effort levels, though frequencies in the signal above 20 Hz were found during spectral analysis that may well be biological in origin. The results show the choice of sample rate and ‘r’ is critical in reliably determining changes in ApEn with effort level. It is suggested that ‘r’ used should be, if possible, a measured estimate of noise, sample rates should be at least 600 Hz and filter cut-offs should not be lower than 40 Hz.

Study 2: Effect of Bimodal Stimulus on Force Control of Elderly and Young Adults

Research shows that elderly adults often exhibit reduced irregularity in force signal data during isometric contractions (e.g. Sosnoff and Newell (2006c). Previous findings revealed that the post-processing of data effects Approximate Entropy (ApEn) values, used to measure the regularity of the force signal. The purpose of the present study was
to examine magnitude of variability (SD, CV, RMSE) and structure of isometric force data using appropriate post-processing methods previously identified. It was hypothesised that in-line with much of the literature there would be differences between young and elderly adults’ force output. Differences in structure of force output between elderly and young adults may be as a result of elderly adults having reduced visuomotor processing capabilities, to assess this, target feedback was provided in the form of three different types of stimuli: 1) audio 2) both audio and visual (bimodal) 3) visual. The audio stimulus changed pitch depending on whether the force trajectory was too high or low and was silenced when force level was correct. This was included with the visual target (on-screen target trajectory) during the bimodal trial. Audio stimulus was used in order to gain more information as to whether differences between elderly and young adults are due to visuomotor processing differences. Young (18-25) and elderly (65-72) neurologically healthy adults produced isometric force contractions using abduction of the FDI at six force levels (5, 10, 25, 40, 50 and 75% MVC) during each of the three conditions. There were no differences found in magnitudes of variability between the age groups nor was there any alteration in force output in the bimodal condition compared to the visual condition for either groups. The audio condition altered all indexes of force structure and variability significantly. ApEn values were significantly higher in younger adults at force levels >25% MVC during all conditions indicating higher irregularity than elderly adults (mean across all conditions and force: elderly = 0.15, SD 0.11, young = 0.19, SD 0.13). In contrast with younger subjects, elderly adults exhibited a higher percentage of relative power in the 0-0.5 Hz frequency bands and exhibited limited alteration in the percentage power in the 0-4 Hz bands with change of force requirement or condition. This suggests differences in processing and behaviour between the two groups, but as there are still differences in audio condition it suggests that the differences in processing are not related to visual processing alone. This research has introduced a novel audio technique
in order to compare groups without visual processing contribution. These results support the postulation that reduced complexity occurs with ageing. As the force signal is more pattern like it may result in a reduced ability to alter force production when required leading to a lower level of functionality.

Study 3: Decreased ApEn values in older adults are associated with increased time to achieve steady muscle force following a change in required force.

Previous findings indicate that elderly adults exhibit reduced irregularity in the force signal compared to young adults when completing an isometric force matching task. Functional significance of lower ApEn values is investigated as reduced irregularity is considered to result in less adaptability (Lipsitz and Goldberger 1992). It was hypothesised that lower ApEn values would be associated with a reduced ability to adapt to a required force change. ApEn of the force signal, functional reaction time, and time to reach a steady state at the new force target was measured. Two different types of stimulus were presented to participants as force targets, bimodal and visual. The audio stimulus in the bimodal task changed pitch depending on whether the force trajectory was too high or low and was silenced when force level was correct. Audio stimulus was used in order to gain more information as to whether differences between elderly and young adults are due to visuomotor processing differences. Young (18-25) and elderly (65-72) neurologically healthy adults produced isometric force contractions using abduction of the FDI at six force levels that either increased, or decreased at a random interval. Increasing force levels were 5 to 25%, 25 to 50% and 25 to 75% of MVC and decreasing force levels were 25 to 5%, 50 to 25% and 75 to 25% of MVC. Each force level was attempted in random order under both visual and bimodal conditions. Results were compared with data collected from a continuous force task under the same conditions. There were no differences found in magnitudes of variability between the age groups nor was there any significant difference in findings during the
bimodal condition compared to the visual condition for either group. Confirming previous findings, ApEn values were higher in younger adults at force levels >25% MVC during both conditions indicating higher irregularity. However, elderly adults displayed increased ApEn values compared to the continuous force trial which suggests that they are able to increase irregularity in force output during certain tasks. Confirming our hypothesis, elderly adults exhibited longer times to reach steady state, even after removal of reaction time at force levels initiated above 5% MVC. Mean time to reach steady state (minus reaction time) was 2.83 s for young subjects and 3.23 s for elderly adults [t=2.14, p=0.03]. These results did not depend on whether the force target moved up or down. These results provide evidence to support the concept that reduced irregularity leads to decreased adaptability to task alterations. This knowledge may be beneficial when modelling ageing movement and force production or used as a pre-clinical tool for identifying those at risk of falls etc.

Part II

Study 4: The determination of Body Segment Inertial Parameters of young female club level athletes

Body segment inertial parameters (BSIPs) must be determined prior to performing any biomechanical analyses. Geometric BSIP models are cost effective, yet collecting the anthropometric data necessary is time consuming and time with athletes is often limited. Also, few anthropometric models have been validated for female athletes. Previous work suggested that modelling limb segments as two instead of four truncated cones per segment produces a negligible difference in predicted segment mass (Forrest 2008) yet whole body volume was overestimated due to inadequate modelling of the trunk segment. The present study aimed to confirm earlier findings using a refined trunk segment model. Thirty females provided written informed consent. A total of 118 anthropometric measurements were taken from each participant. The upper arms,
forearms, hands, thighs, shank and feet were each modelled using four shapes per segment in the full model, and two shapes per segment in the reduced model. The trunk segment was modelled as a series of ten stadium solids in both models. Further refinements of the present model addressed the shoulder area reducing overlap of trunk and upper arm segments. The geometric model predicted segment volume and which was multiplied by cadaver derived density functions (Clauser et al. 1969) to determine segment mass. The root mean square error between actual Whole Body Volumes (WBV), determined using a hydrostatic weighing tank, and predicted WBV was 2.37%, 3.03% and 2.34% of WBV for the full, reduced and basic models respectively. Although the basic model produced the lowest WBV and whole body mass errors, the model had lower correlation than the full model with DXA derived segment masses and as a result is likely to be not such a good BSIP predictor. The model predicted trunk mass with RMSE of just 3.49% of segment mass compared to DXA measured trunk mass. Pearson's correlation showed high correlation between the segment masses predicted by the full model and DXA measured mass \( r \) values ranged from 0.727-0.893, \( p<0.001 \) for the upper arms, forearms, thighs, shanks and feet. The full and reduced model showed high correlation for all segments \( [\text{mean } r=0.9100, \ p<0.001] \) which confirms that reducing the number of anthropometric measurements taken from the limb segments (reducing required measures from 118 measures to 94) causes little difference in the predicted mass for limb segments. These results are of interest to sports biomechanists who are without access to direct imaging techniques, but who wish to compute subject specific BSIPs.
CHAPTER 1

REVIEW OF LITERATURE

1.1 FRACTALS IN PHYSIOLOGICAL SYSTEMS

Physiological systems are highly complex in nature. The integration of multiple control mechanisms allows individuals to adapt to everyday life and the unpredictable changes that occur. These adaptations are only possible when a system is functioning appropriately. When physiological data such as force data or heartbeat activity are displayed as a function of time they take on a fractal like appearance (Mandelbrot 1982; Goldberger and West 1987; Bassingthwaighte et al. 1994). That is, that each data set is self-similar under varying degrees of magnification with each smaller part replicating the structure of the whole (Barnsley 1988; Bassingthwaighte et al. 1994).

Fractal structures owe much of their functionality to their architecture; or more importantly, their dimension. Unlike a smooth line, which can be easily measured with a standard measuring tool, a fractal structure's length will increase concomitantly with increased magnification of the structure. Hence, the length of a fractal is difficult to define (Bassingthwaighte et al. 1994). This was demonstrated by Perkal (1966) when measuring the contours of a coastline with a surveyor's wheel with varying diameters, as the diameter of the circle decreased, the length of the coast appeared to increase. Therefore classic definitions of length are not used to characterise fractal structures. Instead, mathematicians attempt to quantify the fractal dimension of the structure by
determining how densely a fractal occupies the metric space it fills (Barnsley 1988). As opposed to lines, planes and solids which occupy one, two and three dimensions respectively, structures such as tree branches and rugged coastlines, display a fractal dimension which exceeds its topological dimension (Mandelbrot 1982). For example, a fractal curve will have a fractal dimension larger than one but smaller than two; the larger the fractal dimension, the greater the chance the fractal occupies a given region of space (West and Goldberger 1987).

Having a high fractal dimension increases surface area of a structure and is highly beneficial to many biological systems and their functionality. For example, the branched structure of trees increases the contact between the atmosphere and chlorophyll to perform photosynthesis (Escós et al. 1995). Likewise pulmonary arterial, pulmonary venous and bronchial alveolar networks are fractal-like, which facilitates gaseous exchange at the respiratory surface of the human lung (Goldberger and West 1987). Whether to aid in distribution/collection processes, absorption or information processing, it is clear that fractal structures play an important role in the human physiological system. The self-similar structures upon magnification produce a robust system that is more resistant to injury or stressors; a consequence of the natural irregularity or ‘chaotic’ structure they exhibit (Lipsitz and Goldberger 1992; Goldberger et al. 2002a,b).

1.1.1 Fractals And Chaos Theory

The study of fractals is closely related to the concept of chaos theory, which is now considered to be rooted in the discipline of non-linear dynamics. In the last few decades interest in the area of non-linear dynamics and its application in scientific fields
such as physics and biology have increased. Within these fields the focus has shifted toward the study of what was previously considered ‘noise’ or ‘randomness’ in an attempt to predict the complexity or predictability of a systems structure (Thietart and Forgues 1995). Within the field of non-linear dynamics the term ‘Chaos’ describes a system whose output is so highly complex that it appears to be completely random. However, contrary to its colloquial connotation, chaos in non-linear dynamics has a level of regularity which is deterministic in nature but that is highly dependent on its variables (Bassingthwaighte et al. 1994). When a system is deemed chaotic, an alteration in an element of the system will bring about a change in the behaviour. However, the impact this alteration has on the outcome is only predictable for a brief amount of time, making the ability to predict the long term outcomes impossible (Thietart and Forgues 1995). As such, a chaotic time series though appearing self-similar in nature, never repeats itself exactly (Lorenz 1963).

A key feature of fractal geometry within biology is the characteristic of a long-range order or correlation (Goldberger et al. 2002a). It is the emergence of this self-similar or fractal like structure that has led to the study of fractal behaviour and analysis. The goal of fractal analysis is to determine whether or not experimental data contains self-similar features, and if so, applying methods that quantify the disorder of the system (Bassingthwaighte et al. 1994). It has been suggested that physiological time series data contains underlying information that could be crucial to our understanding of control mechanisms (Goldberger et al. 2002a). This has led to an increase in applying statistical concepts and techniques to quantify the complexity of physiological systems. There have been many techniques used in order to determine the complexity of a system, many of which are rooted in the study area of Information Theory and Entropy (Pincus 1991; Shannon and Weaver 1998). In an attempt to increase our understanding of the deterministic and stochastic properties that influence the system, the
aim is to be able to quantify in a single value a ‘description’ of the information content (Vaillancourt and Newell 2002; Bollt et al. 2009).

1.1.2 Power-Law Scaling And Fractals

Using non-linear methods to assess an objects self-similarity is possible by taking a section of the object and re-scaling or magnifying it to the same size as the original object (Peng et al. 2000). Self similarity implies that there is a scaling relationship which can be determined by comparison of the probability distribution of the original to the re-scaled process (Peng et al. 2000). The term used to define this is ‘power-law scaling’, which is expressed in (1.1) (where $A$ is the Amplitude, $f$ is the Frequency).

The slope of the log-log relationship ($\beta$) can be used to assess the self-similarity or long-range correlation of the process. The higher the self-similarity, the closer the $\beta$ value will be to 1. White noise or a process that is completely random will be characterised by a $\beta$ value equal to 0 (Lipsitz 2002). As a result of long-range correlations present in the signal, it is characteristic of fractal like processes to have strong power-law relationships (Bassingthwaighte et al. 1994; Addison 1997).

$$A \propto 1/f^\beta$$

(1.1)

1.2 Complexity And Ageing

The notion that regularity is a healthy condition has been long standing in medicine. Conceptualised by Bernard (1878), homeostasis was based around the theory that in order to maintain a healthy condition, the body’s internal environment must remain relatively constant. Homeostasis (though it has no physical or theoretical foundation)
Yates 2008) had long been considered the ‘optimum’ temporal state for the healthy body. Consequently, it was thought that illness or disease was a result of bifurcations causing erratic responses away from the periodic physiological rhythm. On the contrary, it is now known that healthy physiological mechanics, generate self-sustained oscillations that exhibit both periodic and aperiodic dynamics (Mackey and Heiden 1984; Mackey and Milton 1987; Milton and Black 1995). Healthy function and maintaining the capacity to adapt or respond to perturbations, is a result of multiple electrical, chemical and mechanical components of the physiological system working in synergy (Lipsitz 2004). This description of the temporal structure of living systems, perhaps better described by the term ‘homeodynamics’ (Yates 1994; Lloyd et al. 2001; Yates 2008), is not a new concept. Early investigators such as Richet et al. (1900) and Cannon (1929) comment on the necessity for the body to be “modifiable” and “excitable” in order for it to be able to maintain stable function [In: Cannon, 1929].

Many of the pathological changes that occur due to illness or disease have been associated with a characteristic loss in structural complexity (Kaplan et al. 1991; Hausdorff et al. 1997; Janssens et al. 1999; Goldberger et al. 2002a). For example, though a healthy heart rate is often described as being regular; analysis of heart rate dynamics shows that healthy heart rates fluctuate considerably (Goldberger et al. 1988; Lipsitz and Goldberger 1992; Iyengar et al. 1996; Goldberger et al. 2002a). At the onset of disease, system dynamics such as heart rate variability, have been shown to break down and become more regular, resulting in maladaptive responses to perturbations (Goldberger et al. 1990; Lipsitz and Goldberger 1992; Iyengar et al. 1996; Lipsitz 2002). In fact, some pathological systems demonstrate such extreme periodicity that frequency characteristics similar to those of sinusoidal waves are present in their output (Goldberger et al. 1988; Saul et al. 1988). As a result of such findings, the onset of disease or illness is now considered by some to be a result of a breakdown in the system dy-
amics; and possibly increased periodicity (Goldberger et al. 1990). This has lead to the more recent view that the more chaotic the nature of a physiological system, the more capable it will be to adapt to the onset of stressors. Fractal like, aperiodic system output, is now considered to increase the adaptability of a system (West and Goldberger 1987). Therefore a reduction in fractal architecture, may lead to highly periodic behaviour that is ‘stuck’ in a pattern, resulting in a pathophysiological loss in the ability to adapt to internal or external perturbations (Lipsitz and Goldberger 1992; Yang et al. 1995; Iyengar et al. 1996; Goldberger et al. 2002a; Lipsitz 2002, 2004). Consequently ‘dynamic simplification’ is now considered to be a causal factor or symptom, of loss in dynamic range of physiological function and a decreased ability to perform a range of adaptive responses (Lipsitz and Goldberger 1992; Yang et al. 1995; Lipsitz 2002).

1.2.1 Decreased Complexity With Ageing

As well as disease, normal ageing processes often result in a reduction in the quality of motor activity and output (Kamen et al. 1995; Hausdorff et al. 1997; Christou and Tracy 2005). Similarly to the onset of disease, ageing is often accompanied by a reduction in system complexity (or increase in system regularity) (Goldberger et al. 2002a). Cardiovascular dynamics, human gait dynamics and anatomical structures have all been shown to display lower levels of complexity with ageing (Kaplan et al. 1991; Hausdorff et al. 1997; Janssens et al. 1999; Fukusaki and Kawakubo 2000). For example, cardiac dynamics display a narrowing in heart rate variability over a 24 hour period with increased ageing (Bigger et al. 1993; Tsuji et al. 1996; Umetani et al. 1998) and elderly subjects also display a lower level of fractal scaling of interbeat interval fluctuations (Iyengar et al. 1996). Examples of the decline in complexity of anatomical structures with ageing include degeneration of trabecular bone architecture and
an increase in alveolar dilatation (Mosekilde 1988; Janssens et al. 1999). Consistent with proposals by Lipsitz and Goldberger (1992), the implications of these changes in structural parameters are negative, resulting in a reduction in bone strength and reduced capacity for gas exchange at the lung (Mosekilde 1988; Janssens et al. 1999).

1.2.2 Increased Complexity With Ageing

Though there is evidence in the literature to support degeneration of system complexity with ageing (Lipsitz and Goldberger 1992; Goldberger et al. 2002a) the evidence is not conclusive. It appears that a reduction in complexity, as theorised by Lipsitz and Goldberger (1992), is not always characteristic of ageing or diseased systems. It is suggested that instead, there may be an increase in complexity of some systems depending on the nature and dynamics of the task requirement (Vaillancourt and Russell 2002; Vaillancourt and Newell 2003). This is demonstrated by increased complexity indexes (Approximate Entropy (ApEn), Detrended Fluctuation Analysis (DFA), etc) displayed during a tracking isometric force abduction task by elderly and older-elderly adults compared to young adults (Vaillancourt and Russell 2002). To support the theory that changes in complexity with ageing or disease are non-uniform in nature, Vaillancourt and Russell (2002) highlight studies on gait cycle of Huntingtons patients (Hausdorff et al. 1997) where diseased and elderly patients displayed higher levels of complexity in signal structure than younger adults, reflected in DFA log-log slopes (α) closer to 0.5 (an index of high complexity) (α = 0.6 for Huntingtons; α = 0.68 for elderly; α = 0.87 for young). However, a breakdown in long-range correlations in the same data supports the loss of complexity with disease theory (Hausdorff et al. 1997; Goldberger et al. 2002a). An alternative concept to support an increase in complexity with ageing, is the suggestion that reduction in complexity displayed at output is due to an increase
in mutations at the molecular level (Kirkwood 2002, 2005). Consequently, a decrease in complexity at the behavioural level, may be due to initial increases in complexity at primary levels caused by ageing and disease (Kirkwood 2002).

1.2.3 Overview Of Ageing And Complexity

Though there is evidence to suggest that there is a breakdown in complexity of systems with ageing (Lipsitz and Goldberger 1992; Goldberger et al. 2002a), the concept is not supported by all (Kirkwood 2002; Thaler 2002; Vaillancourt and Russell 2002). Without a complete understanding of the physiological changes and consequences of ageing, it is impossible to generalise whether ageing results in an increase or decrease in complexity of a system. The discrepancies in research may be down to indexes of complexity chosen, the task, the physiological process in question, or the population tested. In order to qualify for participation in research, elderly subjects often have to be devoid of degenerative diseases. Perhaps these elderly participants do not reflect the general aged population due to their unusually healthy physiological condition. It is possible that ageing may lead to both an increase and decrease in complexity at varying physiological and behavioural levels. Therefore attempting to blanket such complex mechanisms with one rule may be inappropriate. However, the information derived from the complexity and structure is generally agreed to inform an understanding of changes in regularity processes with ageing and disease.
1.3 METHODS FOR QUANTIFYING REGULARITY, STRUCTURE AND MAGNITUDE OF VARIABILITY

There are many methods with which to analyse isometric force data in order to try to quantify and compare structural properties. Though those described within this section are by no means definitive, they are commonly used in investigations into force steadiness. Each method analyses various components of the force signal; consequently in an attempt to gain a more conclusive picture of the signal structure, it is recommended that a combination of methods should be used when analysing time series data (Lipsitz and Goldberger 1992)

1.3.1 Standard Deviation And Coefficient Of Variation

The quantification of the variability of force fluctuations is generally determined in literature by the use of the Standard Deviation (SD) of the force signal, or in relative terms as the Coefficient of Variation (CV) of the signal (Laidlaw et al. 2000; Christou and Carlton 2001; Enoka 2002; Taylor et al. 2003; Shinohara et al. 2005; Tracy 2007a; Svendsen and Madeleine 2010). However, as these statistics only measure the magnitude of the variability, other measures have been developed in order to measure the signals structural components and regularity.

1.3.2 Approximate Entropy

Approximate Entropy (ApEn) has been used as a method of analysing the structure of dynamic force data (e.g. Slifkin and Newell (1999)). ApEn is not a direct index of physiological system complexity, but a regularity statistic that can determine whether
a pattern in a signal is repeated over time (Pincus 1991; Pincus and Goldberger 1994; Goldberger et al. 2002b). This is based on the theory of calculating the entropy of a system in order to assess for randomness. Non-linear entropy, a relative to the entropy described by Shannon and Weaver (1998) within the field of Information Theory, is a measure of the quantity of information required in order to predict the future state of a system (Lipsitz and Goldberger 1992). The greater entropy of a system the more random it is and the less system order it has, resulting in lower predictability (Pincus and Goldberger 1994). Two parameters are required for the computation of ApEn; ‘m’ which is the length of the compared run and ‘r’, the parameter that is a value of the estimation or known noise in the signal (effectively a filter) (Pincus 1991). A signal with high regularity that has patterns that repeat will produce conditional probabilities close to 1, the ApEn value is given as the negative or logarithm of this calculation resulting in ApEn values closer to 0 for systems with high regularity. Conversely signals with conditional probabilities closer to 0 (those signals that are highly random in nature) will result in ApEn values closer to 2 (Pincus and Goldberger 1994). ApEn is widely used to assess regularity on physiological data as it can be utilised on both long- and medium- term data recordings, deterministic and non deterministic systems (Pincus and Goldberger 1994). One of the major benefits of the algorithm for its use on physiological data, is its capability to account for noise in the signal (Pincus and Goldberger 1994).

One of the drawbacks of ApEn is that it is dependent on its record length and tends to be biased towards presenting uniformly low ApEn values (Richman and Moorman 2000; Richman et al. 2004). Should there be no, or few, template matches in the signal of data length ‘m’, then ApEn will calculate that the regularity of the signal is of perfect order i.e., the ApEn value is 0 (Richman and Moorman 2000; Richman et al. 2004). However ApEn is still beneficial in order to establish a hierarchy of the regular-
ity of data. The consistency of the algorithm means that although values calculated do not necessarily indicate the complexity of the signal directly (Pincus and Goldberger 1994; Goldberger et al. 2002b; Chon et al. 2009), they are able to produce values that can be used to compare data sets. In effect, signal A can be compared with signal B if all the input parameters are the same; if ApEn is lower for signal A then it is more regular than signal B (Pincus and Goldberger 1994).

1.3.3 Frequency Spectra Methods: PSA And DFA

Generally there are two tools that are used to assess whether there are long range correlations present in signals, ‘spectral domain’ methods such as spectral analysis, or ‘random walk’ methods such as DFA.

Power Spectral Analysis

A signal that fluctuates about a mean, such as in isometric force data (Galganski et al. 1993; Enoka et al. 2003) is composed of several waveforms that vary in both amplitude and frequency. Performing a Power Spectral Analysis (PSA) of the signal determines the frequency components that are present within the signal. For a highly rhythmic periodic signal the frequencies present in the signal will be concentrated at a small number of discrete frequencies and display frequency peaks. For example a sine wave that is perfectly periodic, will have only one frequency component. A more random or complex signal will display a more equally distributed power across its frequency profile as a result of its broader range of frequencies (Peng et al. 2000). Consequently, a signal with a lower complexity is usually characterised by a narrow frequency spectrum. Calculating the $\beta$-exponent in the power law (plotting power Vs frequency) will produce a slope of 0 for a flat spectrum (completely random signal) and a slope of near
about 1 if fractals with long-range correlations are present in the signal (Lipsitz and Goldberger 1992; Iyengar et al. 1996).

PSA is highly influenced by nonstationaries in the signal. A time series is considered stationary if the mean, standard deviation and higher moments, as well as the correlation functions are invariant under time translation (Peng et al. 2000). If the signal does not follow these parameters then the conditions of the signal are non-stationary and may result in an unreliable scaling exponent (Iyengar et al. 1996; Peng et al. 2000). Another factor to consider when carrying out a PSA on data is the filter used. If inappropriate filtering techniques are applied to the data, the results of spectral analysis can erroneously indicate absence of long-range correlation (Rangarajan and Ding 2000). Also, it has its limitations when trying to measure complexity of a signal as it loses the time order component of the structure of the signal (Lipsitz and Goldberger 1992; Deutsch and Newell 2001; Lipsitz 2002).

**Detrended Fluctuation Analysis**

Detrended Fluctuation Analysis (DFA) is an alternative analysis method that can differentiate between erroneous detection of correlation caused by non-stationary artefacts and real long-term correlations that are present in the signal (Peng et al. 1994; Iyengar et al. 1996). Peng et al. (1994) introduced the method using a modified root mean squares analysis, in order to account for the biological properties that change over time i.e. non-stationeries. After integration and de-trending (which is carried out across all scales) self-similarity is calculated and the log-log graph indicates the level of power-law scaling (Peng et al. 1994). DFA of erratic or aperiodic fluctuations, which are often found in a number of complex control systems, generally show an inverse power-law scaling of $1/f$-like; a characteristic of fractals (Keeler and Farmer
1.4 VARIABILITY, REGULARITY AND STRUCTURE OF FORCE DATA: FIRST DORSAL INTEROSSEUS

1.4.1 Isometric Continuous Force Task

When performing an isometric contraction the sub maximal activation of motor units at the muscle causes the force to fluctuate about a mean, the magnitude of which may influence the capacity to effectively achieve a desired force level (Galganski et al. 1993; Slifkin and Newell 1999; Christou and Carlton 2002; Enoka et al. 2003; Taylor et al. 2003; Tracy et al. 2005). Being able to control muscle force is a key function of motor control and is directly related to both the ability to perform simple motor tasks and maintaining postural control (Schultz et al. 1992; Galganski et al. 1993). The ability to perform everyday tasks such as grasping, handwriting and object manipulation is likely to be hindered by a lower ability to control muscle force (Galganski et al. 1993), which may alter quality of life for aged individuals. Evaluating the signals that occur during motor output may increase our understanding of motor output organisation and the changes that occur as a result of ageing. As ageing occurs universally through our population, gaining an increased understanding of its pathophysiological consequences is undoubtedly beneficial (Kirkwood 2005).

Many research laboratories have used abduction of the First Dorsal Interosseus (FDI) to assess force variability, (Galganski et al. 1993; Slifkin and Newell 1999; Burnett et al. 2000; Laidlaw et al. 2000; Tracy and Enoka 2002; Tracy et al. 2005) one of the reasons for this is that data can be collected from the limb with relative ease. As iso-
metric contractions maintain the position of the limb, variables such as the muscle
tendon-complex length, muscle moment arm length and other unwanted biomech-
anical factors that could alter performance are reduced (Deutsch and Newell 2001).
Simple movements, such as abduction of the FDI have low mechanical processes as
there is a sole agonist and the limb can be easily restrained (Also, force recorded from
the single bipennate muscle performing the abduction can be easily recorded using
surface electrodes (Stephens and Taylor 1972)).

Studies have shown mean CV and SD to be greater in elderly subject groups when
carrying out isometric contractions using the FDI (Galganski et al. 1993; Burnett et al.
2000; Semmler et al. 2000; Tracy and Enoka 2002; Vaillancourt and Newell 2003;
Tracy et al. 2005; Marmon et al. 2011b). As target force level increases there is a
concomitant increase in the SD of force signal (Galganski et al. 1993; Slifkin and
Newell 1999; Burnett et al. 2000; Laidlaw et al. 2000; Tracy and Enoka 2002; Tracy
et al. 2005). Simultaneously, the CV of force fluctuations tends to decrease with in-
creased force level across elderly and younger subjects (Galganski et al. 1993; Laidlaw
et al. 2000; Burnett et al. 2000; Semmler et al. 2000; Vaillancourt and Newell 2003;
Tracy et al. 2005). There is a general consensus within the literature that the largest
differences in CV between elderly and younger subjects occurs at lower force levels
<20% of Maximum Voluntary Contraction (MVC) with some studies showing small
differences even up to 50% MVC (Galganski et al. 1993; Burnett et al. 2000). Gener-
ally, the highest CV of force fluctuations occur at the lowest force requirements (e.g.
2.5% or 5% of MVC) (Galganski et al. 1993; Burnett et al. 2000; Laidlaw et al. 2000;
Semmler et al. 2000; Vaillancourt and Newell 2003; Tracy et al. 2005). For example,
Galganski et al. (1993) reported that isometric force contractions of FDI at 5% MVC
had a significantly higher CV of force for both age groups compared to all other force
levels, but that elderly adults were significantly more variable than the younger adults
The evidence to support elderly adults display higher magnitudes of variability is vast, however it does not appear to be conclusive. There are discrepancies between the force levels that display significant differences between elderly and young subjects (e.g. Galganski et al. (1993); Laidlaw et al. (2000)) whereas some studies show no differences at all between the two groups (e.g. Shinohara et al. (2005)). In order to gain further information about potential differences between force data of elderly and young subjects, other techniques such as measuring the entropy of the signal, have more recently been applied to the force signal data.

The regularity of the structure of the force signal output during isometric force abdution of the first dorsal interosseus has been suggested to be represented as an inverted \textit{U} shape. This is reflected in ApEn calculations for the signal increasing with increasing percentage of MVC to a maximum at approximately 45\% MVC before declining (Slifkin and Newell 1999). This suggests that the time-domain structure of the force output is not directly related to the magnitude of variability (represented by CV and SD), as the interactions with the percentage MVC differ greatly (Galganski et al. 1993; Slifkin and Newell 1999; Burnett et al. 2000; Laidlaw et al. 2000; Semmler et al. 2000; Vaillancourt and Newell 2003; Tracy et al. 2005; Marmon et al. 2011b). This is further supported by the complexity of the signal (measured by spectral analyses) displaying proportion of power as an \textit{U}-shape pattern as a function of percentage MVC; proportion of peak power decreased with increased percentages MVC to approximately 35\% MVC and increasing again there after (Slifkin and Newell 1999). With ageing, it appears that the structure of the force signal data breaks down and displays increased regularity; thus elderly adults produce lower ApEn values than their younger counterparts (Vaillancourt and Newell 2003). This implies that there is more predictability in the force signal structure and a lower level of structural complexity; demonstrated
by a more negative DFA spectral slope (elderly subjects $\alpha = -1.9$; young subjects $\alpha = -1.3$) (Vaillancourt and Newell 2003). Overall, during isometric abduction of the FDI the pattern seems to suggest there is a breakdown in indexes of complexity and an increase in magnitude of variability as a result of ageing. However, there are suggestions that this may be task dependant (Kemell 2003).

### 1.4.2 Changes With Task

Organisation of the synaptic inputs that arise from different sources to stimulate and excite motor neurons may be highly variable depending on the motor task required (Kemell 2003). Therefore different isometric tasks performed on the same muscle group may result in different patterns of results. For example, when trying to match a sine wave path by isometric abduction, the indexes of structural complexity and regularity contrast greatly with the same subjects’ attempts at matching a constant force path (Vaillancourt and Newell 2003). Increased ApEn values, lower DFA scaling and an $\alpha$ value that is less negative have all been reported for elderly adults (Vaillancourt and Newell 2003). All of these indexes contradict the general pattern in the literature for isometric continuous force production of the FDI (Galganski et al. 1993; Burnett et al. 2000; Laidlaw et al. 2000; Semmler et al. 2000; Vaillancourt and Newell 2003; Tracy et al. 2005).

There is however, evidence that is in agreement with continuous force studies. Increased magnitude of variability correlated with ageing has been found during pinch contractions (using FDI and thumb in a holding contraction) at 5% of MVC (CVs: young = $1.4 \pm 0.4$; elderly = $2.2 \pm 0.8$) (Marmon et al. 2011b) and endpoint accuracy tasks (Christou et al. 2007). This suggests that the regularity of a signal and the
changes that occur with ageing may be task specific, even across similar contraction types.

The relevance of differences in structure of the force signal data to normal life behaviours is not clear, though correlation has been identified between CV of isometric force and the ability of elderly adults to perform functional tasks that require fine motor skills and dexterity (Marmon et al. 2011b). However, isometric contractions may not simulate more dynamic day to day tasks that require a rapid change or adjustment. Investigation of changes that occur to the force signal with ageing has therefore been carried out using anisometric tasks.

1.4.3 Contraction Type

Though motor unit recruitment order is similar when performing different isometric and slow anisometric contractions (Thomas et al. 1986; Laidlaw et al. 2000; Semmler et al. 2000; Enoka et al. 2003) recruitment thresholds vary across contraction type (Kossev 1998; Linnamo et al. 2003). This may result in differences in magnitudes of variability and fluctuations in accelerations between two tasks using different contraction types (Christou et al. 2003a). Elderly adults demonstrate less steadiness when performing slow shortening and lengthening contractions with the first dorsal interosseus; reflected by higher SD in fluctuations of acceleration (Burnett et al. 2000; Christou et al. 2003a). A lack of strong correlation in results across contraction types led Shinohara et al. (2005) to suggest that there may be a difference in the activity of the motor unit population when attempting different types of contraction, such as recruitment threshold differences or modulation of discharge rate (Tanji and Kato 1973; Kossev 1998; Laidlaw et al. 2000; Baudry et al. 2009).
1.4.4 Isometric Force Data Collected From Other Muscle Groups

Research suggesting that elderly adults display higher CV of force fluctuations during isometric abduction of the first dorsal interosseus has been discussed. However, hand muscles require a greater proportion of the motor unit pool for the same percentage MVC contraction than other limb segments (de Luca et al. 1982). This may lead to higher magnitudes of variability measured at the hand than other limb segments (Graves et al. 2000). As muscle fibre size varies minimally between muscle groups, muscle architecture is the primary determinant of mechanical function and force generation (Lieber and Friden 2000). As architecture varies considerably across muscle groups (Lieber and Friden 2000), it is feasible to theorise that muscle group may influence patterns in motor output and magnitude of variability. This idea is supported by evidence that the level of motor noise produced is related to the number of motor units at the muscle and its position in the body (Hamilton et al. 2004). If magnitude of variability is a reflection of noise in the system, muscle group studied may have an effect on the level of variability and complexity in the force signal (Enoka et al. 2003).

There is evidence that some muscle groups display magnitudes of variability in a pattern comparable to that shown at the FDI (Galganski et al. 1993; Laidlaw et al. 2000; Semmler et al. 2000; Vaillancourt and Newell 2003; Tracy et al. 2005). Forces measured at the knee joint extensors between 5% and 50% of MVC displayed increasing values of SD as force requirement increased (Tracy and Enoka 2002). Again, at low forces (2, 5 and 10% MVC) the CV of force was significantly larger in the sedentary elderly adults compared with the young adult subjects (Tracy and Enoka 2002). The largest differences in magnitude of force variability, as with many studies of the FDI
muscle, were displayed when subjects were required to match the lowest force level (2.5%). For example, in the male subject group young males had a CV of force equal to $2.3 \pm 0.56$ where as elderly males displayed a CV of force equal to $3.77 \pm 0.79$ (Tracy and Enoka 2002).

In contrast, there is a lack of correlation between increased magnitude of variability and ageing during isometric contractions, of both the elbow flexor muscles and quadriceps femoris, whilst performing continuous force tasks (Graves et al. 2000; Christou and Carlton 2001). In contrast to the continuous task, the same elderly participants had higher CV of both impulse and time to peak force for all forces except 65% and 90% MVC and 65% and 80% MVC respectively than younger subjects during discrete rapid contractions (matching a force-time parabola) (Christou and Carlton 2002). This again suggests that the requirement of the task may influence the magnitude of variability of the motor output. Evidence is also strong that the type of contraction alters the output variability at different muscle groups. Elderly subjects exhibit higher magnitudes of variability during eccentric contractions than younger subjects (Graves et al. 2000; Christou and Carlton 2002), suggesting that the ability to lengthen a muscle in a controlled manner may decline with age. The evidence across muscle groups again suggests that task, contraction type and group studies may be implemented for the lack of correlation across the literature regarding changes in complexity and variability due to ageing.

It would appear that muscle group, contraction type and task all have an influence on the magnitude of variability and the structure of a force signal. Tasks that require large muscles or more than one muscle group are associated with lesser fluctuations of force, where as tasks such as abduction of the finger which is achieved almost entirely by contraction of the first dorsal interosseus tend to display higher levels of force.
fluctuation (Graves et al. 2000; Enoka et al. 2003). There is still lack of agreement across studies, but it would appear that properties such as muscle architecture and contractile properties may have an influence on the magnitude of change in the signal caused by ageing. Other factors that need to be considered are related to use or disuse of certain limbs and movement ranges, or differences in the mechanisms that alter neuromuscular functioning at different regions of the body (Vaillancourt and Newell 2003). In conclusion it would seem wrong to suggest that there is conclusive evidence that magnitude of variability or regularity of structure either increases or decreases due to ageing. Muscle group, task and contraction type may all influence the outcome.

1.4.5 The Effect Of Training Adaptations On Force Signal Data

The role of training on the performance of motor output and its variability has been investigated using a variety of training methods. These include strength training (Keen et al. 1994; Laidlaw et al. 1999), martial arts (Christou et al. 2003b) and functional tasks, such as grooved peg board practice or rolling balls in the palm of the hand (Marmon et al. 2011b; Ranganathan et al. 2001); all of which have been shown to improve magnitude of force variability in elderly adults. Strength training using either light or heavy loads has been shown to reduce both SD and CV of force and acceleration fluctuations in both isometric and anisometric contractions in elderly adults (Keen et al. 1994; Laidlaw et al. 1999; Kornatz et al. 2005). Four weeks of training reduced CV of isometric force fluctuations at the FDI by up to 37.7% ± 6.4 after light load training (10% MVC) and 47.2% ± 6.0 after heavy load training (80% MVC) (Laidlaw et al. 1999). Similar results have been found after a 12 week heavy load training program, with maximum improvements occurring at low level isometric contractions (Keen et al. 1994). Interestingly, the younger subjects failed to produce comparable
reductions in magnitude of force variability after the same training protocol; this is despite an increase in MVC post training (Keen et al. 1994). Though there is suggestion that strength is correlated with function (Fukagawa et al. 1995; Marmon et al. 2011a) it would appear that strength does not directly affect the SD or CV (Bellew 2002). Similar to the young subjects in Keen et al. (1994), longitudinal studies have shown an increase in the strength of knee extensor muscles after training, with no concomitant reduction in force fluctuations in motor output (Bellew 2002). Supporting this is the similarity in strength that is often found during MVC of the FDI between elderly and young subjects (Christou 2011), even though there is often a contrast in force fluctuation between the two groups (Galganski et al. 1993; Burnett et al. 2000; Laidlaw et al. 2000; Semmler et al. 2000; Vaillancourt and Newell 2003; Tracy et al. 2005).

The mechanisms behind the training adaptations are not clear; whether it be strength related or possibly adaptations that cause increases in co-activation (Christou 2011). This idea is supported by research that shows strength training in the elderly increases the levels of co-activation displayed (Seidler-Dobrin and Stelmach 1998; de Boer et al. 2007). Changes in muscle activation pattern seem to be a likely reason for the reductions in magnitude of variability. Changes in timing and amplitude of the antagonist muscle is displayed after just 40 goal-directed contractions (Christou et al. 2007; Christou 2011). This results in a reduction in both trajectory and end-point variability (Christou et al. 2007; Christou 2011). These results suggest that alteration in motor output is still possible in adults, possibly through new processing strategies (Dinse 2006). Though the evidence in literature is not conclusive, training does appear to have beneficial effects on magnitude of force variability. This has positive implications for the senescent population as interventions may reverse, or encourage compensatory mechanisms to counteract the negative side effects in motor output caused by ageing.
1.5 MECHANISMS ASSOCIATED WITH FORCE VARIABILITY, IRREGULARITY AND POSSIBLE EFFECTS DUE TO AGEING

Investigators have attempted to isolate a single explanatory mechanism to account for the force fluctuations during isometric contractions. It would appear however, that not one single mechanism can account for the magnitude of variability displayed in isometric force data (Taylor et al. 2003). It is more likely to be the product of a combination of complex control mechanisms and mechanics, many of which are brought about by biophysical properties that occur due to ageing (Galganski et al. 1993; Laidlaw et al. 2000; Taylor et al. 2003).

1.5.1 Noise

In the area of study known as ‘information theory’ (Shannon and Weaver 1998), white Gaussian noise is known to corrupt information that is present in a signal. It is therefore considered a nuisance and attempts are made to minimise its presence. Though the ‘Noise’ that appears to be present in motor output does not generally have the characteristics of white noise (Newell et al. 2006), noise has often been used as a rationale for the amount of system variability and performance variability of motor processes (Jones et al. 2002; Davids et al. 2003; Hamilton et al. 2004). The concept is that noise stemming from either the central command or neuromuscular process corrupts the command signals resulting in increases in the magnitude of variability in behavioural outcome (Meyer et al. 1988; Jones et al. 2002). There may be both central and
peripheral mechanisms that contribute to the noise in the motor output (Meyer et al. 1988; Jones et al. 2002; Hamilton et al. 2004; Newell et al. 2006) but there is generally still a lack of agreement as to its exact origins or the consequence of its presence. A relatively recent consideration is that variability in a system has a functional purpose (Davids et al. 2003). From this perspective, noise in a system allows for flexibility in behaviour that could not be provided within a purely deterministic system (Riley and Turvey 2002). It is considered that noise in the system may actually be a product of deterministic and stochastic processes in the biological system. The evolution of this phenomenon is thought to allow the system to rapidly adapt and respond to demands (Riley and Turvey 2002; Davids et al. 2003). However, whether noise in a system has a positive or negative impact on its output is still not clear. Recent evidence that suggests chaotic systems are more adaptive (Lipsitz and Goldberger 1992; Lipsitz 2002, 2004) would indicate that perhaps noise in the motor system may have some positive biological role.

1.5.2 Visuomotor Impairment

The discharge behaviour of motor units can be influenced by the supraspinal (voluntary) command which in turn, can be modulated by visual information (Tracy 2007a). Visual feedback is used to modify movements that are occurring and provides information that aids error correction when performing a movement outcome or trajectory. Consequently, if vision is unavailable there is a reduction in corrective adjustments resulting in a reduction in accuracy (Slifkin et al. 2000). As elderly adults often rely more on visual information in order to complete a motor task (Seidler-Dobrin and Stelmach 1998) the steadiness of force is partly dependant on the ability to process visual feedback, correct the descending command appropriately, and minimize the fluctu-
ations (Tracy 2007a). Studies have shown that when frequency presentation is altered or visual feedback is varied during an isometric task with the FDI, impaired processing leads to altered inputs to motor neurons and reduced control of force in elderly subjects (Sosnoff and Newell 2006a,c). As a result, elderly adults may display increased magnitude of variability due to visual impairment and/or reduced processing and command capabilities.

1.5.3 Tremor

One of the characteristics of motor control is the phenomenon known as ‘Physiological Tremor’ (PT) (Bye 2010). All persons display unintentional small oscillations of the body (Elble and Koller 1990; Bye 2010), which is thought to be the product of various underlying mechanical and cortical processes (Deuschl et al. 2001). One of the mechanisms underlying PT is known as the 8-12 Hz ‘central component’ (Elble and Randall 1976; Elble and Koller 1990; Deuschl et al. 2001). When performing isometric contractions of the FDI, there is a prevalence of spectral frequency peaks at the 8-12 Hz range (Allum et al. 1978; Vallbo and Wessberg 1993; Burnett et al. 2000). Consequently, it been questioned whether tremor is the underlying cause of magnitude of force variability in isometric force data; is variability merely a description of tremor? (Burnett et al. 2000). Does an increase in magnitude of force variability with ageing reflect increases in tremor related activity? Evidence indicates that this is not the case. Firstly, differences in spectral analysis profiles suggest that the mechanisms that produce unsteadiness and PT are not one or the same (Burnett et al. 2000). Whereas increased loading causes a decrease in the frequency where the peak occurs in subjects with tremor, increased loading in steadiness experiments continues to display the 8-12 Hz frequency peak and also includes an increase in power in the 20-35 Hz (Vallbo
and Wessberg 1993; Burnett et al. 2000). As well as this, the amount of PT present at the finger has not been shown to be correlated with age Raethjen et al. (2000), and the frequency band of the output signal that alters with ageing appears to be around 0-4 Hz, not the frequency range indicative of PT (Vaillancourt and Newell 2003). This evidence suggests tremor is not a contributor to the variations in force signal caused by ageing.

1.5.4 Pattern Of Muscle Co-Activation: Agonist And Antagonist

Though both elderly and young adults display co-activation patterns it is generally agreed that elderly persons display higher-than-necessary levels of co-activation than younger persons (Burnett et al. 2000; Laidlaw et al. 2000), demonstrated during ramp contractions of the FDI (Spiegel et al. 1996). It is suggested that the reciprocal antagonist activation acts as a breaking mechanism during isometric force production in order to reduce the rate of build-up in the net force (Hogan 1984; de Luca and Mambrito 1987). The frequency peaks at 8-10 Hz, are suggested to be associated with biphasic force pulses, measured by EMG from both agonist and antagonist muscles (Vallbo and Wessberg 1993). As a result, an alternate theory to account for the increases in magnitude of force variability with ageing, is that it may be due to increases in pulsatile agonist-antagonist activation. However, the pattern of co-activation displayed by the antagonist muscle to the FDI (second palmar interosseus) during isometric contractions displays an inconsistency in firing behaviour, showing no pattern of alternation (Burnett et al. 2000; Laidlaw et al. 2000). This does suggest that it is not responsible for the consistent 8-10 Hz frequencies displayed in the motor output. Furthermore, antagonist activation increases concomitantly with force target requirement; in contrast, force variability (%CV) decreases (Burnett et al. 2000), thus indicating the two
processes are uncorrelated. Contrary to being a negative factor in motor output variability, there is suggestion that increased co-activation of the antagonist muscle may be beneficial to movement accuracy (Seidler-Dobrin and Stelmach 1998). It would therefore appear that net muscle activity of the agonist or antagonist is not the mechanism behind differences in steadiness between elderly and young subjects.

1.5.5 Reorganisation Of The Motor Unit Pool

Beyond the age of sixty there is a reduction in the number of functioning motor units at the motor-unit pool, with a continuation of the reduction as age increases (Brown 1972; Campbell et al. 1973). This leads to a reorganisation of the motor-unit pool. The surviving motor units appear to increase in cross-sectional area which has been attributed to impairment in the denervation-reinnervation cycle, resulting in wide-scale denervation of the muscle (Brown 1972; Campbell et al. 1973; Evans and Lexell 1995). It is suggested that muscle fibre hypertrophy or adoption of denervated fibres increases motor unit size as a compensatory mechanism for the reduction in functioning motor-units (Campbell et al. 1973; Stålberg and Fawcett 1982). Reinnervation may occur as a consequence of remodelling of synaptic connections at the neuromuscular junction by means of collateral sprouting from axons to motor units (Roos et al. 1997; Gordon et al. 2004). This may result in slow twitch Type I motor units reinnervating Type II muscle fibres (Kugelberg 1976; Evans and Lexell 1995; McComas 1996). In effect, the increase in motor unit size in the senescent muscle translates to more muscle fibres being innervated by fewer motor neurons thereby increasing the innervation ratio (Campbell et al. 1973). Combined with preferential Type II muscle fibre atrophy that occurs with age, the surviving muscle contraction capabilities are predominantly slow (Campbell et al. 1973; Evans and Lexell 1995; McComas 1996).
During a voluntary isometric contraction, the membrane properties and excitation characteristics of the motor-neurons cause them to discharge at rates that optimise the gradation of force generation at the muscle fibres (Kemell 1992). This normal motor-unit recruitment by order of size (Henneman 1965; Mendell and Henneman 1970; Henneman et al. 1974) is preserved in elderly adults; however, the lack of presence of smaller motor units (probably due to their degeneration) results in larger motor units being activated earlier (Galganski et al. 1993). Authors suggest that the increased force fluctuations about a mean displayed by the elderly, especially at lower force levels (Galganski et al. 1993; Burnett et al. 2000; Laidlaw et al. 2000; Semmler et al. 2000; Enoka et al. 2003; Vaillancourt and Newell 2003; Tracy et al. 2005) may be due to these larger motor units having to discharge at low rates in order to produce low force levels (Enoka et al. 2003). The un-fused tetanus profile this would produce would display large peak to peak forces (Allum et al. 1978; Galganski et al. 1993), a possible reason for higher levels of force variability. In contrast, younger subjects would produce the same relative force using smaller motor units, resulting in a lower magnitude of peak to peak forces and thus displaying less force variability (Galganski et al. 1993).

As force requirement increases for higher levels of MVC, the number of motor units that are activated increase in order to produce more muscle force. At the FDI, at force requirements over 40% of MVC few units are recruited and at 50% MVC and above all motor units have been recruited in order to achieve higher forces (de Luca et al. 1982). At force levels above 50% MVC, due to all motor units having been recruited, there may be more similarities in patterns of force fluctuations between elderly and young people as the larger motor units are excited appropriately (Galganski et al. 1993). It is also suggested that due to fewer motor units being present in the aged muscle, the fused tetanus profile may occur at lower percentages of MVC for elderly adults due
to a greater relative proportion of motor units firing (Roos et al. 1997; Connelly et al. 1999). This may account for smaller differences in variability between elderly and young subjects often displayed above 20% MVC, as the large peak to peak forces would be reduced.

Targeting reorganisation of the motor unit pool as a reason for increased magnitude of force variability with ageing seems viable; however, both computer simulations and training studies contradict the theory (Enoka et al. 2003). Simulations demonstrated that reducing the number of motor neurons whilst simultaneously increasing twitch force, results in minimal alterations in the CV of force fluctuations (Enoka et al. 2003; Taylor et al. 2003). This is supported by the effect training has on the CV of force fluctuations Keen et al. (1994). Elderly subjects (59-74 years) were able to reduce the CV of force fluctuations after a 12 week strength training program at 2.5%, 5% and 20% MVC with the lower level of 2.5% displaying the largest changes of 19.3% ± 10.2 (Keen et al. 1994). It is suggested that as the largest reductions in CV were in the first four weeks of training, the changes could not be due to muscle hypertrophy. Secondly there was no alteration in the distribution of spike-triggered average force which would alter the force tetanus profile (Keen et al. 1994). Although the concept sounds likely, the experimental evidence does suggest that motor unit pool reorganisation is not the underlying cause for the increase in CV of force fluctuations displayed by elderly adults (Keen et al. 1994; Enoka et al. 2003; Taylor et al. 2003).

1.5.6 Motor Unit Synchronization

Relative timing of motor-unit activation may influence force variability due to an increase in simultaneous activation of motor units; generally referred to as motor unit
synchronisation (Semmler et al. 2000). Synchrony of motor units is characterised by fluctuations in discharge behaviour in the 1-12 Hz and 15-30 Hz bands of neighbouring pairs of units (Halliday et al. 1999). It is suggested that synchronisation is due to the effect of neighbouring cells exciting each other by chance, or by mechanisms termed ‘common input’ (Taylor 1962; Halliday et al. 1999), the result of which causes a tremulous force production (Taylor 1962). This may account for up to 20% of acceleration fluctuations during position holding isometric tasks (Halliday et al. 1999). As well as experimental evidence, computer simulations have shown increase force fluctuations can be caused by motor unit discharge synchronisation in isometric contractions (Yao et al. 2000). It was assumed that motor-unit synchronization would increase with age and possibly be the cause for increased variability in firing rate and resulting force fluctuations (Semmler et al. 2000). However, experimental findings showed similarities in levels of motor-unit synchrony at the first dorsal interosseus between elderly and young subjects (Kamen and Roy 2000; Semmler et al. 2000). This suggests that it may not be the cause for the decrease in steadiness at low or high forces during isometric contractions attributed to ageing. Instead it appears that the level of synchrony displayed is a reflection of force requirement, as it increases with percentage of MVC (Kamen and Roy 2000).

1.5.7 Discharge Rate And Variability

As well as the motor unit recruitment and rate coding properties of the motor unit pool, the discharge rate of the motor unit has an influence on the tetanus-force profile which is considered to be a primary candidate for causing force fluctuations (Enoka 2002; Taylor et al. 2003). When there is a rapid succession in discharge of action potentials produced by a single motor neuron, the resultant twitches that occur are summated
and produce higher levels of force than each individual twitch (Kemell 2003). The magnitude of force that is produced by the motor unit varies depending on the rate at which the motor neuron discharges action potentials (Enoka 2002). Though low firing rates during voluntary contractions rarely result in a fully fused profile (Andresen and Rosenfalck 1978), the higher the discharge rate the more likely there will be a fused tetanus. Consequently, during low, steady rate discharges, recently recruited motor units produce unfused force profiles displaying peaks and troughs (Christakos 1982).

Peak discharge rates have been seen to be reduced in elderly subjects during maximal and sub-maximal contractions (Kamen et al. 1995; Barry et al. 2007). It would seem reasonable that lower rates of discharge may result in a more extreme unfused profile, resulting in more magnitude of force variability. However, it seems that the contractile speed of the aged predominantly slow-twitch muscle is reduced and relaxation rates are elongated (Connelly et al. 1999); this forms a relatively fused profile and is potentially an adaptation to enable force production at lower firing rates (Kemell 1992; Connelly et al. 1999) and essentially reduce magnitude of force variability.

Once again, the evidence that discharge rates decrease with age is not conclusive, as there is also both evidence that rates may actually increase with age (Galganski et al. 1993) or that there is no significant difference between and young adults (Laidlaw et al. 2000; Semmler et al. 2000). However, the variability of discharge rate may be an underlying factor to consider. Quantified by the CV, discharge rate variability has been shown to alter with age (Laidlaw et al. 2000; Kornatz et al. 2005; Tracy et al. 2005). It is suggested that this has a significant effect on subsequent force fluctuations during isometric contractions and this consequently limits the ability to maintain a desired force or trajectory (Laidlaw et al. 2000; Enoka et al. 2003). Moritz et al. (2005) were
able to adapt a simulated model of motor unit recruitment and rate coding developed by Fuglevand et al. (1993) to match those results seen in experimental observations. Using the adapted model, they simulated the effect of discharge rate variability on CV of force fluctuations. When altering the CV of motor unit discharge rate from 10 to 40% there was a concomitant increase in CV for simulated force fluctuations (Moritz et al. 2005). This has led to the conclusion that motor unit discharge variability is likely to be the primary cause of a reduction in force steadiness with ageing (Laidlaw et al. 2000; Enoka et al. 2003; Moritz et al. 2005).

ApEn has been utilised to analyse single motor unit discharge patterns (Vaillancourt and Newell 2003). ApEn increased with increasing discharge rate, showing the irregularity of discharge pattern increases with increased discharge rate of the motor unit (Vaillancourt and Newell 2003). However, no difference in ApEn values between age groups was found suggesting that the regularity of the discharge pattern of motor units does not alter with age. This is in agreement with studies that report no difference in magnitude of discharge rate variability between elderly and younger subjects (Vaillancourt and Newell 2003; Barry et al. 2007). In addition, at low forces (2.5% MVC and 5% MVC) the CV of discharge rate is lower in elderly adults compared to younger adults despite higher fluctuations in force displayed by the elderly subjects (Semmler et al. 2000). Therefore though significant differences were displayed in CV of force exerted by the FDI, this was not concurrent with differences in CV of discharge rate.

One of the fundamental problems when studying motor unit behaviour is that at high forces it is difficult to discriminate between the discharge patterns of individual motor units (Roos et al. 1997). Due to practicalities, only a few motor units can be studied at a time and this leads to a generalisation and assumption that the behaviour of a few units is representative of the whole motor unit population (Barry et al. 2007). Conflict-
ing results in studies may be due to the motor units selected, a factor that should be considered when performing computer simulations. Generally there is little agreement as to whether discharge rates increase or decrease with ageing, or whether discharge rates are affected by recruitment thresholds or units tested (Moritz et al. 2005). A key finding by Moritz et al. (2005) was that force variability seems to vary dramatically with the level of activation of the motor units. This may be one of the reasons that there is such discrepancy between studies and variability in firing rates. Some studies used low force levels, and others higher. As level of force required will alter level of activation in the motor unit, it is important that measures of variability are compared between similar studies and that measures of variability across populations are not obtained at a single force (Barry et al. 2007). Therefore it would seem that discharge rate variability may be dependent on other factors, such as force exerted by the muscle (Barry et al. 2007).

Though experimental evidence is conflicted, discharge rate and discharge rate variability are now implicated as reasons for changes in magnitude of force variability and force structure with ageing (Laidlaw et al. 2000; Enoka et al. 2003; Moritz et al. 2005). One of the problems researchers face is that discharge rate and its variability are influenced by a number of factors. As well as those previously mentioned, underlying functional and behavioural changes in ageing populations are complex, making it difficult to identify primary causes. For example there is often decreased muscle use in elderly populations due to lower levels of daily physical activity (Matousek et al. 1994), whilst experimental evidence has shown a lack of mobilisation has an effect on motor unit firing rates (Duchateau and Hainaut 1990). One of the fundamental alterations that occurs with ageing that may affect discharge rate behaviour, is down to major biophysical property changes.
1.5.8 Biophysical Property Changes Caused By Ageing

As previously suggested, lower motor unit discharge rates may be due to the loss of small motor units, which in turn, results in larger motor units being innervated by slow motor neurons (Roos et al. 1997; Connelly et al. 1999). Muscle atrophy caused by ageing seems to primarily target Type II fibres resulting in a shift to the presence of predominantly Type I slow twitch muscle (Campbell et al. 1973; Erim et al. 1999). This may result in lower firing rates (Erim et al. 1999). However, some studies have failed to find a reduction in fast twitch motor units or the resultant loss in higher contractile speeds (Doherty and Brown 1997). This suggests there may be other mechanisms that cause reductions in motor unit firing rate or changes in the variability of firing rate which may not be mechanical in nature (Corden and Lippold 1996).

One possible explanation may be an inhibition in motor neurons excitability due to transmission impairments in the corticospinal and reflex pathways (Bae et al. 2008) which are the contributors to the synaptic input to motor neurons. As it has been demonstrated that muscle spindles play a role in the monitoring of motor units (McKeeon and Burke 1983), reduced spindle sensitivity that occurs with ageing (Corden and Lippold 1996) may have an influence on discharge rate. A reduction in the motor nerve impulse conduction velocities in both the upper and lower extremities is characteristic of ageing (Campbell et al. 1973; Doherty and Brown 1997) and this is primarily associated with the loss of the largest alpha motor neurons in the lumbosacral region (Tomlinson and Irving 1977; Eisen et al. 1996). These age-related changes are likely to effect the level of efficiency of signal transmission in the motor pathways (Katzman 2011), and may inhibit motor unit discharge rates.

Reduction in motor neurons in the neocortex has been shown to occur with ageing
(Kemper 1994) with an average of 22% less neuronal cells found in the motor cortex (Shefer 1973), the region of the brain responsible for motor control. This is characterised by dendritic regression of the pyramidal cells in layer V of the motor cortex (Nakamura et al. 1985). As the corticospinal tract originates in the internal pyramidal layer (layer V) of the neocortex and that the corticospinal tract is responsible for distal movements such as hand dexterity (Duque et al. 2003), it would seem likely that degeneration of these cells may affect transmission properties of the pyramidal pathway resulting in altered discharge rate behaviour.

As previously suggested, magnitude of variability in a system has been attributed to the quantity of noise present; therefore, an increase in variability caused by ageing may be due to increased noise in the system (Slifkin and Newell 1999; Jones et al. 2002; Davids et al. 2003). This may support the notion that after-hyperpolarisation time increases in the motor neuron with ageing (Connelly et al. 1999); possibly due to an increase in synaptic noise (Matthews 1996). Findings that after-hyperpolarisation in aged cats is elongated resulting in decreased discharge rates (Engelhardt et al. 1989), suggests that this may be attributable to reduced discharge firing rates in humans. However, there is a lack of experimental evidence that identifies changes that occur in the motor neuron that control after-hyperpolarisation or its susceptibility to synaptic noise (Barry et al. 2007).

1.6 SUMMARY

It is evident that there are changes in the structure and magnitude of variability as a consequence of ageing. Differences in ApEn and magnitudes of variability of force data between elderly and young participants are seen in multiple tasks and muscle
groups (e.g. Galganski et al. (1993); Tracy and Enoka (2002); Marmon et al. (2011a).
The concept that a reduction in system complexity occurs with ageing resulting in
lowered adaptability and function (Lipsitz and Goldberger 1992) is an attractive one
and there is much evidence that supports it (e.g. Kaplan et al. (1991); Hausdorff et al.
(1997); Janssens et al. (1999); Fukusaki and Kawakubo (2000). However, it may not be
appropriate to umbrella everything under one concept. As evidence is not conclusive,
it would appear that changes between elderly and young are likely influenced strongly
by the task and muscle group or system in question (Graves et al. 2000; Vaillancourt
and Newell 2003; Ofori et al. 2010). It must also not be ignored that ageing is not
linear in nature, with mechanical and biophysical properties altering at different rates
between individuals and hand in hand with ageing comes age-related disorders (e.g.
Parkinson’s) (Kirkwood 2005). As a result it is difficult to pry apart what occurs to
force output due to ageing and why? As changes in structure of force signal and
indexes of variability do not follow the same pattern, it appears that they are likely to
be effected by different processes. It is unlikely that the large changes at the motor-
unit pool (Brown 1972; Campbell et al. 1973) that occur with increased ageing would
have no effect on motor output, and evidence does suggest that increased variability
in force production is likely due to changes in motor-unit discharge behaviour (Moritz
et al. 2005). Structure of the force signal on the other hand appears to be more likely
altered by impairment of processing behaviour (Sosnoff and Newell 2006a,b) as a
consequence of ageing. Acquiring a greater knowledge of the changes that occur in
force output due to ageing will be beneficial to our understanding of the processes
involved, provide information to develop pre-clinical markers and potentially identify
methods to aid in maintaining hand dexterity and function in old age. As the population
of over 65s is increasing in the United Kingdom, it is more important than ever to be
able to identify and understand these changes.

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CHAPTER 2

EFFECT OF SAMPLE FREQUENCY AND FILTER FREQUENCY ON THE APPROXIMATE ENTROPY VALUES FOR ISOMETRIC FORCE RECORDS

2.1 ABSTRACT

ApEn has been used to quantify signal complexity in isometric contractions and distinguish between patient groups. Sampling frequencies, ‘r’ values (a parameter needed in the ApEn algorithm which essentially accounts for the noise in the signal (Pincus 1991) and filters may affect signal characteristics reflected in an alteration in ApEn values and subsequent patterns of results. However, there is little standardisation of such procedures for this measure. While the ‘true’ ApEn value cannot be known the approach taken here was to start with the highest resolution signal and to identify the pattern of ApEn results across different percentages of maximum voluntary contraction and then assess the effect of the post-processing changes on this pattern. Isometric contractions of the first dorsal interosseus for 10 seconds at 5, 10, 25, 50, and 75% of maximum voluntary contraction (MVC) were collected at 1200 Hz. Signals were post processed to determine the effect of different filter cutoff frequencies, ‘r’ values, sample rates (by resampling) and lengths of data series. Resampling of the data changed the pattern of ApEn results across the percentages of MVC range dramatically, whereas shortening the length of the time series had no effect on this pattern. This
suggests that it is the sample rate but not the number of samples that affects the pattern of ApEn results across the percentages of MVC range. ‘r’ values representing the noise in the signal that were scaled using the SD of each force record flattened the pattern of ApEn values across the percentage of MVC range, whereas ‘r’ values derived from the transducer noise led to a generally monotonic trend across the %MVC range. The filter cutoff frequency did not alter the pattern of ApEn values across effort levels, though frequencies in the signal above 20 Hz were found during spectral analysis that may well be biological in origin. The results show the choice of sample rate and ‘r’ is critical in reliably determining changes in ApEn with effort level. It is suggested that ‘r’ used should be, if possible, a measured estimate of noise, sample rates should be at least 600 Hz and filter cut-offs should not be lower than 40 Hz.

2.2 INTRODUCTION

Quantifying the complexity of a finite physiological time series can aid in the understanding of complex control systems and the clinical assessment of neurological disorder (Slifkin and Newell 1999; Goldberger et al. 2002a). For example, changes in the complexity of the physiological signal may occur at the onset of degeneration or disease which could prove useful as a preclinical tool to discriminate between healthy and pathological patients. Reliable methods have been developed for quantifying and analysing the correlation function in a physiological time series such as approximate entropy (ApEn) (Pincus 1991). As opposed to traditional methods used to analyse time series data, such as SD or CV, ApEn provides information of the structure or ‘regularity’ of the time series data (Pincus 1991). ApEn calculates the entropy of a signal, giving it a value between 0 and 2. A highly predictable signal that is regular in nature such as a sine wave will result in ApEn values close to 0. In contrast highly unpredict-
### Table 2.1: Sample frequency and filter cut-off rates used in different force steadiness studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Muscle Group Tested</th>
<th>Sample Freq Hz</th>
<th>Filter Freq Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slifkin and Newell (1999)</td>
<td>First Dorsal Interosseus (Abduction)</td>
<td>100</td>
<td>30</td>
</tr>
<tr>
<td>Deutsch and Newell (2001)</td>
<td>First Dorsal Interosseus (Abduction)</td>
<td>100</td>
<td>30</td>
</tr>
<tr>
<td>Vaillancourt and Newell (2003)</td>
<td>First Dorsal Interosseus (Abduction)</td>
<td>100</td>
<td>20</td>
</tr>
<tr>
<td>Deutsch and Newell (2004)</td>
<td>Thumb - Index finger pinch</td>
<td>100</td>
<td>45</td>
</tr>
<tr>
<td>Sosnoff and Newell (2006a,b); Sosnoff et al. (2006)</td>
<td>First Dorsal Interosseus (Abduction)</td>
<td>140</td>
<td>25.6</td>
</tr>
<tr>
<td>Rose et al. (2009)</td>
<td>Ankle Dorsi- Plantarflexor</td>
<td>1000 (Down-sampled to: 5-200)</td>
<td>1000</td>
</tr>
<tr>
<td>Sosnoff et al. (2009)</td>
<td>First Dorsal Interosseus (Abduction)</td>
<td>140</td>
<td>25.6</td>
</tr>
<tr>
<td>Kuznetsov and Riley (2010)</td>
<td>First Dorsal Interosseus (Flexion)</td>
<td>100</td>
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</tr>
<tr>
<td>Ofori et al. (2010)</td>
<td>First Dorsal Interosseus (Abduction)</td>
<td>140</td>
<td>30</td>
</tr>
<tr>
<td>Svendsen and Madeleine (2010)</td>
<td>Elbow and Wrist flexors</td>
<td>500</td>
<td>10.5</td>
</tr>
</tbody>
</table>

ApEn has been used widely in the clinical fields to assess physiological systems in relation to disease onset. For example, changes in the behaviour of heart rate variability may indicate future heart failure or arrhythmia (Goldberger et al. 2002a). ApEn has also been used to quantify the regularity of force fluctuations in the force record arising from isometric contractions (e.g. Vaillancourt and Newell (2003)). Measures of steadiness or force regularity correlate with hand function and motor control (Marmon et al. 2011b). Therefore, the underlying aim of these studies is to quantify variability in the structure of the torque or force time series, in order to assess for changes in the central and or peripheral mechanisms that may be affecting motor unit behavioural patterns. It is thought that such alteration may occur at the onset of disease or ageing (Goldberger et al. 2002a) which has prompted the use of ApEn in studies that attempt to distinguish changes in force structure as a consequence of ageing (Vaillancourt and Newell 2003).

When using algorithms such as ApEn to analyse force signal data, the chosen input parameters, the data collection procedure, and post-processing methods may all have
an influence on the pattern of results obtained. For example, the utility of ApEn stems from the two parameters (‘m’ and ‘r’) used in the algorithm. The parameter ‘m’ determines the length of the compared runs and ‘r’ is effectively a filter that accounts for noise in the physiological signal (Pincus 1991). Defining the ‘r’ value allows for the algorithm to account for anything below that range to be considered as noise. By doing so the investigator is making the assumption that there is no other noise present in the system (e.g. small wrist or arm movements, noise caused by lighting etc) and that all the data in the signal collected is of interest. Noise can be due to subject variability or measurement error, which in some cases can be difficult to quantify (e.g. heart rate data). If the noise in the signal is not known then it is recommended that 0.1-0.2*SD of the signal should be used in the algorithm as an estimation of signal noise (Pincus 1991). Another suggestion is that using an ‘r’ value which produces the maximum ApEn value should be used in order to determine the most representative interpretation of the signal (Chon et al. 2009); this recommendation is probably aimed at counteracting the bias ApEn has towards generating low ApEn Values (Richman and Moorman 2000; Richman et al. 2004). However, in a signal derived from a force transducer, noise can often be determined. As a result, it would seem more suitable to input this assessed noise value directly as the ‘r’ value instead of an estimate. As the ‘r’ is used to account for the noise in the signal, the influence this parameter has on the resulting ApEn values is likely to be large and should therefore be chosen with caution and specifically for the task used.

Two other examples of criterion that should be considered when using ApEn is the quantity of data collected and the filter cut-off frequency chosen, as both are known to have an effect on signal characteristics that may alter ApEn values (Pincus 1991; Rose et al. 2009). Filter cut-off frequencies as low as 20 Hz have been used to filter isometric force data (e.g. Vaillancourt and Newell (2003)). Though most signal power in such
data is generally below 12 Hz, it has been suggested that within the force output during isometric contractions there are frequency components in the 20-25 Hz range (Stitt and Newell 2010). This would mean cut-off frequencies as low as 20 Hz or 25.6 Hz may remove parts of the signal that are due to physiological processes. Although, there may only be a limited amount of power at these higher frequencies, when attempting to draw comparisons between two subject groups the removal of frequencies may eliminate vital information.

The length of the data series analysed is known to affect ApEn results (Pincus 1991). The size of the data set is generally determined by sample rate, collection time, and the inclusion/exclusion criterion of an algorithm used to select steady-state sections of the data set (generally if only the steady-state sections of the force record are wanted for analysis then non-steady state sections are removed prior to analysis). The length of data used by investigators even prior to any post-processing is dramatically different across studies. Sample rates chosen range from 30-1000 Hz (Table 2.1) with some investigators collecting data at high frequencies, and subsequently down-sampling in post-processing and using the average of a given number of observations (Rose et al. 2009).

The length of a data series, the algorithm used to remove non-steady state sections of the contraction history, the filter characteristics, and signal noise estimation are all likely to have an effect on the ApEn value. Despite evidence to suggest that criteria such as ‘r’ values (Chon et al. 2009) and sample frequencies (Rose et al. 2009) effect ApEn values, studies use a variety of different signal processing methods (Table 2.1) which makes interpreting results difficult when the effect each processing technique has on the signal is unknown. Currently, no single approach has been made in regards to the post-processing method used for such data. Therefore, the aim of this study was
to assess changes in the ApEn of physiological time series data values and the subsequent change in pattern of results brought about by sampling and post-processing alterations in order to address a number of questions:

1) What frequencies are present in the signal?

2) What is the effect on the pattern of ApEn due to differing filter frequencies?

3) What happens if the sampling frequency is reduced?

4) Are any changes in ApEn after resampling an effect of having fewer data points or is it to do with the frequencies that are captured?

5) What does changing the size of the minimum variance window do to the pattern of ApEn results?

6) What is the effect on the pattern of ApEn results when using the minimum variance window Vs an alternative criterion?

7) How does altering the parameter ‘r’ affect ApEn patterns?

2.3 METHOD

Participants

Twenty-three, neurologically healthy subjects were assigned to two different age groups; young (n = 12; range 18-25 years; mean = 23 ± 4 years; seven females and five males), and elderly (n = 11; range 65-72 years; mean = 67 ± 5 years; six females and five males). All subjects were assessed for hand dominance by the Edinburgh Handedness Inventory (Oldfield 1971). Twenty out of the twenty-three subjects were deemed right hand dominant (young group = 11(12); elderly Group = 9(11)). Subjects were
excluded if they had history of a serious injury to the hand, suffered from arthritis affecting the hand, had untreated high blood pressure or were taking any medications that they knew to have neurological side effects. Any subjects needing prescriptive lenses to correct for sight were asked to wear the correct prescription and to continue to do so through all testing procedures. All subjects gave informed consent to all the experimental procedures which had been approved by the Aberystwyth University Ethics committee.

**Apparatus**

The participant sat upright on a non-adjustable chair (height = 45 cm) facing the computer monitor which was placed approximately 70 cm away and centred both horizontally and vertically from the eyes. The 60 cm monitor was positioned on a table (height = 71 cm). The participants non-dominant hand was pronated and lay flat resting on a custom made metal plate to which the load cell (HBM, PW6-CC3MR/10 kg, Hottinger Baldwin Messtechnik, Harrow, UK Ltd.; sensitivity 2.2 mV/V), was attached. Output from the load cell was passed through a Hottinger Baldwin Messtechnik, Harrow, UK Ltd. full bridged transducer (AED-9101-B, HBM). The force signal was sampled at a frequency of 1226 Hz.

The participant’s dominant hand was placed on their lap. The non-dominant arm was placed such that the elbow was flexed to approximately 90° with the upper arm slightly abducted. A restraining plate was positioned between the first and second phalanges of the hand to be tested to restrict the motion of the third, fourth and fifth phalanges. A non slip mat was placed between the table and metal plate in order to prevent the device from slipping. The load cell and thumb rest were positioned so that the load...
cell was level with the lateral side of the proximal inter-phalangeal joint with the angle between thumb and index finger being approximately 80° when the finger was in contact with the load cell.

To standardise the hand position from trial to trial, each participant had an outline of their hand traced in position. Before each trial the participant was asked to replace their hand within the trace and maintain it in that position throughout the trial. The participant was asked to maintain contact with the force plate with the palm, wrist, thumb and fingers throughout each trial to ensure moments produced were done so by abduction of the index finger alone. Position of the hand was monitored throughout the trials and the trial was repeated if correct position was not maintained throughout the trial.

**Familiarisation**

Each participant was asked to attend a familiarisation session within a week prior to the test day. During the familiarisation session subjects’ MVC was obtained to limit fatigue during the experimental session and subjects were familiarised with the experimental tasks. Prior to any force tasks the participants performed light fingers exercises in order to prepare the FDI for contractions in order to reduce the possibility of injuring the muscle. To measure MVC subjects were asked to increase an abduction force gradually until they were pushing as hard as possible over approximately 5 seconds holding the maximum force possible for 2-3 seconds. The force applied to the load cell was displayed on the monitor in white pixels. The time count was displayed on the screen and verbal encouragement was given during each trial. After two practice trials a further three trials were performed and the maximum force recorded. Between each trial the participant was given a 3 minute rest period. The single value peak (max-
imum) of the three recorded trials was used as the participants MVC. This value was then used to compute for each individual, target force levels at varying percentages of maximum. Following this each participant practiced a number of the force targeting trials which included familiarisation with the targeting of the force trajectory at force levels varying from 5% to 75% of MVC. All participants performed the same quantity and type of trial during familiarisation.

Testing Procedure

At a subsequent testing session subjects attempted to produce isometric contractions at 5%, 10%, 25%, 50%, and 75% of their MVC for ten seconds. The display was rescaled for each subject so that the force target was displayed as a percentage of maximum from 0-100% to avoid possible effects on resolution due to scaling. Subjects were informed prior to the start of each trial what the force target would be. The target was a force level identified by two red lines two pixels (top line) and four (bottom line) pixels thick displayed on a computer monitor in a LabVIEW 8.2 (National Instruments LabVIEW®) environment (Chapter 3, Fig. 3.2). The error gap between the red lines was scaled with the level of target as the target level ±5%. In order to maintain a gap between the lines at the lowest force levels a minimum of a six pixel gap was set. This represented an error window of ±20% at 5% MVC target and ±10% error at 10% MVC. The participant viewed their force trajectory as a white force-time trajectory two pixels thick moving from left to right across a black screen on the monitor. The participants were instructed to attempt to keep the white trajectory line centrally between the red lines. However, they were asked to focus more on keeping the line as straight or ‘steady’ as possible as opposed to matching the centre of the force target exactly. Participants ramped up contraction from 0% as quickly as possible to the tar-
get. During contractions, the inter-phalangeal joint remained in contact with the centre of the load cell at all times. A one minute rest was given between lower efforts and three minutes rest was given after trials of 50% and 75% MVC and the order of the contractions performed was fully randomised.

Post Processing

Any electrical noise was filtered out prior to further processing using 49.0-51.0 Hz 4th order low-pass Butterworth notch filter (bi-directional). Any data <0.3 N at the beginning of the data set was removed to avoid analysis of any data prior to the participant commencing force production. A rolling minimum variance window was used to select the data to be analysed. The window size determining the amount of data to be analysed could be altered to varying lengths. The rolling window selected the steadiest section of the force data determined by calculating the Standard Deviation (SD) of each window (of selected size) of force data and selecting the window with the lowest SD. All data processing was performed using custom software written in Matlab v9.9 (the MathWorks, Inc). ApEn was used to assess the force structure using the method described in Pincus (1991). Several different processing conditions were applied to the force data in post-processing to answer various questions about the effect the post processing methods had on the subsequently calculated ApEn values for the different percentages of MVC and the subsequent pattern of results. The assessment of the effects that each condition had on calculated ApEn values was carried out by comparing the subsequent pattern of results across force levels. The questions asked were:

1) **What frequencies are present in the signal?**

Frequency spectral analysis of the force data for both the noise (estimated from trials with no load and a known load on the force sensor) and the subjects trials
was carried out in order to identify frequencies present in the signal that are due to physiological processes.

2) What is the effect on the ApEn values due to differing filter frequencies?

The signal was low-pass filtered using a 4th order forward and backwards Butterworth filter. The cut-off frequency was set at 100 Hz, 80 Hz, 70 Hz, 60 Hz, 50 Hz, 30 Hz and 25.6 Hz.

3) What happens if the sampling frequency is reduced?

The original signal sampled at 1226 Hz was resampled using software implemented in MatLab v9.9 (the Mathworks, Inc). The signal was resampled to 613 Hz, 204 Hz, 102 Hz and 31 Hz to simulate sampling at lower sample frequencies. Resampling reduces the original sampling rate for a sequence to a lower rate. The resampling process filters the input data with a low-pass filter and then re-samples the resulting smoothed signal at a lower rate. This process reduces the likelihood of aliasing. For simplification the filtering rates will from this point on be referred to as 1200 Hz, 600 Hz, 200 Hz, 100 Hz and 30 Hz.

4) Are the changes in ApEn with resampling an effect of having fewer data points or is it to do with the frequencies that are captured?

The size of the minimum variance window was altered to capture the number of data points that equalled the total number of data points in each resampled data set. For example resampling a three second length of data sampled at 1200 Hz to 30 Hz reduces the number of points from 3600 to 90 data points. Therefore the minimum variance window was adjusted to collect just 90 data points (or 0.075 s). This method was used to collect 1800, 300 and 90 data points (number of data points equivalent to 600 Hz, 100 Hz and 30 Hz).

5) What does changing the size of the minimum variance window do to the ApEn?
The minimum variance window was adjusted to select the steadiest five seconds, three seconds and half a second of the force data for each trial in order to assess the effect of different lengths on ApEn value.

6) What is the effect on ApEn of using the minimum variance window Vs an alternative criterion?

Five seconds, three seconds and half a second of data was analysed at the fourth second of the force data (e.g. for the five seconds analysed the data selected was from 4-9 seconds section of each force trial, for three seconds 4-7, half a second 4-4.5). Three seconds and half a second sections were analysed at the sixth second of data and half a second was analysed at the eighth second of data. The complete data set was also analysed after removal of the first three seconds of data to allow for ramping up to force level, this resulted in seven seconds of data (3-10) to be analysed.

7) How does altering the parameter ‘r’ affect ApEn value?

The parameter ‘r’ that accounts for the noise in the ApEn algorithm was altered from using the Root Mean Square (RMS) of the measured noise (determined by collecting force signal data with no force exerted and with a known load) to using 0.1* SD and 0.2* SD of the force signal of each trial.

2.4 RESULTS

A number of the post-processing procedures applied to the data altered the pattern of ApEn values calculated. The results are reported in order, ranked by processing method that had highest impact on the pattern of ApEn values.
What happens to the pattern of ApEn results if the sampling frequency is reduced?

Resampling of the signal was carried out to 30 Hz, 100 Hz, 200 Hz and 600 Hz respectively. Resampling drastically changed ApEn values resulting in a reversal of the pattern when compared to non-resampled data (Fig. 2.2). This change in pattern became more extreme with increased resampling resulting in higher ApEn values for lower percentages MVC and lower ApEn values for the higher percentages of MVC when sampling frequency was reduced to 30 Hz. As a result, not only were there differences in absolute values as a result of resampling, but the large differences seen in the pattern mean that comparing ApEn values at different force levels would produce varied outcomes depending on the sampling frequency chosen.

Figure 2.1: Typical signal of force data collected at (a) 5 percent of MVC and (b) 75 percent of MVC
Figure 2.2: Mean ApEn values at % MVC after resampling of the signal to reduce sample rate to 600 Hz, 200 Hz, 100 Hz and 30 Hz (All filtered at 60 Hz).

How does altering the parameter ‘$r$’ affect ApEn value?

Altering the ApEn to use 0.1$^*$ or 0.2$^*$SD alters the ApEn values drastically (Fig. 2.3). The RMS of the unloaded force data was 1.018 and with loaded force cell RMS was 1.127 which was used as the measured noise ‘$r$’ value. Similarly to resampling of the signal, the pattern in the results reverses, reflecting higher ApEn values at lower percentages of MVC than those calculated for higher percentages of MVC. As well as this, the general pattern becomes flattened with increasing percentage of SD used.

A plot of a typical force signal data set at 5% and 75% (Fig. 2.1) demonstrate how deviations of the signal from the mean increase with the increasing force level resulting in higher SD as force level increases (Chapter 3, Fig. 3.6). This would result in ‘$r$’ values that would increase linearly with increasing SD and therefore with increasing force, resulting in a flattened pattern in the ApEn calculations.
Figure 2.3: Mean ApEn values using varying ‘r’ values

Figure 2.4: Mean ApEn results at % of MVC with varying decimation and truncation windows (60 Hz filter cutoff frequency). The time series sections of 300 and 90 data points were selected using the minimum variance window which selected both 300 consecutive and 90 consecutive data points with the lowest SD in the whole time trial. This produced a data set with comparable length to the 3 seconds of data after resampling to 100 Hz and 30 Hz respectively.
Are the changes in ApEn patterns post-resampling an effect of having fewer data points or is it to do with the frequencies that are present in the signal?

Analyses were performed using the original sampled data (1200 Hz) and subsequently truncated using the minimum variance rolling window to capture data of the same length as the data set after resampling (e.g. selecting the steadiest 90 consecutive data points in the trial collected at 1200 Hz would provide equivalent length of data to be analysed as selecting 3 seconds of data after resampling to 30 Hz (also length of 90 data points). When comparing these data sets, the pattern of ApEn results were similar, though the absolute values were different (Fig. 2.4). Once again, despite comparing equivalent lengths (comparable number of data points), sampling at 1200 Hz produces patterns in ApEn values that contrast with the resampled data. As the pattern remains consistent at 1200 Hz despite the large reduction in number of data points analysed, it would suggest that the shift in the pattern occurring after resampling is not due to the lower number of data points used but instead may be due to the frequencies that are removed in the process.

What does changing the size of the minimum variance window do to the pattern of ApEn values?

As expected (Pincus 1991), the size of the minimum variance window did alter the absolute values of ApEn with greater differences exhibited >25% MVC (Fig. 2.5). Reducing the window size leads to lower ApEn values, whilst increasing the size to five seconds leads to very minimal increases in mean values. Although ApEn absolute values changed, this was primarily when using the smallest 0.5 second window size. Comparatively, changes in the window size resulted in very little change in the pattern across the percentages MVC.
What is the effect on the pattern of ApEn values when using an alternative criterion vs the minimum variance window?

Selecting the data at varying positions across the data to sections 0.5, 3 and 5 seconds in length (collected using a sample frequency of 1200 Hz) and analysing sections or the whole data set (minus the initial three seconds of data to allow for ramping up to force level) without using the minimum variance window also resulted in patterns similar to the truncated signal that had not been resampled (Fig. 2.5). The largest differences seen were at percentages of MVC ≥50% using the smallest number of data points which resulted in ApEn values that were generally lower. This was comparable with a reduction in variance window size. Though absolute values are altered the general pattern of data remained the same. Within the context of the data set sizes used in this study, the results suggest that analysing shorter sections of data does not alter ApEn patterns.

What is the effect on the pattern of ApEn values due to differing filter cut-off frequencies?

Filtering with low-pass cut-off frequencies of 25.6 Hz, 30 Hz, 60 Hz, 70 Hz, 80 Hz and 100 Hz were used. As filtering frequencies were lowered the ApEn values decreased across the levels of MVC, though the general trend remained similar using the different filter cut-off frequencies (Fig. 2.6). The resampled force signal was also filtered using the same cut-off frequencies. This had the same effect as it did on the unresampled data by not altering the trend but reducing absolute ApEn values with increased filtering.
Figure 2.5: Mean ApEn values at % of MVC with no resampling (1200 Hz sample rate), filtered at 60 Hz using varying methods for selecting the data section to be analysed (different rolling variance window sizes and selection of steady state sections of varying lengths).

Figure 2.6: Mean ApEn values at varying filter cut-off frequencies.
What frequencies are present in the signal?

Frequency spectral analysis of the trials showed changes in the signal during isometric contractions above frequencies of 20 Hz. This was most prominent in isometric contractions ≥50% MVC with a general pattern of increasing power above 20 Hz with increasing MVC level (Fig. 2.7). As the amplitudes displayed were not present in the noise signal (estimated from trials with no load and a known load on the force sensor), it would suggest that these frequencies occurred due to biological aspects of the signal.

2.5 DISCUSSION

The main findings of this study are: 1) Adjusting the ‘r’ parameters alters ApEn values 2) ApEn values are influenced considerably by resampling or sampling frequency of the signal 3) Altering the rolling window size from 3 to 5 seconds, or selecting steady state sections of data does not alter ApEn patterns 4) Choosing filter frequencies from 80-25.6 Hz does not alter ApEn patterns though there may be frequencies in the iso-
metric force signal above 20 Hz that have a biological origin.

2.5.1 The ApEn ‘r’ Values

Pincus (1991) recommended that ‘r’ values should be in the region of 0.1-0.2*SD of the signal if the noise of the signal is unknown. However, during isometric contraction of the FDI, as force requirement level increases there is a concomitant increase in signal SD (Fig. 2.1 and Chapter 3, Fig. 3.6). As a result, there is a drastic alteration in pattern of ApEn (Fig. 2.3) values seen due to the pattern being suppressed by the scaling of ‘r’ to the SD. In studies where subjects are required to target high forces or target a trajectory with no visual feedback, standard deviations may be unusually high. For example, isometric force signal collected with non-visual (audio only) (e.g. Chapter 3 Fig. 3.6) feedback result in ‘r’ values ranging from 0.04-6.31 (median = 1.89) when using 0.1*SD of the force signal. An estimation of the noise present in an isometric force signal can be measured by using either a known load or no load on the force cell. For example, in this study the RMS of the weighted data was 1.127 which was assumed to be a representation of the noise in the signal across all the trials. It would therefore be advantageous to use this in the algorithm as a constant instead of a figure that is altering with each data set. As a result, when the quantity of noise in the system can be measured it would be more appropriate to use this as a constant ‘r’ value as opposed to SD derived estimates.

2.5.2 Sample Frequency

ApEn values have been shown to result in different patterns between studies, when investigating isometric force and aging (Slifkin and Newell 1999; Deutsch and Newell
Processing methods may account for some these discrepancies. Sampling rate alters patterns in ApEn values drastically, which means that patterns of results in this study are comparable to other research results depending on the sample rate chosen. For example, the pattern of ApEn results after resampling to 200 Hz (displaying an initial increase in ApEn values as% MVC increases followed by a reduction in ApEn after 40% MVC) is in agreement with studies such as Sli-fkin and Newell (1999) who sampled at lower frequencies. When resampling as low as 100 Hz ApEn results are similar to results found in studies investigating FDI abduction and finger-thumb pinch grip (Deutsch and Newell 2004; Sosnoff and Newell 2006b,c), with ApEn values at levels above 25% MVC being lower than those at 5% MVC (Figure 2.2). In contrast the same data un-resampled results in a complete reversal in the pattern of ApEn values, which highlights the impact that data collection methodology or post-processing procedures have on these calculations.

ApEn’s utility, as described by Pincus (1991) is its capability to be used as a comparative tool by reflecting the level of regularity of a data set compared to another. If it is of interest to an investigator to compare changes in ApEn values as a function of MVC the results would differ vastly depending on the sample rate chosen. Comparing 5% MVC to 75% MVC if the data were sampled at 30 Hz would present results that conflict with a comparison if sampling rate was >200 Hz. One of the arguments against sampling at high frequencies is that it reduces ApEn values due to oversampling and thereby leads to an increased sensitivity to noise in the system (Rose et al. 2009). However, when collecting data, the recommendation according to the Nyquist rate is at minimum collect greater than twice the highest measurable frequency present in the signal (Shannon and Weaver 1998). The data is subsequently interpolated in order to define a continuous-time sample. If there is the technological capability to sample at higher rates and remove the necessity for interpolation, then it benefits the investigator.
to be able to capture even small amounts of power in the signal that may be due to biological processes.

The use of higher sample rates may be more appropriate when collecting force signal data at the FDI than when collecting data from other muscle groups. Any force that is produced by the active muscle fibres is transmitted through the tendon structure before reaching the skeleton (Kubo et al. 2001). Therefore the efficacy of the force transmission and conduction of frequencies to the force transducer will depend upon the tensile properties of the tendon structure. The structural architecture of tendons is highly variable (Roberts 2002; Infantolino 2010); tendons such as the Achilles are highly compliant in nature (Lichtwark and Wilson 2005) which may result in an increase in dampening of biological frequencies. This would result in a reduction in frequencies captured when collecting ankle joint torque data and therefore may provide argument to support sampling at 30 Hz. In contrast, the characteristics of the FDI tendon architecture make it relatively stiff (Infantolino 2010) and as a result it may be more prone to conduct frequencies above 15 Hz which would be lost if the sample frequency rate was set at 30 Hz.

2.5.3 Data Selection Criterion

Previously, studies have used various criterion windows in order to select the data section for analyses. It is of use to the investigator to know whether the criterion or the window size makes a large difference on calculated ApEn values so that studies can be compared. These results show selecting different criterion methods for isometric force data in this study did not dramatically alter the pattern of ApEn values once steady state is achieved. It should be noted that in comparison to lengths of data collected in
other studies, our data set was sampled at a high frequency for a relatively short length of time. Therefore identifying whether comparisons can be made between ApEn results collected for greater than ten seconds compared to those calculated from shorter data sets would need further investigation. However, from these results, it is suggested that analysing the complete data set or using a minimum variance rolling window of three or five seconds is comparable when calculating ApEn. These results may be of benefit to the researcher as not only will it save computational time to analyse shorter data sets, but more importantly being able to collect shorter trials will reduce the likelihood of participant fatigue during trials where high percentages of MVC are required.

2.5.4 Frequencies Present In The Signal

Comparatively, except for reducing absolute values of ApEn, the pattern presented by ApEn values did not alter with increased filtering (Fig. 2.6). However, the choice of cutoff frequency of the filter should not be considered as arbitrary when collecting force signal data. There were frequencies above 20 Hz in the force spectrum (Fig. 2.7) particularly at 50% and 75% MVC contractions. Though the power at these frequencies was relatively small, it appears that they were not due to noise in the signal and may therefore be biological in origin. For example, the high frequency fluctuations may be due to increased neuron firing frequencies which is why they are more evident at higher force levels. These frequencies are often considered to be damped or smoothed at the neuromuscular junction and by muscle-tendon interactions; however, as previously mentioned the magnitude of dampening would depend upon tendon length and stiffness. This is highly variable between individuals (Infantolino 2010) and alters with ageing (Carmeli et al. 2003). Biochemical changes in ageing tendons result in stiffer and more irregular connective tissues due to collagen loss and reduction in
water content within the tissue (Carmeli et al. 2003). This may result in either higher or lower levels of dampening in some subjects, and consequently affect the magnitude of biological frequencies captured in the force signal data. When investigating motor output, even small amounts of power in the signal may be of importance when trying to distinguish common characteristics between groups.

In light of this, we suggest that frequency cut-off filters should be higher than those used previously (Table 2.1) when analysing isometric force data using ApEn. As the ApEn algorithm takes into account noise in the signal, the reduced filtering does not alter the pattern dramatically whereas reducing the cut-off frequency may result in biological frequencies being removed.

### 2.6 CONCLUSIONS

Sampling rates and ‘r’ values have been shown to greatly affect the pattern of ApEn values calculated for isometric force data. Previously, there has been little standardisation or guidance in the post the processing of such data. In order for us to effectively compare studies and attempt to draw from them information regarding changes that may be occurring through ageing, disease or interventions, it should be clear to the investigator the effect the capturing and post-processing methods have on the data.

Our results lead us to four main recommendations when collecting isometric force data at the FDI: 1) ‘r’ values should be chosen carefully, the noise in the signal should be measured if possible and input as a constant across trials. 2) Sample rates should be higher than 600 Hz as low sample rates have a dramatic effect on ApEn values. 3) Filter cut-off frequencies should be above 40 Hz, increasing the filter cut-off has a neg-
ligible effect on the pattern of ApEn whereas reducing the cut-off frequency may result in a removal of signal frequencies that may be of biological origin. 4) Within context of the length of data used in this study, criterion such as window size or selection of steady state sections of data has little effect on the pattern of ApEn values. Therefore criterion that reduces likelihood of fatigue or is more convenient for the investigator for effective post-processing is recommended.
CHAPTER 3

EFFECT OF BIMODAL STIMULUS ON FORCE CONTROL OF ELDERLY AND YOUNG ADULTS

3.1 ABSTRACT

Research shows that elderly adults often exhibit reduced irregularity in force signal data during isometric contractions (e.g. Sosnoff and Newell (2006c). Previous findings revealed that the post-processing of data effects Approximate Entropy (ApEn) values, used to measure the regularity of the force signal. The purpose of the present study was to examine magnitude of variability (SD, CV, RMSE) and structure of isometric force data using appropriate post-processing methods previously identified. It was hypothesised that in-line with much of the literature there would be differences between young and elderly adults’ force output. Differences in structure of force output between elderly and young adults may be as a result of elderly adults having reduced visuomotor processing capabilities, to assess this, target feedback was provided in the form of three different types of stimuli: 1) audio 2) both audio and visual (bimodal) 3) visual. The audio stimulus changed pitch depending on whether the force trajectory was too high or low and was silenced when force level was correct. This was included with the visual target (on-screen target trajectory) during the bimodal trial. Audio stimulus was used in order to gain more information as to whether differences between elderly and young adults are due to visuomotor processing differences. Young (18-25)
and elderly (65-72) neurologically healthy adults produced isometric force contractions using abduction of the FDI at six force levels (5, 10, 25, 40, 50 and 75% MVC) during each of the three conditions. There were no differences found in magnitudes of variability between the age groups nor was there any alteration in force output in the bimodal condition compared to the visual condition for either groups. The audio condition altered all indexes of force structure and variability significantly. ApEn values were significantly higher in younger adults at force levels >25% MVC during all conditions indicating higher irregularity than elderly adults (mean across all conditions and force: elderly = 0.15, SD 0.11, young = 0.19, SD 0.13). In contrast with younger subjects, elderly adults exhibited a higher percentage of relative power in the 0-0.5 Hz frequency bands and exhibited limited alteration in the percentage power in the 0-4 Hz bands with change of force requirement or condition. This suggests differences in processing and behaviour between the two groups, but as there are still differences in audio condition it suggests that the differences in processing are not related to visual processing alone. This research has introduced a novel audio technique in order to compare groups without visual processing contribution. These results support the postulation that reduced complexity occurs with ageing. As the force signal is more pattern like it may result in a reduced ability to alter force production when required leading to a lower level of functionality.

3.2 INTRODUCTION

When maintaining an isometric contraction in order to match a force target, the force that is produced is not constant, but fluctuates about a mean value (Slifkin and Newell 1999; Enoka et al. 2003; Tracy et al. 2004). The magnitude of the fluctuations can vary depending on variables such as subject age (Semmler et al. 2000; Vaillancourt
et al. 2003; Marmon et al. 2011a), health status (Vaillancourt et al. 2002; Prodoehl et al. 2006), force level requirement (Galganski et al. 1993; Burnett et al. 2000; Laidlaw et al. 2000) or muscle group used (Galganski et al. 1993; Graves et al. 2000; Christou and Carlton 2001; Tracy and Enoka 2002). In order to gain more information regarding motor output, these fluctuations can be quantified by calculating the Standard Deviation (SD) or Coefficient of Variation (CV) of the force signal, using spectral analysis techniques or by analysing force signal structure by calculating Approximate Entropy (ApEn).

Increases in magnitude of variability, often displayed by elderly adults (Galganski et al. 1993; Burnett et al. 2000; Semmler et al. 2000; Tracy and Enoka 2002; Vaillancourt and Newell 2003; Tracy et al. 2005; Marmon et al. 2011b) is attributed to a reduced ability to control force production. The ability to limit motor output variability at the First Dorsal Interosseus (FDI) is linked with increased manual dexterity capabilities (Kornatz et al. 2005; Marmon et al. 2011b) which may be beneficial for prolonged functionality in senescent life (Carmeli et al. 2003). The occurrence of reduced force control, may be due to biophysical changes that occur with ageing; for example death of α motor neurons or lower transmission efficiency in the corticospinal and reflex pathways (Campbell et al. 1973; Doherty and Brown 1997; Bae et al. 2008). It has been indicated that approximately 25% motor axons at the hand muscles are lost as a result of ageing (Galea 1996; Doherty and Brown 1997). However, as sensory processes deteriorate with age (Spear 1993; Nusbaum 1999) recent attention has focused on alterations in visual processing and its deterioration with ageing as a cause for increased magnitudes of force variability displayed by elderly groups (Sosnoff and Newell 2006c; Ofori et al. 2010).

When tracking an on-screen visual force target, a continual feedback loop allows the
subject to adjust their force output in order to match the requirement of the task. This is accomplished by visuomotor processing and the resultant modulation of the supraspinal descending command to motor neurons (Tracy 2007b). Force variability is commonly considered to be the result of changes in motor unit discharge behaviour (Moritz et al. 2005; Barry et al. 2007). As motor unit discharge characteristics are influenced by the supraspinal command (Welsh et al. 2007), the capability of maintaining a constant force trajectory is partially related to the information presented and the ability to process visual information (Nafati et al. 2004; Tracy 2007b).

Coinciding with a decline in visual system function (Matjucha and Katz 1994), elderly adults show a reduced efficiency to utilise visual feedback during aiming tasks, making more corrections to their motor output than do younger subjects when visual feedback is presented (Seidler-Dobrin and Stelmach 1998), the result of which is an increase in the magnitude of variability (Tracy 2007a). When visual feedback is reduced, the gap in performance variability between elderly and younger subjects is reduced (Seidler-Dobrin and Stelmach 1998; Tracy 2007a; Welsh et al. 2007). This would suggest that elderly adults have inhibited processing capabilities or process information differently. It is suggested that the increased level of feedback provided leads to lower levels of steadiness in elderly adults due to a reduction in the capability to process information (Cerella 1985; Sosnoff and Newell 2006c). The consequence of larger amounts of information received is that it exceeds the processing capabilities of the visuomotor system leading to increased processing times and a delayed motor correction; both of which are displayed in elderly subjects (Sosnoff and Newell 2006a,c).

The type of display or stimulus that is provided to a subject during a targeting task has been shown to effect the outcome of the force variability (Carlton 1992; Ofori et al. 2010). Providing a combination of stimuli has an effect on motor output possibly
due to alterations in neural activation influencing processing across modalities (Schroger and Widmann 1998; Fort et al. 2002). For example, reductions in reaction time are found when using bimodal (audio and visual) stimuli compared to a unimodal stimulus (Schroger and Widmann 1998; Fuhrmann-Alpert et al. 2008), which suggests that using a bimodal stimulus may reduce the processing time required. Elderly subjects are able to utilise bimodal stimuli to a greater degree than their younger counterparts as a result of multi-sensory enhancement (Laurienti et al. 2006). This leads to an improvement in both reaction times and performance when responding to cues presented using unimodal and bimodal stimuli (Laurienti et al. 2006; Peiffer et al. 2007; Hugenschmidt et al. 2009). Providing both audio and visual stimulus may prove useful in accident prevention in elderly age by provoking compensatory mechanisms to enhance information processing and end-performance (Laurienti et al. 2006; Fuhrmann-Alpert et al. 2008).

To date there have been few studies to assess the effect of providing multiple stimuli as a target for isometric force production and its effects on indexes of force. Therefore this study aimed to investigate differences in magnitude of force variability and force signal structure between elderly and young subjects and the effect introducing an audio stimulus has on these observations. It was hypothesised that the addition of an audio stimulus to the visual feedback would reduce information processing time in elderly adults resulting in magnitudes of variability closer to those displayed by younger adults.
3.3 METHOD

Participants

Twenty-three, neurologically healthy subjects were assigned to two different age groups; young (n = 12; range 18-25 years; mean = 23 ± 4 years; seven females and five males), and elderly (n = 11; range 65-72 years; mean = 67 ± 5 years; six females and five males). All subjects were assessed for hand dominance by the Edinburgh Handedness Inventory (Oldfield 1971). Twenty out of the twenty-three subjects were deemed right hand dominant (younger group = 11(12); elderly group = 9(11)). Subjects were excluded if they had history of a serious injury to the hand, suffered from arthritis affecting the hand, had untreated high blood pressure or were taking any medications that they knew to have neurological side effects. Any subjects needing prescriptive lenses to correct for sight were asked to wear the correct prescription and to continue to do so through all testing procedures. All subjects gave informed consent to all the experimental procedures which had been approved by Aberystwyth University Ethics committee.

Apparatus

The participant sat upright on a non-adjustable chair (height = 45 cm) facing the computer monitor which was placed approximately 70 cm away and centred both horizontally and vertically from the eyes. The 60 cm monitor was positioned on a table (height = 71 cm). The participants non-dominant hand was pronated and lay flat resting on a custom made metal plate to which the load cell (HBM, PW6-CC3MR/10 kg, Hottinger Baldwin Messtechnik, Harrow, UK Ltd.; sensitivity 2.2 mV/V), was attached, output from the load cell was passed through a Hottinger Baldwin Messtechnik, Harrow, UK
Limb Limited full bridged transducer (AED-9101-B, HBM). The force signal was sampled at a frequency of 1226 Hz.

The participant’s dominant hand was placed on their lap. The non-dominant arm was placed such that the elbow was flexed to approximately $90^\circ$ with the upper arm slightly abducted. A restraining plate was positioned between the first and second phalanges of the hand to be tested to restrict the motion of the third, fourth and fifth phalanges. A non-slip mat was placed between the table and metal plate in order to prevent the device from slipping. The load cell and thumb rest were positioned so that the load cell was level with the lateral side of the proximal inter-phalangeal joint with the angle between thumb and index finger being approximately $80^\circ$ when the finger was in contact with the load cell (Fig. 3.1).
Prior to any force tasks the participants performed light finger exercises in order to prepare the FDI for contractions and reduce the possibility of injuring the muscle. To standardise the hand position from trial to trial, each participant had an outline of their hand traced in position. Before each trial the participant was asked to replace their hand within the trace and maintain it in that position throughout the trial. The participant was asked to maintain contact with the force plate with the palm, wrist, thumb and fingers throughout each trial to ensure moments produced were done so by abduction of the index finger alone. Position of the hand was monitored throughout the trials and the trial was repeated if correct position was not maintained throughout the trial.

**Familiarisation**

Each participant was asked to attend a familiarisation session within a week prior to the test day. During the familiarisation session, subjects’s MVC was obtained to limit fatigue during the experimental session and subjects were familiarised with the experimental tasks. To measure MVC subjects were asked to increase an abduction force gradually over five seconds until they were pushing as hard as possible and holding the maximum force possible for 2-3 seconds. The force applied to the load cell was displayed on the monitor by a trajectory in white two pixels thick. The time count was displayed on the screen and verbal encouragement was given during each trial. After two practice trials a further three trials were performed and the maximum force recorded as the participants MVC. Between each trial the participant was given a 3 minute rest period. The maximum of the three recorded trials was used as the participants MVC. This value was then used to compute for each individual, target force levels at varying percentages of maximum.
Following the MVC measurement, each participant practiced a number of the force targeting trials which included a reaction task and a familiarisation with the targeting of the force trajectory at force levels varying from 5% to 75% of MVC. For the reaction task, each participant was asked to react to the audio signal and visual signal to ensure that they were able to hear and see the stimulus clearly. In order to familiarise the participants with the constant force task, they each performed 3 trials with just visual stimulus, 4 trials with both audio and visual stimuli (bimodal) and 8 trials with just audio. Largely practising audio trials during familiarisation was to allow the participant to become accustomed to the audio stimulus and the change in tone which reflected how low or high they were from the force target. All participants performed the same quantity and type of trials during familiarisation.

**Constant Force Task**

At a subsequent testing session subjects attempted to produce isometric contractions at 5%, 10%, 25%, 50%, and 75% of their MVC for ten seconds. Each participant repeated each force level under three conditions: 1) visual, only the target and force trajectory 2) audio, the subject was given only audio feedback 3) bimodal, both the audio and visual feedback were provided. The order in which the participants carried out each trial was fully randomised. Prior to the commencement of each trial the participant was informed which condition type and what force level they were going to be attempting. Participants ramped up contraction from 0% as quickly as possible to the target. During contractions, the inter-phalangeal joint remained in contact with the load centre at all times. A one minute rest was given between lower efforts and three minutes rest was given after trials of 50% and 75% MVC.
Visual Condition

For the visual condition the target was a force level identified by two red lines two pixels (top line) and four (bottom line) pixels thick displayed on a computer monitor in a LabVIEW 8.2 (National Instruments LabVIEW®) environment (Fig. 3.2). The error gap between the red lines was scaled with the level of target as the target level ± 5%. In order to maintain a gap between the lines at the lowest force levels a minimum of a six pixel gap was set. This represented an error window of approximately ± 20% at 5% MVC target and ± 10% error at 10% MVC. The participant viewed their force trajectory as a white force-time trajectory two pixels thick moving from left to right across a black screen on the monitor. The display was rescaled for each subject so that the force target was displayed as a percentage of maximum from 0-100% to avoid possible effects on resolution due to scaling. Subjects were informed prior to the succession of each trial which force level they would be attempting. The participants were instructed to attempt to keep the white trajectory line centrally between the red lines.
However, they were asked to focus more on keeping the line as straight or ‘steady’ as possible as opposed to matching the centre of the force target exactly.

**Audio Condition**

The force target criteria and error window was the same for the audio condition as it was for the visual condition. However, instead of a visual display, the monitor was blacked out and the participant was only presented with feedback in the form of an audio tone. A high pitched tone signalled a force trajectory that was above target level, whereas a low pitched tone signalled dropping beneath the target level. The further away from the target the force trajectory became, the more extreme the pitch of the stimulus. The frequency of the audio signal was approximately 200 Hz when the force was too low (and decreasing as force decreased away from target) and approximately 600 Hz when it was too high (increasing as force increased away from target). When the force trajectory was at the correct target level the stimulus became silent. Therefore the aim of the task was for the participant to adjust the level of force produced in reaction to whether the audio pitch was high or low and steady the force production when the tone was silenced.

**Bimodal Condition**

During the bimodal trials the participant had both the visual feedback and audio feedback presented to them simultaneously.
Data Analysis

Any data < 0.3 N at the beginning of the data set was removed to avoid analysis of any data prior to the participant commencing force production. All data processing was performed using software written in Matlab v9.9 (the MathWorks, Inc). Prior to data analysis the signal was passed through a fourth order Butterworth filter (bidirectional) with a low-pass cut-off of 60 Hz. Any electrical noise was filtered out prior to further processing using 49-51 Hz 4th order low-pass Butterworth notch filter (bi-directional). A rolling minimum variance window was used to select the data to be analysed. The rolling window selected the steadiest section three seconds in length of the force data determined by calculating the Standard Deviation (SD) of each window and selecting the window with the lowest SD to be analysed.

Analysis For Magnitude Of Force Variability

The magnitude of variability in the selected section of signal was determined by calculating the SD and the CV. The root mean square was also calculated using equation (3.1)

\[
RMSE = \left[ \frac{1}{N-1} \sum_{i=1}^{N} (x_i - t)^2 \right]^{1/2}
\]

(3.1)

Approximate Entropy

Approximate Entropy (ApEn) (Pincus 1991) was used in order to analyse the time-dependant structure of the force signal. ApEn reflects the likelihood that the signal structure can be predicted. A value close to 2 reflects a signal that is less predictable (e.g. white Gaussian noise), where as a value closer to 0 reflects a time series that is
highly predictable (e.g. a sine wave). The parameter settings \( m = 2 \) (which reflects the length of compared data points) and \( r = 1.127 \) (which reflects the noise in the signal). The \( r \) value was calculated using the RMS of the force signal captured with a known force being exerted on the transducer as a representation of the noise that is in the signal.

**Detrended Fluctuation Analysis**

Analysis of the time domain structure was carried out using the Detrended Fluctuation Analysis (DFA) method as described by Peng et al. (1994). The process, which initially integrates and de-trends the force signal, quantifies the contribution of frequency components in the signal. It then determines the fractal scaling index or \( \alpha \) of the signal, taking into consideration non-stationary artefacts by using an RMS technique. Alterations in the \( \alpha \) value reported by the frequency analysis of the signal informs us of changes in the signal due to underlying physiological processes (Bassingthwaighte et al. 1994; Peng et al. 1994), where \( 0 < \alpha < 0.5 \) indicates long-range anti-correlations, \( \alpha = 0.5 \) indicates completely uncorrelated or white noise, \( 0.5 < \alpha < 1.0 \) long-range correlations, \( \alpha = 1.0 \) indicates \( 1/f \) noise, and \( \alpha = 1.5 \) indicates brown noise which is indicative of slow repeating processes.

**Signal Power**

The power in the signal was also calculated by performing a fast Fourier transform function (FFT) on the data using custom written software in Matlab v9.9 (the MathWorks, Inc). The total power in the signal between 0 and 30 Hz was calculated and the power that was in the frequency ranges 0-0.5 Hz and 0.5-4 Hz were calculated.
as a percentage of total power in the signal. These frequency bands were chosen as visuomotor correction processes are considered to be focused at the 0-4 Hz (Pew 1974; Slifkin et al. 2000; Vaillancourt and Russell 2002)

**Statistical Analysis**

The independent variables of age (young adults, elderly adults), force level (% of MVC) and condition (audio, visual, bimodal) were placed in a repeated-measures ANOVA with subjects as a nested factor. Post hoc differences were assessed using Tukey comparisons. An independent sample t-test was used to determine differences between MVC values. Significance for all statistical analyses was set at \(p<0.05\). All statistical analyses were completed in Minitab v15 Minitab\textsuperscript{\textregistered} Statistical Software).

### 3.4 RESULTS

A comparison of means using a t-test resulted in no significant difference in MVC between the age groups (Young: 23.5 N ± 1.6, Elderly: 23.9 N ± 2.0 [\(t=0.15, p=0.885\)]).

#### 3.4.1 Structure Of The Force Signal

**ApEn**

ApEn values increased as effort rose from 10% of MVC to 40% MVC for both subject groups; this trend was displayed across all conditions (Fig. 3.3). The ANOVA reported a significant main effects of condition \([F(2,210)=22.7, p<0.01]\) with the audio
condition presenting higher ApEn values than the both audio and visual conditions. When performing analysis across all three conditions there was a significant interaction effect of age*force \([F(5,210)=2.42, p=0.041]\). Tukey comparisons were carried out to investigate further. Elderly and young were significantly different from one another in audio, bimodal and visual conditions \([t=4.86, p<0.001]\), \([t=5.11, p<0.001]\) and \([t=5.32, p<0.001]\) respectively. Analysis of the force levels showed that there was a difference between elderly and young such that ApEn was reduced for elderly adults at force levels \(\geq 25\% \text{ MVC}\) \([p<0.05]\) (Fig. 3.4) where as below 25\% MVC there was very little differences in ApEn between the age groups.

**DFA \(\alpha\) values**

There was a significant interaction of force*condition \([F(10,210) = 1.99; p=0.035]\) with both groups displaying increasing \(\alpha\) values with increasing percentage of MVC
and highest $\alpha$ values for the audio conditions (Fig. 3.5). Tukey comparisons showed that the effect of condition was due to the audio condition which was significantly different to the visual condition for both the young [$t=7.58$, $p<0.01$] and elderly [$t=5.68$, $p=0.016$] when all force levels were pooled. In contrast the bimodal and visual conditions were not significantly different from each other [$p=0.99$]. There was no significant age interactions between the groups [$p>0.05$].

Figure 3.4: ApEn as a function of % MVC and age groups using audio condition (top), bimodal and visual conditions (bottom). Bars indicate standard error.
Figure 3.5: Plot of $\alpha$ values as a function of % MVC and condition (pooled across the two age groups). Bars indicate standard error.

3.4.2 Power In The Signal

0.5-4 Hz

The ANOVA found a significant effect of force $[F(5,210)=3.17, p=0.01]$ and condition $[F(2,210)=7.25, p=0.002]$ on the percent of power present in the 0.5-4 Hz ranges of the force signal. Post-hoc analyses using Tukey comparisons identified that for the young subject group there was an increase in the percent of power in the 0.5-4 Hz frequency bandwidths of the spectra during the audio condition compared to the bimodal condition $[t=3.63, p=0.005]$ but no difference between audio and visual $[t=2.35, p=0.18]$ and no change between the bimodal and visual tasks $[p>0.79]$. In contrast there was no significant difference in the percentage change of power in the same bandwidth for the elderly subject group across any of the conditions $[p>0.59]$. This was supported by ANOVAs performed on the two subject groups separately which resulted in signific-
ant condition effect for the younger subject group \(F(2,110)=5.96, p=0.009\) but found no significant effect of condition on the percentage of power for the elderly subject group \(F(2,195)=0.69, p=0.502\). Again, there was a significant effect found due to force level for the younger group \(F(5,110)=4.04, p=0.003\) but not the elderly group \(p>0.05\).

Though the effect due to age was not significant \(F(1,210)=2.44, P=0.134\), with the exception of 5% MVC, at all force levels and all conditions the mean percentage of power in 0.5-4 Hz range was lower for elderly adults compared to younger adults (Table 3.1). The mean of each condition across all force conditions was higher for the young group. Post-hoc Tukey comparisons showed means of the elderly group Vs the young group (lumped across all forces and conditions) were significantly different \(t=4.587, p<0.001\).

**0-0.5 Hz**

The effect on the percentage of power in the 0-0.5 Hz frequency range that was closest to significant was due to age \(F(1,264)=3.24, p=0.086\), though this was not significant \(p>0.05\). In contrast to the 0.5-4 Hz range, with the exception of 5% MVC the means were higher for elderly subjects than younger subjects (Table 3.1). Post-hoc Tukey comparisons showed elderly subjects presented significantly higher percentage of power in the 0-0.5 Hz range than younger subjects when pooled across all conditions and forces \(t=4.31, p<0.001\). Further ANOVAs performed on elderly and young subjects separately found a strong force level effect for young subjects \(F(5,132)=3.4, p=0.01\) but no significance for force level for elderly subjects \(p>0.5\).
Table 3.1: Percentage of the total power and standard errors in the 0-0.5 Hz and 0.5-4 Hz frequency bandwidths (as a percentage of power in 0-30 Hz bandwidth) as a function of % MVC target forces and conditions.

<table>
<thead>
<tr>
<th>MVC</th>
<th>5%</th>
<th>10%</th>
<th>25%</th>
<th>40%</th>
<th>50%</th>
<th>75%</th>
<th>Mean</th>
</tr>
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<tbody>
<tr>
<td>0-0.5 Hz</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elderly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio</td>
<td>24.6 ± 4.8</td>
<td>35.3 ± 8.0</td>
<td>34.9 ± 5.1</td>
<td>39.2 ± 7.9</td>
<td>38.7 ± 7.2</td>
<td>50.5 ± 7.2</td>
<td>37.2</td>
</tr>
<tr>
<td>Bimodal</td>
<td>38.3 ± 5.6</td>
<td>44.2 ± 6.4</td>
<td>37.0 ± 9.0</td>
<td>37.6 ± 6.09</td>
<td>36.9 ± 5.4</td>
<td>41.8 ± 6.55</td>
<td>39.3</td>
</tr>
<tr>
<td>Visual</td>
<td>36.2 ± 8.0</td>
<td>41.5 ± 5.7</td>
<td>33.2 ± 7.0</td>
<td>38.5 ± 6.8</td>
<td>28.2 ± 6.0</td>
<td>37.3 ± 6.2</td>
<td>35.4</td>
</tr>
<tr>
<td>Young</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio</td>
<td>30.7 ± 5.6</td>
<td>29.4 ± 6.2</td>
<td>31.0 ± 5.0</td>
<td>25.8 ± 3.6</td>
<td>26.3 ± 3.1</td>
<td>29.6 ± 5.2</td>
<td>28.8</td>
</tr>
<tr>
<td>Bimodal</td>
<td>47.2 ± 6.6</td>
<td>39.1 ± 5.9</td>
<td>33.6 ± 6.9</td>
<td>27.4 ± 5.0</td>
<td>27.4 ± 5.0</td>
<td>26.0 ± 4.2</td>
<td>33.5</td>
</tr>
<tr>
<td>Visual</td>
<td>36.1 ± 6.9</td>
<td>39.2 ± 5.4</td>
<td>27.0 ± 3.8</td>
<td>27.9 ± 3.5</td>
<td>21.4 ± 3.3</td>
<td>31.4 ± 5.0</td>
<td>30.5</td>
</tr>
<tr>
<td>0.5-4 Hz</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Elderly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio</td>
<td>65.7 ± 7.2</td>
<td>53.9 ± 8.9</td>
<td>60.8 ± 5.0</td>
<td>56.8 ± 7.6</td>
<td>56.6 ± 7.2</td>
<td>48.0 ± 7.1</td>
<td>56.95</td>
</tr>
<tr>
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<td>45.3 ± 6.4</td>
<td>55.2 ± 8.1</td>
<td>50.2 ± 6.3</td>
<td>57.2 ± 5.50</td>
<td>55.3 ± 6.4</td>
<td>52.50</td>
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<tr>
<td>Visual</td>
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<td>52.0 ± 5.8</td>
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<td>64.3 ± 5.3</td>
<td>59.3 ± 6.3</td>
<td>54.89</td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Audio</td>
<td>65.7 ± 5.9</td>
<td>65.0 ± 6.9</td>
<td>64.9 ± 5.4</td>
<td>69.2 ± 4.1</td>
<td>70.0 ± 3.4</td>
<td>68.3 ± 5.1</td>
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</tr>
<tr>
<td>Bimodal</td>
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<td>52.5 ± 4.4</td>
<td>56.8 ± 6.2</td>
<td>58.9 ± 4.1</td>
<td>63.3 ± 4.7</td>
<td>69.9 ± 4.3</td>
<td>57.54</td>
</tr>
<tr>
<td>Visual</td>
<td>51.3 ± 5.4</td>
<td>51.9 ± 5.4</td>
<td>64.1 ± 4.0</td>
<td>63.1 ± 3.1</td>
<td>69.8 ± 3.4</td>
<td>64.8 ± 4.5</td>
<td>60.93</td>
</tr>
</tbody>
</table>
3.4.3 Magnitudes Of Force Variability

Standard deviation

As shown in Figure 3.6, the mean SD for both the bimodal and visual stimuli increased linearly with increasing MVC levels for both subject groups which is consistent with previous observations regarding SD and muscle force requirement (Galganski et al. 1993; Slifkin and Newell 1999; Burnett et al. 2000; Laidlaw et al. 2000; Tracy and Enoka 2002; Tracy et al. 2005). Similarly to this the SD of the signal using just the audio stimulus generally increased with increasing MVC requirement; though the increase in SD from the 25% MVC trials to the 40% MVC trials was more acute than both the visual and bimodal trials 3.6. There was also more of a plateau in the increase in the SD of the signal at the higher force requirements during the audio task. There was significant main effect of force level \([F(5,210)= 110.05, p<0.01]\) and condition \([F(2,210)=36.27,p<0.01]\) on SD of force. Post-hoc Tukey comparisons showed that the significant effect of condition was likely as a result of the audio condition having
a significantly higher SD compared to both the bimodal and visual conditions when pooled across elderly and young subjects [t=11.43, p<0.01 and t=11.09, p<0.01 respectively]. In contrast, there was no significance at any force level between bimodal and audio conditions [p>0.99]. Although generally elderly adults displayed lower SD of force than younger adults (Fig. 3.6) there was no significant effect due to age on the SD of force [p>0.05].

Coefficient of variation

In contrast to the SD, CV was highest for the lower force levels (Figure, 3.7). Pooled across all conditions, the CV of force decreased as target force increased for both subject groups from 5-25% MVC [F(5,408)= 12.12, p<0.01), however, from 25%-75% MVC the CV of force did not change significantly [F(2,272)=0.51, p=0.673]. This pattern was demonstrated for both elderly and young adults and across all conditions. The ANOVA showed a significant effect of force∗condition [F(10,210)=3.87, p=0.00] on the CV of force. The mean CV increased by 250% [t=7.56, p<0.01] and 260%
[t=7.83, p=0.00] during the audio task against visual and bimodal conditions respectively when pooled across both ages and all forces. The bimodal condition only reduced the mean CV compared to the visual condition by approximately 3% (both age groups and forces pooled) which was non-significant [t=0.37, p= 0.713]. As a result, there was no significant difference between bimodal and visual conditions when pooled across elderly and young and all force levels [p>0.5]. There was also no age effect on the CV of force production [p > 0.05].

**Root mean square error**

There was a main effect due to both force and condition on the RMSE of the signal. Similar to the pattern displayed by the SD, RMSE tended to increase with increasing force requirement and was highest during the audio condition with the overall mean (pooled across subjects and force levels) being significantly higher than the bimodal [t=2.72, p=0.007] and almost significantly higher than the visual condition [t=1.86, p=0.064]. As the visual condition had a much higher SD it was not significant. Similarly to CV, the addition of audio to the visual condition resulted in a reduction in the mean RMSE by 15% for the bimodal condition (pooled across all subjects and forces), again this was not significant [p>0.5].

### 3.5 DISCUSSION

The purpose of this study was to examine the magnitude of variability and structure of isometric force signal data as a function of ageing, force requirement and the stimulus provided. The main findings of this study were: 1) There was no significant
differences between elderly and young in indexes of magnitude of force variability (SD, CV, RMSE), 2) Elderly adults display lower ApEn values (reduced irregularity) in force signal data than younger adults, 3) The bimodal condition had no effect on magnitude of force variability or force structure for both age groups, 4) There are differences shown in the amount of power at lower frequencies (0-4 Hz) between the two age groups.

3.5.1 Magnitude Of Variability

In contrast to previous studies (Galganski et al. 1993; Burnett et al. 2000; Semmler et al. 2000; Tracy and Enoka 2002; Vaillancourt and Newell 2003; Tracy et al. 2005; Marmon et al. 2011b), we found no significant effect of age on the indexes of force variability (SD, CV and RMSE). However, despite the lack of significance, at lower percentages of MVC (≤10% MVC) elderly adults displayed higher CV of force than younger adults which is in agreement with the trend identified in these studies.

There is a suggestion that removal of visual feedback results in a reduction in differences in measures of magnitude of variability generally found between elderly and young subjects (Tracy et al. 2007). However, in this study the removal of visual feedback exacerbated differences between the subject groups, with larger differences seen between elderly and young during the audio condition than any other condition (Figs. 3.6 and 3.7). One difference in this study compared to other literature involving visual feedback removal is the addition of the audio stimulus. Force response to audio stimuli in comparison to visual has shown to be higher during reaction tasks which may provide an insight into increases in CV of force during the audio condition (Jaskowski et al. 1995). The reason for higher force output is thought to be due to higher arousal
levels in reaction to audio stimuli (Jaskowski et al. 1995). A higher force output coupled with slower reaction times (Ratcliff et al. 2001) and a reduced ability to focus attention during motor tasks (Pesce et al. 2005) exhibited by elderly adults may be the source of the divergence in magnitude of variability during the audio condition in this study.
3.5.2 ApEn

The results from this study support the Lipsitz and Goldberger (1992) theory that ageing is associated with reduced complexity. ApEn values were lower for elderly participants during all conditions >10% MVC (Fig. 3.4). This reflects a more consistent and predictable pattern of force production which is thought to coincide with a reduced ability to adapt to perturbations (West and Goldberger 1987). In contrast the higher irregularity found in younger participants is thought to allow for adjustment to sudden changes as opposed to being ‘stuck’ in a pattern. The performance of elderly and young in this study in terms of magnitude of variability was comparable. It may well be the case that when attempting to match a steady force target which requires no sudden alterations, negative consequences of increased force regularity may not be apparent. However, if participants were required to quickly alter force production, changes in performance outcome may be more reflective of ApEn values.

In contrast to CV of force results, where generally larger differences have been identified between elderly and young subjects at low force levels ((Galganski et al. 1993; Burnett et al. 2000; Laidlaw et al. 2000; Semmler et al. 2000; Vaillancourt and Newell 2003; Tracy et al. 2005) and Figure 3.7, differences in ApEn values tend to be larger the higher the force level (Fig. 3.4); a pattern also found by Sosnoff and Newell (2006b) and Sosnoff et al. (2006). However, whereas the reported patterns regarding CV of force are relatively consistent across the literature, for ApEn this is not the case (Slifkin and Newell 1999; Deutsch and Newell 2004; Sosnoff and Newell 2006b,a). We have reported that with increased force requirement above 10% MVC there is a concomitant increase in ApEn until a plateau at forces >50% MVC. In contrast, studies have reported comparative increases up to 45% MVC followed by a large reduction in ApEn values with the lowest ApEn values reported at 95% MVC (Slifkin and Newell
1999) as opposed to 5% MVC in this study (Fig. 3.3).

The absolute values reported in these studies also reflect contrasting results to those found in our study. Sosnoff et al. (2009) report calculated ApEn values at 10% MVC to be approximately 0.4 in contrast to approximately 0.06 in this study at the same force requirement. The level of regularity reflected by our low ApEn values is proportional to those found in sine-wave traces (Sosnoff et al. 2009) which suggests extremely high signal regularity. When performing the trials at low force levels (≤10% MVC) the subjects were able to maintain an extremely steady force trajectory producing very few fluctuations (Figs. 3.9 and 3.9). As the task requirement was to maintain a steady path between two lines and not one single force target, it may be possible that the participants limit the amount of error correction during the task. Fewer corrective force fluctuations would likely lead to a steadier and more regular signal which may be a reason for low ApEn results in this study.

Differences in sampling and post-processing techniques between studies will also have had an effect on the outcome of ApEn values and the pattern exhibited. The sample frequency chosen, the input of the ‘r’ value (which accounts for the noise in the signal) and to a lesser degree the size of the data analysed all have an effect on the calculated ApEn value (Chapter 2.4). It is important therefore that methodology is scrutinised when comparing such studies. The sampling rate chosen by Sosnoff et al. (2009) was 140 Hz as opposed to 1226 Hz for this study. During post-processing, resampling the signal collected in our study to a sample rate equivalent to 102 Hz led to mean ApEn values of approximately 0.5 for isometric contractions at 10% MVC (Chapter 2.4). This value is comparative to the ApEn value of approximately 0.4 found by Sosnoff et al. (2009) and suggests that it is primarily the sample rate that causes discrepancies between these studies.
At low force requirements <30-40% MVC controlling muscle force at the FDI is generally contributed to recruitment threshold (Kamen et al. 1995). Consequently, it is suggested that difference in recruitment behaviour are a key contributor to magnitudes of variability at lower force levels. As patterns in CV of force and ApEn differ there is a clear indication that mechanisms that contribute to variability of force production and ApEn are not the same. This has led investigators to consider that regularity of the signal may be attributed to motor processing behaviour which is supported by evidence that manipulating feedback has a strong effect on ApEn values (Sosnoff and Newell 2006a). Reduced regularity displayed by elderly adults may well be a consequence of reduced processing abilities as an effect of ageing. If this is the case then structure of the force signal during various feedback conditions may prove useful when investigating the mechanisms behind the changes that occur as a function of ageing.

3.5.3 Effect Of Condition

The removal of the visual stimulus for the elderly led to an increase in ApEn values resulting in mean values similar to those displayed by the younger adult groups during the visual task. However, though irregularity of the force signal increased so too did the magnitude of variability of force production which suggests that the overall result was not positive. The younger adults displayed similar increases in ApEn values, which substantiates that manipulation of the feedback caused the changes in ApEn results. In contrast there were no differences in ApEn or magnitudes of variability of force between the bimodal or visual stimulus. As there were still differences in ApEn values between elderly and young adults in the audio condition (at force levels >25% MVC) it does suggest that differences between the ages are not as a result of
visuomotor processing as previously suggested (Sosnoff and Newell 2006c). It may be that there is a reduction in processing capabilities in elderly adults that alters motor output, but if this is the case then it spans modalities effecting both audio and visual processing.

The evidence, in contrast to our hypothesis, implies elderly subjects do not improve task performance (measured by magnitude of variability) or display changes in ApEn values as a result of multiple stimuli. This is likely due to the nature of this task. Bimodal stimulus has been shown to improve task performance during reaction type tests and naming of cue cards (Laurienti et al. 2006; Peiffer et al. 2007; Hugenschmidt et al. 2009) but has never to our knowledge been used as an addition to a visual force target. It's suggested that an increased ability to utilise an integrative technique in order to process audio and visual stimuli, leads to a reduction in reaction times in elderly. In contrast, there is evidence that the ability to selectively process multiple stimuli, whether visual or auditory is greatly reduced in the elderly (Alain and Woods 1999). However, in this study, type of condition affected both elderly and young participants in a relatively similar manner. Feedback from the participants after the task suggests that at least consciously the majority of the subjects focused on the visual stimulus alone when provided with the bimodal feedback. This supports the idea that if a subject has already reached their limit of processing capacity (Sosnoff and Newell 2005) then they may result in few improvements. As the condition effected ApEn values in a similar manner for both groups it suggests that the processing stimulus itself may not be differentiating the two groups from one another. Instead it may be down to the manner in which elderly and young adults make corrections during the task.
3.5.4 Frequencies Present In The Signal: 0-4 Hz

The majority of power in the force signal that is due to visuomotor processing and corrections is considered to be below 4 Hz (Miall et al. 1985; Sadato et al. 1996; Sliifkin et al. 2000; Taniwaki et al. 2003). When performing very slow movements of the index finger <0.5 Hz during target tracking, the corrections that are being made are considered to be as a result of correcting errors which means the process involves feedback processes (Pew 1974; Vaillancourt and Russell 2002; Sosnoff and Newell 2005). In contrast, >0.5 Hz the type of process to match a target frequency is thought to be predominantly a feed-forward process or ‘pattern-generation’ (Vaillancourt and Russell 2002). As younger subjects in this study consistently produced higher levels of power in the 0.5-4 Hz frequency range, it could be suggested that they tend to complete isometric force targeting predominantly by generating a pattern using forward-feeding process. In contrast, elderly adults showed significantly higher 0-0.5 Hz frequency power than younger adults. As error correction is considered to be <0.5 Hz, during the visual and bimodal conditions it would appear that elderly adults respond to the feedback and attempt to adjust for the error; a different processing pattern than their younger counterparts.

The nature of the task in this study when visual and bimodal feedback was presented was pursuit-like; the force trajectory and history were displayed clearly on the monitor. The pursuit task is likely to be highly influenced by a pattern-generation feed-forward process as opposed to compensatory tasks that rely on feedback control strategies (Ranganathan et al. 2001). This study has provided evidence that elderly subjects tend to have a higher percent of power in the <0.5 Hz frequency range than younger subjects which reflects a heavier reliance on the feedback processing method, making slower error corrections. As the accurate control of limbs in motor control is
heavily reliant on the ability to use feed-forward control, relying on having processing dominance in feedback frequencies may lead to unstable movements (Katayama et al. 1998). This may provide anecdotal evidence that a shift in processing capabilities and dominant processing techniques reduces elderly subject’s ability to perform at, or adapt to certain tasks.

The increased amount of power between ranges of 0.5-4 Hz in the audio task, (particularly during the lower force levels) compared to the visual and bimodal conditions may be as a result subjects reducing their reliance on the audio cue, focusing on the maintenance of a constant force once the silence has been achieved and thus developing a more pattern-generating behaviour. This is in agreement with the theory that when visual feedback is removed there is an increased reliance on pattern-generation (or feed-forward) processes (Sosnoff and Newell 2005).

An interesting finding was that in contrast to young subjects; there was no effect of force or condition on the percent of power present in the 0-0.5 Hz or 0.5-4 Hz frequency bands for the elderly subject group. Perhaps this is evidence of a lack of adaptability to the force and condition. One of the theories behind the negative consequence of reduced structural irregularity that occurs as a result of ageing is the consequential lack of adaptability it causes (Lipsitz and Goldberger 1992). This study would provide evidence to support this theory. Structurally, elderly adults show an increased regularity reflected in lower ApEn values. As there was no alteration in relative power in the 0-0.5 Hz or 0.5-4 Hz bandwidths due to condition or force displayed by the elderly group, it may again be an indication that elderly adults are unable to adjust motor processing requirements in order to adapt to different tasks. However, it must not be forgotten that this did not result in reduced ability to maintain a constant force, reflected in no significant effect of age for CV and SD of force.
3.5.5 DFA: $\alpha$ Values

Consistent with previous studies (Sosnoff et al. 2009), the continuous isometric force resulted in weak long-range correlations. The results from this study show that all the mean $\alpha$ values are above 1.0 with the Audio showing highest $\alpha$ values, reflecting more characteristics of brown noise (Sosnoff et al. 2009). Large differences between $\alpha$ calculated from audio condition compared to the visual/bimodal conditions corroborate the suggestion that are differences in the motor processing involved between conditions. The higher proportion of power at the lower frequencies during the audio condition reflected in higher $\alpha$ values and higher percentage of mean power at 0-4 Hz which suggests that there are fewer dominant processes involved in the processing compared to bimodal and visual conditions (Sosnoff et al. 2009). As the non-audio conditions resulted in improved performance outcome (reflected in lower magnitudes of force variability) this study provides evidence to support the theory that having a broader frequency spectrum is related to an increase in performance outcome in isometric tasks (Slifkin et al. 2000; Sosnoff and Newell 2005).

3.5.6 Considerations

Many of the studies investigating reduced vision on magnitude of force variability have involved intermittency or the removal of visual feedback during the task (Slifkin et al. 2000; Sosnoff and Newell 2005; Kennedy and Christou 2011). This study differs from previous studies using non-visual conditions in two key ways. Firstly, during the non-visual trials feedback was still provided via an audio stimulus. Though subjects did find it harder to make error corrections in comparison to visual feedback, it is clear
they were able to use the audio cues effectively to target the force levels (Figs. 3.9 and 3.9). Secondly, the target was not a single line but a double line representing the target with an error margin.

Pilot testing for the audio condition demonstrated that it was nigh impossible to maintain a silent status with a target trajectory with a width of one or two pixels. As a result, it was decided that an error window was needed. It was decided that it should scale with increased force production due to the increased difficulty at maintaining the silence at higher forces. In order to keep trials consistent, the same window was used for bimodal and visual trials. Though subjects were asked to try to maintain the force trajectory roughly in the centre of the window, this may not have always occurred, especially during audio conditions when no visual feedback was given. As a result some subjects may have been at the lower end of the error window whilst another subject may have maintained steady at the higher end of the window. At the highest value of 75% of MVC this may result in actual contractions to meet the target as low as 71.25% MVC or as high as 78.75% of MVC. However, the aim of the task was to produce the steadiest force trajectory not necessarily aim to keep as close to the target as possible. Having a target which is very narrow may result in larger error corrections and more excessive fluctuations. During every day tasks, it is unlikely that the force requirement needed has to be an exact amount therefore having an error window may in fact reflect a more normal pattern of force production.

The benefit of using audio in this manner is that there is no need to remove any of the signal to account for drift. For example Tracy (2007a) removed frequencies below 0.5 Hz in order to correct for any slow moving drift away from the target after removal of visual feedback. As we can see from our results there are differences between elderly and younger subjects in the percent of power at frequencies below 0.5 Hz. It is
therefore of benefit to be able to keep these frequencies in the signal during analysis. This study therefore contributes new information regarding how young and elderly compare when using an audio stimulus as a guide for force production.

3.6 CONCLUSIONS

In conclusion, we have provided further evidence to support Lipsitz and Goldberger (1992) that ageing leads to a reduction in irregularity in force production. Differences in the relative power in 0-4 Hz frequencies in the force signal suggests that elderly adults may use different processing behaviour than younger adults. The use of a bimodal stimulus did not alter force signal structure or variability in elderly or young adults. As differences in ApEn values between elderly and young adults remained in the audio feedback condition, it suggests that changes in force structure are not likely due to reductions in visuomotor processing. Instead differences between the groups may be a result of reduced information processing capabilities in elderly adults across modalities or, that elderly adults rely more heavily on feedback mechanisms to correct for errors. A positive outcome of this study was that participants of both ages were able to control force production by using an audio stimulus. This provides a new tool to use in measuring force variability between groups when visual feedback is not desired.
CHAPTER 4

DECREASED APEN VALUES IN ELDERLY ADULTS ARE ASSOCIATED WITH INCREASED TIME TO ACHIEVE STEADY MUSCLE FORCE FOLLOWING A CHANGE IN REQUIRED FORCE

4.1 ABSTRACT

Previous findings indicate that elderly adults exhibit reduced irregularity in the force signal compared to young adults when completing an isometric force matching task. Functional significance of lower ApEn values is investigated as reduced irregularity is considered to result in less adaptability (Lipsitz and Goldberger 1992). It was hypothesized that lower ApEn values would be associated with a reduced ability to adapt to a required force change. ApEn of the force signal, functional reaction time, and time to reach a steady state at the new force target was measured. Two different types of stimulus were presented to participants as force targets, bimodal and visual. The audio stimulus in the bimodal task changed pitch depending on whether the force trajectory was too high or low and was silenced when force level was correct. Audio stimulus was used in order to gain more information as to whether differences between elderly and young adults are due to visuomotor processing differences. Young (18-25) and elderly (65-72) neurologically healthy adults produced isometric force contractions.
using abduction of the FDI at six force levels that either increased, or decreased at a random interval. Increasing force levels were 5 to 25%, 25 to 50% and 25 to 75% of MVC and decreasing force levels were 25 to 5%, 50 to 25% and 75 to 25% of MVC. Each force level was attempted in random order under both visual and bimodal conditions. Results were compared with data collected from a continuous force task under the same conditions. There were no differences found in magnitudes of variability between the age groups nor was there any significant difference in findings during the bimodal condition compared to the visual condition for either groups. Confirming previous findings, ApEn values were higher in younger adults at force levels >25% MVC during both conditions indicating higher irregularity. However elderly adults displayed increased ApEn values compared to the continuous force trial which suggests that they are able to increase irregularity in force output during certain tasks. Confirming our hypothesis, elderly adults exhibited longer times to reach steady state, even after removal of reaction time at force levels initiated above 5% MVC. Mean time to reach steady state (minus reaction time) was 2.83 s for young subjects and 3.23 s for elderly adults [t=2.14, p=0.03]. These results did not depend on whether the force target moved up or down. These results provide evidence to support the concept that reduced irregularity leads to decreased adaptability to task alterations. This knowledge may be beneficial when modelling ageing movement and force production or used as a pre-clinical tool for identifying those at risk of falls etc.

4.2 INTRODUCTION

One of the pre-requisites of capably carrying out everyday tasks is being able to control motor output and muscle force to the requirement of the task. For example, when a person manipulates an object such as a glass, if the object becomes caught or is heavier
than expected, adaptation in terms of alteration in muscle force would be required in order to complete the task successfully.

Motor output and function declines with increased ageing. For example, compared to younger adults elderly adults often display increased response times to stimuli (Fozard et al. 1994; Porciatti et al. 1999), reduced strength (Marmon et al. 2011b), increased magnitude in variability of force production (Galganski et al. 1993; Burnett et al. 2000; Semmler et al. 2000; Tracy and Enoka 2002; Vaillancourt and Newell 2003; Tracy et al. 2005; Marmon et al. 2011b) and changes to structural characteristics of motor output signal (Chapter 3). Although it is not yet clear the direct cause or combination of causes behind such changes, it is likely that there is an association between these indexes, senescent functionality (Lipsitz 2002) and prolonged quality of life. Being able to minimise force fluctuations (measured as Coefficient of Variation, (CV)) during steady isometric contractions using the First Dorsal Interosseus (FDI) has been associated with improved performance in tasks that require manual dexterity such as groove peg board and the Operation™ game (Marmon et al. 2011b). As a result, being able to distinguish differences in isometric force signal between elderly and younger adults may provide information as to the changes that occur with ageing.

The level of entropy in an isometric force signal can be measured by Approximate Entropy (ApEn) which can be utilised to determine the regularity of the signal (Pincus 1991). During isometric contractions using the FDI, elderly adults have shown to have increased regularity and reduced complexity in structure of motor output during isometric force tasks, exhibiting lower ApEn values and higher percent of spectral power at low frequencies (Chapter 3). Research indicates that increasing age and disease leads to lower levels of complexity in multiple control systems (Lipsitz and Goldberger 1992), and as a consequence it is assumed that this reduced complexity is a negative
alteration. It is based around the concept that a signal that is highly regular and stuck in a pattern is less able to be disrupted and shift if necessary in response to outside perturbations that undoubtedly occur in everyday life. Consequently, a system with a higher level of irregularity would be more adaptable and therefore function to a better degree (West and Goldberger 1987). If lower levels of ApEn and increased regularity do lead to a lessened adaptability, then elderly adults who display lower ApEn values would be likely to be less able to rapidly adjust to an abrupt change in force level. As a result, elderly adults would exhibit increased times to reach a steady state at new force levels.

When performing an isometric force contraction using the FDI the visual stimulus presented affects the force output by altering ApEn values and force structure (Sosnoff and Newell 2007; Ofori et al. 2010) both of which demonstrates the influence visuomotor-processing has on force control. When visual feedback provided is delayed or removed, differences in ApEn values between elderly and young subjects are reduced (Sosnoff and Newell 2007; Tracy et al. 2007) which has led some investigators to suggest that differences in ApEn values may be down to elderly adults having slower visual processing times.

The use of audio stimulus has been shown to result in differences in motor output (Jaskowski et al. 1995) and has been shown to be utilised in improving reaction times in elderly subjects (Schroger and Widmann 1998; Fuhrmann-Alpert et al. 2008). This suggests that the processing of audio signals is not delayed in the elderly. Though the addition of an audio stimulus to a visual stimulus does not alter ApEn values in a continuous force task (Chapter 3) as of yet there have been no studies to our knowledge that have utilised a bimodal target for a changing isometric force task at the FDI. Having information regarding the effect a bimodal target has on force signal data may
shed more light on whether differences in the signal as a function of ageing are down to processing differences.

Therefore the aim of this study is to identify whether lower complexity in force signal data leads to less adaptability and therefore an increased time to reach a steady state at a new force level. It is hypothesised that as elderly adults display lower ApEn values during constant force tasks (Chapter 3) that they will have increased times to steady state than younger adults.

4.3 METHOD

Participants

Twenty-three, neurologically healthy subjects were assigned to two different age groups; young (n = 12; range 18-25 years; mean = 23 ± 4 years; seven females and five males), and elderly (n = 11; range 65-72 years; mean = 67 ± 5 years; six females and five males). All subjects were assessed for hand dominance by the Edinburgh Handedness Inventory (Oldfield 1971). Twenty out of the twenty-three subjects were deemed right hand dominant (younger group = 11(12); elderly group=9(11)). Subjects were excluded if they had history of a serious injury to the hand, suffered from arthritis affecting the hand, had untreated high blood pressure or were taking any medications that they knew to have neurological side effects. Any subjects needing prescriptive lenses to correct for sight were asked to wear the correct prescription and to continue to do so through all testing procedures. All subjects gave informed consent to all the experimental procedures which had been approved by Aberystwyth University Ethics committee.
**Apparatus**

The participant sat upright on a non-adjustable chair (height = 45 cm facing the computer monitor which was placed approximately 70 cm away and centred both horizontally and vertically from the eyes. The 60 cm monitor was positioned on a table (height = 71 cm). The participants non-dominant hand was pronated and lay flat resting on a custom made metal plate to which the load cell (HBM, PW6-CC3MR/10 kg, Hottinger Baldwin Messtechnik, Harrow, UK Ltd.; sensitivity 2.2 mV/V), was attached, output from the load cell was passed through a Hottinger Baldwin Messtechnik, Harrow, UK Ltd. full bridged transducer (AED-9101-B, HBM). The force signal was sampled at a frequency of 1226 cm.

The participant's dominant hand was placed on their lap. The non-dominant arm was placed such that the elbow was flexed to approximately 90° with the upper arm slightly abducted. A restraining plate was positioned between the first and second phalanges of the hand to be tested to restrict the motion of the third, fourth and fifth phalanges. A non-slip mat was placed between the table and metal plate in order to prevent the device from slipping. The load cell and thumb rest were positioned so that the load cell was level with the lateral side of the proximal inter-phalangeal joint with the angle between thumb and index finger being approximately 80° when the finger was in contact with the load cell.

Prior to any force tasks the participants performed light finger exercises in order to prepare the FDI for contractions and reduce the possibility of injuring the muscle. To standardise the hand position from trial to trial, each participant had an outline of their
hand traced in position. Before each trial the participant was asked to replace their hand within the trace and maintain it in that position throughout the trial. The participant was asked to maintain contact with the force plate with the palm, wrist, thumb and fingers throughout each trial to ensure moments produced were done so by abduction of the index finger alone. Position of the hand was monitored throughout the trials and the trial was repeated if correct position was not maintained throughout the trial.

**Familiarisation**

Each participant was asked to attend a familiarisation session within a week prior to the test day. During the familiarisation session subjects MVC was obtained to limit fatigue during the experimental session. To measure Maximum Voluntary Contraction (MVC) subjects were asked to increase an abduction force gradually over five seconds until they were pushing as hard as possible and holding the maximum force possible for 2-3 seconds. The force applied to the load cell was displayed on the monitor by a trajectory in white two pixels thick. The time count was displayed on the screen and verbal encouragement was given during each trial. After two practice trials a further three trials were performed and the maximum force recorded as the participants MVC. Between each trial the participant was given a 3 minute rest period. The maximum of the three recorded trials was used as the participants MVC. This value was then used to compute for each individual, target force levels at varying percentages of maximum. Following the MVC measurement, each participant practiced a number of the force targeting trials (as described in the experimental section). All participants performed the same quantity and type of trials during familiarisation.
Changing Force Task

At a subsequent experimental session prior to the isometric force task each participant was asked to react to the audio signal and visual signal to ensure that they were able to hear and see the stimulus clearly. No subjects failed to react to the stimulus. During the force trials, participants used isometric abduction of the FDI in order to match two red target lines that represented the target as a percent of MVC. The target was a force level identified by two red lines two pixels (top line) and four (bottom line) pixels thick displayed on a computer monitor in a LabVIEW 8.2 (National Instruments LabVIEW®) environment (Figs. 4.1 and 4.2). The error gap between the red lines was scaled with the level of target as the target level ± 5% for the 25, 50 and 75% levels of MVC. In order to maintain a gap between the lines at the 5% MVC trial, a minimum of a six pixel gap was set. This represented an error window of approximately ± 20% at 5% MVC target. The participant viewed their force trajectory as a white force-time trajectory two pixels thick moving from left to right across a black screen on the monitor (Figs. 4.1 and 4.2). The display was rescaled for each subject so that the force target was displayed as a percentage of maximum from 0-100% to avoid possible effects on resolution due to scaling.

Each trial lasted 15 seconds. The force target started at the first force level (pre-jump) and at a random interval between 5 and 10 seconds of trial succession, the force target changed (jumped) to a second level (post-jump). There were a total of six trials for each condition (bimodal and visual) which represented three magnitudes of force change:

The participant was informed that a force level change would be required and the force level that it would change to prior to the trial. Participants were asked to ramp up
contraction from 0% as quickly as possible to the target and were instructed to attempt to keep the white trajectory line centrally between the red lines. They were asked to focus more on keeping the line as straight or ‘steady’ as possible as opposed to matching the centre of the force target exactly. Participants were asked to change their force to the new target as soon as possible when it changed and once again attempt to keep the force target as steady as possible at the new force level (post-jump).

The participants performed twelve trials in total under the two conditions; visual and bimodal. The order in which the conditions and force levels were attempted was randomised. In order to minimize fatigue the participants had a 60 second rest period after all trials under 50% of MVC and 3min rest period after 50 and 75% of MVC trials.
During contractions, the inter-phalangeal joint remained in contact with the load centre at all times. A one minute rest was given between lower efforts and three minutes rest was given after the moderate and high level force trials.

**Bimodal Condition**

In order to assess the effect addition of an audio stimulus on the force signal characteristics a bimodal condition was also investigated. For this condition, as well as the visual target as described above the participant was presented with feedback in the form of an audio tone. A high pitched tone signalled a force trajectory that was above target level, whereas a low pitched tone signalled dropping beneath the target level. Increased deviations away from the target trajectory led to increase in the relevant pitch of the stimulus. The frequency of the audio signal was approximately 200 Hz when the force was too low (and decreasing as force decreased away from target) and
approximately 600 Hz when it was too high (increasing as force increased away from target). When the force trajectory was at the correct target level the stimulus became silent. Therefore the aim of the task was for the participant to use both audio and visual feedback simultaneously to adjust force level to target.

**Data Analysis**

Any data <0.3 N at the beginning of the data set was removed to avoid analysis of any data prior to the participant commencing force production. Trials where the subject had reacted within 100 milliseconds of target change were considered to have been pre-empted (Rousseau and Rousseau 1996) and were therefore removed from data analysis. In total, two trials were removed using this criterion, both of which were elderly participants. All data processing was performed using software written in Matlab v9.9 (the MathWorks, Inc). Prior to data analysis the signal was passed through a fourth order Butterworth filter (bidirectional) with a low-pass cut-off of 60 Hz (Chapter 2). Any electrical noise was filtered out prior to further processing using 49.0-51.0 Hz 4th order low-pass Butterworth notch filter (bi-directional). A rolling minimum variance window was used to select the data to be analysed. The rolling window selected the steadiest section three seconds in length of the force data from the pre- and post-jump force data, by calculating the Standard Deviation (SD) of each window and selecting the window with the lowest SD to be analysed.

**Functional Reaction Time**

After pilot testing, it was decided that a functional reaction to the stimulus had occurred once the participant had changed force trajectory in the direction of the new
force target for greater than 50 milliseconds (Fig. 4.3). It must be noted that this is not a traditional ‘reaction time’ but a standardised method in this study of determining when the subject had made a change in force target in the correct direction.

**Time To Steady State**

The rolling window that selected the steadiest section for data analysis was selected as marking the initiation of the steadiest section of the data. The data point that marked the beginning of the three second rolling window with the lowest SD was considered to be when the participant had reached the steadiest section of the trial (Fig. 4.3).

![Figure 4.3: Typical force trials of participant attempting 25% down to 5% MVC during visual condition.](image)

**Analysis For Magnitude Of Force Variability**

The magnitude of variability in the selected section of signal was determined by calculating the CV of the signal.
ApEn

Approximate Entropy (ApEn) (Pincus 1991) was used in order to analyse the time-dependant structure of the force signal. ApEn reflects the likelihood that the signal structure can be predicted. A value close to 2 reflects a signal that is less predictable (e.g. white Gaussian noise), whereas a value closer to 0 reflects a time series that is highly predictable (e.g. a sine wave). The parameter settings \( m = 2 \) (which reflects the length of compared data points) and \( r = 1.127 \) (which reflects the noise in the signal). The \( r \) value was calculated using the RMS of the force signal captured with a known force being exerted on the transducer as a representation of the noise that is in the signal.

DFA

Analysis of the time domain structure was carried out using the Detrended Fluctuation Analysis (DFA) method as described by Peng et al. (1994). The process, which initially integrates and de-trends the force signal, quantifies the contribution of frequency components in the signal. It then determines the fractal scaling index or \( \alpha \) of the signal, taking into consideration non-stationary artefacts by using an RMS technique. Alterations in the \( \alpha \) value reported by the frequency analysis of the signal informs us of changes in the signal due to underlying physiological processes (Bassingthwaighte et al. 1994; Peng et al. 1994), where \( 0 < \alpha < 0.5 \) indicates long-range anti-correlations, \( \alpha = 0.5 \) indicates completely uncorrelated or white noise, \( 0.5 < \alpha < 1.0 \) long-range correlations, \( \alpha = 1.0 \) indicates \( 1/f \) noise, and \( \alpha = 1.5 \) indicates brown noise which is indicative of slow repeating processes.
**Signal Power**

The power in the signal was also calculated by performing a Fast Fourier Transform function (FFT) on the data using custom written software in Matlab v9.9 (the MathWorks, Inc). The total power in the signal between 0-30 Hz was calculated and the power that was in the frequency ranges 0-0.5 Hz and 0.5-4 Hz were calculated as a percentage of total power in the signal. These frequency bands were chosen as visuo-motor correction processes are considered to be focused at the 0-4 Hz (Pew 1974; Slifkin et al. 2000; Vaillancourt and Russell 2002).

**Statistical Analysis**

For time to steady state and functional reaction time the independent variables of age (young adults, elderly adults), force change (whether force change was low, mod or high), change in level (whether the force target increased or decreased at the jump) and condition (visual, bimodal) were included in a repeated measures ANOVA with subject as a nested factor. For CV, ApEn and $\alpha$ scaling the dependant variables of age (young adults, elderly adults), force level (% of MVC), section (pre-target jump, post target-jump, continuous) and condition (visual, bimodal) were placed in a repeated-measures ANOVA with subject as a nested factor.

Post hoc differences were assessed using Tukey comparisons. An independent sample t-test was used to determine whether there was a difference in MVC between elderly and young adults. Significance for all statistical analyses was set at $p<0.05$. All statistical analyses were completed in Minitab v15 (Minitab© Statistical Software).
4.4 RESULTS

A t-test resulted in no significant difference in MVC between the age groups (young: $23.5 \pm 1.6$, elderly: $23.9 \pm 2.0$ [t=0.15, p=0.885]). Although the time that the target changed was randomised elderly subjects spent slightly longer in the second (post-jump) section of the force on average than younger subjects (mean change in force time: young =7.71 s, SD =1.47, Elderly: =7.20 s, SD =1.50, [t=2.85, p=0.005].

4.4.1 Functional Reaction Times

There was significant main effect of age [F(1,246)=26, p<0.001]. Young adults were faster than elderly adults to react to the change in force level (Fig. 4.4). Both groups reduced reaction times with the addition of the audio stimulus (bimodal condition) though this was not significant [p=0.253].
4.4.2 Time To Steady State

Younger subjects were faster than elderly subjects to reach steady state at all force levels (Fig. 4.5) [F(1,246)=8.34, p=0.009]. As there was a significant effect due to age on functional reaction time [F(1,246)=26.00, p<0.01] the time to steady state was also analysed after removing the this to identify whether the increased times displayed by elderly adults was primarily due to the increased reaction time. Time to steady state after removal of reaction time was 2.83 s for young subjects and 3.23 s for elderly subjects, analyses using these values also resulted in a significant main effect due to age [F(1,244)=5.83, p=0.025] which confirms that the difference in time was not due to the reaction time of the elderly subjects alone. Further analysis using Tukeys comparisons to investigate steady state as a function of starting force requirement confirmed age differences between the groups [t=2.136, p=0.034], though these were not significant at individual force levels [p>0.05].
Figure 4.6: Mean ApEn values as a function of age, force requirement and section (i.e. pre target-force change, post target-force change or constant force task).

4.4.3 ApEn

There was a significant interaction of age*section $[F(2,224)=3.72, p=0.026]$. Elderly adults exhibited lower mean ApEn values than young adults for all sections, post-hoc Tukey tests showed this was significant for both the post-jump section (Fig. 4.7) $[t=2.923, p=0.0438]$ and as previously reported, the continuous force task ($Chapter 3$, $[t=5.674, p<0.001]$). Post-hoc Tukey comparisons showed that for the younger group, there was no significant differences in ApEn values (pooled across all MVC force levels) between the sections, so that ApEn values did not alter significantly between pre-jump post-jump or continuous data sets $[p>0.9]$. In contrast, elderly subjects exhibited significantly lower ApEn values during the continuous force task compared to both the pre-jump $[t=3.626, p=0.005]$ and post-jump sections $[t=4.153, p<0.001]$, but pre and post jump sections were not significantly different from each other $[p=0.99]$. There was a significant interaction between age*force $[F(3,244) = 10.45, p<0.001]$. Post-hoc Tukey comparisons for this interaction showed that at 50% and 75% of MVC elderly adults exhibited significantly lower ApEn values than the younger adults. 

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**Figure 4.7:** Mean ApEn values as a function of age and section (i.e. pre target-force change, post target-force change or constant force task).

**Figure 4.8:** Mean ApEn values from pre-jump section as a function of age and force level (top) and time to reach steady state post-jump as a function of age and force requirement (bottom).
This confirms previous findings regarding the effect of age on ApEn, where MVC requirement >25% leads to differences in ApEn values between elderly and young adults (Chapter 3). In support of our hypothesis, elderly adults took a longer time to reach steady-state compared to young adults when moving from pre-jump force levels greater than 5% MVC (Fig. 4.8). Results from force levels <75% MVC provide evidence to suggest that increased time to reach steady state is associated with lower ApEn values.

There was a significant section*force interaction [F(6,224)=2.67, p=0.016]. Confirming previous findings (Chapter 3), ApEn values increased with increasing MVC requirements no matter the state. There was no effect due to condition on ApEn results with results under the bimodal condition reflecting those in the visual.

**Figure 4.9:** Mean CV at each force requirement (elderly and young participants pooled) during pre-jump, post-jump and continuous force section. Post-jump CV at 5% MVC is significantly higher than both the pre-jump and continuous force data [t=10.95, p<0.01 and t=6.86, p<0.01 respectively].
Coefficient Of Variation

Confirming previous findings (Chapter 3) the highest CVs were displayed at the lowest force targets with 5% MVC contractions being significantly higher than all other force levels \( p<0.05 \) (Fig. 4.9). There was a significant interaction of section*force level \( F(6,224)=5.38, p<0.01 \) meaning that the pattern of CV values at different force levels was different for the different sections. Post-hoc Tukey comparisons showed CV of force for 5% MVC for the post-jump section to be significantly higher than both pre-jump and continuous task sections \( t=10.95, p<0.01 \) and \( t=6.86, p<0.01 \) respectively. However, the pre-jump and continuous task sections at 5% MVC were not significantly different from each other \( t=2.240, p=0.5229 \). There was also a significant difference between post-jump CV of force at 25% MVC compared with continuous force production \( t=3.517, p=0.260 \). These findings suggest that when trying to stabilise to a new force level, participants were more variable than during a constant force task at low force levels only \( p>0.05 \).

Elderly adults showed an increase in CV of force during the bimodal condition (Fig. 4.10) when compared to the visual condition and were more variable during the bimodal
condition only. However post-hoc Tukey comparisons found no significant differences between elderly and young at any of the individual force levels and general pattern of results was comparable to those found for the visual task.

4.4.4 DFA: α Scaling Index

There was a significant force*section interaction [F(6,218)=2.65, p=0.017]. Post-hoc Tukey comparisons showed that the post-jump α values were all significantly different to those at the same MVC level for both pre-jump and continuous force data [p≤0.004] (Fig. 4.11). However, pre-jump α values and continuous force α values were not significantly different from each other [p>0.8]. There was no effect of age on the pattern of results, nor did the pattern change with stimulus condition.

![Figure 4.11: Mean α values as a function of state (i.e. pre target-force change, post target-force change or constant force task). * Indicates significant differences between the groups.](image)
4.4.5 The 0-0.5 Hz And 0.5-4 Hz Frequency Ranges

The $\alpha$ value reflects global changes in the frequency spectrum; however, they do not provide information that identifies exactly where these changes occur. As in this study we are predominantly looking to identify changes in visuomotor correction the frequencies between from 0-0.5 Hz and 0.5-4 Hz were determined in terms of the percent of power in the 0-30 Hz bandwidth that is distributed in each of these two ranges. There was a main effect on 0-0.5 Hz due to force requirement [F(3,592)=7.07, p<0.001] with the percentage of power in the bandwidth decreasing with increasing force requirement for both elderly and young adults.

There was a main effect on the 0.5-4 Hz frequency ranges due to section (pre-, post-jump, continuous) [F(2,460)=4.6, p=0.011] (Fig. 4.12) and force level [F(3,460)=17.82, p<0.001]. Relative power increases were seen in the 0.5-4 Hz bandwidth with increasing force level, and post-jump percentage of power was higher than pre-jump. Post hoc Tukey analysis identified this to be significant (difference between pre-jump and post-jump [t=3.03, p=0.007]) but also identified that there were no significance differences
between pre or post-jump and the continuous force production task [p > 0.1].

4.5 DISCUSSION

Previous literature has generally focussed on examining force structure and magnitudes of variability during either constant force tasks or tasks that require following a sinusoidal or ramped trajectory (for example, Deutsch and Newell (2001); Vaillancourt and Newell (2003); Sosnoff and Newell (2006c); Ofori et al. (2010)). It has been demonstrated that elderly adults display force output that has a reduced level of irregularity than younger subjects. This is particularly the case at higher force levels (Chapter 3). Structural regularity demonstrated by elderly adults may result in a decreased ability to respond to perturbations and thereby reducing the ability to adapt to a situation (West and Goldberger 1987; Goldberger et al. 2002b; Lipsitz 2002). Despite previous studies identifying differences in force output between elderly and young adults, no other study to date has investigated the functional effects of this difference. Therefore the purpose of this study was to test the hypothesis that lower ApEn values exhibited by elderly adults would be associated with an increased time taken to re-steady if required to change force level during an isometric contraction. The main findings from this study are: 1) confirming previous results, elderly adults exhibit lower ApEn values when compared to younger adults at force levels above 50% MVC. However as differences between young and elderly adults were reduced, compared to those found reported in a constant isometric force task, there is an indication that elderly adults are able to produce force output with increased irregularity. This suggests that the level of irregularity may be task specific 2) time to reach state was longer for elderly adults 3) the addition of bimodal improved functional reaction time for both elderly and young subjects but had no effect on time to steady state.
4.5.1 Steadiest Time

In agreement with literature on reaction times, elderly adults showed a delayed functional reaction time to the onset of the force change requirement (Fig. 4.4) which is likely as a consequence of reduced neural processing capabilities (Spear 1993; Nusbaum 1999). Taking into account differences in reaction time, elderly subjects continued to display increased time to steady state than younger adults (Fig. 4.5), this is despite the fact that coincidently elderly adults spent on average a longer time in the post-jump section. In agreement with our hypothesis when ApEn values between elderly and young are similar (5% MVC) time to steady state between the groups is also similar (Fig. 4.8). Results at 25% and 50% MVC support the Lipsitz and Goldberger (1992) theory, reflecting lower irregularity leading to a decreased ability to adapt to the task, the result of which is an increased time to reach steady state. This is more prominent in the elderly subjects, who display characteristics that suggest they produce force output that is more ‘stuck’ in a regular pattern which inhibits their ability to alter their force trajectory. At 75% MVC ApEn values are highest (or similar to at 50% MVC) for both groups which would suggest a high level of adaptability resulting in lowest times to steady by our hypothesis. In contrast times to steady state at 75% MVC were the longest for both groups. As the target level starting at 75% MVC reduces to 25% it represents the largest jump in force requirement of the tasks. The increased time to steady state exhibited by both groups may therefore be a reflection of the participants finding the task more difficult to accomplish.
4.5.2 Changes Between Tasks

In agreement with our previous findings investigating continuous isometric force (*Chapter 3*), elderly adults exhibited lower ApEn values than elderly adults at force levels above of 25% MVC. However, there was a large decrease in the difference between the groups indicating that elderly adults are able to produce a slightly more irregular force signal pre- and post-jump compared to the continuous force task. Previous studies have shown that task alters ApEn values and the patterns exhibited between elderly and young participants. For example, compensatory tasks tend to reduce the effect of age on ApEn and spectral differences in the signal compared to pursuit tasks (Ofori et al. 2010). Also, when adjusting force output to match a sine wave task, elderly adults showed increased ApEn values so that they were above those of younger subjects (Vaillancourt and Newell 2003). In the same study, the participants also performed a constant isometric force task which resulted in elderly adults having the lowest ApEn values. These results add to the evidence that elderly adults are able to display higher levels of system complexity, but that it may be task orientated.

The $\alpha$ values calculated by DFA increased in value post jump compared to the constant force task for both young and elderly groups. This suggests that after a change of force level, the processes involved in maintaining a constant force become slower and repeating. The higher $\alpha$ value also reflects a narrowing of the frequencies present in the signal which is associated with a decrease in performance outcome measured by SD and CV (Slifkin et al. 2000). The finding that increases in $\alpha$ values post-jump were paired with higher CV values does support this theory. Furthermore, the pattern shows the highest increase in $\alpha$ values from pre-jump to post-jump signal occurred at 5% of MVC which is the same force level that the highest increase in CV occurred.
Elderly adults have been previously shown to have a higher reliance on correcting for feedback as opposed to feedforward processing techniques, indicated by higher power in the 0-0.5 Hz frequencies (Chapter 3). It has been suggested that in motor control systems, heavy reliance on feedback control results in unstable and jerky outcome of movement (Katayama et al. 1998) and that utilising feed-forward control can reduce the magnitude of response required after perturbations such as slips or falls (Pavol and Pai 2002). In contrast to the continuous force task, during this study, there were no differences between age groups in relative percentage of power at 0-0.5 Hz or 0.5-4 Hz frequency ranges between the groups and a concomitant reduction in the differences between groups in ApEn values. This may be a consequence of the task requirement and a shift in the corrective processing technique of elderly participants, particularly post-jump (Fig. 4.12), that is closer to that utilised by the younger group.

As age differences in force structure are thought to be down to visuomotor processing (Sosnoff et al. 2006; Ofori et al. 2010), the primary reason for using the bimodal stimulus in this study was to provide extra information to the participants to aid processing. Limiting or removing of visual feedback has been shown to reduce differences between elderly and young (Sosnoff and Newell 2006c), so the aim in this study was to identify what would happen when adding information. On the whole, addition of the audio stimulus did not alter ApEn, CV or force structure of the signal. Although the bimodal condition reduced reaction time for both elderly and young participants, it did not reduce time to steadiness. In contrast, steadiest times increased with addition of the audio for both groups (Fig. 4.5). This reflects a higher SD for longer in the signal during the bimodal condition. As the introduction of an audio stimulus leads to increases in force output response (Jaskowski et al. 1995) it may be that over-compensation when reacting to the signal led to higher force fluctuations.
As ApEn values between elderly and young became more similar in both pre-jump and post-jump in this study compared with a previous isometric contraction task, it suggests that task dynamics are the key influences on force structure in this case. When attempting to identify differences between elderly and young subjects, it is difficult to decipher whether changes are due to processing or biophysical/mechanical changes that may occur with ageing. Removing visual feedback leads to reductions in differences between elderly and young, but concluding that lower ApEn values are down to visuomotor processing may be erroneous. This change in pattern may not a consequence of reduced visual processing capabilities, but just a reflection of the negative effect of removing feedback on both populations. The addition of the audio in this study allowed extra information for processing, yet this had no effect on ApEn values for either of the groups. Also, at lower force requirements there is little difference seen between age groups in terms of ApEn values (Chapter 3, Figs. 4.6, 4.8 and Sosnoff et al. (2006)). Instead, evidence does suggest that the level of regularity is task specific (Vaillancourt and Newell 2003; Ofori et al. 2010) and dependant on force requirement.

4.5.3 Limitations

When investigating changes in motor output and attempting to measure functional differences, it is difficult to replicate a functional task in a controlled environment. Therefore one of the key limitations in this study is the task is not reflective of a functional day to day situation. When altering motor output to respond to a perturbation such as a glass catching on a something as you are trying to move it, a change of force production is likely to be required. Change of force requirement was therefore used in this task, however it does not replicate the trajectory movements that are likely to be required, nor the feedback that a person would usually receive. For example, much of the feed-
back received when attempting to change force requirement in day to day life would be proprioceptive and not just responding to a visual target. Also, the participant knew that force requirement would alter and were therefore expecting a necessary change in motor output. This is likely to produce different behaviour to that exhibited if a perturbation was unexpected which is a common occurrence in daily life. As such, the environment in which the task is set is highly artificial. Whether results reflect real-life motor output behaviour is not clear.

4.6 Conclusion

This study has provided evidence to support the case that lower levels of regularity lead to reduced ability to adapt to a situation or task (Lipsitz and Goldberger 1992). While there were increases in ApEn values in elderly people in this task they were still consistently lower than those exhibited by younger adults (who’s ApEn values do not change with task). Elderly adults took a longer time to reach steady state after a force change, despite having on average a longer time in the post-jump section. Therefore, we conclude that lower ApEn are associated with an increased time to reach a steady state after a change in force level (post-jump). Increased understanding of changes in force signal that occur as a consequence of ageing may lead to the ability to identify pre-cursors for the identification of those of risk of falls etc. It also of use to the investigator when modelling the ageing body to use a force signal data relevant to the population. Another benefit of this study is that it has provided supporting evidence that elderly adults are able to produce more complex structure in force production during certain tasks. This may be beneficial in the study of senescence in order to try to improve functionality in elderly adults.
CHAPTER 5

THE DETERMINATION OF BODY SEGMENT INERTIAL PARAMETERS: a REVIEW OF LITERATURE

5.1 USES FOR BSIPS IN BIOMECHANICS

Resultant joint moments are the sum of all muscle forces, ligament forces and forces due to articular surface contact acting about a joint (Challis 1996). Being able to effectively calculate joint moments is important in order to gain an understanding of human motion (for example, walking gait or lifting objects). Such analyses can be utilised in areas such as injury prevention (Gatt et al. 1998), technique analyses for coaches (Burden et al. 1998) or in order to calculate joint net loads for designing prosthetics (Robert et al. 2007). To calculate moments, body segment masses, Centre of Mass (COM) and segmental moments of inertia or Body Segment Inertial Parameters (BSIPs) are required. Being able to accurately estimate BSIPs for various populations is important as errors in BSIPs result in errors in joint moment calculations especially during high speed movements (Pearsall and Costigan 1999; Ganley and Powers 2004).

Despite there being the necessity for calculating joint moments for females (for example for athletes or prosthetic development) currently the only methods used to calculate BSIP data specifically for young females are derived from scanning methods.
such as Dual-energy X-ray Absorptiometry (DXA) which is both expensive and radiating, or the use of a models that account for sex (e.g. Hatze (1980)). Though models such as these account for gender, they are not designed specifically for use on females. As gender has shown to have an effect on BSIP estimates in both elderly (Jensen and Fletcher 1994) and obese (Chambers et al. 2010) populations, specific gender models should be developed to predict BSIPs as accurately as possible. Therefore, having a method that can accurately determine the BSIPs of females but that is efficient in terms of time spent with the participant would be beneficial. This chapter will discuss the current use of cadaver, DXA and geometric model derived BSIP data.

5.2 IN VITRO METHODS

5.2.1 Cadavers

Since the early 19th century cadavers have been studied in order to determine BSIPs (Weber and Weber 1836; Harless 1860). These pioneering studies involved the dissection of segments and the measuring of segment COM using balance plates and scales. Though rudimentary, these investigations were the first to study humans in segmentation and to introduce the concept of modelling the body in the form of geometric shapes.

Cadaver studies continued through the 20th century by the likes Dempster (1955); Clauser et al. (1969); Chandler et al. (1975). Mass, volume, density and/or centre of mass of the total human body and of selected segments was determined and used to create equations to predict parameters using mass and anthropometric measures. Average densities of each segment were approximated from the proportions of muscle/skin/adipose
tissue present in each segment. These values are now widely used when average density values are required.

One of the benefits of using cadavers is that the inertial parameters of a segment can be measured directly; though it does assume that frozen or embalmed tissue is comparable to living tissue. Unfortunately, the cadavers used in these studies were representative of only one population group (elderly Caucasian males). Depending on age, sex, somatotype, racial or ethnic origin, the proportions and density of tissues in the body vary (Wagner and Heyward 2000). For example, females aged between 20-29 have been shown to have an average whole body density of 1.034 g/cm$^3$ whereas males of the same age had an average whole body density of 1.064 g/cm$^3$ (Durnin and Womersley 1974).

There are also larger differences in densities depending on the segment in question. Wicke et al. (2008) have provided average density profiles of the trunk of men and women using dual X-ray absorptiometry. The Clauser et al. (1969) density function derived from males for the trunk is set at a uniform 1.019 g/cm$^3$ whereas the female trunk density profile ranges from approximately 0.79-1.05 g/cm$^3$ (Wicke et al. 2008) along the length of the trunk. It is therefore questionable whether parameters derived from elderly male cadavers should be used in the determination of BSIPs of other populations such as athletes, females or children. For example elderly adults have a greater amount of mass on their trunk and less on their limbs compared to young adults (Jensen and Fletcher 1994; Chambers et al. 2010) and females have higher mass in the lower extremity segments (e.g. shank and thighs) (Jensen and Fletcher 1994; Durkin and Dowling 2003; Chambers et al. 2010).

Currently, there is no cadaver data available for women and as the availability of cada-
vers is restricted to those donated, it is unlikely that there will ever be a representative sample for the female populations making further in vitro BSIP investigations improbable. Regression equations, designed to extend the use of cadaver data for the wider population (e.g. Hinrichs (1985)) were developed, but suffer as they are only applicable to populations from which the data was collected (e.g. elderly males). The limited applicability of cadaver data led to further efforts to establish BSIP models, such as the modelling of the body as a series of geometric shapes.

5.3 IN VIVO METHODS

5.3.1 Geometric Models

Geometric modelling involves modelling the body segments as a series of geometric shapes; the dimensions of which are obtained by taking anthropometric measurements, such as segment lengths and perimeters, from the experimental participants. Density sets derived from cadaver studies such as Dempster (1955) are then used in conjunction with volumes calculated from the anthropometric measurements in order to determine segment mass, COM and moments of inertia. The density of each segment is generally presumed to be uniform throughout the segment although some studies have investigated the effect of using non-uniform densities in segments such as the shank and trunk (Ackland et al. 1988; Wicke et al. 2008; Wicke and Dumas 2010). The assumption of uniform density does have some influence on BSIP results. A geometric model of the lower trunk region showed mean standard deviation errors in mass ranging from 7.4 ± 2.6% using a uniform density function compared to trunk mass measured by DXA. The range of errors was reduced to -2.4 ± 2.6% when using a non-uniform density function (Wicke and Dumas 2010). Errors for the moments of inertia about the anti-
posterior axis were also a lot larger for the uniform density function (9.3 ± 4.1% as opposed to 0.4 ± 3.0 %) (Wicke and Dumas 2010). However, this study suggested that although uniform density functions are a cause of error, volume error has a larger influence on BSIP which suggests that the geometric shape used to model each segment should be chosen with care (Wicke and Dumas 2010).

Geometric models are suggested to be more sensitive to the variability in mass distribution between subjects which results in better BSIP estimates than regression equations (Durkin and Dowling 2003). Models range in complexity from basic models such as that of Hanavan (1964), which used just twenty-five anthropometric measures, to highly complex models such as that of Hatze (1980), which requires two-hundred and forty-two measurements. The Hatze (1980) model utilises varying density functions determined by measures of subcutaneous fat at the hip, therefore it takes into account exomorphic differences between participants and sexes. The mean of the relative errors for scale measured mass and computed masses using this model were just 0.26%. One of the benefits of the Hatze (1980) model was that it was designed to be able to determine BSIPs for females. However, although the mean of the relative errors for measured and computed masses for the female subject was very low (0.116%) it should be noted that the female was athletic in build, perhaps not similar to all females requiring BSIP estimates. Another downfall to the model is that it is highly complex and taking such a large number of measurements is a time consuming process (taking approximately 80 minutes per subject (Hatze 1980)) and is highly impractical when limited time is available with a subject.

It likely that errors in model predictions may be due to body segments being modelled using inappropriate geometric shapes, particularly the trunk segment (Wicke and Dumas 2010). The trunk represents a large percentage of whole body volume (22-50%
of whole body volume, (Forrest 2008)); therefore errors in the modelling this segment will have a large effect on the whole body volume and resultant BSIPs (Forrest 2008). The trunk has the greatest intra-individual variation and inter-individual differences compared with any other body segment (Wicke and Dumas 2007; Wicke et al. 2008) and as the anterior and posterior contours of the segment are not symmetrical in nature it is difficult to choose appropriate shapes to use in the modelling of the segment. Stadium solids (Sady et al. 1978; Yeadon 1990), ellipses (Jensen 1978) and sectioned ellipses (Wicke and Dumas 2007) (Fig. 5.1) have previously been used to model the trunk. Sectioned ellipse were used in the upper region of the trunk in order to account for the insertion of the shoulder section which was thought to be a cause of large errors in estimated trunk volume (Wicke and Dumas 2007), this led to a reduction in the absolute error in volume at the upper trunk from 18.19% to 5.14%. The model was used on both males and females with later research validating the model further with another twenty-five females (Wicke et al. 2009). The absolute errors in predicted trunk (upper and lower) mass in this study for the female participants was 6.44%. However, it is not stated whether these are mean squared errors or whether errors having merely been added together which would have a large influence on reported values. Also, the females used in the first study were Olympic athletes and in the latter study the females
had a low average BMI 21.8 kg/m$^2$ (SD 1.5). Whether this model would be applicable to non athletic women with a larger BMI is yet to be seen.

Summary

In summary, one of the benefits of using a geometric model is that the technique requires basic equipment; an anthropometric measuring tape and computer software. Not only is this beneficial when time with subjects is limited, but costly equipment such as scanners are not required, making the process cost effective and practical as measures can be taken outside of the laboratory. However, there are limitations; assumptions such as uniform density may lead to systematic errors in models and choice of geometric shape used should be made with care as this has been shown to be a large source of error (Wicke and Dumas 2010). What is clear is that although geometric models are subject specific, shapes chosen for modelling and assumptions such as uniform density (generally derived from cadaver data such as Dempster (1955); Clauser et al. (1969); Chandler et al. (1975)) are assumed. The fundamental problem in this research area is the identification of where errors occur in the BSIP estimations. Such errors are difficult to identify without criterion values of segmental inertial parameters with which to compare the calculated values. As a result, measuring BSIPs using scanners such as DXA has become more popular as a validation tool for models and a direct method of measuring subject specific BSIPs.

5.3.2 Dual X-Ray Absorptiometry

Single photon absorptiometry was introduced as an imaging technique originally designed to assess bone mineral density (Cameron and Sorenson 1963). As radionuclide
emitted photons pass through the human tissue, physical interactions take place that reduce the beam intensity. The process, generally referred to as attenuation, is an outcome of atomic interactions between photons and elements within the tissue. This results in a scattering or absorption of the photons. The main processes are elastic scatter, Compton scatter, photoelectric absorption and pair production. As the effects of unmodified scatter and pair production are negligible the attenuation process is essentially a result of two physical interactions; Compton scatter and photoelectric absorption (Pietrobelli et al. 1996; Ball et al. 2008). The degree to which a material attenuates photons is generally referred to as the mass attenuation coefficient \((\mu/\rho)\), where \((\mu)\) is the attenuation coefficient and \((\rho)\) the density of the matter. The reduction of flux caused as a result of the attenuation is measured using a photon detector (Heymsfield et al. 1997). This technique was then developed further evolving into a system using two X-ray photon beams of different energy levels, thereby making it possible to treat the tissue in the photon pathway as a two-component mixture consisting of both bone minerals and soft tissue (Mazess et al. 1990; Heymsfield et al. 1997). This method is generally referred to as Dual-energy X-ray Absorptiometry (DXA).

DXA involves the measurement of the transmission through the body of the two X-ray photon beams (Genton et al. 2002). For each pixel the attenuation at the lower energy level is then expressed as a ratio \((R)\) to the attenuation observed at the higher energy level. \(R\) values of specific elements are directly related to the atomic number of each element, the higher the atomic number the higher the \(R\) value. For example Hydrogen (atomic Number 1) and Calcium (atomic number 20) have \(R\) values of 1.0891 and 3.5422 respectively (Pietrobelli et al. 1996). As real tissues are complex in nature and are comprised of more than one element, the resultant \(R\) value of each tissue type reflects the mass fraction of each of the elements present within the tissue (Pietrobelli et al. 1996; Heymsfield et al. 1997). The attenuation characteristics of pure fat \((R_F)\)
and of bone-free lean tissue \((R_L)\) are known from theoretical calculations and in vitro measurements (Jebb 1997). When these two components are present in a pixel it is therefore possible to calculate (using equation (5.1) (Jebb 1997)) the proportion of lean tissue \((\infty)\) and fat tissue \((\beta)\) using the DXA measured \(R\) values and the assumption that the two components’ mass attenuation coefficients at the two energy levels are known and constant (Pietrobelli et al. 1996).

\[
R_{st}\text{(low energy)} = \infty(R_F) + \beta(R_L)
\]

\[
R_{st}\text{(high energy)} = \infty(R_F) + \beta(R_L)
\] (5.1)

However in pixels that contain bone, lean tissue and fat tissue which account for approximately 40% of all pixels in the body (Jebb 1997) a problem arises as there are three components present when DXA can only calculate for two unknowns. In this case DXA calculates using known \(R\) values for pure bone and all mass in the pixel that is not bone is considered to be soft tissue. Algorithms are then used to predict the soft tissue content, this is estimated as containing the same fraction of fat and lean tissue as those pixels neighbouring the bone pixel (Pietrobelli et al. 1996; Heymsfield et al. 1997; Jebb 1997). This may result in errors in estimations in body segments that have a high amount of bone to soft tissue ratio such as the limbs and thorax as there are fewer bone-free pixels available from which to get fat and lean mass calculations (Laskey 1996). As with any measuring method where assumptions are made, subsequent calculations made using such assumptions lead to uncertainties.
Errors

Differences between DXA machines exist due to different algorithms used for converting the beam attenuations into raw data and the type of beam used (fan or pencil). There is a lack of standardisation and across DXA models. As well as differences in hardware and calibration standards, there are differences in software used for edge detection between machines and between software versions produced by the same manufacturers resulting in discrepancies in tissue estimations (Tothill and Avenell 1994; Ambrosius and Hui 2004). Unfortunately manufacturers refuse to disclose the complex algorithms used making comparisons between software difficult (Roubenoff et al. 1993). Previous investigators have extracted the raw data from the machinery making it possible to create custom software in order to analyse data (Durkin et al. 2002). This is no longer possible as manufacturers no longer release conversion data for the more recent machines. Also comparisons against such studies are difficult as the software used is no longer available.

Researchers have investigated the differences between whole body composition determination using DXA scanners made by the three main manufacturers (Hologic, Lunar and Norland) compared with underwater weighing (UWW) (Tothill et al. 1994) previously considered as the “Gold Standard” for body composition measurement (van der Ploeg et al. 2003). Results showed that the Hologic scanner produced total body fat percentages comparable with UWW (23.4% and 23.6% respectively) where as results obtained from both Lunar and Norland machines were more than 3.5% and 6.2% higher than the UWW value (Tothill et al. 1994). However, when comparing with other methods of calculating body composition the researcher should be aware of the assumptions upon which such methods are based. UWW relies on the assumption that fat free tissue density, hydration levels of the lean tissue mass and bowel gas present
are all constant. Consequently, identification of the source of error when comparing results determined from different techniques in vivo remains problematic.

5.3.3 Using DXA To Measure BSIPs

One of the advantages of the DXA is that the software allows custom segmentation and analysis of the scan. Subdividing the body into sections allows for the assessment of individual custom segment parameters making it an ideal tool for estimating BSIPs. Other scanning methods such as Gamma-mass scanning, Computerised Tomography (CT) scanning (Huang and Wu 1976; Zatsiorsky and Seluyanov 1983) and Magnetic Resonance Imaging (MRI) (Mungiole and Martin 1990) have been used to determine subject specific BSIPs over the last few decades. However, CT and Gamma mass scanning involve high amounts of radiation and MRI scanners are expensive and are not as readily available. Research into using DXA to measure BSIPs began in an attempt to develop a more rapid and cost-effective method for measuring subject specific parameters (Durkin et al. 2002). Unlike the Gamma mass and CT scans, the radiation dose per whole body scan is relatively low at 0.02 mSv (Durkin et al. 2002) (annual doses from natural sources is 1 mSv) and scans take just a few minutes to complete. Whole Body Mass (WBM) has been shown to be accurately measured using DXA with maximum errors as low as 2.79% (Durkin et al. 2002) (assessed by using scales to measure WBM) of whole body mass, which supports the use of the technology in BSIP research.

Primarily the use of DXA in determining BSIPs has been used as a validating tool for geometric models (e.g. Durkin et al. (2002); Durkin and Dowling (2003, 2006); Wicke et al. (2009). The previously mentioned Wicke and Dumas (2007) geometric
trunk model was compared with the Chandler et al. (1975) model for use on females. Estimated trunk mass using each model resulted in errors of 6.44% and 14.63% (of segment mass) respectively, using trunk mass derived from DXA as criterion. Wicke et al. (2009) also used a photogrammetric method similar to that used by Jensen (1978) combined with DXA in order to develop a density profile of the trunk segment. The trunk was chosen, as it has been shown to have the most variability in density across its length in comparison to any other body segment due to the fluctuation of tissue type and amount present (Wicke et al. 2009). The density profile can then be used in conjunction with geometric models in order to eliminate the uniform density assumption that is generally assumed when using such models. However, it should be noted that using a geometric model based on data collected from the photogrammetric method may introduce volume errors, thus leading on to errors in the estimated density profile.

One of the drawbacks to using the DXA in BSIP studies is the way in which the segmentation of the scan is carried out during analyses. Although manual segmentation of DXA scan images has shown to be repeatable (maximum within-measurer segment mass errors of 4.45% and between-measurer maximum errors of 5.05% of segment mass (Burkhart et al. 2009)) the boundaries used are generally custom to each study. This lack of standardisation of segment boundaries makes it difficult to compare models. Another limitation to the device is that scans can only be performed in the frontal plane and are only 2D in nature unlike MRI that can produce 3D mappings of the body. This means that inertial estimates of COM in the anteroposterior direction and moments of inertia in both the sagittal and transverse planes are unknown (Durkin and Dowling 2003).
Summary

To summarise, DXA are now more readily available, have a low per subject cost and time per scan is low (approximately three minutes per scan). However, access to such equipment is still limited and radiation however low should be limited and cannot be delivered to some populations such as pregnant females. Though DXA measured WBM estimations of females have been shown to be accurate against WBM measured by scales (mean errors = 0.39% WBM ± 0.84 (Wicke and Dumas 2008)) when comparing segmental inertial parameters against those derived from models there will always be uncertainties. These could arise from segmentation of the scans or assumptions such as pixel composition which may lead to errors in BSIPs estimates and subsequent moments calculated.

5.3.4 Effect Of Inaccuracies On BSIP Estimation

Performing an analysis of human movement can be beneficial for many different reasons such as for performance analysis (Burden et al. 1998) or injury prevention techniques (Gatt et al. 1998). During such investigations in order to calculate resultant joint moments (RJM), BSIPs of the segments studied must be known. Uncertainties in BSIP estimates will propagate within RJM calculations. For example, between BSIP models variations in thigh segment mass (23%), moments of inertia (33.81%) and COM (10.12%) estimates leads to variations of up to 20% in moments calculated at the hip joint during stance phase of fast walking gait (Rao et al. 2006). Although it has been shown that for some movements, such as slower limb movements with a high level of ground contact (e.g. slow walking gait) resultant errors in RJM due to BSIP estimates are minimal (Challis 1996; Challis and Kerwin 1996; Pearsall and Costigan 1999; Ganley and Powers 2004). For movements with high accelerations and limited
ground-limb interaction (e.g. golf swing) errors in BSIPs have a much higher influence on RJM calculations (Pearsall and Costigan 1999; Ganley and Powers 2004). Also if mean differences in RJMs between populations are subtle (e.g. pre-clinical individuals vs. healthy individuals) then reducing errors would be vital in order to distinguish between groups. As a result, having subject specific models that are more likely to reflect the population group is more likely to lead to better estimations in BSIPs and therefore calculated RJMs.

5.4 SUMMARY

Currently there are no BSIP models specifically designed for use on females despite morphological difference between the sexes. The trunk segment of the body is highly variable in nature within sexes and of course between sexes. Currently the modelling of the female form using models designed on males is likely to be insufficient in producing accurate BSIPs for the general population of females. BSIPs are used in multiple fields such as coaching athletes or clinical settings (Burden et al. 1998; Robert et al. 2007). Within these settings females will undoubtedly be present. Errors in BSIPs are known to propagate in joint moment calculations (Rao et al. 2006), therefore minimising errors from BSIP input is important to be able to gain an accurate understanding of female movement. Therefore, developing a female specific model that can accurately determine BSIPs of females is of importance and will be utilised by those requiring BSIPs for females.
CHAPTER 6

THE DETERMINATION OF BODY SEGMENT INERTIAL PARAMETERS OF YOUNG FEMALE CLUB LEVEL ATHLETES

6.1 ABSTRACT

Body segment inertial parameters (BSIPs) must be determined prior to performing any biomechanical analyses. Geometric BSIP models are cost effective, yet collecting the anthropometric data necessary is time consuming and time with athletes is often limited. Also, few anthropometric models have been validated for female athletes. Previous work suggested that modelling limb segments as two instead of four truncated cones per segment produces a negligible difference in predicted segment mass (Forrest 2008) yet whole body volume was overestimated due to inadequate modelling of the trunk segment. The present study aimed to confirm earlier findings using a refined trunk segment model. Thirty females provided written informed consent. A total of 118 anthropometric measurements were taken from each participant. The upper arms, forearms, hands, thighs, shank and feet were each modelled using four shapes per segment in the full model, and two shapes per segment in the reduced model. The trunk segment was modelled as a series of ten stadium solids in both models. Further refinements of the present model addressed the shoulder area reducing overlap of trunk and upper arm segments. The geometric model predicted segment volume and which was
multiplied by cadaver derived density functions (Clauser et al. 1969) to determine segment mass. The root mean square error between actual Whole Body Volumes (WBV), determined using a hydrostatic weighing tank, and predicted WBV was 2.37%, 3.03% and 2.34% of WBV for the full, reduced and basic models respectively. Although the basic model produced the lowest WBV and whole body mass errors, the model had lower correlation than the full model with DXA derived segment masses and as a result is likely to be not such a good BSIP predictor. The model predicted trunk mass with RMSE of just 3.49% of segment mass compared to DXA measured trunk mass. Pearson's correlation showed high correlation between the segment masses predicted by the full model and DXA measured mass \( r \) values ranged from 0.727-0.893, \( p < 0.001 \) for the upper arms, forearms, thighs, shanks and feet. The full and reduced model showed high correlation for all segments \( \text{mean } r = 0.9100, p < 0.001 \) which confirms that reducing the number of anthropometric measurements taken from the limb segments (reducing required measures from 118 measures to 94) causes little difference in the predicted mass for limb segments. These results are of interest to sports biomechanists who are without access to direct imaging techniques, but who wish to compute subject specific BSIPs.

6.2 INTRODUCTION

In order to study, analyse or optimise human movement the mass, location of the centre of mass and the moments of inertia of the body segments (BSIPs) must be known (Winter 2004). Errors in BSIPs affect calculations in Resultant Joint Moments (RJM) during activities which involve high accelerations and small amounts of ground-limb contact time such as throwing or kicking (Pearsall and Costigan 1999; Ganley and Powers 2004). For example, during the swing-phase of gait, high Root Mean Square
Error (RMSE) scores (0.100 Nm/kg body weight SD = 0.031) were calculated in resultant joint moments as a result of large differences in DXA-derived and cadaver-based BSIPs of the thigh segment (Ganley and Powers 2004).

There are several methods of estimating BSIPs, scanning techniques for example, such as Dual X-ray Absorptiometry (DXA) or Magnetic Resonance Imaging (MRI) have been shown to be an accurate way of estimating BSIPs (Mungiole and Martin 1990; Durkin and Dowling 2003, 2006). However the equipment required for this is both costly and bulky needing a large area in which to house the equipment; thus it’s largely inappropriate for many researchers who do not have the equipment readily available. In contrast, methods based on anthropometric measurements have been used for centuries in the study of BSIPs (e.g. Harless (1860). These methods are inexpensive as they require a small amount of readably available equipment. Measurements are taken of body segments with a tape measure and callipers and then used in conjunction with geometric models or regression equations to predict BSIPs. The geometric modelling techniques such as Jensen (1978), Hatze (1980) and Yeadon and Morlock (1989) represent the shapes of the body segments as geometric solids. The dimensions of these shapes are then obtained by anthropometric measurements on the experimental subject (e.g. segment length and perimeter) allowing segment volume to be estimated. Density values are obtained from cadaver data and are generally presumed to be uniform throughout the segment, allowing estimations of BSIP to be calculated (Challis 1996). The geometric models vary from those which use a small sample of geometric solids (e.g. Hanavan (1964); Yeadon and Morlock (1989)) to those that are more complex using a larger set of measures and model some body segments as a composite of more than one shape and density (Hatze 1980). Mean errors for Whole Body Mass (WBM) estimations using geometric models have been as little as 1% (Yeadon and Morlock 1989) and 0.26% (Hatze 1980) when compared to scale measured WBM.
Geometric models have been developed utilising a variety of different shapes, density functions and number of measurements required. For example early models used ellipsoids when modelling the trunk region (Hanavan 1964; Jensen 1978). However, based on a design by Sady et al. (1978), Yeadon and Morlock (1989) developed a model that modelled the trunk segment as a series of stadium solids on the basis that this geometric shape was more representative of the body segment in question. When compared with scale measured WBM, maximum errors in predicted whole body mass were 2.3%. The shape that is chosen for modelling the trunk seems to be significant as it appears that the trunk segment is primarily to blame for errors in geometric modelling predictions (Pearsall et al. 1996; Wicke and Dumas 2007; Forrest 2008). As this segment represents such a large percent of whole body volume it would seem reasonable to suggest that any errors in this segment will result in large errors in whole body estimations.

Reasons for the complications in measuring the trunk volume are suggested to be overestimation in trunk volume due to the inclusion of the upper arm or shoulder region during the trunk measurements (Duval-Beaupère and Robain 1987) and the lack of symmetry between the anterior and posterior contours of the chest (Wicke and Dumas 2007) which are misrepresented using shapes such as ellipsoids or stadium solids. Studies have tried to eliminate the volume overestimation caused by the inclusion of the upper arm segment by using sectioned ellipses at this section of the trunk model (Wicke and Dumas 2007; Wicke et al. 2009). However this does not address the issue of the lack of symmetry due to the chest contours that would be particularly problematic when modelling the female form due to breast tissue.

Studies have been undertaken to assess the validity of geometric models on females
(Hatze 1980; Wei and Jensen 1995; Wicke and Dumas 2007; Wicke et al. 2009), however, there have been no geometric models for biomechanical analysis developed primarily for the female. As differences in BSIPs are expected between and within various populations including sexes (Reid and Jensen 1990; Winter 2004; Chambers et al. 2010) it would be beneficial to create a model that is developed primarily for the female form which uses geometric shapes more reflective of the female form.

Though the Hatze (1980) model was developed for use across variable populations such as sexes, the model involved taking 242 measurements. Athletic trainers, sports biomechanists and those working within the field of sports medicine may wish to work with a large amount of athletes. Acquiring this number of measurements is an extremely time consuming procedure which in itself may be costly to both subjects and researchers who are limited with time. Thus the large number of measurements needed limit the models utility despite its accuracy (compared to scale measured mass, maximum errors in predicted whole body mass were just 0.52%, (Hatze 1980)). Reducing the amount of anthropometric measures required in a model whilst still maintaining the accuracy in estimations would therefore be beneficial to researchers across varying fields such as sports medicine and sports biomechanics.

DXA has recently been utilised to determine BSIPs. It measures the amount the material being scanned attenuates the photon beams to determine the mass of the material (Pietrobelli et al. 1996; Ball et al. 2008). It has been shown to reliably predict whole body mass of subjects (Scafoglieri et al. 2011) and segmentation of the scan can be customised in order to determine the mass of individual body segments. This makes it a valuable and reliable tool for measuring BSIPs (Durkin and Dowling 2003, 2006). The most commonly used regression and geometric models have been tested using the segmentation of the DXA scans as criterion (Durkin and Dowling 2003, 2006; Wicke
et al. 2009). Results from these studies suggest that no current full body mathematical model can be considered a “gold standard” leading the way for introducing new geometric models that produce better BSIP estimations of segments such as for the shank (Durkin and Dowling 2006) and thigh (Durkin et al. 2005). Durkin and Dowling (2006) used DXA mass distribution plots of the shank in order to choose geometric solids that best matched the mass distribution properties of the segment. These results showed maximum errors of 3.2% of segment mass when comparing modelled shank mass with DXA measured shank mass (Durkin et al. 2002). Though DXA can be utilised to measure BSIPs, having access to the machinery is needed which is both costly and limiting, and scans subject participants to unnecessary radiation doses. Therefore, if for example a coach wanted to perform a kinematic analysis on a university athletic team, it would likely to be impractical to rely on DXA scans for BSIP measurements. For this reason, although DXA can be used to determine subject specific BSIPs, its utility is more practical as a validating tool for geometric models.

The aim of this study is to demonstrate the validity of a new geometric model for calculating BSIPs of females. The significant difference between this model and previous models is the trunk segment which aims to model the female form more accurately. The second aim of this study is to identify whether lesser anthropometric measurements can predict BSIPs of females in order to expedite the measuring process. The model will be validated against whole body volume, measured by underwater weighing; whole body mass and individual segment masses will be compared with those measured by DXA. It is hypothesised that the more anthropometric measurements used in modelling will result in BSIP predictions closer to the subject’s actual measures.
6.3 METHOD

Participants

Thirty Caucasian females volunteered to take part in the study. Age, height, weight, BMI and body fat measures are displayed in Table 6.1. All subjects gave written informed consent and the procedure was approved by the Ethics Committee for Research Procedures at Aberystwyth University.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean</th>
<th>SD</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (yrs,months)</td>
<td>24.7</td>
<td>39.3</td>
<td>19.2</td>
<td></td>
</tr>
<tr>
<td>Whole Body Mass (kg)</td>
<td>64.78</td>
<td>7.70</td>
<td>81.6</td>
<td>47.3</td>
</tr>
<tr>
<td>Height (m)</td>
<td>1.65</td>
<td>5.88</td>
<td>1.80</td>
<td>1.54</td>
</tr>
<tr>
<td>Body fat % DXA</td>
<td>32.11</td>
<td>5.90</td>
<td>42.9</td>
<td>21.7</td>
</tr>
<tr>
<td>Body fat % UWW (Siri 1961)</td>
<td>27.35</td>
<td>7.35</td>
<td>41.3</td>
<td>15.7</td>
</tr>
<tr>
<td>Body fat % UWW (Brozek et al. 1963)</td>
<td>26.45</td>
<td>6.76</td>
<td>39.4</td>
<td>15.8</td>
</tr>
<tr>
<td>BMI (kg/m^2)</td>
<td>23.8</td>
<td>3.02</td>
<td>31.5</td>
<td>17.8</td>
</tr>
</tbody>
</table>

Table 6.1: Mean values of participant age, mass, height and fat measures.

Geometric Model

Measurements were taken from each participant by one trained investigator. A total of 118 anthropometric measures were taken at landmark positions marked using a non-permanent fine line marker or tailors chalk. Measurements were taken to the nearest 0.5mm using a flexible metal measuring tape and sliding callipers with participants standing in the anatomical position. Measurements were dictated to tape and later transcribed in order to reduce time required for data collection. The sectioned points were similar to those used by Hanavan (1964) taken at anatomical reference points.
with the addition of a number of trunk measurements. † Two of the thirty participants had measurements taken with a different material type tape.

**Table 6.2:** Trunk model stadium solid boundaries

<table>
<thead>
<tr>
<th>Trunk Section</th>
<th>Upper Plane Boundary</th>
<th>Lower Plane Boundary</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_1$</td>
<td>Clavicular Notch</td>
<td>Oxter</td>
</tr>
<tr>
<td>$t_2$</td>
<td>Oxter</td>
<td>Above Bust</td>
</tr>
<tr>
<td>$t_3$</td>
<td>Above Bust</td>
<td>Nipple</td>
</tr>
<tr>
<td>$t_4$</td>
<td>Nipple</td>
<td>Under Bust</td>
</tr>
<tr>
<td>$t_5$</td>
<td>Under Bust</td>
<td>7th Rib (Approx)</td>
</tr>
<tr>
<td>$t_6$</td>
<td>7th Rib (Approx)</td>
<td>Waist</td>
</tr>
<tr>
<td>$t_7$</td>
<td>Waist</td>
<td>Navel</td>
</tr>
<tr>
<td>$t_8$</td>
<td>Navel</td>
<td>Iliac Crest</td>
</tr>
<tr>
<td>$t_9$</td>
<td>Iliac Crest</td>
<td>ASIS</td>
</tr>
<tr>
<td>$t_{10}$</td>
<td>ASIS</td>
<td>Pubic Symphasis</td>
</tr>
</tbody>
</table>

**Figure 6.1:** Trunk segment indicating where distal and proximal horizontal boundaries were measured for all models.
Geometric shapes

The body segments were modelled using different geometric shapes in order to determine volume, mass, centre of mass and the inertial properties of each segment. The model comprised of 15 segments which were in turn segmented into a number of sections depending on the model type used. The ‘full’ model comprised 56 geometric solids, the ‘reduced’ 36 geometric solids and the ‘basic’ 24 geometric solids (Table 6.3). These parameters were determined using the 118 anthropometric measurements. A typical example of the breakdown of a segment of each model can be seen in Figure 6.2. For all models, the trunk segment was modelled using an adapted model comprised of ten stadium solids. The anthropometric measurements were taken at points on the trunk chosen to best map the curvature of the female trunk (Fig. 6.1 and Table 6.2).

Table 6.3: Breakdown of geometric solids used for the full, reduced and basic models.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Model Type</th>
<th>Full</th>
<th>Reduced</th>
<th>Basic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head</td>
<td>1 extended ellipsoid</td>
<td>1 extended ellipsoid</td>
<td>1 extended ellipsoid</td>
<td></td>
</tr>
<tr>
<td>Neck</td>
<td>1 truncated cone</td>
<td>1 truncated cone</td>
<td>1 truncated cone</td>
<td></td>
</tr>
<tr>
<td>Trunk</td>
<td>10 stadium solids</td>
<td>10 stadium solids</td>
<td>10 stadium solids</td>
<td></td>
</tr>
<tr>
<td>Upper-arms</td>
<td>4 truncated cones</td>
<td>2 truncated cones</td>
<td>1 truncated cone</td>
<td></td>
</tr>
<tr>
<td>Fore-arms</td>
<td>4 truncated cones</td>
<td>2 truncated cones</td>
<td>1 truncated cone</td>
<td></td>
</tr>
<tr>
<td>Hands</td>
<td>3 stadium solids</td>
<td>2 stadium solids</td>
<td>1 stadium solid</td>
<td></td>
</tr>
<tr>
<td>Thighs</td>
<td>4 truncated cones</td>
<td>2 truncated cones</td>
<td>1 truncated cone</td>
<td></td>
</tr>
<tr>
<td>Shanks</td>
<td>4 truncated cones</td>
<td>2 truncated cones</td>
<td>1 truncated cone</td>
<td></td>
</tr>
<tr>
<td>Feet</td>
<td>3 stadium solids</td>
<td>2 stadium solids</td>
<td>1 stadium solid</td>
<td></td>
</tr>
</tbody>
</table>
Whole Body Mass, Volume And Segment Volume Measurement

Measuring whole body volume using underwater weighing

Whole body volume was measured using the hydrostatic weighing technique. Participants were familiarised with the water tank and the procedure and were allowed to practice the technique until they felt comfortable. Underwater weight was measured when the subjects were seen to be fully submerged, motionless and the load cell display stabilised on a value. Three measurements were taken with the max value taken as the underwater weight. Adjustments were made for water temperature. Residual lung volume was estimated using height and age and intestinal gases were assumed to be 100 ml (Miller et al. 1998). Whole body volume and average density was calculated using the equations from McArdle et al. (2001).
**Whole body mass**

Whole body mass was determined by using an upright set of weighing scales and recorded to the nearest 0.01 kg. Participants were asked to wear a bathing suit during weighing to minimise the addition of clothing mass to the measurement.

**Whole body centre of mass determination**

For measuring whole body centre of mass the reaction board technique was used using a rigid board with a pivot point placed on weighing scales (Winter 2004). Subjects lay supine with palms of hands flat against the proximal side of the thighs. Subjects wore bathing suits whilst measures were taken.

**DXA**

**DXA scan**

Participants underwent a whole body DXA scan (Hologic Discovery) wearing bathing suits. The scan was performed with the subjects lying supine on the table with forearms pronated so that the palms of their hands were facing the lateral side of their thighs. DXA uses two x-ray beams of different energy levels. Atomic interactions lead to a reduction in photon beam intensity generally referred to as attenuation, which is directly related to the mass attenuation coefficient ($\mu/\rho$) and the area density of the tissue (g/cm$^2$) (Pietrobelli et al. 1996). Bone free pixels are assessed; proportions of lean tissue to pure fat can be calculated as the attenuation coefficients for these tissues are known through theoretical calculations and human experimentation (Roubenoff et al. 1993). Radiation exposure for a whole body scan is 0.02 mSv (Durkin et al.
Three operators were responsible for the scanning process.

**Figure 6.3:** DXA scan showing segmentation of upper body.

**DXA segmentation**

The digitised scan was used in order to locate bony landmarks and segment the body sections to correspond with the anthropometric data collected. Segmentation boundaries used can be found in Table 6.4. The software allows the mass of the custom regions of interest to be calculated (Fig. 6.3). Summation of the masses of these custom re-
regions was carried out and compared to whole body mass calculated by the scanner in order to identify any overlapping of the segments and the boundaries were adjusted accordingly. In order to estimate potential errors in segment masses caused by the manual segmentation of the scan, mass differences were recorded after moving the trunk/thigh boundaries by one pixels vertically both distally and proximally. In order to assess for differences between scans, ten subjects were scanned twice. The participants were scanned before having anthropometric measures taken, and then repositioned on the scanner and scanned again. Whole body mass differences were calculated between scans as well as mass differences between the segments. One operator performed all of the segmentation of the scans.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head and neck</td>
<td>All mass superior to a transverse plane through C7</td>
</tr>
<tr>
<td>Upper arms</td>
<td>Proximal: Sagittal plane through the acromioclavicular joint, proximal to the acromion process</td>
</tr>
<tr>
<td>Forearms</td>
<td>Proximal: Distal endpoint of the upper arm</td>
</tr>
<tr>
<td>Hands</td>
<td>Proximal: All arm mass distal to the distal plane of the forearm</td>
</tr>
<tr>
<td>Thighs</td>
<td>Proximal: Transverse plane distal to the pubic symphysis</td>
</tr>
<tr>
<td>Shanks</td>
<td>Proximal: Endpoint of the thigh</td>
</tr>
<tr>
<td>Feet</td>
<td>Proximal: All leg mass distal to the distal endpoint of the shank</td>
</tr>
<tr>
<td>Trunk</td>
<td>All mass superior to the thigh segments and proximal to the arms, head and neck sections</td>
</tr>
</tbody>
</table>

**Table 6.4: Scanner segmentation points**
Computation Of BSIPs

The segment densities determined by Clauser et al. (1969) were used. In order to determine segment masses, segment volumes (determined by the geometric shape used) were multiplied by each density set. This was carried out for the full, reduced and basic models. COM of the major axes of each segment was computed. For computing the inertial properties of the segments modelled as stadium solids the procedure given by Yeadon (1990) was used. The computed segment volumes, masses and centre of masses were summed to predict whole body volume, whole body mass and whole body centre of mass. These were then compared with measured whole body volume, measured whole body mass and measured whole body COM. Average whole body density was computed and compared to the whole body density calculated from the hydrostatic weighing procedure. All computations were made using custom software performed in Matlab 2009b (the Mathworks, Inc).

Statistical Analysis

Normality of the data was assessed using an Anderson Darling test of normality. All data had normal distribution therefore Pearson correlations were calculated between segment masses measured from the DXA and model estimates, whole body masses, volumes and COM. Bland and Altman plots were carried out for each comparison. Root Mean Square Errors (RMSE) and Standard Deviations (SD) were also calculated. All statistical analysis was performed in Minitab v15 (Minitab© Statistical Software).
Table 6.5: Comparison of model estimates with criterion. ‘Scanner mass’ refers to whole body mass reported by the scanner software. ‘Grouped scanned’ segments is the sum of all the separate segment masses, which indicates the added mass due to overlapping of pixels from one segment to the next.

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>SD</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full model vol (L)</td>
<td>65.34</td>
<td>8.71</td>
<td></td>
</tr>
<tr>
<td>UWW vol (L)</td>
<td>62.90</td>
<td>7.91</td>
<td></td>
</tr>
<tr>
<td>Whole body vol</td>
<td></td>
<td></td>
<td>2.37%</td>
</tr>
<tr>
<td>Full model mass (kg)</td>
<td>67.8</td>
<td>9.02</td>
<td></td>
</tr>
<tr>
<td>Actual mass (kg)</td>
<td>64.78</td>
<td>7.70</td>
<td></td>
</tr>
<tr>
<td>Whole body mass</td>
<td></td>
<td></td>
<td>4.67%</td>
</tr>
<tr>
<td>Scanner mass (kg)</td>
<td>65.38</td>
<td>7.69</td>
<td></td>
</tr>
<tr>
<td>Grouped scanned segments (kg)</td>
<td>66.38</td>
<td>7.84</td>
<td></td>
</tr>
<tr>
<td>Segment overlap</td>
<td></td>
<td></td>
<td>1.53%</td>
</tr>
<tr>
<td>Model COM (m)</td>
<td>0.936</td>
<td>0.041</td>
<td></td>
</tr>
<tr>
<td>Board COM (m)</td>
<td>0.908</td>
<td>0.039</td>
<td></td>
</tr>
<tr>
<td>COM</td>
<td></td>
<td></td>
<td>1.7%</td>
</tr>
<tr>
<td>Density model (g/cm$^2$)</td>
<td>1.039</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Density tank (g/cm$^2$)</td>
<td>1.037</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td>Density</td>
<td></td>
<td></td>
<td>0.19%</td>
</tr>
</tbody>
</table>

6.4 RESULTS

6.4.1 DXA

Although DXA scans were segmented by one operator, there will undoubtedly be some intra- and inter-operator error when selecting segment boundaries on the scan. This will result in the criterion segment estimations from the DXA either increasing or decreasing in measured mass. In order to assess this error, the effect of adjusting the line segmenting the thighs from the trunk by one pixel in both a proximal and distal direction was measured. This was carried out on 24 scans taken from 14 subjects. The trunk segment was chosen as it accounts for the largest percentage of whole body mass.
(Table 6.7) of all the segments. It is therefore, likely to produce the largest changes in segment mass when altering segment boundaries. The average DXA scanned mass of the trunk segments analysed was 35.0 kg (SD 5.39) which accounts for approximately 54% of WBM. Moving the boundary by a pixel resulted in an average absolute change in trunk mass of 0.738 kg (2.14% of segment mass, max = 0.58%, min = 3.95%, mean = 1.13% of whole body mass).

For 10 of the subjects two DXA scans were taken in order to compare differences in whole body mass and segment masses due to subject positioning. After the first scan, the subject left the scanning table before being repositioned on the scanner for a second time. Absolute mean differences in whole body mass measured by the DXA during the first scan compared to the second was 0.024 kg (SD 8.8). Segmentation of the second scan was again performed and comparisons between the segment mass from the first and second scans were made in order to assess for likelihood of error when selecting boundaries of the segments as previously described. As trunk section again would likely have the largest changes (as it has more boundaries than any other segment, (Fig. 6.3) these results are reported. The mean RSE between the first and second scanned trunk segments was 1.26% of segment mass (segment mass was determined as the first scan segment mass).

Whole body mass determined by the DXA scan was higher for all participants than that measured using traditional scales (RMSE = 0.6 kg, SD 0.24) which is comparable with previous literature that found mean differences between scanned WBM and scale measured WBM to be approximately 0.4 kg (SD 0.84) (Wicke and Dumas 2008). As well as this overestimation in mass estimation by DXA, when DXA derived segment masses are summed they result in a higher mass value than DXA determined WBM (Table 6.5). Differences in scale derived mass and summed segment masses derived
from DXA are comparable to an overestimation of WBM by 2.47%. This is likely due to pixels at segment boundaries being included in the mass estimations in both of the adjacent segments. This issue has previously been reported where DXA derived lengths (Wicke and Dumas 2008; Chambers et al. 2010) and masses (Chambers et al. 2010) are summed and do not match measured whole body height and mass using traditional methods (scales and stadiometers).

These results show that there are likely to be inaccuracies in individual segment masses measured by DXA as a consequence of the scanning procedure overestimating WBM. However larger errors in segment mass are likely due to positioning of segment boundaries and overlapping of pixels across boundaries. This suggests that precision when defining boundaries must be taken into consideration when using DXA in order to calculate BSIPs. As there is an overestimation in both scanned and model mass, it is difficult to determine where errors arise and this results in uncertainties in results.

6.4.2 Modelled Whole Body Volume Versus Measured (Underwater Weighing) Volume

Whole Body Volume (WBV) estimations using the full model are highly correlated with measured UWW volume \([0.984, p<0.001]\) with a RMSE of estimated whole body volume of just 2.37\% (SD 2.13) (Table 6.5). Confirming previous findings (Forrest 2008), using the reduced model resulted in larger errors (3.03\%, SD 2.05) in WBV estimations whereas the basic model reduced RMSE to just lower than the full model (2.34\%) but with a larger error SD (SD 2.76). Further analysis using Bland and Altman plots identified two key outliers across all the models (Fig. 6.4). Subjects 14 and 15 exhibited higher errors in model volume estimates than any other subjects when
compared with UWW (model overestimated whole body volume by >7.3%). Both of these subjects had data collected on the same day and were the only two subjects to be measured using a non-metal, material based measuring tape. Therefore, the higher error exhibited by these two subjects may be as a result of the equipment used. Removal of the two subjects results in a reduction in the full volume model error to just 1.9% (RMSE, SD 1.44) compared to UWW. Though this is identified as a possible error, for this investigation the subjects were included in analysis unless otherwise stated.

Figure 6.4: Bland and Altman plot of full model volumes against UWW volume. The dotted circles indicate subjects 14 and 15 who were measured with different equipment.

6.4.3 Modelled Whole Body Mass Versus Measured Mass (Using Scales)

The pattern of WBM estimations using the full, reduced and basic models are similar to those demonstrated in whole body volume estimates. The reduced model produced the largest RMSE when comparing against measured WBM (5.52% WBM) followed by the full (4.67% WBM) and basic (3.74% WBM). Again removal of subjects 14 and 15 reduced the errors by approximately 0.4%.
6.4.4 Trunk Segment

The same trunk model was used for the full, reduced and basic models. Previous results using the same limb modelling but with a more basic trunk model resulted in mean errors in predicted whole body volume close to 15% (Forrest 2008) as opposed to just 2.37% in this study which confirms the importance of modelling this section appropriately. Pearson’s correlation coefficients indicated that the modelled trunk and DXA segmentation had the highest correlation of all segments (Table 6.7). RMSE as a percentage of DXA segment mass was the lowest for the trunk region at just 3.49% which is lower than previous trunk specific geometric models tested on females using a similar uniform density and DXA comparison method (mean error across upper and lower trunk = 5.7% of segment mass (Wicke and Dumas 2007)).

Analyses using Bland and Altman showed good agreement between the two measures with an estimated mean of the differences being 0.5 kg (SD 1.55). There were three outliers indicated on the plots (Fig. 6.6), two of whom had body fat percentages above 38% (derived from DXA). This may indicate that the modelling of the trunk

Figure 6.5: Bland and Altman plot of full geometric model against reduced model.
segment is not as accurate at estimating trunk parameters of obese individuals.

Figure 6.6: Bland and Altman plot of trunk model masses against DXA trunk masses. Participants circled both had body fat percentages above 38%.

Figure 6.7: Bland and Altman plot of right shank model masses against DXA shank masses. Participants circled all had body fat percentages above 38%.
### Table 6.6: Segment masses predicted by the basic geometric model compared with segment masses measured by DXA

<table>
<thead>
<tr>
<th>Segment</th>
<th>Basic Model</th>
<th>DXA</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (kg)</td>
<td>SD</td>
<td>Mean (kg)</td>
</tr>
<tr>
<td>Left Upper Arm</td>
<td>2.447</td>
<td>0.39</td>
<td>2.005</td>
</tr>
<tr>
<td>Right Upper Arm</td>
<td>2.362</td>
<td>0.39</td>
<td>2.078</td>
</tr>
<tr>
<td>Left Forearm</td>
<td>0.790</td>
<td>0.11</td>
<td>0.882</td>
</tr>
<tr>
<td>Right Forearm</td>
<td>0.820</td>
<td>0.10</td>
<td>0.910</td>
</tr>
<tr>
<td>Left Hand</td>
<td>0.217</td>
<td>0.40</td>
<td>0.337</td>
</tr>
<tr>
<td>Right Hand</td>
<td>0.231</td>
<td>0.45</td>
<td>0.360</td>
</tr>
<tr>
<td>Left Thigh</td>
<td>6.200</td>
<td>1.03</td>
<td>5.820</td>
</tr>
<tr>
<td>Right Thigh</td>
<td>6.226</td>
<td>1.03</td>
<td>5.974</td>
</tr>
<tr>
<td>Left Shank</td>
<td>3.379</td>
<td>0.53</td>
<td>3.163</td>
</tr>
<tr>
<td>Right Shank</td>
<td>3.437</td>
<td>0.55</td>
<td>3.182</td>
</tr>
<tr>
<td>Left Foot</td>
<td>0.917</td>
<td>0.09</td>
<td>0.759</td>
</tr>
<tr>
<td>Right Foot</td>
<td>0.877</td>
<td>0.09</td>
<td>0.765</td>
</tr>
<tr>
<td>Trunk</td>
<td>35.02</td>
<td>5.67</td>
<td>35.52</td>
</tr>
<tr>
<td>Neck and Head</td>
<td>4.645</td>
<td>0.55</td>
<td>4.600</td>
</tr>
<tr>
<td>Whole Body</td>
<td>67.04</td>
<td>8.76</td>
<td>65.38</td>
</tr>
</tbody>
</table>

### Table 6.7: Segment masses predicted by the full geometric model compared with segment masses measured by DXA

<table>
<thead>
<tr>
<th>Segment</th>
<th>Full Model</th>
<th>DXA</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (kg)</td>
<td>SD</td>
<td>Mean (kg)</td>
</tr>
<tr>
<td>Left Upper Arm</td>
<td>2.171</td>
<td>0.36</td>
<td>2.005</td>
</tr>
<tr>
<td>Right Upper Arm</td>
<td>2.106</td>
<td>0.35</td>
<td>2.078</td>
</tr>
<tr>
<td>Left Forearm</td>
<td>0.849</td>
<td>0.12</td>
<td>0.882</td>
</tr>
<tr>
<td>Right Forearm</td>
<td>0.890</td>
<td>0.12</td>
<td>0.910</td>
</tr>
<tr>
<td>Left Hand</td>
<td>0.347</td>
<td>0.07</td>
<td>0.337</td>
</tr>
<tr>
<td>Right Hand</td>
<td>0.365</td>
<td>0.06</td>
<td>0.360</td>
</tr>
<tr>
<td>Left Thigh</td>
<td>6.437</td>
<td>1.12</td>
<td>5.820</td>
</tr>
<tr>
<td>Right Thigh</td>
<td>6.449</td>
<td>1.15</td>
<td>5.974</td>
</tr>
<tr>
<td>Left Shank</td>
<td>3.527</td>
<td>0.48</td>
<td>3.163</td>
</tr>
<tr>
<td>Right Shank</td>
<td>3.580</td>
<td>0.53</td>
<td>3.182</td>
</tr>
<tr>
<td>Left Foot</td>
<td>0.759</td>
<td>0.09</td>
<td>0.759</td>
</tr>
<tr>
<td>Right Foot</td>
<td>0.749</td>
<td>0.09</td>
<td>0.765</td>
</tr>
<tr>
<td>Trunk</td>
<td>35.02</td>
<td>5.67</td>
<td>35.519</td>
</tr>
<tr>
<td>Neck and Head</td>
<td>4.663</td>
<td>0.50</td>
<td>4.660</td>
</tr>
<tr>
<td>Whole Body</td>
<td>67.8</td>
<td>9.02</td>
<td>65.38</td>
</tr>
</tbody>
</table>
6.4.5 Full, Reduced And Basic Models - Limb Segments

Basic model

The full, reduced and basic model whole body mass estimates were all highly correlated with scale measured whole body masses (r = 0.984, r = 0.976 and r = 0.959 respectively [p<0.001]). Although the basic model produced mass estimations closer to scale measured WBM compared to both the full and reduced models, it exhibited the lowest correlations with whole body mass of the models and largest (SD 8.75). As well as this, the basic model produced higher (than the full and reduced models) individual segment mass errors and lower correlation when compared with DXA segment masses (Table 6.6). This suggests that the segment estimations using the basic models are inconsistent, sometimes overestimating mass and sometimes underestimating segment mass. As a consequence, the resulting whole body mass when the segments are combined results in closer matching whole body mass to that measured as some segments are under- whilst some are over-estimated. Due to this, the basic model is not a good predictor of BSIPs despite its close matching whole body volume and mass.
As the models used for both the trunk and head/neck segments remained constant regardless whether the full, reduced or basic model was used, differences in estimated mass between models is due to differences in limb modelling. Further investigation indicates that the likely cause of lower WBM estimations in the basic model was due to a reduction in leg volume (thigh and shank) estimation combined with an underestimation of many of the smaller limb segments (Fig. 6.8). Therefore the basic model may not be as accurate at determining BSIPs as it would appear when looking at whole body mass predictions alone.

**Full and reduced model**

Pearson correlation coefficients are high for all segments modelled using the full model compared to DXA derived segment masses (Table 6.7) with the exception of the hands. This suggests that the full model can accurately predict BSIPs of the females studied in this study. As both Bland and Altman plots and Pearson correlation coefficients show small differences between means and high correlations (Table 6.8 and Fig. 6.5) when comparing the reduced and full model limb volume predictions, using a reduced model to estimate BSIPs when time is limited would be effective.

**6.5 DISCUSSION**

The goal of this study was to a) establish the validity of a geometric model for estimating BSIPs for female college and club athletes including a trunk model specifically for females, b) determine the minimum number of anthropometric measurements re-
Table 6.8: Mean of differences, SD of differences and Pearson correlations of segment volume estimations using reduced and basic models compared to the full model.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Reduced Model</th>
<th>Basic Model</th>
<th>Reduced Model</th>
<th>Basic Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Difference between means (L)</td>
<td>SD Difference</td>
<td>Pearsons Correlation r value</td>
<td>Difference between means (L)</td>
</tr>
<tr>
<td>Left Upper Arm</td>
<td>0.07</td>
<td>0.05</td>
<td>0.988, p&lt;0.001</td>
<td>0.27</td>
</tr>
<tr>
<td>Right Upper Arm</td>
<td>0.06</td>
<td>0.04</td>
<td>0.992, p&lt;0.001</td>
<td>0.25</td>
</tr>
<tr>
<td>Left Forearm</td>
<td>-0.01</td>
<td>0.04</td>
<td>0.954, p&lt;0.001</td>
<td>-0.06</td>
</tr>
<tr>
<td>Right Forearm</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.983, p&lt;0.001</td>
<td>-0.07</td>
</tr>
<tr>
<td>Left Hand</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.700, p&lt;0.001</td>
<td>-0.12</td>
</tr>
<tr>
<td>Right Hand</td>
<td>-0.02</td>
<td>0.04</td>
<td>0.745, p&lt;0.001</td>
<td>-0.12</td>
</tr>
<tr>
<td>Left Thigh</td>
<td>-0.06</td>
<td>0.12</td>
<td>0.878, p&lt;0.001</td>
<td>-0.27</td>
</tr>
<tr>
<td>Right Thigh</td>
<td>-0.03</td>
<td>0.21</td>
<td>0.982, p&lt;0.001</td>
<td>-0.23</td>
</tr>
<tr>
<td>Left Shank</td>
<td>0.16</td>
<td>0.12</td>
<td>0.968, p&lt;0.001</td>
<td>-0.15</td>
</tr>
<tr>
<td>Right Shank</td>
<td>0.18</td>
<td>0.13</td>
<td>0.969, p&lt;0.001</td>
<td>-0.13</td>
</tr>
<tr>
<td>Left Foot</td>
<td>0.02</td>
<td>0.05</td>
<td>0.862, p&lt;0.001</td>
<td>-0.14</td>
</tr>
<tr>
<td>Right Foot</td>
<td>0.02</td>
<td>0.04</td>
<td>0.903, p&lt;0.001</td>
<td>-0.14</td>
</tr>
<tr>
<td>RMS</td>
<td>0.05</td>
<td>0.08</td>
<td>0.91</td>
<td>0.16</td>
</tr>
</tbody>
</table>

required for the limb segments to accurately calculate BSIPs. In addition, uncertainties that should be considered when using DXA as a criterion measurement for BSIP studies have also been highlighted.

6.5.1 Whole Body Mass and Density Function

There was an increase in RMSE error from the volume (2.37%) estimate to whole body mass estimates (4.67%). Two reasons why this may have occurred are: 1) Errors due to the under water weighing procedure. If participants failed to fully exhale then under water weight would be lower resulting in an overestimation in whole body volume measured. This would then reduce the error margin in the volume measured and the volume estimated by the model. This may be why the error is less in volume prediction, compared to mass prediction and is one of the problems when using a method with uncertainties such as UWW as a comparative measurement. 2) The density function may also be too large when using the (Clauser et al. 1969) model. This is supported by a comparison of the average density used in the model and the average.
density calculated from UWW (Table. 6.5). As the density function used in the model is higher than that estimated through measurement techniques, it is likely that this accounts for some of the increases in RMSE values displayed in the WBM estimates. As the Clauser et al. (1969) density function is derived from males it is likely that it is not as applicable to the female population due to variations particularly seen at the trunk section (Pearsall et al. 1996; Wicke et al. 2008) which accounts for the majority of the whole body mass (Table. 6.7 and Forrest (2008)). Though errors in BSIPs are more heavily influenced by the geometric shapes used as apposed to the density function chosen, when attempting to reduce errors in WBM estimations to below 4%, refining the model with female specific density functions may be required.

6.5.2 Trunk

Overall the results show that the trunk segment offers a good estimate of inertial parameters demonstrated by high correlation with DXA (Table. 6.7) and whole body volume predictions with mean errors of just 2.37% WBV (using the full model). Previous research using just 4 stadium solids to model the trunk, but utilising the same limb model resulted in much higher errors in whole body volume predictions closer to 15% (Forrest 2008). We are not the first to show that the geometric solids chosen to represent the trunk segment requires careful consideration (Duval-Beaupèere and Robain 1987; Wicke and Dumas 2007). Groups have developed models that utilise shapes such as stadium solids and sectioned elliptical disks (Sady et al. 1978; Yeadon and Morlock 1989; Wicke and Dumas 2007) that more closely reflect the segment shape and have shown good agreement with DXA scans (error as a percentage of segment mass, upper trunk = 4.0%, lower trunk = 7.4%) (Wicke et al. 2009; Wicke and Dumas 2010). It should be noted that it is not indicated whether these errors are averaged or
root mean squares, in these studies the latter would be more appropriate as an indicator of true errors.

To our knowledge this is the first geometric model developed specifically for females and has produced to our knowledge the lowest errors in modelled trunk segment mass versus DXA derived trunk mass (3.49% of segment mass), using a uniform density model. It is suggested that density function has a limited effect on trunk mass estimations (Wicke and Dumas 2010); the use of a non-uniform density sets have been shown to only affect lower trunk mass errors, reducing the mean segment error from 7.4% to -2.7%. However, the female participants in the Wicke and Dumas (2010) study had relatively low BMIs (mean = 22.4 kg/m$^2$, SD 1.5) compared to those in our study, therefore male density sets may have had a lessened impact on their results due to generally higher density participants. As previously mentioned (Chapter 5) trunk density values used in calculating trunk mass (Clauser et al. 1969) are higher than female trunk densities (measured using DEXA (Wicke and Dumas 2008)). As the trunk segment is the largest body segment in volume, errors in the density are likely to have a large influence on predicted WBM. Therefore further refinement of the trunk model should include investigation into a non-uniform density function or at least a female specific density function.

### 6.5.3 Limb Segments

The second aim of this study was to identify the effect of using fewer anthropometric measures when modelling the limb segments. This model confirms previous findings that support a reduced amount of measurements taken at limb segments results in minimal changes in prediction errors (difference between model means: max =
0.71% min = 0.03% of WBV). A comparison of estimated limb masses and DXA limb masses suggests that all models overestimate the larger limbs to some extent (upper arms, thigh and shanks) (Fig. 6.7 and Table 6.7). Of these larger segments, the shank had the largest RMSE of predicted segment mass (mean = 12.46%) when compared with the DXA values. Bland and Altman plots indicated that the shank segments also showed the highest number of outliers (differences between DXA and model estimates >1.96*(SD of the means) Fig. 6.7) when using the full model with the exception of the trunk. This is in agreement with previous modelling of the shank by Durkin and Dowling (2006) using the Hanavan (1964) method, which resulted in errors in predicted segment mass of 14.1% when applied to the female population aged 19-30 years. It has been suggested that using proximal leg circumferences (as used in the Hanavan (1964) method) leads to an overestimation in leg segment volumes (Durkin and Dowling 2006) which may be reflected in our results.

Using the basic model reduced estimated shank mass by an average of 210 grams from a mean (left and right shanks) of 3.62 kg to 3.41 kg, closer to DXA measured masses (Fig. 6.8 and Table 6.8). However, this is not due to a more accurate model but is likely to be a reflection of where the measures are taken. The basic model fails to take a circumference around the belly of the gastrocnemius muscle which is often the largest circumference of the shank. This results in a narrower truncated cone and lower shank volume predictions which may in this case negate the over predictive tendency of the Hanavan (1964) model. Shank models demonstrated by Durkin and Dowling (2006) reduced shank segment mass errors of young female adults to just 2.83% of DXA mass, which could be considered as an alternative shank model. Yeadon and Morlock (1989) also demonstrated taking shank measurements at locations at the widest part of the muscle belly and the ankle which may also warrant investigation.
In order to reduce time with subjects it is possible to take a reduced number of measurements at the limb segments, but further refinement of the shank may lead to further reductions in volume and mass estimation errors. Previous work has shown that attempting to reduce trunk measurements results in excessive errors in whole body volume and mass estimations (Forrest 2008). In light of this it is recommended that if time is limited with subjects or patients the reduced model can be used in order to estimate BSIPs of females, requiring just 94 anthropometric measures.

A novel approach that was used in this study was the dictation of measures to tape so that they could be later transcribed. This allows one operator to take the measures alone with hands free to take quick measures. This speeds up data collection so that even 118 measures could be taken in under twenty minutes. As there has been a vast improvement in voice recognition technology, the utility of this could also be investigated for data collection in geometric model research.

### 6.5.4 Morphology Of Outliers

There were four participants that displayed more outlying results than other participants on the segment Bland and Altman plots when compared with DXA (indicated for example on Figs. 6.6 and 6.7). These subjects had the highest body fat percentage measured by DXA or UWW ranging from 36.8% to 42.9% (DXA values) (BMIs = 25.6-31.5 kg/m²). Pearson correlations indicated that magnitude of error in whole body mass (RMSE) was correlated with participants body fat percentage [0.748, \( p < 0.001 \)] (Fig. 6.9). This suggests that the model is not as adequate at predicting BSIPs for females with higher body fat. This may be down to the model generally overestimating volume which is therefore scaled up and magnified due to larger body volume in
obese adults (Chambers et al. 2010) or errors due to density functions. For example, one subject with approximately 40% body fat had a measured (UWW) average density of 1.008 g/cm$^3$ whereas the model for this subject used an average density function of 1.038 g/cm$^3$. Using the measured (UWW) density with the full model volume estimate leads to WMB estimates of 79.87 kg, compared to the estimated 82.26 kg using the Clauser et al. (1969) model. This reduces predicted whole body mass error for the subject from 5.87% to 2.79% by more closely matching scale measured WBM (77.7 kg). This goes to show that density functions should also be population specific.

One of the novelties of this study was that females of varying ages and morphologies were used as opposed to one population alone. This allows for an approximation of the utility of this model on female club and college athletes who are often representative of a convenient sample for general research. As the females in this study were not athletic in physique (Table. 6.1) this model is likely to be accurate at calculating BSIPs for the general population of young females. However, its utility may not be as effective on females with a large amount of adipose tissue. Errors in calculated joint moments increase when using a BSIP model that is not specific to obese individuals (Achard De Leluardière et al. 2006). Errors in BSIP estimation using this model may

Figure 6.9: Plot of percent error in whole body mass estimations against participants body fat percentage obtained via under water weighing.
arise for females >37% body fat and this would lead to subsequent errors in RJM calculations.

6.5.5 Limitations

When estimating BSIPs there is inherently a level of uncertainty in the estimations and where errors are derived. It is impossible to measure BSIPs directly in vivo therefore comparative tools such as DXA have to use some form of assumptions in their algorithms. Whether DXA can accurately measure the masses of the various body components is still questioned (Scafoglieri et al. 2011) and this is before consideration is taken for operator error in segmentation of the scans as previously discussed. Although in this study only one operator segmented the DXA scans, repeating the segmentation led to errors, and in large segments such as the trunk, changes in segmentation by one pixel accounts for a large amount of mass. Summing of the segment led to an average body mass of 101.53% of scanned mass, and scanned mass over estimated whole body mass by an average of 600 g. Therefore the addition of both of these possible overestimations leads to DXA over predicting mass by an average of 2.46% of mean measured whole body mass by scales. As a consequence of this, it is impossible to be sure whether errors in segment mass estimations are a result of differences in segmentation, or DXA mass calculations.

Additional limitations when using DXA should also be considered. For example, anthropometric measures for the model were taken with subjects standing upright in the anatomical position, where as DXA scans were taken supine. This means that the assumption was made that soft tissue distribution of an upright participant was comparable to when they were lying down. For females and particularly those with a
higher percentage of body fat, there is undoubtedly going to be some level of soft tissue deformation in areas such as the breasts when lying supine, and distally when standing upright. As a result it may be difficult to define boundaries comparatively to those taken with anthropometric tape when segmenting DXA scans. Also the manner in which the scan output converts the 3D body into a 2D image results in soft tissue appearing in areas which make the dissection comparable to direct tape measuring difficult. This may have had an impact on segment estimations and comparisons between DXA segment masses.

6.6 CONCLUSIONS

In conclusion, as sex has a significant impact on BSIPs (Chambers et al. 2010) we propose the use of a female specific geometric model when calculating the body segment inertial parameters of females. As moments are calculated from BSIP estimates, developing population specific models such as this will provide more accurate estimates BSIP and resultant moment calculations and are therefore of use for motion analysis studies, or for use in anthropometry or ergonomic research. As subjects with higher percent body fat tended to have larger errors in predicted body mass estimations, specific models for obese females may be of more use in that population. Despite this, even with the inclusion of those obese individuals, mean whole body estimations using this model predicted volume with just 2.37% error. Errors in segment mass are difficult to determine when comparing with DXA. For example, thigh mass estimation resulted in mean segment mass error of 11.7%, half of this could be accounted for if the segment boundary line on the scan was moved by just one pixel. The benefits of this model are that it utilises a female specific trunk section model, and can be used with fewer limb segment measures (full model = 118 measures, reduced = 94 measures) in
order to speed up data collection with small effects on the BSIP estimates.
CHAPTER 7

GENERAL DISCUSSION

7.1 PART I: CHANGES IN MUSCLE FORCE OUTPUT WITH AGEING AND ITS FUNCTIONAL SIGNIFICANCE

As the population of over 65 is currently increasing, there is much attention on identifying changes that occur due to aging. Much research has focused on measuring the regularity of muscle force output during contractions utilising algorithms such as Approximate Entropy (ApEn) (Pincus 1991), in order to identify differences between old and young populations (e.g. Vaillancourt and Newell (2003); Sosnoff and Newell (2006a)). There are changes that occur with increasing senescence that lead to reductions in motor function in tasks that require dexterity or grasping for example (Cole et al. 1998; Marmon et al. 2011a). In order to gain an understanding of the changes it is important to be able to initially distinguish differences between the two population groups.

In order to investigate potential differences between groups, it is important that we first understand the effect different post-processing techniques have on our results. To gain a better understanding it important that we are not blindly comparing studies that treat data differently and that there is a transparency in the way that data collection and processing is carried out. We have identified that patterns alter drastically with common variations in post-processing techniques, such as sampling rate and input parameters.
in the ApEn algorithm. Consequently, we have suggested that the following approach should be taken when processing such force data: 1) If the ApEn (Pincus 1991) algorithm is being used to measure signal irregularity then the ‘r’ parameter should be, if possible, a measured estimate of the systems noise. 2) Sampling frequency rates should be as higher than 600 Hz. 3) Filter cut-offs should not be lower than 40 Hz to avoid removal of possible frequencies in the signal that are of a biological origin. Also we have shown the effect of post-processing techniques on ApEn values, which clearly demonstrates that treatment of such data should be clearly described by authors.

In agreement with previous research (Vaillancourt and Newell 2003; Sosnoff and Newell 2006a, 2007) we identified that older adults are less irregular than younger adults, however this may not be as a result of reduced visuomotor processing as previously suggested (Sosnoff and Newell 2006c; Ofori et al. 2010). Differences exist between old and young when only an audio target stimulus is provided, this suggests that the differences seen between the groups is not a consequence of reduced visuomotor processing alone, but may be a result of reductions processing capabilities across both audio and visual modalities.

Another possibility is that these changes are not due to reduced processing capabilities but are instead due to changes in the processing behaviour and alterations in motor control technique. Older adults displayed higher percentage of power in the frequency bandwidths that are thought to reflect feedback control during isometric continuous force tasks (Pew 1974; Slifkin et al. 2000; Vaillancourt and Russell 2002). Changes in motor output with aging may be due to slower movements, requiring first to process feedback and subsequently make corrections resulting in a slower more regular force output (resulting in lower ApEn values). As reliance on feedback force control is associated with jerky and inadequate motor output, this may be why evidence shows that
older adults have reduced end-point accuracy (determined by Coefficient of Variation) when trying to control muscle force through a trajectory (Christou et al. 2003a; Enoka et al. 2003). It is also considered that the use of feed-forward motor control reduces the likelihood of falls, by reducing the amount of change required to adapt to a perturbation (Pavol and Pai 2002; Pai et al. 2003). Therefore, identifying alterations in motor control behaviour may prove useful as a pre-clinical tool for patients in falls clinics.

Previously, the functional effect of reduced irregularity in muscle force output has not been assessed. Investigating differences in force output between these populations is the initial step in this type of research, but the actual functional significance of the changes needs to be understood in order to utilise this knowledge. We have provided evidence that supports the concept that a reduced level of irregularity results in a reduced ability to adapt (Lipsitz and Goldberger 1992); measured in this case by a longer time to reach a steady state at a new force trajectory after a change in muscle force is required. This new information may be used when modelling elderly force behaviour and provide useful information for use as pre-clinical tools to identify between patients. For example, currently there is much research to identify elderly patients at risk of falls due to the high prevalence in the elderly population and the related morbidity risk (Gillespie et al. 2009). If reduced irregularity of muscle force signal leads to a lessened ability to adapt this may be a pre-cursor for those at high risk of falls for example.

Future directions should attempt to recreate a more functional type task that better reflects force change requirements in everyday life. Due to the nature of this task, it is not possible to take the results too far out of context of the artificial environment from which they were obtained. Introducing a task that could include the use of both visual and proprioceptive feedback may be more reflective of a real life situation. Despite
this, our results indicate that the changes in muscle force output exhibited by elderly adults are linked with a reduced ability to spontaneously adapt to a required muscle force change.

7.1.1 PART I: Conclusion

In conclusion this work has established recommendations for the treatment of isometric force records prior to the calculation of ApEn, then following these recommendations to confirm and extend the findings that older adults have a reduced ApEn compared to younger adults. Novel findings here were that these differences exist across a wide range of effort levels (25%-75%) and when using audio and bimodal stimuli. This reduction in ApEn reflects a decrease in irregularity and this has been shown to be associated with an increased time to reach a steady state after a change in force level is required. The knowledge from this research is of importance to those who are using the ApEn algorithm to investigate force signal data, for those who wish to model muscle force output in older adults, and the knowledge is of use potentially as a pre-clinical tool to distinguish between patient groups (e.g. falls patients).

7.2 PART II: A NEW MODEL FOR THE DETERMINATION OF BODY SEGMENT INERTIAL PARAMETERS OF FEMALE CLUB ATHLETES

Previously there have been no geometric models developed for females. As such, when estimating BSIPs of females (e.g. female athletes or patients) models that were developed on males are used. The profiles of male and female bodies differ vastly.
For example fat distribution between the sexes is highly variable which results in a very different body form especially at the trunk segment (Ley et al. 1992; Wicke et al. 2008). It would seem logical to use a specific model for females given these differences. However, until now this has not been established.

Some geometric models previously developed, have been assessed for use on women; however, women in these studies are generally athletes with low Body Mass Index (BMI) and are not necessarily representative of the general younger female population (Hatze 1980; Wicke and Dumas 2007; Wicke et al. 2009; Wicke and Dumas 2010). For example club and college level athletes are often not as lean as these participants. Our study measured thirty females college/club level field hockey players with average body fat measured by Dual X-ray Absorptiometry (DXA) being 32.11%. Despite this our model still predicted trunk segment mass with a Root Mean Square Error (RMSE) of just 3.49% compared to DXA measured trunk mass.

The accuracy of the trunk model introduced here derives from the location points of the anthropometric measures which better map the contours of the female form. The new trunk model, in conjunction with the full limb model (118 measures needed) leads to whole body volume predictions with RMSE of just 2.37% compared to under water weighing volume. Also limb segment measures can be reduced if necessary (using 94 measures results in RMSE of 3.03% of WBV) which is one of the utilities of this model as it allows for a reduced amount of contact time with the participant/patient. This may be of importance if studying large teams of athletes or in clinical settings where time with patients is limited. Further work to increase the utility of this model may be to attempt to reduce the number of measurements required further without losing the accuracy of the models BSIP predictions. Testing the model with the removal of a number of the trunk measures should be investigated, as well as identifying where
the measurements should be taken on the limb segments to produce the most accurate predictions. If available, a comparison of model segment predictions to MRI scanned data may also be of use as a model validating tool.

Though there are modern techniques that can accurately predict segment volume (e.g. white light technology) and mass (e.g. DXA or Magnetic Resonance Imaging) equipment is limited and expensive therefore being able to estimate BSIPs using basic equipment (measuring tape and callipers) is useful. Although DXA has previously been utilised in BSIP studies and appears to be a useful tool for measuring segment masses, DXA software is generally not developed for this kind of use. We have highlighted that the segmentation process using this software leads to uncertainties when measuring mass of segments, therefore careful consideration needs to be taken when using it as a criterion tool for BSIP investigation.

Though differences in BSIP estimation may result in small errors in resultant joint moment calculations (Challis 1996), in clinical fields differences between classified groups can be subtle. Minimising errors in BSIPs will reduce propagating errors which is vital in order to have accurate moment calculations. In order to minimise any errors when calculating joint moments further refinement of this model will involve making minor adjustments to the shank segment to minimise overestimation in segment volume. In addition, as density differences exist between males and females, the addition of a female density set would be beneficial in order to reduce errors in computed segment masses.
7.2.1 PART II: Conclusion

In conclusion, this work has introduced and validated a new model to predict BSIPs of young females. This knowledge can be utilised in clinical fields, athletic coaching, simulation and modelling.


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Clauser, C. E., McConville, J. T., and Young, J. W. (1969). Weight, volume, and


human lower leg using an elliptical model with validation from DEXA. *Annals of Biomedical Engineering*, 34(9):1483–1493.


Tracy, B. L. and Enoka, R. M. (2002). Older adults are less steady during submaximal isometric contractions with the knee extensor muscles. *Journal of Applied Physiology, 92*(3):1004–1012.


### 7.3 Appendix
Title of Project: The effect of ageing on the response to varying force targets and the variability of force production

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Other research personnel:  
Samantha L. Winter, Ph. D. (Lecturer)  
Mark Burnley, Ph. D. (Lecturer)  
Ruth Hughes (Senior Technician)  
Maggie Powell (Technician)

1. Purpose of the Study:

This study will compare various aspects of the steadiness of human isometric (static) force production in a finger muscle (called the First Dorsal Interosseus) between older and younger adults.  

It is anticipated that this information will be useful in understanding the factors that affect the steadiness of force production and movement in humans.

2. Procedures to be followed:

In this study you will be asked to perform maximum effort and less than maximum effort static finger abduction muscle contractions. Finger abduction is the term describing the movement of the index finger towards the thumb.

At the familiarisation session you will be asked to complete a short questionnaire that will assess which hand is your dominant hand. All testing will then be performed on your non-dominant hand. You will perform a short warm up by performing two minutes of sub-maximal finger and hand exercises. This warm up will include rotating the wrist, clenching the fist, flexing and extending the fingers, spreading and closing the fingers, and sub-maximal practice contractions. You will then perform practice contractions, three maximum effort contractions and will practice targeting the required force levels. Visual or audio feedback will be provided during the contractions via a computer monitor and speakers in order to help you produce the required force. Your response time to
visual, audio and both audio and visual stimuli will also be tested. This session will enable you to practice the targeting of force levels using both the visual and audio stimuli in order for you to become familiar and comfortable with both stimuli before the testing takes place. In particular, plenty of time will be provided to become familiarised with the audio stimulus and the variation in pitch that occurs depending on force produced.

You will then return for two separate testing sessions when you will again be asked to perform a short warm up. Then you will be asked to perform three initial contractions with as much effort as possible. During these maximum effort contractions you will be asked to increase your force level gradually until you are exerting a maximum force. If you experience any pain or discomfort you should stop contracting the muscle and report the pain to the investigator. You will be given a one minute rest period between low effort contractions and three minutes rest between higher effort contractions (over 50% of maximum effort).

You will then be asked to perform contractions at various percentages of your maximum effort in a random order. You will be asked to increase the force to the required level gradually during each contraction. You will then be asked to hold each contraction as steadily as possible for ten seconds. Visual or audio feedback will be provided during the contractions via a computer monitor and speakers in order to help you produce the required force. A one minute or three minute rest period will be given between each contraction as previously mentioned.

At the second testing session you will then be asked to perform contractions which jump between different levels of your maximum contraction value. As with previous contractions you will be provided with feedback in order to help you produce the required force. A one or three minute rest period will again be given between contractions. These two sessions should last no longer than thirty minutes each.

3. Discomforts and Risks:

During testing of maximum voluntary strength or during the strength training sessions there is a slight risk of muscle strain, sprains, or muscle soreness that wears off over 48 hours following exercise. This soreness may temporarily restrict movement slightly. This risk is no more than would be associated with grasping something with all of one’s strength and the likelihood of these discomforts occurring can be reduced by resting between efforts, by warming up, by performing practice contractions, and by building up the force gradually during the maximum effort contractions.

Please report any soreness lasting longer than 48 hours, discontinue training and consult your doctor for further treatment.
Remember that you may ask to stop at any time during the test procedure or during the training. If you do experience any discomfort please report this to the Principal Investigator immediately.

4. Duration/Time:

You will be asked to participate in the familiarisation session and two testing sessions lasting thirty minutes each. Your maximum time commitment will be one and half hours over one to two weeks.

5. Pre-test Instructions

Please avoid high intensity or exhausting exercise using the hands in the 24 hours prior to testing. Do not consume alcohol during the day before the test, and please refrain from consumption of caffeine (caffeinated drinks such as coffee, cola and tea, and foods containing caffeine such as chocolate) for four hours prior to the test. Please tell the Investigator if you have been ill in the two weeks prior to the test, or if you are suffering from any injury.

6. Safety

All procedures in the laboratory are subject to audit by the University Ethics Committee for Research Procedures and are carried out in accordance with the University's Health and Safety procedures and good practice guidelines issued by the British Association of Sport and Exercise Sciences.

7. Statement of Confidentiality:

Your participation in this research is confidential. Your data will be stored using numeric codes and the list of participant names and the corresponding numeric identifiers will be stored in a locked office. Your medical questionnaire and informed consent document are kept for a period of five years in a locked filing cabinet and will be shredded at the end of this time. The researchers retain the right to publish and disseminate results arising from this study, however no information that could lead to your identification will be disclosed.

8. Right to Ask Questions:

You can ask the Principal Investigator for additional information before giving your consent if you do not understand this form. You can also ask questions about this research at any time once the study has commenced by contacting the Principal Investigator (Sarah Forrest at 01970 622306). You can also call this number if you have complaints or concerns about this research.

9. Voluntary Participation:
Your decision to be in this research is voluntary. You can stop at any time and you do not have to give a reason for withdrawing. You do not have to answer any questions that you do not want to answer. Declining to participate or withdrawing once the test has started will not affect your position as a student.

You must be 18 years of age or older to consent to take part in this research study. If you agree to take part in this research study and the information outlined above, please sign your name and indicate the date below. You will be given a copy of this signed and dated consent form for your records.

If you are happy with the procedures demonstrated, and the information given in this form and if you have no further questions then please read and sign the following consent. If you need more time to consider whether to participate then please say now.

I agree to take part in the Aberystwyth University research project entitled ‘The effect of ageing on the response to varying force targets and the variability of force production’. The project has been explained to me and I have read the Subject Information above, which I may keep for my records. I understand that agreeing to take part means that I am willing to perform the procedures given in Part 2 of this document. I have read and understood all other parts of this document. In particular, I understand that any information I provide is confidential, and that no information that could lead to my identification will be disclosed in any reports on the project, or to any other party.

I understand that my participation is voluntary, that I can choose not to participate in part or all of the project, and that I can withdraw at any stage of the project without being penalized or disadvantaged in any way.

__________________________________________________________________
Participant Signature Date

__________________________________________________________________
Person Obtaining Consent Date

Thank you for your help
Participant Information and Informed Consent Document

Title of Project: Validation of an anthropometric model for determining body segment inertial parameters in female athletes.

Principal Investigators:
Sarah Forrest
Department of Sport and Exercise Science
Aberystwyth University
e-mail: smf08@aber.ac.uk
Phone: 01970 622306

Other research personnel:
Dr Joanne Wallace
Dr Samantha Winter Wallace
Ruth Hughes
Maggie Powell
Fiona Higgs

1. Purpose of the research study:

The purpose of this study is to assess the accuracy of measurements that allow researchers to determine quantities such as the mass of individual body segments like the upper arm, or the trunk. This information is necessary in order to conduct a mechanical analysis of sporting skills.

2. Procedures to be followed:

You will be asked to visit the Department of Sport and Exercise Science on one occasion for one and a half hours.

You will be given a two whole body DEXA scans, which stands for dual energy X-ray absorptiometry. It is a common procedure for testing bone mineral density and body composition and involves lying on a bed (left) while a low radiation X-ray scanner passes over you. Two scans will be taken to assess any differences in results after repositioning the body. Therefore one scan will be taken prior to body measuring and one will be taken post measuring.

Various measurements such as the length and circumference of your limbs will be taken. During this procedure you will be able to wear a swimming costume or similar lycra suit.
You will be asked to undertake an activity and lifestyle questionnaire, detailing your training patterns, menstrual health and diet.

The last part of the procedure involves wearing a harness and being submerged in a small water tank which will measure body volume. You will be asked to put on the safety harness, and then climb into the water tank. The water tank is warm and shallow with the safety harness attached to you merely as a safety precaution. The water is disinfected so there is no danger to you from infections from water conditions. You will be asked to fully exhale and be still under the water for a very short amount of time. As the water is rather shallow, to be submerged in the water you will need to duck under in a crouched position. You will be fully briefed and have practice runs of this procedure so that you feel fully comfortable in the water. The volume of various individual limbs will be measured by inserting your arms or legs into containers of water.

3. Discomforts and Risks:

DXA scans involve low energy X-rays and this form of radiation is known to cause damage to the body in large doses. However, the scans are designed to provide low dosages of radiation, and in the 20 minute time period taken to carry out the test you will be exposed to the same amount of radiation that you would ordinarily be exposed to during a transatlantic flight.

Some may feel uncomfortable at being seen or measured wearing swimwear. To minimise any possible embarrassment I will be taking all measurements in a private room with covered windows. If the subject feels more comfortable they may bring a friend along. All subjects will remain anonymous in regards to the write up.

As being submerged in water there are of course risks involved. As being submerged in any depth of water may result in injury, these must be considered. The water is very shallow (about waist deep), you will be wearing a safety harness and you will have plenty of opportunity to become accustomed to the water before testing.

4. Pre-test Instructions

During the DXA scans you will be asked to remove all jewellery and metal items. You should not undergo these scan if you have any metal implants or joint replacements, or if there is a possibility that you are pregnant.

Please bring a towel and change of clothes as this procedure involves getting wet. Private changing areas and showers are situated in the building.

5. Safety
All procedures in the Department of Sport and Exercise Science are subject to audit by the University Ethics Committee for Research Procedures and are carried out in accordance with the University’s Health and Safety procedures and good practice guidelines issued by the British Association of Sport and Exercise Sciences.

6. **Statement of Confidentiality:**

   Your participation in this research is confidential. Any anthropometric data collected during the procedures will be stored using codes and the list of participant names and the corresponding codes will be stored in a locked office. Your DXA scans will be stored on a password protected computer hard drive. Your activity questionnaires and informed consent document are kept for a period of five years in a locked filing cabinet and will be shredded at the end of this time.

7. **Right to Ask Questions:**

   You can ask any of the investigators for additional information before giving your consent if you do not understand this form. You can also ask questions about this research at any time by contacting the supervisor of this work (Dr Samantha Winter at 01970 622295). You can also call this number if you have complaints or concerns about this research.

8. **Voluntary Participation:**

   You must be 18 years of age or older to consent to take part in this research study. Your decision participate in this research is voluntary. You can stop at any time and you can withdraw your consent for any reason. Declining to participate or withdrawing once the testing has started will not affect your standing as a student at Aberystwyth University. You may be asked the reason for withdrawal so that the investigators are aware of and can address any problems arising as a result of the research. To ensure that we are acting fairly, the ways in which we get your consent and the ways in which we run the research will be audited to check that you have been given all the information you need and that you gave your consent voluntarily.

**CONSENT**

If you are happy with the study procedures and the information given in this form, and if you have no further questions then please read and sign the following consent. You will be given a copy of this signed and dated information and consent form for your records. If you need more time to consider whether to participate then please say now.

I agree to take part in the Aberystwyth University research study 'Validation of an anthropometric model for determining body segment inertial parameters in female athletes'. The project has been explained to me and I have read and understood the
subject information above, which I may keep for my records. I have been given the opportunity to ask questions. I understand that my participation is voluntary and that I can withdraw at any stage of the project without being penalised.

Participant Signature ___________________________ Date ___________________________

Person Obtaining Consent ___________________________ Date ___________________________
function \[ \alpha \] = dfa( x, ioption )

% performs detrended fluctuation analysis
% John H. Challis, The Penn. State University
% May 24, 2001
% calling ( alpha ) = dfa( x, ioption )
% -------
% input
% -----
% x - data
% ioption - option to graph data (plots if ioption = 1)
% -------
% output
% alpha - scaling exponent
% -------
% notes
% 1) Based on algorithm described by Peng et al. (1994) ...
% Physical Review E, 49(2), 1685-1689.
% 2) Basic model is Fd(L) \neq L^\alpha
% 3) alpha greater than 0 and less than 0.5 indicates ... 
% long-range anti-correlations,
% alpha of 0.5 indicates completely uncorrelated or ...
% white noise,
% alpha greater than 0.5 and less than 1.0 indicates ...
% long-range correlations,
% alpha of 1.0 indicates 1/f noise,
alpha of 1.5 indicates brown noise.

% how much data and compute mean 

ntot = length(x);
ave = mean(x);
\[ z_r = 2^{(1 / 8)}; \]
\[ n_r = 1; \]
\[ i_r = 1; \]
\[ r_s(1) = k_1; \]
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\[ \text{while } r_s(n_r) < k_2 \]
\[ \% \]
\[ \% \]
\[ i_r = i_r + 1; \]
\[ r_w = \text{round}(k_1 z_r^{(i_r-1)}); \]
\[ \text{if } r_w > r_s(n_r) \]
\[ n_r = n_r + 1; \]
\[ r_s(n_r) = r_w; \]
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\[ pos(1) = x(1) - \text{ave}; \]
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\[ i = 2 : \text{ntot}; \]
\[ pos(i) = pos(i-1) + x(i) - \text{ave}; \]
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\texttt{k1 = 1;}
\texttt{k2 = ntot;}
\texttt{ntot = k2 - k1 + 1;}

\texttt{\%}
\texttt{for i=1:rs(nr)}
\texttt{\hspace{1em}x(i) = i;}
\texttt{end}

\texttt{\%}
\texttt{for i=1:nr}
\texttt{\hspace{1em}ll = rs(i);}
\texttt{\hspace{1em}stat = round( ntot / ll) * ll;}
\texttt{\hspace{1em}rms(i) = 0;}
\texttt{\hspace{1em}for j=k1:ll:k2-ll}
\texttt{\hspace{2em}for jj=1:ll}
\texttt{\hspace{3em}y(jj) = pos(j + jj -1 );}
\texttt{\hspace{2em}end}
\texttt{\hspace{1em}[ p ] = polyfit( x(1:ll), y, 1);}
\texttt{\hspace{1em}chi2 = 0;}
\texttt{\hspace{1em}for ij = 1:ll}
\texttt{\hspace{2em}chi2 = chi2 + ( y(ij) - p(2) - p(1) * x(ij) )^2;}
\texttt{\hspace{1em}end}
\texttt{\hspace{1em}rms(i) = rms(i) + chi2;}
\texttt{\hspace{1em}end}
\texttt{\hspace{1em}rms(i) = sqrt(rms(i)/stat);}
clear x y

for i=1:nr
    x(i) = log10( rs(i) );
    y(i) = log10( rms(i) );
end

% fit straight line to data
[p] = polyfit( x, y, 1);

% generate data to show fit
for i=1:nr
    yp(i) = p(2) + (p(1) * x(i) );
end

% extract alpha
alpha = p(1);
if ioption == 1

figure(4)

plot( x, yp, x, y,'+')

legend('Best Fit','Data')
xlabel('Log10(l)')
ylabel('Log10(Fd(l))')
title(['Detrended Fluctuation Analysis, alpha = ...
    ',num2str(alpha)])

end

function [ ApEn ] = approxen( x, m, r )

% approxen - routine to compute the approximate entropy of a ... signal
%
% John H. Challis (August 22, 2001)
%
% calling [ ApEn ] = approxen( x, m, r )
% -------
10 % input
11 % ----- 
12 % x - array of data to be analyzed
13 % m - run length
14 % r - filter threshold
15 %
16 % output
17 % ------
18 % ApEn - estimate of entropy of signal
19 %
20 % Notes
21 % ----- 
23 % 2. If ApEn tends to 0 then the signal is highly regular ... (low entropy).
24 % 3. If ApEn value is high then the signal is highly ... irregular (high entropy).
25 %
26 %
27 % number of vectors to compare
28 %
29 n = length(x);
30 nsum = n - m;
31 %
32 for i=1:nsum,
33 id(i) = 0;
34 ic(i) = 0;
35 %
36 for j=1:nsum,
jj = 0;

for k=1:m,
    dif = abs( x(i + k - 1) - x(j + k - 1) );
    if (dif > r)
        jj = 1;
        break
    end
end

if jj == 0
    ic(i) = ic(i) + 1;
    dif = abs( x(i + m) - x(j + m) );
    if dif < r | dif == r
        id(i) = id(i) + 1;
    end
end

% compute ApEn(m,r,n) from id(.) and ic(.)
% mean of logs of conditional probability of staying close, ...
% if already close.
ApEn = 0.0;
for i=1:nsum,
    ratio = id(i) / ic(i);
    ApEn = ApEn + ( log( ratio ) );
end

%
ApEn = -1.0 * (ApEn / nsum);

The End

%