Dynamic body acceleration as a proxy for human energy expenditure.

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DYNAMIC BODY ACCELERATION AS A PROXY FOR HUMAN ENERGY EXPENDITURE

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ABSTRACT

RATIONALE: The use of dynamic body acceleration (*DBA*) has previously been used as a proxy for energy expenditure (*EE*) in humans with promising results. Two forms of dynamic body acceleration have been used; overall dynamic body acceleration (*ODBA*) which comprises of the sum of acceleration data from three orthogonal axes and vectorial dynamic body acceleration (*VeDBA*) which constitutes of the vector of the acceleration data from three orthogonal axes. *VeDBA* is the mathematically correct calculation of body acceleration however there is strong biological rationale for the use of *OBDA*. This study sought to ascertain which *DBA* metric is the most accurate predictor of *EE* and in addition, how accelerometer orientation and placement, body anthropometrics, body composition and aerobic capacity might influence these relationships.

METHODS: Twenty-one voluntary participants [seventeen males, four females; age = 22.44 ± 3.28 years, height = 1.75 ± 0.07 m; weight = 70.66 ± 9.78 kg] performed an incremental maximal exercise test on a motor driven treadmill [0% grade]. Volume of oxygen utilised per minute ($\dot{V}O_2$) was measured using an online gas analyser and body acceleration (g) measured simultaneously, via three tri-axial accelerometers; two attached to the upper back (one in a straight orientation and the other skewed 30° in each axis) and one attached to the right hip (in a straight orientation). Body composition data was collected using the skinfold method.

RESULTS: Both *ODBA* and *VeDBA* were good proxies for $\dot{V}O_2$ with r^2 values exceeding 0.78, although *ODBA* accounted for slightly but significantly more of the variation in $\dot{V}O_2$ than did *VeDBA* ($p = 0.002$). There were no significant differences between *ODBA* and *VeDBA* in terms of the change in $\dot{V}O_2$ estimated by the acceleration data in a simulated situation of the accelerometer being mounted straight but becoming skewed. In terms of placement, *ODBA* and *VeDBA* values were significantly greater at the waist than the upper back (straight orientated device only) ($p = 0.000$) however when plotted against $\dot{V}O_2$ the differences between the hip and upper back became insignificant for both metrics. Fat-free mass, fat mass and age added significantly to the $\dot{V}O_2$ *versus ODBA* and $\dot{V}O_2$ *versus VeDBA* relationship in terms of r^2.

CONCLUSIONS:
ODBA was found to be a marginally better proxy for $\dot{V}O_2$ than *VeDBA* although should only be used where researchers can guarantee a reasonably consistent device orientation. The upper back and hip are equally appropriate placements and should be chosen depending on the practicality. The ability of *DBA* to predict $\dot{V}O_2$ can be improved by adding additional variables to the regression equation. In this case fat-free mass was the most significant covariate in terms of the improvement in r^2.

DECLARATION AND STATEMENTS

DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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STATEMENT 1

This thesis is the result of my own investigations, except where otherwise stated. Where correction services have been used, the extent and nature of the correction is clearly marked in a footnote(s).

Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

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PUBLICATIONS ARISING FROM THIS THESIS

Peer-Rewiew Publications

Qasem, L., Cardew, A., Wilson, A., Griffiths, I., Halsey, L. G., Shepard, E. L.C., Gleiss, A.C. and Wilson, R., 2012. Tri-Axial Dynamic Acceleration as a Proxy for Animal Energy Expenditure; Should We Be Summing Values or Calculating the Vector? *PLoS ONE* , 7(2): e31187. doi:10.1371/journal.pone.0031187.

Chapter 1

Introduction

1.1 Introductory paragraph

Measurement of human *energy expenditure* (*EE*) is essential for informing decisions regarding weight management programmes. The gold standard technique for measuring *EE*, direct calorimetry, is not possible in free living environment. Thus, a plethora of methods designed to predict *EE* exist.

Previous studies suggest *dynamic body acceleration* (*DBA*) is an excellent proxy for *EE*. There currently two forms of dynamic body acceleration; *overall dynamic body acceleration* (*ODBA*) which comprises of the sum of acceleration data from three orthogonal axes and *vectorial dynamic body acceleration* (*VeDBA*) which constitutes of the vector of the acceleration data from three orthogonal axes. *VeDBA* is the mathematically correct calculation of body acceleration however there is strong biological rationale for the use of *OBDA*.

For this study, *volume of oxygen uptake* ($\dot{V}O_2$), which represents *EE*, and body acceleration, which was converted to *DBA,* was measured simultaneously on human participants walking and running on a treadmill. This study sought to ascertain which *DBA* metric is the most accurate predictor of *EE* and how device orientation, device placement, body anthropometrics, body composition and aerobic capacity might influence the relationship between *DBA* and *EE*.

The thesis is separated into five distinct chapters. Chapter 1 provides an overview of the links between *EE*, obesity and accelerometery; describing the relationship between *EE* and survival, defining obesity and its current prevalance, summarising the components of *EE* and providing a brief overview of the methods of assessing of *EE* including the use of *DBA*.

Chapter 2 provides a comprehensive literature review with regard to obesity (causes, associated health risks, prevalence and treatment), the components of *EE*, current methods of measuring *EE*, use of body motion to predict *EE*, a description of all published acceleration metrics (including *DBA*) and finally a thorough appraisal of the use of acceleration metrics (including *DBA*) to predict *EE*.

Chapter 3 entails a detailed description of the study methodology including participant details, equipment specifications, the protocol, data processing techniques and statistical analysis techniques.

Chapter 4 presents the results of the study in both graphical, tabular and text forms.

Chapter 5 provides the major conclusions of the study including the limitations and recommendations for future research.

1.2 The role of energy expenditure in survival

EE plays a critical role in survival of all animals including man, *Homo Sapiens,* and has therefore been the subject of intensive research (Schmidt-Nielson, 1972; Ainslie, et al., 2003; Levine, 2005).

When considering animals in the wild, the central concept is that animals should behave in such a way as to maximise their lifetime reproductive success by maximising their net rate of *energy intake* (*EI*) (Pyke, 1984; Murray, 1991). This includes both optimising harvesting solutions and minimising locomotion costs. Thus, ultimately, the efficiency of movement affects the survival of wild animals (Alexander, 2003).

On the contrary, for *Homo sapiens* living in the developed world, the state of affairs is almost reversed. The industrial revolution of the 19th century brought pivotal modernisation of agriculture and transport, leaving food in plentiful and easily accessible supply. The introduction of foods high in fat and sugar greatly increased calorific value of meals, and both the reduction in food prices and rise in disposable income encouraged a greater food intake (Grigg, 1995). In addition, a large increase in industry and service sector jobs, introduction of labour-saving technology and a shift in work patterns that involved reliance on transport (as opposed to walking/cycling) all increased the likelihood of leading a sedentary lifestyle. So today, it is not the efficiency of movement but lack of movement that decreases chances of survival (Fox and Hillsdon, 1997). With high probability of excess calorie

consumption and no use for this excess energy, the body stores this fuel in the form of fat which eventually leads to obesity (Musingarimi, 2009).

1.3 Definition and prevalence of obesity

Obesity is a disease state where excess fat has accumulated to a point where it becomes a health risk (World Health Organisation, 2011c). It is most accurately assessed using percentage body fat however, in order to evaluate large scale populations a simplified metric Body Mass Index [*BMI* = weight (kg)/ height^2 (m)] is used. In general, a *BMI* over 30 kg.m^{-2} is classified as obese and over 25 kg.m^{-2} as overweight (World Health Organisation, 2011a). Recent reports state that obesity doubles 'the risk of all-cause mortality, coronary heart disease, strokes, type 2 diabetes' (Department of Health, Physical Activity, Health Improvement and Prevention, 2004, p.45), as well as increasing the risk of some cancers (particularly hormone related, gallbladder and large-bowel cancers), loss of function and musculoskeletal problems, and all life threatening diseases (Department of Health, Physical Activity, Health Improvement and Prevention, 2004; World Health Organisation, 2011a). In addition, early symptoms such as osteoarthritis, infertility, respiratory difficulties and skin problems are common (World Health Organisation, 2011a).

Obesity has now hit epidemic proportions in most of the developed world. Data collected in 2007, classified 61% of the UK population as being overweight or obese i.e. a *BMI* above 25 kg.m^{-2} (The NHS Information Centre, Lifestyles Statistics, 2010). Statistics from the Welsh Health Survey (2010) report that 57% of adults living in Wales are overweight and 22% are obese. Wales also has the lowest health expectancy in both men and women compared to other UK countries (Welsh Assembly Government, 2011).

Moreover, and perhaps most alarmingly, this problem is not isolated to the adult population alone. In 2006, 29.7% of children in England aged between 2 and 15 years were catalogued as either overweight or obese (The NHS Information Centre, Lifestyle Statistics, 2008). Similarly, 33% and 28.2% of children between the ages of 2 and 15 years were classified as overweight or obese (over 85th percentile based

on 1990 UK reference population curves for all of the above child obesity statistics) in Wales in 2008 and Scotland in 2009 respectively (Welsh Assembly Government, 2008; Scottish Centre for Social Research, 2010).

In order to understand obesity, it is logical that two approaches are needed; an assessment of (i) *EI* and (ii) *EE*. This thesis will focus on the latter.

1.4 Components of energy expenditure

All bodily functions require energy, which is initially gained from food sources and released via metabolic processes. Energy metabolism can be defined as 'the conversion of chemical energy into heat' (Randall, 2002, p.668) and is often quantified in terms of *total daily EE (TDEE)* i.e. *EE* over 24 hours. *TDEE* can be split into four main bodily functions; basal metabolic rate (*BMR*), temperature dependent *EE*, specific dynamic action and *physical activity* (*PA*) (Welk, 2002; Wilson, et al., 2006).

1.4.1 Basal metabolic rate

The *BMR* represents the energy needed to maintain only the basic processes of life i.e. circulation, breathing, ion pumping etc. when the body is in a post-absorptive resting state, in a neutrally temperate environment (Eston and Reilly, 2001b; Mann and Truswell, 2007). It accounts for approximately 40-75% of *TDEE* (Welk, 2002) and varies considerably between individuals due to genetics, body composition, body mass, gender, age and training status to name a few. An approximate *BMR* for a 70kg, 18-30 year old male is 1746 kcal/day and for an age and weight-matched female, 1524 kcal/day (Food and Agriculture Organization of the United Nations (FAO) / World Health Organization (WHO) / United Nations University (UNU), 2001).

1.4.2 Temperature dependent energy expenditure

Temperature dependent *EE* refers to the effect of environmental temperature on internal temperature and therefore metabolism. This has a negligible effect in terms of *TDEE* so is not usually considered.

1.4.3 Thermic effect of food

The thermic effect of food denotes the rise in *EE* due to digestion and absorption. It contributes to approximately 10% of *TDEE* but can vary between individuals by around 24.1% (Houde-Nadeau, de Jonge and Garrel, 1993; Welk, 2002).

1.4.4 Physical activity

PA is a broad term for any movement or physical work (e.g. isometric muscle contraction) that requires *EE* (Mann and Truswell, 2007). It includes many forms of activity such as working, playing, active transportation and exercise; where exercise can be defined as structured and purposeful *PA* with the objective of improvement or maintenance of physical fitness (World Health Organisation, 2011b). *TDEE* due to *PA* varies between 10-50% (Welk, 2002) mainly due to lifestyle choice and health status but also due to body composition, aerobic capacity, exercise intensity and range of muscular contraction.

PA, and more specifically exercise, is a key component of weight management strategies. The effect of exercise on *TDEE* can be significant, with average *TDEE* in long-term non-exercising women (aged 57.5 ± 3.9 years) reported to be approximately 2221 kcal and in long-term exercising women (aged 55.1 ± 7.1 years) 3103 kcal (Withers, et al., 1998). Furthermore, as an example of the extremes of *PA*, Saris, et al. (1989) reported the average *TDEE* of cyclist during the Tour de France at 6067 kcal.

Moreover, not only does *PA* have large potential to substantially increase *TDEE* but it brings about a multitude of positive effects on both physical and psychological wellbeing including decreasing the risk of stroke, diabetes, hypertension, coronary

heart disease, colon and breast cancer, risk of falls and depression, and increasing bone density and functional health (World Health Organisation 2011b). *PA*, in particular combined endurance and resistance exercise, has additional benefits over dieting as it increases the ratio of lean to fat mass, which in general subsequently increases *BMR* (Stunkard and Wadden, 1993). In contrast, dieting alone depletes both fat and lean tissue.

Physical activity can be complex to define as it can be subcategorised into type, frequency, intensity, duration and domain; all of which are desired information when assessing health and *EE* (Assah, et al., 2011).

1.5 Assessment of total daily energy expenditure

Numerous subjective and objective techniques are available for the monitoring of *EE*. Most focus on measurement of physical activity and/or *BMR*. Temperature dependent *EE* and the thermic effect of food are usually either controlled for or incorporated into the *TDEE* measurement.

The most commonly used subjective assessment of *TDEE* includes direct observation and self-reports, although the validity of these methods is usually poor. Objective assessment is largely preferred as it leaves much less room for error and explores a greater range of subcomponents of physical activity (Assah, et al., 2011). Objective techniques include direct calorimetry, indirect calorimetry, heart rate monitoring, doubly labelled water (*DLW*), electromyography (*EMG*), thermography, actometry and pedometry (Welk, 2002). The first four systems are the most commonly used in research but all have disadvantages (reviewed by Butler, et al., 2004; Levine, 2005) which distil out into being confined to a laboratory situation (direct and indirect calorimetry), needing extremely expensive equipment (doubly labelled water), giving poor temporal resolution (doubly labelled water) and being influenced by largely variable every day factors such as psychological stress, type and intensity of exercise and temperature (heart rate monitoring).

1.6 Motion sensors

Beyond these methods, investigators have examined the use of mechanical motion sensors (Mathie, et al., 2004). In fact, these devices have been used for centuries and the concept that body motion is related to *EE* was proposed as early as 1963 (Cavagna, et al., 1963). This theory was based on the observation that 'in order to elicit movement, energy must be expended, with more pronounced and vigorous movement presumed to arise as a result of more energy expended' (Qasem, et al., 2012, pp.1-2).

Initial studies made use of simple fixed-body motion sensors such as actometers and pedometers, however the last few decades have given rise to significant developments in miniature technologies, which have facilitated the production of small, light-weight accelerometers (Mathie, et al., 2004). Subsequently, a wide array of research on accelerometer-based proxy's for *EE* has developed. Inappropriately, the majority of human research in accelerometry uses a rather primitive and dimensionless metric, 'activity counts' which doesn't make use of the caliber of the technology (Torino, et al., 2006). Conversely, animal based research, particularly in the last decade, has improved markedly in scope and quality due to the use of more complex acceleration metrics, developed because of the necessity to obtain highly detailed movement patterns to assess behavior in the wild.

1.6.1 Overall dynamic body acceleration

In 2006, a new acceleration metric was proposed which focused on using *DBA* gained from a tri-axial accelerometer set to record at high frequencies (>10 Hz) and placed near the individual's centre of gravity. The device contained three orthogonally placed accelerometers and was aligned with the main axes of the body; surge, heave and sway (Fig. 1.1). The specific proxy was *ODBA* and was calculated by summing the *DBA* of all three axes.

Strong linear correlations between *ODBA* and *EE*, explicitly *volume of oxygen uptake* ($\dot{V}O_2$), have been confirmed in birds (Wilson, et al., 2006; Green, et al.,

2009), fish (Gleiss, et al., 2010), amphibians (Halsey, et al., 2010) and mammals (Halsey, et al., 2009) including man (Halsey, et al., 2008).

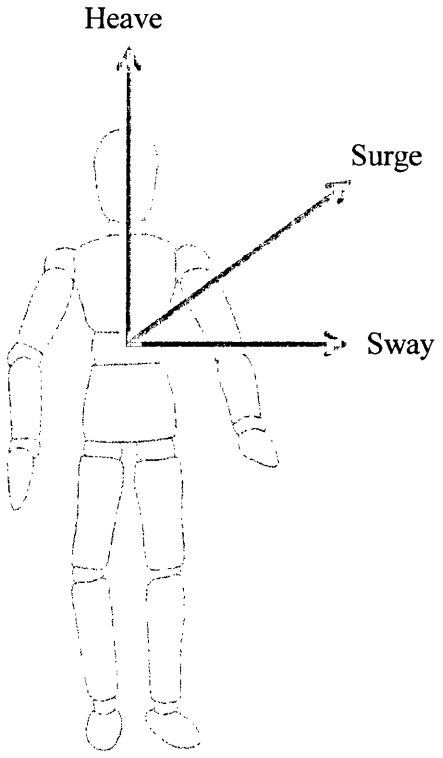


Figure 1.1. A diagrammatic representation of the axis upon which the accelerometers were aligned against.

1.6.2 Vectorial dynamic body acceleration

In spite of the indicative potential of the *ODBA* metric as a proxy for $\dot{V}O_2$, recent authors (e.g. Gleiss, et al., 2011) have highlighted the ambiguity in its formulation. In physics terms, acceleration is described as vectorial quantity, yet *ODBA* treats each axis independently, effectively overestimating the work done for any specific movement. Furthermore, due to the nature of formulation, *ODBA* is susceptible to variation in acceleration values according to the orientation of the device with respect to the participant. Conversely, this should not influence a vectorial solution (Gleiss, et al., 2011). In this respect, it is theorised that the 'correctly' formulated

VeDBA may prove a more accurate and appropriate predictor of $\dot{V}O_2$ than *ODBA*. No studies to date have tested this theory.

Additionally, there is still controversy regarding the effect of device placement in accelerometer based research and the effect of placement on *ODBA* and *VeDBA* metrics has received little attention.

Finally, a recent study indicates that addition of other variables such as body weight may improve the ability of acceleration metrics to predict *EE* (Halsey, et al., 2009) but again this has scarcely been considered.

1.7 Aims and objectives

The aim of this thesis is to investigate dynamic body acceleration as a proxy for human *EE*.

The specific objectives are to investigate:

i) *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$.

ii) *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$ in relation to device orientation (straight *versus* skew logger).

iii) *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$ in relation to device placement (straight *versus* waist logger).

iv) The influence of body anthropometrics, body composition and aerobic capacity on the relationship between *DBA* and $\dot{V}O_2$.

1.8 Null hypotheses

i. There is no difference between *ODBA* and *VeDBA* in terms of their ability to predict $\dot{V}O_2$.

ii. Differences in accelerometer orientation will not influence the ability of *ODBA* to predict $\dot{V}O_2$.

iii. Differences in accelerometer orientation will not influence the ability of *VeDBA* to predict $\dot{V}O_2$.

iv. Differences in accelerometer placement on the body will not influence the ability of *ODBA* to predict $\dot{V}O_2$.

v. Differences in accelerometer placement on the body will not influence the ability of *VeDBA* to predict $\dot{V}O_2$.

vi. Body composition does not influence the relationship between $\dot{V}O_2$ and *ODBA*

vii. Body composition does not influence the relationship between $\dot{V}O_2$ and *VeDBA*

viii. Body anthropometrics do not influence the relationship between $\dot{V}O_2$ and *ODBA*

ix. Body anthropometrics do not influence the relationship between $\dot{V}O_2$ and *VeDBA*

x. Aerobic capacity does not influence the relationship between $\dot{V}O_2$ and *ODBA*

xi. Aerobic capacity does not influence the relationship between $\dot{V}O_2$ and *VeDBA* relationship

Chapter 2

Literature Review

Literature Search Keywords: *Accelerometer, Obesity, Energy Expenditure*

Sources: *Pub Med, Web of Knowledge, The UK Department of Health, The World Health Organisation, The UK Office of National Statistics, The Welsh Assembly Government, The NHS Information Centre, The UK House of Commons Health Committee, The UK Department of Health, Physical Activity, Health Improvement and Prevention, The UK Department for Environment, Food and Rural Affairs.*

2.1 Obesity

Obesity can be defined as 'abnormal or excess fat accumulation that presents a risk to health' (World Health Organisation, 2011c). For simplicity, it is often assessed using Body Mass Index (*BMI*); *BMI* = weight (kg)/ height^2 (m). In general, a *BMI* over 30 kg.m^{-2} is classified as obese and over 25 kg.m^{-2} as overweight (World Health Organisation, 2011a; The NHS Information Centre, Lifestyles Statistics, 2010).

2.2 Causes of obesity

A widely held view is that obesity occurs due to a mismatch in the *energy intake* (*EI*) – *energy expenditure* (*EE*) relationship; either due to an excess *EI*, a reduced *EE*, or an amalgamation of both (Foresight, 2009).

However, this rather simplistic view hides the intricate details that build the complete picture of obesity as a complex and multidimensional disease. Thus, health professionals now accept a more compound explanation where the cause of obesity can be attributed to an individual's 'latent biological susceptibility interacting with a changing environment that includes more sedentary lifestyles and increased dietary abundance' (Foresight, 2009, p. 43).

The Foresight report (2009) identifies five major causes of obesity; biology, early life and growth patterns, behaviour, the living environment and economic drivers of food and drink consumption. These are summarised in Table 2.1.

Table 2.1. Causes of obesity.

Causes of obesity	Evidence base
Biology	• 250+ genes have been linked to obesity (Scuteri, et al., 2007). • The fat mass and obesity associated gene (FTO) and the melanocortin-4 receptor gene (MC4R) have the greatest evidence base (Farooqi, et al., 2003; Hinney, et al., 2007; Scuteri, et al., 2007). • These genes are thought to impair body weight regulation via changes in the central nervous system, particularly the hypothalamus, although exact mechanisms are unclear (Willer, et al., 2009). • Adipose tissue plays a central role in obesity as it releases leptin which acts as a controller of satiety. When fat stores increase, leptin levels rise and subsequently reduce stimulation of hunger and the drive to eat (Foresight, 2009). • It is theorised that obese individuals have poorly controlled leptin release which predisposes them to obesity (Foresight, 2009).
Early life and growth patterns	• There is some evidence linking pattern of growth in early life to obesity, although exact mechanisms are unclear (Foresight, 2009). • Risk of obesity is thought to be related to the mothers diet during development in the womb and the baby's diet (including how and what the baby is feed) (Foresight, 2009). • Risk of obesity has also been linked to adiposity rebound in early childhood. This can be defined as 'the period of time in early childhood when the amount of fat in the body falls and then rises again' (Foresight, p.47). The earlier the rebound occurs, the higher the risk of obesity later on in life (Foresight, 2009).

Behaviour	• There are two critical behavioural influences on energy balance; eating behaviour and physical activity behaviour (Foresight, 2009). • These behaviours are formed by a combination of social, cultural and psychological influences (Foresight, 2009). • Eating behaviour is determined by the motivation to eat as well as the availability of food and time to eat. Dietary risk factors for obesity include high fat, low fibre, sugar-rich diets combined with large portion sizes (Foresight, 2009). • *Physical activity* (*PA*) *c*an be defined as 'as any bodily movement produced by skeletal muscles that requires energy expenditure' (World Health Organisation, 2011b.). *Exercise* is a form of physical activity and is defined as structured and purposeful physical activity with the objective of improvement or maintenance of physical fitness (World Health Organisation, 2011b). • Social and cultural factors influencing physical activity and eating behaviour include (Foresight, 2009): -fewer manual jobs -longer working hours -increased car ownership -increased use of labour-saving devices at work and home -family dynamics -school policies -urban design -media impact • Psychological factors influencing physical activity and eating behaviour include (Foresight, 2009): -habits (repeated behaviours, often difficult to change) -beliefs (perceived importance)

	-translating intention to action (the risk of failing to start or failing to continue) -attitudes (whether an individual true attitude is in line with the attitude they portray) -moral climate (the shared belief of the population/community etc.).
Obesogenic environment	• The obesogenic environment can be defined as 'sum of the influences that the surroundings, opportunities or conditions of life have on promoting obesity in individuals and populations' (Foresight, 2009, p. 52). • Technology and opportunities for *PA* are particularly influences on an obesogenic environment although further research is needed to ascertain the strength of the relationships (Foresight, 2009). • Technology - Technological developments have engineered physical effort out of the environment (Foresight, 2009). • Opportunities for *PA* - *PA* was higher in areas where there are good access to leisure centres, a high land-use mix and in suburban environments. Lack of *PA* was linked with deprivation, poverty and perceptions of social nuisances in the neighbourhood (Foresight, 2009).
Economic drivers of food and drink consumption	• Key economic drivers of food and drink consumption include the price, marketing and purchasing capacity (Foresight, 2009). • Price - Since the 1960's, food and drink prices in the UK and the amount of household income allocated to food and drink has steadily declined. In part this could be due to large increases in cheap high-calorie, nutrient-poor foods. The price – consumption relationship is also effected by income level, age and number of individuals in a household (Foresight, 2009).

- Promotional marketing - Marketing such as special offers, discounts, checkout displays, product presentation, advertising, sponsorships and market segmentation, elicits considerable influence (Foresight, 2009).
- Purchasing capacity - An increased the number of individuals eating out (which is linked with an increased risk of obesity) is rising due to higher average incomes (Foresight, 2009).

2.3 Health risks associated with obesity

The unequivocal links of obesity with numerous diseases has led to its identification as a leading cause of premature morbidity (Peeters, et al., 2003). From the point of view of clinicians and researchers, the major concern of obesity, is its effect in causing or aggravating secondary medical conditions (see section 2.3.1) which severely affect health-related quality of life (see section 2.3.2) and overall life expectancy (see section 2.3.3).

2.3.1 Secondary medical conditions associated with obesity

Secondary medical conditions associated with obesity (measured via *BMI*) include metabolic syndrome, type 2 diabetes, hypertension, dyslipidaemia, coronary artery disease and stroke, respiratory effects, cancers, reproductive function, osteoarthritis, liver and gall bladder disease to name a few. It should be noted that abdominal obesity is a particular risk factor for these diseases which suggests future studies should assess the link between weight distribution and disease, rather than *BMI*. However, currently *BMI* is the most commonly recorded measure of obesity. Thus, this section will consider the health risks associated with increasing *BMI*. These have been reviewed by Kopelman (2007) and are summarised in Table 2.2.

Table 2.2. Medical conditions associated with obesity and overweight (measured via BMI) (Kopelman, 2007, p. 14).

Disease	Health risks associated with an increasing *BMI*
Metabolic Syndrome	30% of middle-aged people in developed countries have features of metabolic syndrome
Type 2 diabetes	90% of type 2 diabetics have a *BMI* of >23 $kg.m^{-2}$
Hypertension	5× risk in obesity
	66% of hypertension is linked to excess weight
	85% of hypertension is associated with a *BMI* >25 $kg.m^{-2}$
Coronary artery disease (CAD) and stroke	3.6× risk of CAD for each unit change in *BMI*
	Dyslipidaemia progressively develops as *BMI* increases from 21 $kg.m^{-2}$ with rise in small particle low-density lipoprotein 70% of obese women with hypertension have left ventricular hypertrophy
	Obesity is a contributing factor to cardiac failure in >10% of patients
	Overweight/obesity plus hypertension is associated with increased risk of ischaemic stroke
Respiratory effects	Neck circumference of >43 cm in men and >40.5 cm in women is associated with obstructive sleep apnoea, daytime
	somnolence and development of pulmonary hypertension
Cancers	10% of all cancer deaths among non-smokers are related to obesity (30% of endometrial cancers)
Reproductive function	6% of primary infertility in women is attributable to obesity

	Impotency and infertility are frequently associated with obesity in men
Osteoarthritis	Frequent association in the elderly with increasing body weight – risk of disability attributable to osteoarthritis equal to heart disease and greater to any other medical disorder of the elderly
Liver and gall bladder disease	Overweight and obesity associated with non-alcoholic fatty liver disease and non-alcoholic steatohepatitis (NASH) 40% of NASH patients are obese 20% have dyslipidaemia 3× risk of gall bladder disease in women with a *BMI* of >32 $kg.m^{-2}$ 7× risk if *BMI* of >45 $kg.m^{-2}$

In general, the review highlights that relative risk of developing these diseases increases with increasing *BMI.*

Furthermore, in some cases, weight loss has been shown to elicit a reversible effect on these diseases. For instance, Neter, et al. (2003), assessed 25 randomised controlled trials with exercise interventions and reported decreased systolic blood pressure of 1.05 mmHg and diastolic blood pressure by 0.92 mmHg per kg of weight loss.

2.3.2 The effect of obesity on health-related quality of life

A growing number of studies consider the effects of obesity on health-related quality of life (*HRQL*). *HRQL* is 'a multidimensional construct, encompassing emotional, physical, social and subjective feelings of well-being which reflect an individual's subjective evaluation and reaction to health or illness' (Fontaine and Barofsky, 2001, p.174). It is measured most commonly via questionnaire such as the SF-36

questionnaire which assesses eight distinct domains: general health perception; mental health; role limitations i.e. work, school etc; physical functioning; physical problems; bodily pain; vitality and social functioning (Fontaine and Barofsky, 2001).

Fontaine and Barofsky (2001) highlighted multiple studies that report negative associations between obesity and several domains of *HRQL* including; anxiety, depression, bodily pain, perceived health, and physical functioning, social functioning and functional status i.e. the capacity to perform activities relating to self-care, physical activity and role activities i.e. work, school etc. Moreover, in a study which included more than 40,000 female participants (the largest body weight-health-related quality of life study to date) a weight gain of 2.25kg or more was accompanied with increased body pain and decreased physical function, irrespective of baseline body weight (as assessed with the SF-36 questionnaire) (Fine, et al., 1999).

2.3.3 The effect of obesity on life expectancy

Few studies have assessed the effect of being overweight or obese on life expectancy due to the complex interactions of both variables with smoking, age and obesity-related diseases. In general, those that have, report large reductions in life expectancy in individuals that are overweight and obese (Peeters, et al., 2003). Peeters, et al. (2003) demonstrated that individuals who are overweight or obese at the age of 40 years (assessed via *BMI*) all display reductions of life expectancy regardless of smoking status or gender; ranging from a loss of 3.1 years in overweight male non-smokers to 13.7 years in obese male smokers.

2.4 Prevalence and trends of obesity in England and Wales

Ominously, the past 20 years has presented substantial global increases in obesity prevalence (Musingarimi, 2009).

In England, obesity prevalence has more than tripled since the 1980's (Canoy and Buchan, 2007). Currently, obesity levels have reached a new high with results of the Health Survey for England Adult Trend Tables (2010) reporting 62.8% of adults

(aged 16+) as overweight or obese ($BMI \geq 25$ kg.m^{-2}) and 26.1% as obese ($BMI \geq 30$ kg.m^{-2}) (Health and Social Care Information Centre, 2011). This represents a steady increase from 2003 when prevalence was 60.5% and 22.6% respectively.

Similarly, the Welsh Assembly Government (2010) totalled 57% of adults (aged 16+) as overweight or obese ($BMI \geq 25$ kg.m^{-2}) including 22% obese ($BMI \geq 30$ kg.m^{-2}) again representing a steady rise from 2003/2004 (54%, 18% respectively; Welsh Assembly Government, 2003/2004). Moreover, it should be noted that the Welsh Heath Survey uses self-report questionnaires rather than direct measurement therefore results are likely to be underestimated (Robert, 1995). Robert (1995) reported that in a sample of participants from the Welsh Heart Health Survey 1985, both men and women had a propensity to overestimate their height and underestimate weight (Robert, 1995).

The limitations of using self-reports to obtain accurate data on obesity further distils into measurements of its relating factors such as *EI* and *EE* (see section 2.5 for more detail). The main issues being that information on *EI* is often estimated or ignored and accurate measurement of *EE* is not available to the general public. Interestingly, although this information may not reduce the occurrence of the disease, it is essential to developing our understanding of the effectiveness of current methods of prevention and treatment as well as the dose-response relationship between physical activity and health. Furthermore, it is possible that the development of accurate measurement tools may be just a small price to pay in comparison to the growing economic burden of obesity.

2.5 Economic cost of obesity

The rapid rise in the prevalence of obesity and its comorbidities is cause for concern not only with regard to morbidity and mortality but also in terms of the concurrent economic implications. Obesity is a typically longstanding condition and in cases where concurrent diseases occur, can be highly medical-care intensive. Subsequently, recent years have given rise to numerous studies aimed at quantifying obesity in financial terms. For example, Withrow and Alter (2011) reviewed eight studies from six different countries (Brazil, Canada, China, New Zealand,

Switzerland and United States of America) that used similar *BMI* categories and reported that obese individuals ($BMI \geq 30$ kg.m^{-2}) accrue medical costs 30% higher than normal weight individuals ($BMI < 25$ kg.m^{-2}). Furthermore, with relation to the UK although a recent review by Allender and Rayner (2007) estimate the direct cost of overweight and obesity in the UK at ~£3.23 billion per year (approximately 5% of total NHS costs), this figure does not include indirect costs such as home care, private healthcare, days lost to sickness and premature mortality. An earlier report from the House of Commons Health Committee (2004) conservatively estimates both direct and indirect costs of the overweight and obese population in the UK at £6.6–7.4 billion per year.

2.6 Interventions to treat and prevent obesity

Current methods of preventing obesity focus upon reducing *EI* by promoting healthy eating and reduced calorie consumption and/or increasing *EE* through exercise.

Both, calorie restriction and exercise have been shown to significantly reduce body weight and percentage body fat (Bauman, 2004; Redman, et al., 2007). If assessments occur a few days after the last exercise session, both exercise-induced weight loss and caloric restriction are just as effective as one another in causing both a reduction in fat mass and secondary changes in adipose tissue function (Thompson, et al., 2012).

However, exercise (in particular combined endurance and resistance exercise) has additional benefits over dieting as it increases the ratio of lean to fat mass. In contrast, dieting alone depletes both fat and lean tissue. Furthermore, exercise elicits numerous physiological benefits in addition to weight loss including increased cardiovascular fitness, decreased blood pressure, increased coronary blood flow, increased cardiac function, reduced body fat, increased insulin sensitivity, improved lipid lipoprotein profiles i.e. reduced cholesterol and increased high density lipoproteins and improved autonomic tone to name a few. These distil into reduced risk of secondary diseases such as cardiovascular disease, type 2 diabetes etc. (Warburton, Nicol and Bredin, 2006).

Current evidence (Wu, et al., 2009; Larson-Meyer, et al., 2010) suggest that combining both calorie restriction and exercise creates the most effective weight loss program. This is represented in the current UK National Institute for Health and Clinical Excellence (NICE) guidelines for treatment of obesity.

Nevertheless, NICE also stresses the need for further randomised trials to further refine the effects of diet and exercise as interventions for obesity (NICE, 2006). Thus, in order to evaluate these interventions both *EI* and *EE* must be accurately measured during long-term free-living scenarios.

Measurement of *EI* is particularly difficult as the most commonly used and practical technique is the self-report method (including a diet diary and weighing equipment). This technique is limited due to underreporting of calorie intake which has been described in many populations including non-obese adolescents (Livingstone, et al., 1992) and more importantly in obese individuals (Litchman, et al., 1992). For example, Litchman, et al. (1992) found obese individuals underreport by ~ 47%.

Consequently, recent attention has focused upon providing accurate predictions of *EE*, usually expressed in terms of *total daily EE* (*TDEE*), to validate against reported *EI* and changes in body weight.

2.7 Components of total daily energy expenditure

TDEE can be split into four components; basal metabolic rate, temperature dependant *EE*, the thermic effect of food and physical activity. Current methods of predicting *TDEE* measure all or differing combinations of these components therefore before these methods can be discussed, the constituents of *TDEE* must be understood.

2.7.1 Basal metabolic rate

Basal Metabolism (*BM*) can be defined as the energy needed to maintain only the basic processes of life such as cell function and repair; synthesis, secretion, transportation and metabolism of hormones, enzymes, proteins and other substances;

uninterrupted cardiac and respiratory rhythm; circulation, brain function and maintenance of homeothermy (Food and Agriculture Organization of the United Nations (FAO) / World Health Organization (WHO) / United Nations University (UNU), 2001). When quantified against time, *BM* is termed *Basal Metabolic Rate* (*BMR*) (FAO/WHO/UNU, 2001). The units are typically quoted as kilocalories (kcal) although should technically be described in Watts (joules/second,) according to the Systeme International. The conversion is shown in equation 2.1.

1kilocalorie = 4.2 kilojoules (2.1)

(Eston and Reilly, 2001b)

Basel metabolic rate (*BMR*) is measured using indirect calorimetry under strictly standardised conditions. The individual should be (i) adult (eradicating the energy cost of growth), (ii) healthy, (iii) awake, (iv) not pregnant (eliminating energy cost of pregnancy) (v) inactive, in a resting supine position, (vi) mentally relaxed e.g. familiar with the equipment to avoid undue stress, (vii) in a post-absorptive state not having eaten for 12 hours prior, (viii) in a physically relaxed state, not having undertaken any undue muscular exertion 12 hours prior, (ix) in a thermonetural environment (usually 22-26°C) i.e. an environment where no thermoregulatory processes in the body are needed (McNab, 1997; Eston and Reilly, 2001b; Mann and Trusswell, 2001; Henry, 2005).

In practice it is often impossible to obtain all the above stipulations, therefore, in cases where most but not all of the above conditions are met, the measurement is referred to as *Resting Metabolic Rate* (*RMR*) (Mann and Trusswell, 2001). However, even *RMR* is equipment and time dependent, which, especially during large group assessment, is very limited. Consequently, numerous *BMR* prediction equations have been developed.

The relative percentage of *BMR* to *TDEE* ranges between 40-75% primarily due to variation in physical activity, with *RMR* in truly sedentary individuals reaching 80% (FAO/WHO/UNU, 2001; Landsberg, et al., 2009).

2.7.2 Temperature dependent energy expenditure

Temperature dependent EE refers to the inevitable effect that a change in environmental temperature will cause a corresponding change in core temperature albeit on a much smaller scale. Increased core temperature increases the rate of metabolic reactions and therefore greater oxygen (O_2) consumption i.e. *EE*. For example, an increased core temperature of 1°C is coupled to an increased metabolic rate of 10-13% (Landsberg, 2009). Nevertheless, in general, as long as the environmental conditions are known, temperature dependent *EE* can be ascribed.

2.7.3 Thermic effect of food

The thermic effect of food (also termed the heat of nutrient metabolism, heat increment of feeding, specific dynamic action, specific dynamic effect or diet-induced thermogenesis) is the process of digestion, absorption, transport and storage of the constituents of food and comprises approximately 10% of *TDEE* (Rosen and Trites, 1997; Mann and Truswell, 2007).

The thermic effect of food can be measured using calorimetry (direct or indirect) after consuming a controlled meal representing the typical diet of the UK population. This usually comprises of a meal constituting of; 50% carbohydrate, 35% Fat and 15% protein and with the amount representing 10 $kcal.kg^{-1}$ of body weight or $1/3^{rd}$ daily energy requirements (Welk, 2002).

2.7.4 Physical activity

PA is a complex phenomenon to quantify. Firstly, it can be characterised as *obligatory* or *discretionary*. Obligatory activity is imposed on an individual by the nature of their social, economic and cultural environment i.e. going to work. Discretionary activity is that which occurs by choice, often for reasons of personal enjoyment, social interaction or purely with the aim of gaining health benefits (FAO/WHO/UNU, 2001) e.g. exercise.

Assessment of the social, psychological and cultural influence on an individual's *TDEE* are particularly important and can be used as a starting point to build in *PA* to daily life to help achieve weight loss. However, it is the frequency (number of times), intensity (rate), duration (time period), type (activity) and domain (location of the exercise) of *PA* that define the exact amount of energy expended and health benefits gained (Assah, et al., 2011). Hence, it is essential that these factors are measured.

Physical activity is the most variable component of energy metabolism, between 10-50% of *TDEE*. It is the easiest and most effective to manipulate (usually via exercise) hence its prominence in weight loss interventions in comparison to the other components of *EE* (Welk, 2002; FAO/WHO/UNU, 2001). Consequently, measurement of *physical activity energy expenditure* (*PAEE)* is vital in development and assessment of weight loss programs. Furthermore, this measurement needs to be accurate and repeatable for any individual across the population, hence, it must incorporate any factors that affect intra and inter individual variation.

2.8 Intra and inter-individual variation in total daily energy expenditure

Variation in *TDEE* is dependent on the variation associated with its components. These will be discussed separately. *Temperature* dependent *EE* is not usually included in models of human *EE* since the temperature of the human body usually remains close to 37°C and the environmental temperature is normally controlled within certain comfortable limits. The heat loss from the body then remains relatively stable due to complex homeostatic mechanisms and so does not act as a major component of *TDEE*.

2.8.1 Variation in basal metabolic rate

Intra-individual variation in *BMR* or *RMR* measurements have been reported at approximately 5-8% and are usually attributed to discrepancies in the conditions of the test e.g. amount of physical activity prior to the test, stage of the menstrual cycle in women or the accuracy of the equipment used to take the measurement (Donahoo, Levine, and Melanson, 2004).

Inter-individual variation in *BMR* or *RMR* have been linked to numerous factors including; i) body composition: fat-free mass and fat mass, ii) body mass, iii) gender, iv) age and v) training status, many of which are included in prediction equations in an attempt to control for these effects.

i) *Body composition*

In the simplest of terms, body composition can be described using the two-compartment model; i) *fat mass* and ii) *fat-free mass*. *Fat mass* consists of all extractable lipids from all tissues (Heyward and Stolarczyk, 1996) and *fat-free mass* can be defined as the non-lipid mass (Lohman, 1992). Additionally, the term *lean body mass* is commonly defined as all components of *fat-free mass* with the inclusion of essential lipids (Cunningham, 1991; Heyward and Stolarczyk, 1996).

In this section, *fat-free mass* and *lean body mass* represent the same concept and, although they are used interchangeably depending on the study in question, they are considered as one. The same is true of *BMR* and *RMR* and *resting EE* (*REE*).

Fat mass

There are highly mixed results regarding the relationship of *fat mass* to absolute *BMR*, *RMR* or *REE*. Many early studies reported an insignificant relationship, explained by the fact that *fat mass* is on the whole metabolically inactive. For example, a review by Cunningham (1991) suggests *fat mass* makes no independent contribution to the prediction of *REE* in the general population. This is further supported by Heshka, et al. (1990) who found that after *fat-free mass* had been taken into account, fat mass was not a significant predictor of *RMR*.

More recently, some studies have supported the role of *fat mass* in influencing individual variation in *BMR*, *RMR* or *REE*, albeit on a much smaller scale than *fat-free mass* and *lean body mass* (Nielson, et al., 2000; Johnstone, et al., 2005). In general, an increase in *fat mass* has been found to relate to an increase in absolute *BMR*, *RMR* or *REE*. For example, Johnstone, et al. (2005) established that *fat mass* explained 6.7% of between-subject variations in *BMR* in a sample of both males and

females, with varying *BMI* (lean to obese). Nielson, et al. (2000) also studied a similar population and found *fat mass* to be a significant predictor of *REE*.

Fat-free mass

Ample studies have reported strong and significant associations of *fat-free mass* and/or *lean body mass* on absolute *BMR*, *RMR* or *REE* (Cunnigham, 1980; Berstein, et al., 1983; Ravussin and Bogardus, 1989; Nielson, et al., 2000; Johnstone, et al., 2005; Lazzer, et al., 2010; Taguchi, et al., 2011).

Early studies identified lean body mass or *fat-free mass* as the most important predictor of resting metabolic rate. Cunningham (1980) reported that lean body mass explained 70% of the variability in *BMR* in 223 adults (mean *BMI* = 21.2 $m.kg^{-2}$ based upon sample mean for mass and height) and Bernstein, et al. (1983) stated 71-81% of the variability in *RMR* could be ascribed to *fat-free mass* (depending on method of measurement) in 202 adults (9.1 -230.6% above the median desirable weight for height).

Recent studies show similar results with *fat-free mass* alone explaining 62.3%, 60% and 82% of the variability of *BMR* in white adults (underweight to obese based upon *BMI*), obese white children & adolescents and Japanese female athletes respectively (Johnstone, et al., 2005; Lazzer, et al., 2010).

Finally, the extent of variation about the regression line between *BMR* and *lean body mass* has been approximated at 600 kcal per day which equates to a total calorific expenditure of between 1600 - 2200 kcal per day for an individual of 70kg lean mass (Silva, 2006). This signifies that although *lean body mass* should be a main factor in predictive equations for *BMR* other variables must also be taken into account to achieve an accurate estimation.

ii) *Body mass*

The majority of the literature reports that sub-variables of body mass such as *fat-free mass* supersedes the use of body weight as an independent predictor of *RMR* (Javed, et al., 2010).

On the other hand, Taguchi, et al. (2011) found very similar coefficients of determination between *REE* and body weight and *REE* and *fat free mass* ($r^2 = 0.66$, $p = 0.001$ and $r^2 = 0.67$, $p = 0.001$ respectively). This could be explained as all participants where athletes and were likely to have a high *fat-free mass* to body mass ratio.

iii) Sex

Sex differences in *REE* can on the whole be explained by body size and body composition differences, especially *fat-free mass/lean body mass* (Cunningham, 1980; Johnstone, et al., 2005; Lazzer, et al., 2011). Cunningham (1980) demonstrated that gender has little contribution in the estimation of *BMR* above *lean body mass* when data is kept gender specific or combined prior to analysis. Later studies also produced similar results. Johnstone, et al. (2005) also found no influence of sex on *BMR* and Lazzer, et al. (2011) agreed that sex had little influence on *BMR* in adults and children once *fat-free mass*, *fat mass* and body weight were used as predictors.

iv) *Age*

An *age*-related reduction in *BMR* is commonly described (Cunningham, 1980; Rauvussin and Bogardus, 1989; Piers, et al., 1998). Many studies indicate that this is nearly entirely due to simultaneous changes in body composition, namely *fat-free mass* (Cunningham, et al., 1980; Rauvussin, et al., 1989).

In contrast, other authors found a small but significant effect of age alone. Piers, et al. (1998) found the *BMR* of older individuals (mean age = 62 years) was 644 KJ/day lower than younger individuals (mean age = 23 years) after adjustment of *fat-free*

mass, and Johnstone (2005) established that age explained 1.7% of between participant variation in *BMR*.

v) ***Training status***

It is commonly thought that trained individuals have a higher *BMR*. A specific difficultly in testing this hypothesis is that certain types of exercise produce acute increases in *BMR*. For example, many studies report that $\dot{V}O_2$ can remain elevated up to 24-48 hours after high intensity aerobic exercise training (greater than 70% $\dot{V}O_2$max). Therefore, in some cases it has been difficult to deduce whether an increase in *BMR* is due to an improvement in fitness, an increase in *fat-free mass* or produced by the exercise period itself (Treuth, Hunter and Williams, 1996).

In terms of chronic changes in *BMR*, it is widely accepted that continual resistance training will induce increases in lean tissue mass which, in turn, results in increased *BMR* (Campbell, et al., 1994). However, it is unclear whether increases in *BMR* or *RMR* above that which can be attributable to *fat-free mass* occur with increased fitness. Many studies report no association between *BMR* or *RMR* (expressed with respect to *fat-free mass*) and increased fitness after a period of 10 weeks resistance training or combined resistance and endurance training (Dolezal and Potteiger, 1998), nine weeks of aerobic training (Bingham, et al., 1989) and twelve weeks of aerobic training (Lee, et al., 2009). Another study indicates a significant increase in *RMR* (corrected for *fat-free mass*) in men but not women as a result of 24 weeks of strength training (Lemmer, et al., 2001). Although, these authors also note that the current literature regarding gender differences in the influence of fitness on *RMR* is inconclusive.

2.8.2 Variation in the thermic effect of food

Intra-individual and inter-individual variation in the thermic effect of food has been previously demonstrated to be around 10.7% and 24.1% respectively (Houde-Nadeau, de Jonge and Garrel, 1993).

Explanations for the intra-individual variation include the timing of the measurements i.e. length of time and continuous or intermittent nature, energy content of food (number of calories), composition of meal (carbohydrate, fats, proteins), diet and exercise in the previous days prior to measurement (de Jonge and Bray, 1997; Donahoo, Levine and Melanson, 2004).

The main influencing factors on inter-individual variation are the *fat-free mass* or *lean body mass*. In general, *lean body mass* is strongly related to the thermic effect of food, with a greater lean mass producing a larger dietary induced *EE* (Donahoo, Levine and Melanson, 2004). Furthermore, a reduced dietary-induced thermogenesis has also been reported in obesity although this remains controversial (Donahoo, Levine and Melanson, 2004). Segal, et al. (1985) reported significantly lower thermic effect of food for obese individuals in comparison to lean individuals at rest, during exercise and post-exercise. Further studies by the same authors also support the blunted thermic effect of food with obesity during rest and during exercise (Segal, et al., 1992).

2.8.3 Variation in physical activity energy expenditure (*PAEE*)

Assuming physical activity *per se* between individuals is equal, a small amount of intra-individual and inter-individual variation still occurs. Few studies have assessed the variation in *PAEE* alone. Still, it is possible to make some general observations based upon the available evidence.

With regard to intra-individual variability in *PAEE*, a review by Donahoo, Levine and Melanson (2004) suggests that variation is small and very reproducible in highly trained and moderately trained individuals, estimated at 1.5-2%.

Nevertheless, a small amount of intra-individual variation in *PAEE* may occur in any individual due to the possibility of a circadian rhythm in *volume of oxygen uptake* ($\dot{V}O_2$). A circadian rhythm can be described as a natural rhythmic fluctuation over time, most commonly 24 hours (Massin, et al., 2000). A review by Noordhof, et al., (2010) report that numerous studies show a circadian rhythm in $\dot{V}O_2$, with higher *maximal oxygen uptake* ($\dot{V}O_2$max) values in *post meridiem* compared to *ante*

meridiem. $\dot{V}O_2$max can be defined as 'the maximal rate at which an individual can take up and utilise oxygen while breathing air at sea level' (Eston and Reilly, 2001b, p.161). Conversely, other authors report no evidence of daily variation (Besnott, et al., 2011).

Inter-individual variation in *PAEE* and has been shown to occur with; i) *fat-free mass*, ii) *fat mass*, iii) aerobic capacity, iv) exercise intensity and to a smaller extent v) range of motion of muscular contraction.

i) Fat-free mass

Fat-free mass is significantly related to non-resting (i.e. activity) *EE*, with greater *fat-free mass* producing a larger absolute *PAEE* (Liebel, Rosenbaum and Hirsch, 1995; Johnson, Russ and Goran, 1998). Conversely, the relationship seems to be much less prevalent in comparison to *REE*. For example, by Johnson, Russ and Goran (1998) found that *fat-free mass* explained only 10% of the variation in *PAEE*.

Nevertheless, as few studies consider the effects of *fat-free mass* on *PAEE* alone and strong positive associations have been found between *fat-free mass* and both *REE* and *TDEE* it will be included as a variable in the present study.

ii) Fat mass

In general, it would seem logical for obese adults to have a greater absolute *PAEE* than their lean counterparts (if matched for *fat-free mass*) due to the additive energy needed to overcome the inertial resistance both for whole body movement and for cardiorespiratory work created by the excess weight of the *fat mass*.

Conversely, Liebel, Rosenbaum and Hirsch (1995) report that *fat mass* is related to *TDEE* and *REE* but not non-resting *EE* and Goran, et al., (1997) also found no significant relationship. However, little research has been conducted on the relationship between *fat mass* and *PAEE* specifically. Thus, as many studies suggest *fat mass* has an additional influence on *RMR* over and above that of *fat-free mass*, it should be considered in the present study.

Furthermore, loss of *fat mass* seems to have important metabolic implications in addition to the reduced *EE* that might occur with reduced body fat. For example, numerous studies report *PAEE* to be lower in formerly obese individuals in comparison to those matched for age, *fat-free mass* and *fat mass* that have never been obese (Astrup, et al., 1999, Doucet, et al., 2003). This has also been confirmed for *RMR*. For instance, Doucet, et al. (2003) used 83 participants with $BMI \geq 27$ kg.m^{-2} and $BMI < 45$ kg.m^{-2} as controls to create a regression equation for net exercise *EE* based upon age, *fat-free mass* and *fat mass*. This was used to predict net exercise *EE* in obese individuals who underwent a 15 week drug based and calorie restricted weight loss programme (average *BMI* before 33.7 kg.m^{-2} and after 30 kg.m^{-2}). This phenomenon is particularly important as it may predispose subsequent weight gain, although it is possible that the greater than expected decrease in exercise *EE* could be short-lived (Doucet, et al., 2003).

iii) Aerobic capacity

Aerobic capacity can be represented by $\dot{V}O_2$max. With endurance training, $\dot{V}O_2$max will increase producing a subsequent increase in exercise economy. Exercise economy can be defined as 'the oxygen uptake required at a given absolute exercise intensity' (Jones and Carter, 2000, p. 375). Hence, an increase in aerobic capacity brings about a decrease in O_2 uptake and, therefore, *PAEE* for a given exercise intensity (Jones and Carter, 2000).

Conversely, this is not always the case, as even individuals with the same aerobic fitness display substantial inter-individual variability in O_2 utilisation at submaximal intensities (Jones and Carter, 2000). For instance, McGregor, et al. (2009) reported that trained individuals exhibited a higher O_2 cost than untrained individuals for the same walking speed. This was attributed to differences in substrate utilisation. For example, it is theorised that endurance training causes the body to prioritise fat utilisation over carbohydrates (Saunders, et al., 2004). Fat utilisation requires a greater amount of O_2 per g than carbohydrate.

iv) *Exercise intensity*

Mechanical efficiency can be defined as 'the percentage of total chemical energy expended that contributes to external work, with the remainder lost as heat' (McArdle, Katch and Katch, 2007, p.211). This is further supported by Noordhof, et al. (2010) who reported no significant differences in gross efficiency (mechanical power output/metabolic power input) within or between days during maximal and submaximal cycling tests in 18 active males. However, these studies were based upon active or trained individuals and as a high number of obese individuals are unlikely to meet the national recommendations for physical activity (as discussed previously), the obese population may not follow the same trend). Considerable decreases in muscular efficiency have been shown to occur with increases in exercise intensity. For example, 12 times more energy is needed to perform a bench press at 80% of 1 repetition-max compared to 20% of 1 repetition-max even though it is only four times the work (Hunter, et al., 1988). Importantly, this negative relationship between exercise intensity and efficiency is not typical in running, probably due to use of elastic recoil of the tendons (Hunter, et al., 1998).

This could cause confusion if studies were not based upon relative fitness. In the present study, individual gas exchange thresholds are identified and used as means of controlling for relative fitness (see section 2.15.2).

v) Range of motion of muscular contraction

Muscular efficiency may differ depending on muscle length. For example, it is theorised that less energy is need for contraction when a muscle is stretched as it is better able to store elastic energy as opposed to when it is flexed (Hunter, et al., 1998). This could cause differences between the *EE* of each individual due to differences in running style and subsequently range of motion of muscular contraction but the differences are likely to be negligible, therefore this will not be considered during this thesis.

2.9 Methods of measuring energy expenditure

Numerous methods are available for measuring *EE* including *direct and indirect calorimetry* (section 2.9), *doubly labelled water* (section 2.10), *heart rate monitoring* (section 2.11), *electromyography* (section 2.12), *infrared thermography* (section 2.13) and via *motion sensors* (section 2.14). Each have strengths and weaknesses relating to and in no specific order; i) accuracy and reliability of measurement, ii) ability to predict $\dot{V}O_2$, iii) invasive or non-invasive nature of the equipment, iii) cost, iv) mobility and practicality of equipment and v) the number of components of *EE* that can be measured separately.

2.10 Whole body metabolic calorimetry

2.10.1 Principle

The basic principle of whole body metabolic calorimetry involves the direct measurement of heat *loss* of an organism (*direct calorimetry*) or the indirect measurement of heat produced via calculation from measurements of metabolic by-products (*indirect calorimetry*).

Heat is a direct by-product of all metabolic reactions and thus represents *EE*. Heat can be defined as 'the thermal energy that is exchanged between two masses because of a temperature difference between them' (Battley, 1995, p. 338). In order to maintain homeostasis i.e. prevent hyperthermia, heat is continually released from the body via convection, conduction, radiation and evaporation creating a constant heat flux (although there is a small lag time due to temporary storage) (Mann and Truswell, 2007).

2.10.2 History

The first studies to establish the basic concept of *EE* by measuring heat loss was conducted by Antonie Lavoisier in the 1700's. It involved keeping a guinea pig in a small chamber containing ice and computing energy metabolism in relation to the amount of ice that had melted (Mann and Truswell, 2007). Lavoiser was also the first

to note the increased heat loss due to thermogenesis. Although, it wasn't until the 1800's that Max Rubner defined this as specific dynamic action, now referred to as the thermic effect of food (Kopelman, et al., 2010).

Today measurement of whole body metabolic calorimetry takes places in two forms; *direct calorimetry* and *indirect calorimetry*.

2.10.3 Direct calorimetry

Although the basic principle remains the same, the construction and instrumentation of a direct calorimeter is highly complex involving use of intricate thermocouple sensors and heat exchangers. A direct calorimeter measures heat loss as a product of evaporative and non-evaporative heat. Evaporative heat is the heat energy used to convert water into vapour denoted by an increase in humidity in the surrounding air. Non-evaporative heat is the heat given off as conduction, convection and radiation (McLean and Tobin, 1987).

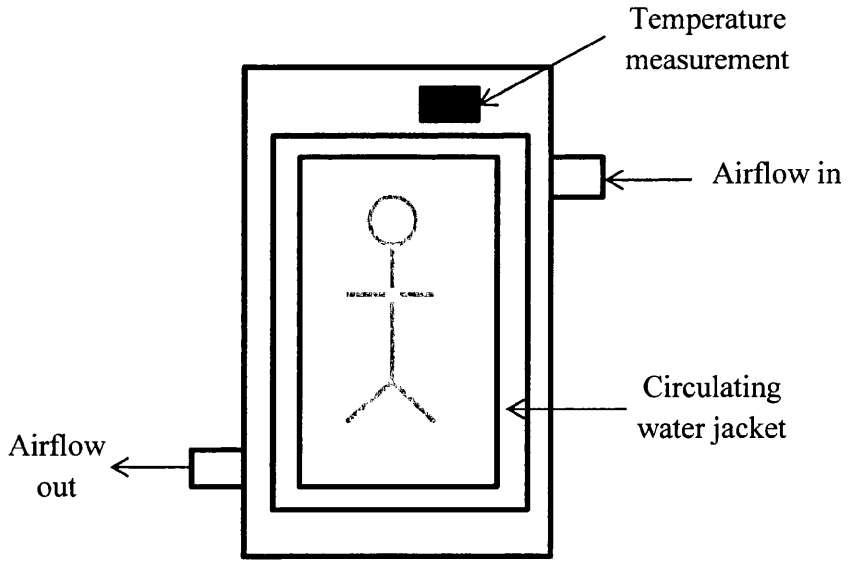


Figure 2.1. A simple diagrammatic representation of a calorimeter used to measure production of body heat.

An example of a direct calorimeter includes a 'human sized', airtight thermally sealed chamber, constructed with coiled water tubes running through the top (Fig. 2.1). A known volume of water flows through the coiled tubes and the temperature of the water entering and leaving the chamber is measured. The difference in water temperature reflects the subject's heat production and therefore *EE*. *EE* is calculated based on the theory that for 1g of water to rise in temperature by 1°C, 1 calorie of energy is required. A constant flow of air is re-circulated in and out of the chamber and during each cycle the air is cooled, *oxygen* (O_2) added and *carbon dioxide* (CO_2) and water vapour filtered to ensure no net loss or gain of water vapour or heat. The chamber is thermally sealed so that change in water temperature directly corresponds to the individual's *EE* (Powers and Howley, 2001).

Direct calorimetry is the criterion or gold standard method of measuring *EE* in *Homo sapiens* due to the one-step procedure in measuring heat loss (Kopelman, et al., 2010; Battley, 1995). It is non-invasive and extremely precise, displaying an accuracy of up to 2-3% using a variety of dry and wet heat sources (Daly, et al., 1985). This tiny error is mainly due to the unavoidable fact that a small percentage of heat produced is absorbed into further metabolic reactions rather than liberated from the body (Battley, 1995). Finally, direct calorimetry has an additional benefit of measuring the rate of heat loss as well as the total heat loss (Battley, 1995).

Nevertheless, due to the technical complexity, the extremely high cost of both the calorimeter and instrumentation as well as the lack of relevance to free-living situations, this method is rarely used and there are now only a handful of direct calorimeters in commission worldwide (Mann and Truswell, 2007). Instead indirect alternatives are employed.

2.10.4 Indirect calorimetry

By 1949, the first indirect calorimeter (measuring respiratory gases) had been produced, later to become the preferred method of calorimetry (McLean and Tobin, 1987).

Indirect calorimetry has been widely validated against direct calorimetry and is often used as the criterion for validating new techniques. It is a non-invasive technique that involves calculation of heat production based on the measurement of pulmonary gas exchange. It uses the quantity of substrate use and chemical by-products of metabolism, namely O_2 utilisation (assuming that O_2 utilised is related to heat produced) and CO_2 production in order to calculate *EE* (Haugen, Chan and Li, 2007). There are two types of indirect calorimeter systems available; i) closed circuit and ii) open circuit.

2.10.5 Closed circuit calorimetry

Closed circuit calorimeters are relatively inexpensive and constructed of simple instrumentation. The basic conformation includes a sealed gas circuit either in the form of a chamber or mask/mouthpiece. This circuit is filled with 100% O_2 and contains a device that absorbs all CO_2 (Eston and Reilly, 2001b; Arch, et al., 2006). As the participant utilises the O_2 and produces CO_2 (which is immediately absorbed) a drop in pressure occurs. This triggers the opening of a value, allowing entry of O_2 into the chamber or mask/mouthpiece until the pressure is restored. The change in volume represents the combined O_2 usage and CO_2 production (Arch, et al., 2006). In combination with the amount of CO_2 absorbed, *EE* can be accurately computed.

The system has the additional benefit of providing a measured inspired minute ventilation (V_I) value (in comparison to open circuit systems in which V_I is calculated via the Haldane equation). Nonetheless, closed circuit systems require consistent adjustments to be made to the ventilator in order to overcome the increased breathing resistance and increased inspiratory time which raise the work of breathing (Matalese, 1997). In addition, they are greatly affected by changes in lung volume and leaks in the chamber (Matalese, 1997). Finally, due to the build-up of ammonia, studies are typically limited to 1 hour (Arch, et al., 2006).

2.10.6 Open circuit calorimetry

Several pieces of equipment are available as an open circuit calorimeter including; i) Douglas bags, ii) a metabolic cart and iii) portable calorimeters.

i) ***Douglas Bags*** - The participant breathes into a mask or mouth piece attached to a tube with a one-way value which feeds into a large airtight bag. Expired gas is collected in a different bag for each stage of exercise. A sample from each bag is analysed to give the relative concentrations of CO_2 and O_2 via electronic gas analysers (Haugen, et al., 2007).

ii) ***Metabolic Cart*** – The mask/mouth piece is similar to the Douglas Bag device but the tube is connected to a metabolic cart. Gas and airflow samples are continuously collected and analysed through breath-by-breath, mixing chamber or dilution systems (Matarese, 1997; Haugen, et al., 2007). An example system includes the Oxycon Pro which has been shown to be both valid and reliable with coefficients of variation for $\dot{V}O_2$ and $\dot{V}CO_2$ between 4.7–7.0% for breath-by breath measurements (Carter and Jeukendrup, 2002).

iii) ***Portable Indirect Calorimeters*** – This is a similar process to the metabolic cart with some integrated sensors to measure barometric pressure, ambient temperature and relative humidity (these values are manually entered into the metabolic cart) (Haugen, et al., 2007).

2.10.7 Calculation of energy expenditure

Although there are numerous formulae for calculation of *REE* the Weir equation (Eq. 2.2) or the modified Weir equation (Eq. 2.3) are the most commonly used. These formulae are based on the assumption that production of 1 L of CO_2 equates to an energy production of 1.11 kcal and utilisation of 1 L of O_2 equates to 3.941 kcal (Haugen, et al., 2007).

Weir Equation

$$REE(kcal.day^{-1}) = [(3.941 \times \dot{V}O_2) + (1.11 \times \dot{V}CO_2) + (2.17 \times uN_2) \times 1440 \qquad (2.2)$$

Modified Weir Equation

$$REE(kcal.day^{-1}) = [(3.941 \times \dot{V}O_2) + (1.11 \times \dot{V}CO_2) \times 1440 \quad (2.3)$$

REE = Resting energy expenditure (kcal.day)
uN = Urinary nitrogen (g.day)
$\dot{V}O_2$ = Volume of oxygen uptake (ml.min^{-1})
$\dot{V}CO_2$ = Volume of carbon dioxide production (ml.min^{-1})

(Haugen, et al., 2007, p.378)

The modified Weir equation is currently most popular as it alleviates the need for 24 hour urine collection which is often very difficult and in addition presents its own intrinsic errors (Matarese, 1991). In addition, the error produced from the modified equation is only 1-2% (Weir, 1949).

2.10.8 Limitations

A major limitation of indirect calorimetry is due to the prediction of V_I. Ideally, $\dot{V}O_2$ and $\dot{V}CO_2$ would be computed from the difference between V_I and mass of inspired O_2 and V_E and mass of expired O_2 (Eq. 2.4 and 2.5).

$$\dot{V}O_2 = V_I(F_IO_2) - V_E(F_ECO_2) \quad (2.4)$$

$$\dot{V}CO_2 = V_E(F_ECO_2) - V_I(F_ICO_2) \quad (2.5)$$

V_I = volume of inspired air
V_E = volume of expired air
F_IO_2 = fraction of inspired oxygen
F_EO_2 = fraction of expired oxygen

(Haugen, et al., 2007, p.379)

However, V_I is equal to V_E only when RQ is equal to 1 (i.e. $\dot{V}CO_2 = \dot{V}O_2$). Therefore, the technical difficulty in measuring the small differences between V_I and V_E, as well as the relative difficultly in measuring V_I, has led to the sole measurement of V_E and the prediction of V_I using the Haldane equation (Haugen, et al., 2007).

The Haldane transformation calculates V_I based on the concept that nitrogen (N_2) is essentially inert, hence will have exactly the same number of molecules (mass) in inspired and expired air (Eq. 2.1). Assuming a constant mass, concentration of N_2 will vary directly with volume. Thus, if the concentration or fraction of inspired N_2 (F_IN_2) and expired N_2 (F_EN_2) is known, V_I can be computed (Eq. 2.6 to 2.11) (Eston and Reilly, 2001b).

$$Mass\ of\ inspired\ N_2 = Mass\ of\ expired\ N_2 \tag{2.6}$$

$$Concentration = \frac{Mass}{Volume} \tag{2.7}$$

$$Mass\ of\ N_2 = V_I \times F_IN_2 \tag{2.8}$$

$$Mass\ of\ N_2 = V_E \times F_EN_2 \tag{2.9}$$

$$V_I \times F_IN_2 = V_E \times F_EN_2 \tag{2.10}$$

$$V_I = \frac{V_E \times F_EN_2}{F_IN_2} \tag{2.11}$$

(Eston and Reilly 2001b, p.147)

The problem occurs as F_IO_2 increases, for example in the case of ventilated patients. Here the denominator '1- F_IO_2' gets smaller, greatly increasing the error in the calculation of $\dot{V}O_2$ consumption (Haugen, et al., 2007).

Other limitations include lack of steady state with changing nutritional intakes or medication and technical issues such as system leaks.

2.11 Doubly labelled water technique

2.11.1 Principle

The doubly labelled water (*DLW*) technique involves estimation of CO_2 production and subsequently *EE* through measurement of the body's rate of elimination of O_2 and hydrogen (*H*) (Welk, 2002).

The fundamental basis of the technique stems from the notion that O_2 removal from the body is a function of both body water turnover and CO_2 production. However, *H* removal is solely a function of body water turnover (Fig. 2.3). The surveillance by Lifson in the 1940's that O_2 in respiratory CO_2 is in equilibrium with the O_2 in body water means that the amount of O_2 lost through CO_2 can be represented as the difference between the O_2 and *H* water turnover curves (Welk, 2002; Butler, 2004).

The elements are traced via non-radioactive, harmless, stable isotopes, most commonly oxygen-18 (^{18}O) and deuterium (^{2}H). Each isotope possesses the same chemical identity but a different atomic mass as its parent element, permitting identical function while allowing differentiation (Welk, 2002).

Prior to testing a pre-dose sample of body water is needed to ascertain baseline valves of ^{18}O and ^{2}H in the body, as trace amounts of these isotopes are naturally occurring (Welk, 2002).

Dosing typically involves 0.25g of ^{2}H and 0.12g of ^{18}O oral consumption or injection. A series of body water samples, most commonly in the form of saliva or urine, then track the decline of isotope enrichment over a certain time period or back to baseline levels (Fig. 2.3; Butler, 2004; Mann and Truswell, 2007). The samples are then analysed by gas isotope ratio mass spectrometry and CO_2 usage delimitated (Welk, 2002).

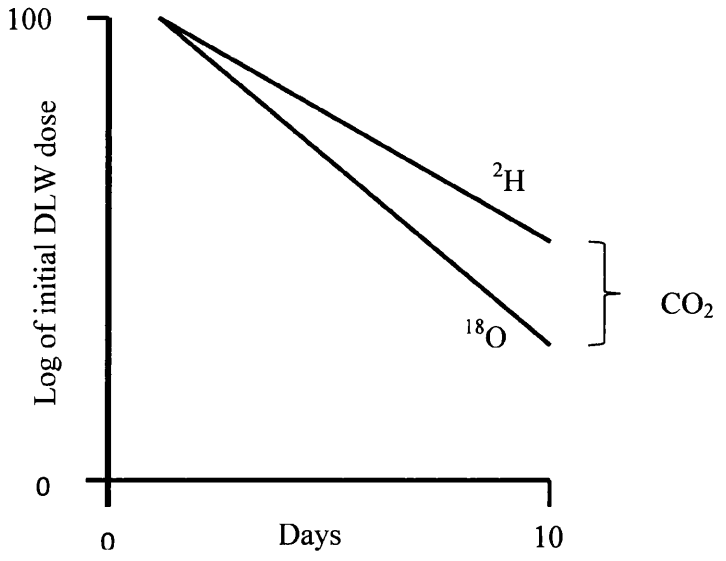


Figure 2.2. The basic principle of the doubly labelled water technique where the difference between the decline in oxygen-18 (^{18}O) and deuterium (^{2}H) represents CO_2 production. In this example the sample period is 10 days.

The total duration of the measurement period lasts approximately 2 to 3 half-lives of the isotopes which can vary between 8-18 days as the rate of isotope flush out is dependent on both the size of the body water pool (larger water pools take longer) and the activity level (Welk, 2002; Butler, 2004).

Two different protocols are available; the 'two-sample curve fitting approach' and the 'multiple-sample curve fitting approach'. The former, involves two samples, one immediately post dose and the other at the end of the measurement period. The latter is only realistic to perform in human participants because it involves repeated sampling throughout (Butler, 2004).

The first post dose sample must only be taken once complete isotopic distribution has occurred; now reasonably well enumerated as approximately 6 hours for a participant with a body mass of 70-100kg, with route of administration proving largely irrelevant (Speakman 1998; Butler, 2004).

Time of dosing and all samples are strictly documented and participants must ensure they drink from the same water source throughout the test period, as different sources can contain varying levels of ^{2}H an ^{18}O (Welk, 2002).

2.11.2 History

The *DLW* technique was first used in humans by Schoeller and van Santen (1982), although invented by Lifson (1955) nearly three centuries earlier. During the early years even the cheapest of O_2 tracers, ^{18}O, was too costly to warrant its use in research. Yet, large improvements in the mass spectrometry technique justified a significant reduction in the amount of isotope needed per unit of body mass largely broadening its application (Speakman, 1998). Subsequently, the *DLW* technique was subject to extensive validation which eventually led to refinement in calculations.

The *DLW* technique has been widely cross-validated with direct calorimetry and presents a direct estimate of CO_2 with reasonably high precision (Welk, 2002; Butler, 2004). On average it differs from calorimtery by only 2-3% (for a group of 9 or 10 individuals); the variation depending on the assumptions made (Speakman, 1998, Butler, 2004). It is completely harmless and gives no restrictions to the participant's activities therefore capturing an exact replica of 'typical' daily activity. In addition, as the dose is contained in water it is easy to implement double blind trials, increasing credibility of the study (Welk, 2002).

2.11.3 Limitations

A major disadvantage of the *DLW* technique is that it can only provide estimates for group data. When considering individual differences rather than using group means, many studies have shown much larger discrepancies between *DLW* and indirect calorimetry. Speakman (1998) reviewed 29 studies comparing *DLW* with indirect calorimetry and found standard deviations of individual estimates to be approximately 10%, with some above 20%. It was also noted that the results of multiple laboratory comparison have shown large disagreement when different groups analysed the same sample, indicating that the discrepancies in relation to indirect calorimetry may be due to analytical errors. This is supported by a review of

16 studies which valued the repeatability of the DLW method at only 7.8% (Schoeller, 1996).

In addition, disregarding analytical errors, the technique is still bound in large assumptions. Details of these are described in Butler, et al. (2004) and a brief summary can be found below:

i) It is assumed that the flow of water and size of the water pool is constant throughout testing. This is obviously untrue of any living organism.

ii) It is assumed that the fluid leaving the body contains the same isotope enrichment as the body water. This is untrue due to physical isotopic fractionation events i.e. when a molecule changes its state it carries a slightly different make up of elements. For example, when water evaporates it carries slightly less H than O_2.

iii) It is postulated that the isotopes are only involved in reactions that generate water and CO_2. However, there are two common occurrences that make this untrue. The isotopes may combine with other substances leaving the body thus increasing elimination rate or can exchange with other substances, effectively increasing the size of the body water pool when based on isotope sample dilution (Butler, 2004).

iv) It is presumed that 'isotopes do not re-enter the body' and 'unlabelled CO_2 does not enter the body' (Butler, 2004, p.171). The former is highly unlikely so often ignored. The latter will occur in places of restricted space where excess CO_2 build up leads to elevated CO_2 inhalation (Butler, 2004). This is obviously unusual in humans and mainly a concern for animal research i.e. animals living in burrows.

v) The final assumption is that the baseline isotope values are stable throughout the measurement period. This is of particular relevance to human or large animal studies as the size of the original isotope dose is limited due to cost therefore fluctuations in baseline levels will have a more significant effect on the accuracy of the results (Horvitz and Schoeller, 2001).

Attempts have been made to 'correct' for the first three assumptions by inclusion into the CO_2 and EE calculations however the fourth and final assumptions offer a possible explanation for discrepancies.

Further error could be produced if energy expenditure was estimated using an unsuitable respiratory quotient ($\dot{V}CO_2/\dot{V}O_2$ at cellular level). For example, the respiratory quotient is often assumed to be 0.8 (Schmidt-Neilson, 1997) or 0.85 (Welk, 2002) but this value is highly dependent on the food consumed and activity level. Metabolism of pure carbohydrate gives a respiratory quotient of 1 and pure fat a respiratory quotient of 0.7 hence large errors of up to 2.5 to -5 % and 9 to -18 % have been reported when using $\dot{V}O_2$ and $\dot{V}CO_2$ respectively to predict EE (Butler, 2004). In an attempt to reduce this error, the food quotient can be used (Ainslie, Reilly and Westerterp, 2003). The food quotient involves a time consuming process of keeping a food record and calculating respiratory quotient assuming complete oxidation of all food (Butler, 2004).

Finally, the cost of analysis even for small animals is still significant and development of the technique in order to reduce cost is unlikely to improve much further (Butler, 2004). In addition, even today, there are a limited number of specialist centres that have the capacity to perform the technically complex and extremely precise measurements required (Mann and Truswell, 2007).
Besides this, unlike other methods, DLW provides no detail on intensity, duration, frequency and type of activity and most importantly cannot distinguish between any of the four components of EE during a free living situation.

2.12 Heart rate monitoring

2.12.1 Principle

Heart rate (HR) monitoring (measured in terms of beats per minute), is based on the observation that a linear relationship exists between heart rate and $\dot{V}O_2$ for increasing activity levels above rest (Mann and Trusswell, 2007). This was first demonstrated in humans during exercise by Boothby in 1915 (Welk, 2002). Increasing activity levels require increased metabolic activity and subsequently a greater O_2 supply. This is

achieved through the combined effect of increased tidal volume and respiratory rate, increased cardiac output and increased venous return (Seifter, Ratner and Sloane, 2005).

The *HR* method relies on the principle that change in *HR* is a major constituent in the body's response to a change in O_2 requirements (Butler, 2004). Hence, it provides an estimate of $\dot{V}O_2$ utilisation using Fick's law (Eq. 2.12).

$$\dot{V}O_2 = HR \times Versus\ (C_aO_2 - C_vO_2) \quad (2.12)$$

$\dot{V}O_2$	Volume of oxygen per minute
HR	Heart rate
Versus	Stroke volume
C_aO_2	Oxygen content of arterial blood
C_vO_2	Oxygen content of mixed venous blood
Versus $(C_aO_2 - C_vO_2)$	Oxygen pulse (*OP*) = quantity of oxygen consumed per heartbeat

A linear relationship between C_vO_2 and *HR* will only exist if the *OP* is constant or changes systematically. In exercise this is unlikely as *OP* will increase with increased exercise intensity; a curvilinear relationship. Furthermore, this relationship is likely to change throughout the life cycle due to several physiological and environmental factors, all leading to limitations in the original $\dot{V}O_2$ *versus HR* model (Butler, 2004).

2.12.2 Limitations

i) Exercise intensity

During very heavy or very light exercise, the *HR versus* $\dot{V}O_2$ relationship becomes non-linear (Achten and Jenkendrup, 2003). In the case of heavy exercise, O_2 uptake may increase disproportionately to *HR* due to greater utilisation of O_2. This is represented by an increased value for $C_aO_2 - C_vO_2$ and is due primarily to redistribution of blood flow to skeletal muscles and a shift in the oxyhemoglobin disassociation curve to the right. The latter is termed the 'Bohr effect' and allows a

greater oxyhemoglobin disassociation for a set O_2 pressure (Astrand and Rodahl, 1970).

ii) Lag time

A lag in *HR* response exists when a quick transition in exercise intensity occurs. This creates inaccuracies in predicting *EE* from *HR* (Achten and Jenkendrup, 2003).

iii) Cardiorespiratory fitness

Improved cardiac contractility and in particular left ventricular function and ejection time occurs with an increase in cardiorespiratory fitness. This provides a greater *SV* per heart beat which results in a lower *HR* for any given $\dot{V}O_2$ requirement. Previous studies have found that increases in cardiovascular fitness showed significant systematic changes in the relationship between *HR* and $\dot{V}O_2$ (Butler, 2004). These changes can either be adjusted for in the prediction equations or acknowledged as a limitation. Strath et al., 2000 attempted the latter by using predicted *HR* reserve and $\dot{V}O_2$ reserve to adjust *HR* and $\dot{V}O_2$ values, changing the *HR* to *EE* relationship from r = 0.68 to r = 0.87.

iv) Psychological stress

Psychological stress has proven to result in an elevated *HR* without an according increase in $\dot{V}O_2$ during a rested state. This is caused by an increase in sympathetic nervous system activity and was demonstrated by Carroll, Phillips and Balanos (2009) who assessed 24 healthy males during a paced auditory serial addition test (i.e. a stress tested based upon solving mathematical questions) and 4 minute bouts of cycling at a variety of submaximal speeds whilst seated on a semi reclined couch. These authors found that substantial increases in cardiac parameters arise during the stress test with only a moderate rise in O_2 consumption. This cardiac response was significantly greater than that predicted by the exercise response.

v) Muscle groups and types of muscular contraction

Differences in cardiovascular responses to extension and flexion have been shown between upper and lower limb movements during static muscular contractions. For example, in upper limb joints (wrist and elbow) extension evoked a greater *HR* response than flexion and in lower limb joints (ankle and knee) the opposite was true (Tokizawa, et al., 2006).

Furthermore, static (isometric) exercise also exhibits higher *HR* in contrast to dynamic exercise (Arimoto, Kijima and Muramatsu, 2005). The mechanism for this response is not well understood but theories are based around the relationship between *HR* and *SV* (Astrand and Rodahl, 1970).

vi) Cardiovascular drift, hydration and heat stress

After 2-3 minutes of exercise at a light to moderate intensity a 'steady-state' occurs; O_2 uptake is equal to O_2 utilisation. At this point cardiac output, *HR* and pulmonary ventilation should reach a constant level (Astrand and Rodahl, 1970). However, even in steady state conditions, *HR* will gradually increase over time in parallel with a decrease in *SV* but a steady $\dot{V}O_2$. This phenomenon is named 'cardiac drift' (Achten and Jeukendrup, 2003).

Cardiac drift has been shown in numerous studies (see review by Achten and Jenkendrup, 2003). For example, Kimura, et al. (2010) reported increases of eleven beats per minute between 3 and 30 minutes of arm-cranking exercise at a steady intensity and ten beats per minute for leg-pedalling exercise).

There have been several theories to explain this. Firstly, cardiac drift has been strongly related to hydration status. This can be explained as a decrease in blood volume which will reduce central venous filling pressure and end diastolic volume. This subsequently decreases *SV* so *HR* increases to compensate (Wilmore and Costill, 1999). Hamilton, et al. (1991) reported the % *HR* increase halved when the participants consumed fluid.

Heat stress is also speculated to explain cardiac drift (Wilmore and Costill, 1999). In a hot environment, thermal stress leads to increased peripheral blood flow to enhance heat loss. This is likely to result in an increased *HR* without a subsequent increase in $\dot{V}O_2$ (Butler, 2004). In an attempt to cool the body a greater percent of cardiac output is directed at the peripheral blood vessels of the skin. This leads to slower venous return and reduced end diastolic volume and *SV* by the mechanisms explained above (Wilmore and Costill, 1999). There is current debate as to whether the *HR versus* $\dot{V}O_2$ relationship is similar during heat stress and exercise in humans (Butler, 2004).

vii) Temperature – cold

In cold environments, two main physiological adjustments occur. Firstly, shivering starts in order to increase metabolic rate and secondly, vasoconstriction of the peripheral blood vessels occur in order to reduce heat loss, augment central blood volume and, therefore, venous return (Achten and Jeukendrup, 2003).

These events commonly cause an increase in $\dot{V}O_2$ without a subsequent increase in *HR*. McArdle, et al. (1976) tested individuals exercising at differing intensities at 18°C and 25°C in water and 26°C in air. A significant increase in $\dot{V}O_2$ was found during the water exercise, the difference becoming more pronounced at lower intensities whilst *HR* remained the same. It was speculated that this was due to increased cardiac output due to augmented *SV*.

viii) Hypoxic conditions

At an altitude of only 4000m, partial pressure of O_2 may be only 30% of that at sea level (Achten and Jenkendrup, 2003). Varying physiological responses take place to compensate for this. A review by Achten and Jenkendrup (2003) reports that during submaximal exercise at altitude, *HR* increases in comparison to the same work rate at sea level, in order to compensate for the reduced partial pressure of O_2. However, during maximal exercise, individuals are only able to reach approximately 70% of their $\dot{V}O_2$max at sea level i.e. $\dot{V}O_2$ is reduced for a similar maximal *HR*.

2.13 Electromyography

Electromyography involves measurement of muscular activity via electrical signals. There are two types of electromyography; intramuscular (involving insertion of a thin needle) and interferential (using electrodes placed on the skin) (Latash, 1998). The latter is much more commonly used particularly in *Homo Sapiens* due to the difficultly of obtaining ethical approval for invasive procedures. Interferential electromyography involves placement of two surface electrodes over the muscle belly on suitably prepared skin. The difference in the electrical potential between them is measured, amplified, filtered and then the absolute values taken (Latsh, 1998; Eston and Reilly, 2001a). In addition, the body is grounded with a large indifferent electrode in order to reduce noise (Latash, 1998). In the case of measuring *EE*, use of very large electrodes placed as far apart is recommended in order to pick up electrical activity from as many motor units as possible (Latash, 1998).

Very few studies have assessed the use of electromyography as a proxy for *EE* due to the large difficulty in measuring all muscle groups and as well as the impossibility of collecting free living data. Tsurumi, et al. (2002) assessed the relationship between *EE* relative to body weight and the electromyography signal from the medial deltoid and anterior deltoid muscle. Average coefficients of determination were small but significant; $r^2 = 0.46$ ($p = 0.0$)1 and $r^2 = 0.31$, ($p = 0.01$) respectively.

2.14 Infrared thermography

Infrared thermography is a non-invasive technique used to measure surface temperature in humans or animals in order to quantify heat loss (Shuran and Nelson, 1991). It is particularly useful in animal studies as it does not require physical contact (Speakman and Ward, 1998).

Infrared radiation is emitted from every living being. This is detected by an infrared imaging radiometer which converts the radiation to an electrical signal and produces an infrared thermogram (a television compatible image of thermal patterns) (Shuran and Nelson, 1991).

A study by Shuran and Nelson (1991) found highly definitive results when comparing infrared thermography with indirect calorimetry in healthy individuals (fasting and non-fasting) and post-surgical patients (fed continuously via total parenteral nutrition). No significant differences were found between infrared thermography and indirect calorimetry in healthy fasting individuals or post-surgical patients indicating high validity in measuring heat loss. However differing results occurred after feeding, the main features including higher indirect calorimetry values throughout and a lag in infrared thermography compared to indirect calorimetry (Shuran and Nelson, 1991).

Unfortunately, there are very few human and animal studies in which to compare this to perhaps due to the following limitations. Truly accurate results require knowledge of complex air flow characteristics around the body as well as emissivity (ability of the surface to emit radiation) which are particularly difficult to obtain in animals. In addition, the device requires the use of liquid nitrogen and needs to be frequently topped up (approximately every hour), largely restricting the time available for use (Speakman and Ward, 1998). Finally, the device is not suited to a free living scenario so has limited application.

2.15 Motion sensors

2.15.1 History

A variety of commercially available fixed-body motion sensors are available to measure human movement in free-living conditions including mechanical devices such as goniometers (to measure joint angles), gyroscopes (to measure orientation), and actometers (to measure tilt) to electronic devices such as pedometers (measures vertical oscillations i.e. number of steps), accelerometers (to measure whole body motion or segment motion in terms of magnitude of acceleration) and electromechanical switches (placed under the heel to measure heel strike frequency) (Mathie, et al., 2004). Early, most commonly used activity monitors included actometers and mechanical and electronic pedometers.

2.15.2 Actometer

An actometer is a 'self-winding wrist watch modified to record movement rather than time' (Eaton, 1983, p.720). Similar to a watch, an internal pivot weight acts as a pendulum and swivels clockwise or anticlockwise in response to movement of the watch. The movement of the pivot weight is then reflected in movement of the hands and the results read off dial, comparable to time (Johnson, 1971).

Despite good reproducibility for standard movements and for re-test, actomoters have shown large inter-instrument variability which necessitates the need for individual calibration (Meijer, et al., 1991). For large scale population measurements this is completely impractical and even on a small scale makes other methods more appealing.

2.15.3 Pedometer

A pedometer is a small device used to measure vertical oscillations of the body i.e. steps (Mathie, et al., 2004). There are three main mechanisms that can be used. The first and most simplified involves a 'horizontal, spring-suspended lever arm that moves up and down with each step' i.e. vertical movement (Welk, 2002, p.164). This continually completes and breaks an electrical circuit. Each time the circuit is completed a count is registered and it is added to the cumulative count display on the screen. The second incorporates a magnet into the spring-suspected level arm and a step is registered as the magnetic field activates a proximity switch. The third, is the most sophisticated as it includes piezoelectric material and unlike the other mechanisms allows for measurement of intensity however as this mechanism is similar to an accelerometer it will be excluded from this current discussion.

In relation to the first two mechanisms, numerous studies have shown pedometers are reasonably accurate in predicting the number of steps. Schneider et al., (2003) reported 6 out of 8 pedometers produced similar values to the actual number of steps during walking at self-selected speeds (excluding those with an accelerometer based mechanism) in 20 participants and Bassett et al., (1996) found 3 out of 5 pedometers

produced similar 'step' readings to actual steps in 22 participants over a 3.03 miles. Nevertheless, the devices have several other major limitations.

A pedometer is only able to detect movement in one axis and so is largely limited to tracking ambulatory activity (i.e. walking or that of a similar movement pattern such as running) where most of the body acceleration is displayed in one direction (the vertical axis). It is therefore attached to the waist or another position near the body's centre of gravity (Welk, 2002). Furthermore, the devices are largely insensitive due to the primitive mechanism used to detect movement. With each device (depending on the subtly of mechanism) a 'threshold' of body acceleration is needed in order to trigger and register a count. This may limit the accuracy of assessing 'steps' in slow walking. For example, Bassett, et al. (1996) found that the Eddie Bauer pedometer only recorded 40% of steps taken when walking at a speed of 2.0 mph. Additionally, distance can only be calculated if stride length is known. However, a definite figure is somewhat difficult to attain as stride length has been shown to increase at fast walking speeds (Bassett, et al., 1996). Finally, pedometers do not provide information regarding frequency (i.e. patterns of movement within a day) and intensity (Bassett, et al., 1996) and the reliability and validity is relatively poor (Meijer, et al., 1991; Schneider, et al., 2003).

2.15.4 Accelerometer

In the early 1970's, came the development of electronic telemetric devices that allowed continuous recording, although this was largely limited as the device needed to remain in close proximity to the receiver. The mid-1970's early 1980's gave rise to significant advances in technology refining the devices to be completely self-contained with integrated circuitry, transducers, timing and memory thus producing a basic accelerometer (Redmond and Hegge, 1985).

Today, accelerometers are small devices used to measure acceleration. Acceleration can be defined as 'change in velocity with respect to time' (Eq. 2.13 and Eq. 2.14).

$$\text{acceleration } (m.s^{-2}) = \Delta \text{ velocity } (m.s^{-1}) / \Delta \text{ time } (s) \quad (2.13)$$

$$a = dv/dt \quad (2.14)$$

In general, the devices are fabricated out of a plastic casing, a transducer and a small seismic or inertial mass suspended by both a dampener and a spring and capacitor although many now contain piezoelectric material.

The principle is based on the fact that when the device experiences acceleration, acceleration of the internal mass will lag behind due to the restraining effect of the spring and the relative displacement of the mass is proportionate to the acceleration of the device. An electric current is generated that is proportional to the amount of acceleration experienced by the internal mass and this is outputted as acceleration units (Fig. 2.4). Only during steady state i.e. stationary or moving at a constant velocity, will the acceleration of the mass be the same as the casing (Morris, 2006).

Accelerometers can have one (uni-axial), two (bi-axial) or three (tri-axial) sensing axes depending on the number of displacement measuring instruments used (Mathie, et al., 2004). Each sensing axis is positioned orthogonally to one another, aligned along the geometric axes x, y and z or anatomically termed cranial-caudal, anterior-posterior and medio-lateral axes (Grundy, 2008).

The devices can vary largely in terms of the displacement measuring instruments including the type of spring and transducer and form of dampening (Morris, 2006). Human movement studies most commonly use piezoresistive or variable capacitance accelerometers (see Mathie, et al., 2004).

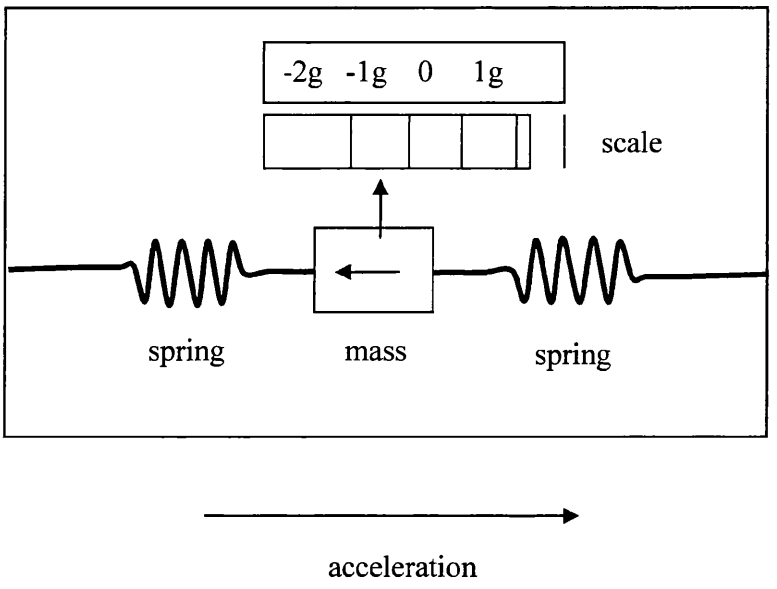


Figure 2.3. A simplified diagrammatic representation of a single axis (uni-axial) accelerometer.

2.16 Predicting energy expenditure using an accelerometer

2.16.1 Principle

Use of accelerometry as a proxy for *EE* is based on the following principle. Physical activity involves the conversion of chemical energy within the muscles to mechanical work via muscular contraction. Muscular contraction produces acceleration of the limbs and subsequent proportional movement of the connecting trunk. The centre of gravity, which is located in the lower trunk during standing, moves in the opposite direction to the limbs in order to maintain balance (Shepard, et al., 2008a). In theory, the amount of body acceleration should be related to the amount of energy expended (Wilson, et al., 2006; Gleiss, Wilson and Shepard, 2011).

A variety of accelerometers are commercially available. Each has its own unique predictive equation for *EE* that have been developed through a series of studies involving the comparison of $\dot{V}O_2$ with an acceleration metric, usually during a variety of different types and intensities of physical activity.

In terms of the components of *EE*, an accelerometer measures the physical activity component only (Fig. 2.5). The device cannot be used to predict *BMR* as this component is measured during lying i.e. a stationary position. Subsequently, *BMR* is predicted using one of many published equations. Additionally, accelerometers do not account for the thermic effect of food and temperature-dependent *EE*. Instead, when developing predictive equations these components of *EE* are usually controlled although this is obviously unrepresentative of free living situations.

During development of predictive equations it is important to be aware that the $\dot{V}O_2$ *versus* acceleration relationship will differ depending on the relative contribution of aerobic and anaerobic respiration for *EE*. This is related to intensity of physical activity. Although both aerobic and anaerobic respiration occurs at all intensities of physical activity, the point at which respiration changes from mainly aerobic to mainly anaerobic is termed the *gas exchange threshold* (*GET*) (McArdle, Katch and Katch, 2007). *GET* can be defined as an 'over proportional increase in carbon dioxide output as related to oxygen uptake' (Meyer, et al., 2005, p.S40). The *GET* will vary between individuals depending on training status and disease (Beaver, Wasserman and Whip, 1986). In general, most activities of daily living are aerobic so the regression equations are based upon aerobic conditions alone. Additionally, $\dot{V}O_2$ is not as closely related to *EE* during anaerobic metabolism which gives further reason to use only aerobic conditions.

To produce a realistic reflection of the $\dot{V}O_2$ *versus* acceleration relationship as many data points as possible should be gathered. This is commonly embarked upon by a maximal exercise test in which the exercise intensity is gradually increased until volitional exhaustion, incorporating both aerobic and anaerobic metabolic phases. Volitional exhaustion is indicated by a plateau in $\dot{V}O_2$, which is thought to indicate $\dot{V}O_2$ max. The *GET* is then located and any data above the *GET* is discarded.

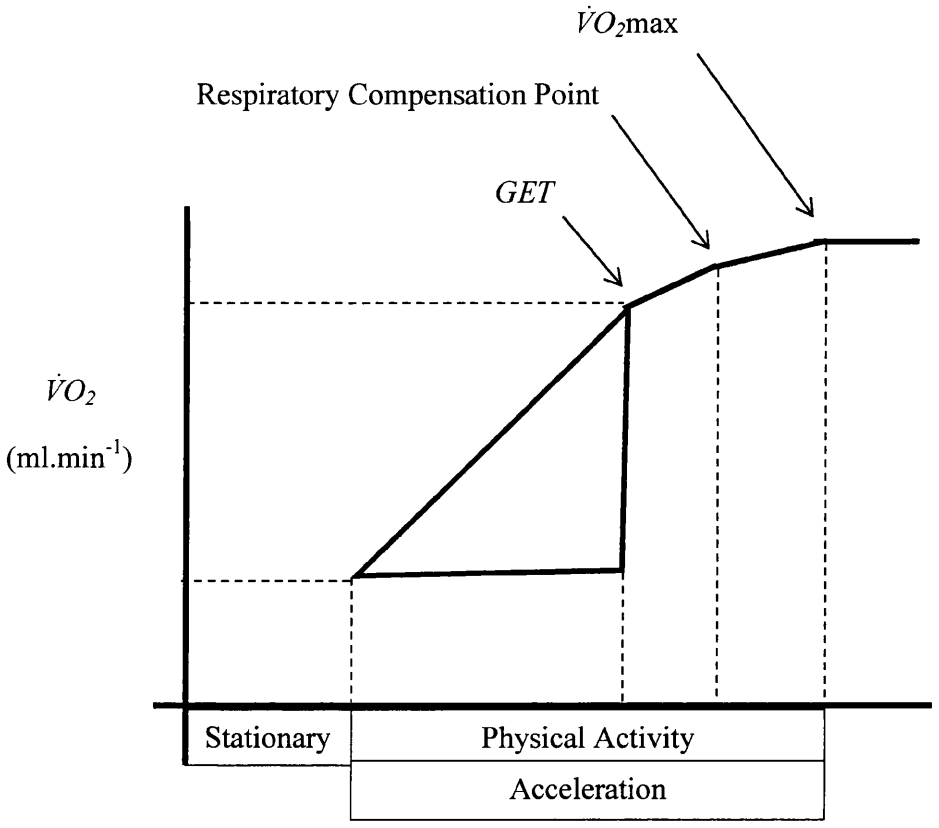


Figure 2.4. A simplified diagrammatic representation of the components of EE measured via an accelerometer. The shaded box represents that which can be measured. GET represents the point at which there is a significant anaerobic contribution.

2.16.2 Locating the gas exchange threshold

i) Definitions and general concepts

The gas exchange threshold is a respiratory parameter thought to be closely related to the lactate threshold. The concept of lactate and gas exchange thresholds provide a complex, largely unresolved debate. The terms were originally generalised under the expression, 'anaerobic threshold', defined as 'an intensity of exercise, involving a large muscle mass, above which measurement of O_2 uptake cannot account for all of the required energy' i.e. the onset of predominantly anaerobic metabolism (Svedahl and MacIntosh, 2003, pp.300-301).

The 'anaerobic threshold' was initially represented by an inflection point on either a blood lactate concentration model (indicating an increase in lactate) or a model of respiratory parameters (indicating increased CO_2 and V_E) during incremental exercise. However, it has recently been acknowledged that there are two inflection points in a blood lactate and respiratory model and a clear distinction must be made between them (Jones and Poole, 2005). This thesis will focus upon respiratory parameters as they are often preferred over blood lactate parameters due to their non-invasive nature.

On a respiratory model, the term 'gas exchange threshold', refers to the first inflection point (Jones and Poole, 2005) and 'respiratory compensation point', to the second inflection point (Beaver, Wasserman and Whipp, 1986).

The *GET* occurs at approximately 45 – 60 % of $\dot{V}O_2$max in those free from disease, although the exact percentage will depend on training status (Jones and Poole, 2005). The term is important in accelerometer based research as it defines the cut-off point between aerobic and anaerobic metabolism. This phenomenon signifies a significantly elevated degree of bicarbonate buffering via lactic acidosis and therefore production of non-respiratory CO_2 which will subsequently increase total expired CO_2 (Jones and Poole, 2005).

This point has numerous terms in the literature including aerobic gas exchange threshold (Meyer, et al., 2005), aerobic-anaerobic threshold (Kindermann, Simon and Keul, 1979), ventilatory threshold (McArdle, Katch and Katch, 2007), ventilatory threshold 1 (Hug, et al., 2003), and most commonly in earlier studies, the anaerobic threshold (Wasserman, et al., 1973: Beaver, Wasserman and Whipp, 1986; Caiozzo, et al., 1982). Furthermore, it is a respiratory representation of the first inflection point on a blood lactate model, often termed the lactate threshold (McArdle, Katch and Katch, 2007), 'the first increase in blood lactate concentrations above resting values during incremental exercise' (Meyer, et al., 2005, p.S39). This blood lactate value is often approximated to be around 2.5 mM (McArdle, Katch and Katch, 2007).

ii) Techniques used to locate the gas exchange threshold

There are several means of detecting the aerobic gas exchange threshold. The most common comprising of a respiratory exchange ratio (*RER*) of over 1, the first systematic rise in $V_E/\dot{V}O_2$ without a corresponding rise in $V_E/\dot{V}CO_2$ (ventillatory equivalent method) and an over proportional increase in $\dot{V}CO_2$ in comparison with $\dot{V}O_2$ (*V*-slope method) (Caiozzo, et al., 1982; Myers and Ashley, 1997; Meyer, et al., 2005).

Early reports suggest *RER* is a useful measure of *GET* although later evidence found it to be largely insensitive to lactic acid (Ciaozzo, et al., 1982). Other authors suggest the use of the ventilatory equivalent method. A study by Ciaozzo, et al. (1982) compared four respiratory measures of calculating gas exchange threshold (Time *versus* V_E, Time *versus* $\dot{V}CO_2$, Time *versus RER*, Time *versus* $V_E/\dot{V}O_2$) with lactate threshold in 16 male and 2 female subjects (age range = 20-31 years). The results showed the point at which $V_E/\dot{V}O_2$ displayed a systematic rise without an associated rise in $V_E/\dot{V}CO_2$ was the method with the highest correlation with lactate threshold ($r^2 = 0.93, p > 0.001$). In addition, this method also had the highest test-retest results. But, this method was deemed inappropriate as individual variation in chemoreceptor sensitivity to CO_2 will affect the ventilator response. For example, in obesity it is common for individuals to have insensitive chemoreceptors and mechanical weaknesses so ventilation might not match increased CO_2 making *GET* difficult to detect (Beaver, Wasserman and Whipp, 1986).

Wasserman, et al. (1986) recommends the *V*-slope method as the criterion. The original *V*-slope method involved use of $\dot{V}O_2$ *versus* $\dot{V}CO_2$ (to find the *GET*) and $\dot{V}CO_2$ *versus* V_E (to find the respiratory inflection point to confirm that the *GET* is correct i.e. below this point). Meyer, et al. (2005) also supports use of this method but endorses that metabolic measurements ($\dot{V}CO_2$ and $\dot{V}O_2$) should be used alone and ventilatory data only in a supportive manner where results from the $\dot{V}CO_2$ *versus* VO_2 graph are indeterminate. This caution is again due to individual variability in terms of chemoreceptor sensitivity to CO_2 (Meyer, et al., 2005).

Conversely, other authors endorse combining methods. For example, Gaskill, et al., 2001 compared three different methods of comparing the *GET* with lactate threshold in 132 athletes, 31 active individuals and 22 sedentary individuals. Methods considered included i) ventilatory equivalents (V_E/O_2 and V_E/CO_2), ii) excess CO_2 production ($\dot{V}CO_2^2/\dot{V}O_2$) - $\dot{V}CO_2$ iii) a modified *V*-slope method (20 second gas collection averages). The study concluded that the *GET* and lactate threshold were not significantly different for all methods used and for all groups ($p > 0.20$) but that a combination of the methods of detection of the *GET* gave the strongest relationship with lactate threshold ($r^2 = 0.98$ for all group data combined).

Conversely, combining methods is not always practical so in study the *V*-slope method seemed most appropriate.

2.16.3 History

Over the last decade use of accelerometers to predict *EE* has expanded exponentially in animal and human research (Troiano, 2005). The first attraction includes the availability to record both frequency and intensity data, giving superiority over both pedometers and actometers and allowing the technique to compete with the well-established indirect calorimetry, *HR* method and *DLW* (Mathie, et al., 2004). Furthermore, substantial developments in microelectromechanical systems have facilitated development of very small, lightweight and relatively cost effective devices with both increased memory and recording frequencies (Mathie, et al., 2004). The device is easily attachable to the waist (on the belt) or any other part of the body (Hendelman, et al., 2000).

Unfortunately, although a vast number of studies have assessed the use of body acceleration as a proxy for *EE*, the data processing methods and the metrics used are widely varied making comparisons between studies more difficult.

2.17 Metrics of acceleration

2.17.1 Acceleration 'counts'

Traditionally, body acceleration data was expressed in the dimensionless units 'activity counts' (Troiano, 2006). These are largely ill-defined throughout the literature but in general represent the total number of pulses/peaks above a set threshold obtained over a set time interval (epoch). These features are counted one by one irrespective of size (wavelength and amplitude) which greatly simplify the originally highly detailed signal. In addition, this makes it somewhat similar to pedometry even though the accelerometers are capable of yielding more-detailed acceleration data based on amplitude and frequency-content. After each epoch, the data is summarised (usually totalled) and stored to the memory card and the integrator reset to zero (Trost, 1998). This effectively maximises the memory capacity and explains why in the early stages of accelerometer development the continuous signal could not be considered. Later, the count data is often separated into classifications based on cut-off levels that resemble low, moderate and high intensity exercise in order to relate to health benefits and exercise recommendations. Still, the energy expended from one 'step' or 'count', will vary considerably between individuals (depending on weight, limb length, cardiovascular capacity) and the substrate and gradient of the surface over which the activity is taking place. All these factors would be much more closely represented firstly if three-dimensional body acceleration was considered and secondly if standardised units, *meters per second* ($m.s^{-2}$) or *gravity* (g) were used. McGregor, et al. (2009) noted that this would allow better scientific transparency to facilitate more detailed cross-study comparisons. Nevertheless, even this primitive measure of body acceleration gives surprisingly high correlations with measured *EE* and fuelled the quest for advanced technology and signal processing.

2.17.2 The integral of acceleration

Bouten, et al. (1994) used a more sophisticated method of data processing, similar to methods suggested in this thesis. These authors used the integral of the absolute value of the accelerometer output for each axis and calculated the sum of the

integrals. This type of integral represents the area under the acceleration-time curve (Eq. 2.15).

$$\text{integral} = \int_0^T |a|\, dt \tag{2.15}$$

over a time interval from 0 to T.

Other authors have modifications of the data processing using by Bouten, et al. (1994). For example, Parkka, et al. (2007) sums of the absolute acceleration for each axis to give one single signal and then integrates of a given period. Conversely, Kim et al. (2009), integrates each individual axis first but totals the positive and negative area i.e. uses absolute acceleration for each axis.

2.17.3 Dynamic body acceleration

Dynamic Body Acceleration (*DBA*) involves the use of a tri-axial accelerometer aligned with the major axes of movements and usually placed nearest the centre of gravity i.e. trunk (Wilson, et al., 2006). The device is set to record at infra-second rates of greater than 10 *Hz* (Qasem,et al., 2012) although Shepard, et al. (2008b) pointed out that the exact frequency of recording should be a function of the speed of movement. Currently, there are two distinct metrics based on *DBA*. These will be discussed in detail below.

Dynamic body acceleration can be defined as the acceleration caused by body movement. Accelerometers that measure *proper acceleration* (acceleration relative to free fall) will register a *constant acceleration* value representing the earth's gravitational field (9.8 $m.s^{-2}$ or +1 g) if aligned with their sensitive axis vertical, in addition to any dynamic acceleration.

Only the dynamic acceleration relates to *EE* therefore constant acceleration (often referred to as *static acceleration* as it will be termed throughout this thesis) needs to be extracted (Grundy, 2008). This is a relatively simple procedure if the device is

aligned directly with the x, y and z axes as static acceleration will act solely on the vertical axes so will always read + $1g$ (9.8 $m.s^{-2}$). However, most dynamic movements involve some degree of tilting through change in posture. This deviation from the x, y, z alignment results in the static acceleration component manifesting itself in 2 or 3 axes and therefore needs independent calculation and extraction (Grundy, 2008). Deriving 'true' readings for static acceleration components along x, y and z accelerometer axes involves the additional requirement of estimates of heading usually via a sensor that tracks the earth's magnetic field, a gyroscope or high speed video recording (Shepard, et al., 2008b).

However, Wilson, et al. (2006) describe a very simple method of approximating static acceleration from acceleration values alone, based on the observation that animal gait in all 3 dimensions oscillates equally around a set point. This allowed the assumption that a running mean of the whole or part of the signal for each axis is indicative of static acceleration of that axis. This component could then be subtracted from the total acceleration leaving the remaining dynamic acceleration (Eq. 2.16) to be converted to absolute positive values and summed. The use of absolute positive values avoids negative acceleration in one axis cancelling out positive acceleration in another as the negative sign only represents a directional component and even during negative acceleration energy is expended.

Total body acceleration =

Dynamic body acceleration (DBA) + Static body acceleration (2.16)

i) Vectorial dynamic body acceleration

Vectorial Dynamic Body Acceleration (*VeDBA*) is the vectorial sum of the *DBA* of each axis, also termed vector magnitude (Eq. 2.17).

$$VeDBA = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (2.17)$$

Mathematically, this is the correct way in which to represent three-dimensional acceleration, as acceleration is a vectorial quantity i.e. is determined by both magnitude and direction. Yet, movement in biological organisms is never produced by a single muscle (magnitude) contracting in the same plane as the movement (direction). Instead muscles work in groups, with each movement incorporating a combination of contracting and extending muscles with varied forces in order to elicit both the intended body movement whilst maintaining stability of joints (i.e. restricting range of movement in order to prevent injury) and whole body balance. This highly complex process, although obviously essential, effectively 'wastes' energy as muscles are always working against each other to a certain extent. This led to the proposal of overall dynamic body acceleration (*ODBA*) for estimation of *EE*.

ii) Overall dynamic body acceleration

Overall Dynamic Body Acceleration (*ODBA*) is defined as the summed *DBA* of all three axes (Eq.2.12; Wilson et al., 2006).

$$ODBA = |A_X| + |A_Y| + |A_Z| \tag{2.18}$$

ODBA is theorised to be superior to *VeDBA* for the purposes of estimating *EE* on the basis that *ODBA* accounts for the 'wasted' *EE* during movement as the energy required for movement in each axis is considered. In other words, all stabilising motion as well as tracking motion is reflected in this metric.

Conversely, Gleiss, Wilson and Shepard (2011) suggest that the error in *ODBA* may be high during movements other than locomotion where orientation of the accelerometer may not be in line with the major planes of movements. In this case *VeDBA* may be more appropriate. No studies to date have compared these metrics and neither *ODBA* nor *VeDBA* have received much attention in human research.

2.18 Validating body acceleration against indirect calorimetry

The following sections will consider previous research on the use of accelerometry as a proxy for *EE* in humans. Inclusion criteria for this part of the review include studies that use indirect calorimetry as the gold standard method of assessing *EE* and accelerometry as the new method. Due to a lack of human studies using *DBA*, all metrics were included.

In addition, the following table gives the basic specifications of the accelerometers included in the literature to avoid repetition of technical information throughout this review. The exact specifications vary slightly with the model number however, due to the already large variability in number of axes, placement and epoch this detail has been excluded from the analysis.

Device	Number of Axis	Location
CSA (later called MTI Actigraph)	Uni-axial	Anywhere
Caltrac	Uni-axial	Anywhere
Bio-Trainer Pro	Uni-axial (tilted at 45° angle)	Anywhere
SenseWear Armband	Bi-axial	Arm
TriTrac-R3D	Tri-axial	Anywhere
RT3 (next generation of the R3D)	Tri-axial	Anywhere

Table 2.3. Basic information regarding accelerometers assessed in this review; number of axis and possible location on the human body.

(Balogun, Martin and Clendenin, 1989; King et al., 2004)

2.18.1 Locomotive activity

A multitude of studies have found strong linear relationships between body acceleration measured in 'counts' and *EE* calculated from indirect calorimetry during level locomotive activity both in adults (Balogun, Martin and Clendenin, 1989; Hendelman, et al., 2000; Freedson, Melanson and Sirard, 1998; Welk, et al., 2000; Howe, Staudenmayer and Freedson, 2009) and children (Eston, Rowlands and Ingledew, 1998; Trost, et al., 1998), with accelerometer metrics explaining 58 – 92% and 48 - 77% of the variance in *EE*, respectively.

i) Consistency

Despite these seemingly large disparities in explained variance, much of the literature shows that reasonable consistency exists between similar studies for both uni and tri-axial devices (Table 2.4).

Table 2.4. Examples of the consistency between studies in terms of the ability of acceleration metrics to explain the variance in EE metrics.

Authors	Population	Accelerometer	Metrics	Protocol	Explained variance
Eston, Rowlands and Ingledew (1998)	Children	TriTrac (right hip mounted)	$s\dot{V}O_2$ (expressed as a ratio of body mass to the power of 0.75) and vector magnitude	Locomotion on a treadmill at 4 6, 8 and 10 km/h	$r^2 = 0.78$
Trost, et al. (1998)	Children	CSA (right hip mounted)	*EE* and acceleration counts and	Locomotion on a treadmill at 3, 4 and 6 mph	$r^2 = 0.74$
Hendelman et al., (2000)	Adults	CSA (left hip mounted)	Metabolic equivalent of task (METS)* and acceleration counts	Level over ground walking at self-selected speeds	$r^2 = 0.79$

*Metabolic equivalent of task (*METS*) can be defined as '$\dot{V}O_2$ activity (ml.O_2.kg^{-1}.min^{-1})/3.5 ml.O_2.kg^{-1}.min^{-1} i.e. multiples of the resting metabolic rate' (McArdle, Katch and Katch, 2007, p.203).

ii) Repeatability

In addition, particularly high repeatability of the coefficient of determination (r^2) for the relationship between acceleration counts and *EE* has been shown for studies using both uni-axial and tri-axial devices (Table 2.5).

Table 2.5. Examples of the repeatability within studies in terms of the ability of acceleration metrics to explain the variance in EE metrics.

Authors	Population	Accelerometer	Metrics	Protocol	Explained Variance (r^2)	
					1st Trial	2nd Trial
Hendelman, et al., (2000)	Adults	CSA (left hip mounted)	*METS* and accelerometer counts	Level over ground walking at self-selected speeds	0.61	0.61
		TriTrac (right hip mounted)			0.77	0.77
Welk, et al. (2000)	Adults	TriTrac (right hip mounted)	$\dot{V}O_2$ and accelerometer counts	Treadmill locomotion at 3, 4 and 6 mph	0.86	0.85
		BioTrainer (right hip mounted)			0.77	0.72

iii) DBA metrics

In terms of *DBA* metrics, several studies have shown strong relationships between *ODBA* and $\dot{V}O_2$. The majority of research has been in animals, with coefficients of determination values ranging from 0.74 to 0.91 (Wilson, et al., 2006; Halsey, et al., 2008; Halsey, et al., 2009; Halsey, et al., 2010). To date, only one study has assessed humans (Halsey, et al., 2008) and reported of extremely high r^2 values of 0.91-0.93 depending on logger placement.

Although, *VeDBA* has been deemed the 'proper' way to calculate acceleration few studies have assessed the use of *VeDBA* as a proxy *EE*. Instead, human studies have tended to use the vectorial product of the more primitive 'count' data (as above) (Eston, Rowlands and Ingledew, 1998; Howe, Staudenmayer and Freedson, 2009). McGregor, et al., (2009) and Manohar, et al., (2011) are the only studies to date that have used *VeDBA* specifically, although Manohar does not term it as such. Both report extremely high coefficients of determination, 0.982 and > 0.9, respectively. McGregor, et al., (2009) assessed $\dot{V}O_2$ ($ml.kg.min^{-1}$) *versus VeDBA* during a maximal treadmill test and Manohar, et al., (2011), *EE* (kcal.hr.kg) *versus VeDBA* treadmill walking.

2.18.2 Activities of daily living

Due to the relatively high success of accelerometers in the predicting *EE* in locomotive activity, assessment of activities of daily living was the next crucial phase in developing a device that can predict *TDEE*. Regrettably, in general, studies on adults have elicited relatively weak relationships with activities of daily living (Hendelman, et al., 2000; Welk, et al., 2000; Howe, Staudenmayer and Freedson, 2009).

Howe, Staudenmayer and Freedson, 2009 reported a coefficient of determination of only 0.13 between measured *PAEE* (total *EE* – individually measured *RMR*) and hip mounted vector magnitude counts for activities of daily living compared to that of r^2 = 0.64 for treadmill activity alone, with a combination of the two at r^2 = 0.35. Welk, et al. (2000) also found that the combined data for two hip mounted uni-axial devices

and one hip mounted tri-axial device showed relationships between acceleration counts and $\dot{V}O_2$ of only $r^2 = 0.30$ for lifestyle activities in comparison to $r^2 = 0.74$ to treadmill activity. Furthermore, Hendelman, et al. (2000) reported mean coefficients of determination of 0.38 and 0.35 during combined lifestyle and walking activities for tri-axial and uni-axial data respectively, significantly lower than walking trials only ($r^2 = 0.79$ and $r^2 = 0.59$).

Conversely, the results for children are much less conclusive and in some cases largely opposing research in adults. For example, Eston, Rowlands and Ingledew (1998), found higher relationships in unregulated play activities between tri-axial vector magnitude counts and $s\dot{V}O_2$ ($r^2 = 0.86$) & uni-axial counts and $s\dot{V}O_2$ ($r^2 = 0.73$) compared to treadmill activities ($r^2 = 0.78$, $r^2 = 0.48$ respectively).

Few other studies have compared locomotive and activities of daily living in children however many studies still report much higher r^2 values for activities of daily living or locomotive and activities of daily living combined, in comparison to adults. Ott, et al. (2000) also found a significant relationship between TriTrac counts per minute and METS in 'free-play' activities, where 2 out of 8 activities were locomotive ($r^2 = 0.48$). Puyau, et al. (2002) also reported coefficients of determination of $r^2 = 0.44$ and $r^2 = 0.61$ between *EE* and activity counts in two right hip mounted, uni-axial accelerometers; CSA and Mini-Mitter Actiwatch during combined activities (activities of daily living and locomotive).

In opposition, other authors report significant but relatively low coefficients of determination for activities of daily living. For example, Mattocks, et al. (2007) found a relationship of only $r^2 = 0.13$ ($p < 0.001$) between *EE* and right hip mounted actigraph accelerometer counts per minute for hopscotch activities. Ott, et al. (2000) also reported similar results for the relationship between uniaxial accleration counts and *METS* in 'free-play' activities where $r^2 = 0.18$ ($p < 0.001$).

The trend for children to produce higher relationships between *EE* and accelerometer count relationships during activities other than locomotion in comparison to adults indicates that separate regression equations may need to be considered for this population.

2.18.3 Linear *versus* quadratic relationship

A small number of authors have suggested quadratic equations (to the power of 2) are more appropriate in describing the relationship between acceleration and *EE* on the basis that the law of kinetic energy $\frac{1}{2}mv^2$ is quadratic and that this directly relates to both movement and *EE* (Bouten, et al., 1994). Kumahara, et al. (2004) reports an extremely high coefficient of determination of 0.93 ($p < 0.001$) using a quadratic equation representing *METS* (measured in a respiration chamber) against accelerometer counts and states that this relationship is more appropriate than linear relationships when a large range of activity levels are undertaken. Conversely, Bouten, et al. (1994) found no additional benefit of a quadratic equation.

Due to the large body of research that reports reasonably strong linear relationships between acceleration and *EE*, this study used linear relationships only.

2.18.4 Uni-axial *versus* tri-axial accelerometers

Multiple studies have compared the use of uni-axial and tri-axial accelerometers in predicting *EE* during both locomotive and lifestyle activities. In general, there is strong evidence to support the use of tri-axial accelerometers over uni-axial devices due to higher coefficients of determination for the relationship between tri-axial data and metabolic rate (Eston, Rowlands and Ingledew, 1998; Hendelman, et al., 2000; Welk, et al., 2000; Rothney, et al., 2008). For example, Hendelman, et al. (2000) found that for both adult walking trials only and combined activities, r^2 for the relationship between tri-axial counts and METS (0.79 and 0.38, respectively) superseded that of the relationship between uni-axial counts and METS (0.59 and 0.35, respectively). Eston, Rowlands and Ingledew (1998) also reported similar results in children where for both walking/running on a treadmill and for combined activities, stronger relationships existed between $s\dot{V}O_2$ and the tri-axial vector magnitude counts ($r^2 = 0.77$, $r^2 = 0.81$) than uni-axial counts ($r^2 = 0.48$, $r^2 = 0.61$). These results are expected as the use of three axes allows much greater sensitivity in detecting movement in all dimensions. This was shown by Rothney, et al. (2008) who reported a higher sensitivity of the tri-axial (RT3) compared to uni-axial devices

(Actical and Actigraph) denoted by a lower proportion of measured zero's ($r^2 = 0.25$, $r^2 = 0.35$ and $r^2 = 0.37$ respectively).

The expanding use of tri-axial acceleormetry in human research as well as its use in development of new metrics such as *ODBA* and *VeDBA* has determined its use in this study.

2.18.5 The effect of epoch length and averaging

In studies using acceleration counts, an epoch of 60s is most commonly used, giving units of 'counts per minute'. This effectively summarises all counts recorded over a minute as the device stores the average count.

The nature of this data processing technique means that short periods of vigorous activity are blunted. For example, Nilsson, et al. (2002) provided evidence that short periods of very high intensity coupled with low intensity activity does no always reach the count threshold to be included into the 'high intensity' classification . The time period classified as 'high intensity' activity (11.7, 7.9, and 3.8 minutes) decreased with increasing epoch (5, 10, and 20 s, respectively).

In the case of the *DBA* metric, the time period of the running mean depicts the exact attribution of dynamic and static components, with a longer time period causes greater smoothing and so a higher ascription to the dynamic component (Shepard, et al., 2008a). Effectively, this influences whether the acceleration attributed to a stationary position or to 'very low intensity' activity.

In order to accurately define the static component the oscillations in dynamic acceleration caused by each gait cycle must be eliminated. Ideally, this would be achieved by averaging total acceleration over a certain number of complete gait cycles (Bouten, et al, 1997). However, the gait cycle varies depending on numerous factors including limb length and speed of locomotion. It would be inappropriate to measure this for each individual therefore averaging must be based upon a time period that includes at least one full gait cycle (Shepard, et al., 2008a).

As of yet, no specific recommendations have been made for the time period of *DBA* smoothing in humans. Still, until further investigation, generalisations can be made based upon the findings of animal research.

The first use of *DBA* was in research was conducted on imperial cormorants (*P atricep)* where a running mean of 1s was chosen (Wilson, et al., 2006). Furthermore, the first study using *DBA* in Homo Sapiens, also followed Wilson, et al. (2006) using running mean of 1s (Halsey, et al., 2008). Shepard, et al. (2008b) later reported that the period of smoothing should be related to body size on the assumption that the greater the body size the larger the stroke/gait cycle. In general, *ODBA* has been shown to vary with the time period of smoothing up to a point where it stabilises i.e. static acceleration is represented as a straight line through the total acceleration. The length of the running mean should therefore be based upon the point of stabilisation of the static component (or any point afterwards) however the smallest possible time period is preferred in order to reduce the changes of error which is particularly prevalent during short bursts of differing activity and postures (Shepard, et al., 2008b).

Although, Shepard, et al. (2008a) recommends a minimum running mean of 3s for species with a stroke or gait cycle of up to this value the data used was based upon walking, swimming and flying. When considering walking behaviour alone a stable running mean appears slightly earlier. For example, for walking behaviour in imperial shags static acceleration became stable for running means of $\geq$ 2s. This is well within published human gait cycle time of 0.51s for an average walking speed of 5.8kph (Saris and Binkhorst, 1977). Furthermore, no significant differences were found between the imperial shags for *ODBA* values calculated using a running means that varied by 1s. If the same were assumed for human data, using a running mean of 2s would allow for comparison to previously published data by Halsey, et al. (2008). Consequently, a running mean of 2s was chosen for this study (Fig. 2.6).

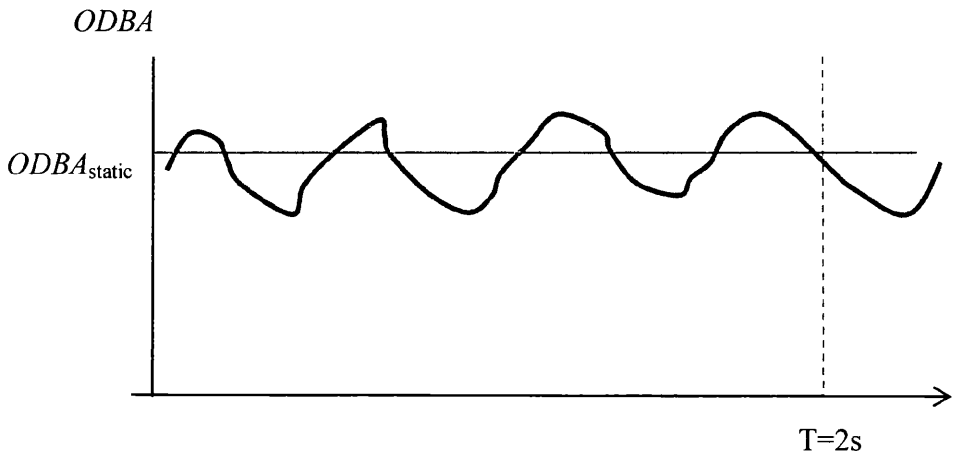


Figure 2.5 Illustrating the idea of a running mean, i.e. averaging over a specific time period T to find the static component of ODBA.

2.18.6 The effect of inclined/declined terrain

In general, in comparison to locomotion on level ground, positive gradients elicit a greater energy cost due to the additional mechanical work needed to produce greater propulsion in order to overcome gravity. Small to moderate negative gradients require reduced energy cost as less mechanical work is required due to greater mechanical energy exchange i.e. gravitational potential energy is salvaged and used for propulsion. However, as downward gradient increases a metabolic minimum occurs. Any steeper negative gradients then require an increase energy cost due to the work that is done to counterattack gravity via the use of active braking (Gottshall and Kram, 2006; Bidders, et al., 2012).

It is therefore appropriate to conclude that acceleration *versus* *EE* regression equations for level locomotion will produce inaccurate estimates of *EE* when used for graded locomotion. This was demonstrated by Terrier, et al. (2001), who found large error when comparing $\dot{V}O_2$ estimated from level walking (using the vectorial sum of acceleration counts from the hip) with $\dot{V}O_2$ measured during locomotion on inclined (-53% error at +15% incline) and declined (+55% error at -15% incline) terrain.

Moreover, development of regression equations for inclined locomotion has proven difficult as many studies report acceleration metrics fail to show any substantial changes in overall acceleration during inclined locomotion. For example, Levine, et al. (2001) concluded that the sum of the integrated acceleration curves from a tri-axial accelerometer placed on the lower back were unable to mirror the significant increase in *EE* that occurred during different speeds at inclination of 17.5° and 22.1°.

Conversely, Campbell, et al. (2002) reports high agreement between the TriTrac prediction equations for measured *EE* during inclined and declined locomotion. However, the authors also suggest that this may false positive and in actual fact the TriTrac underestimates on inclines and overestimates on declines.

In relation to *DBA*, Halsey, et al. (2008) developed separate regression equations for locomotion on the flat and on an incline and reported lower coefficients of determination during inclined walking from 1.1° to 8.3° (lower back: $r^2 = 0.60$, upper back: $r^2 = 0.77$) than on the flat (lower back: $r^2 = 0.92$, upper back: $r^2 = 0.91$). Although, it should be noted that these r^2 values are still reasonably high and show that *ODBA* certainly shows some change with $\dot{V}O_2$ during inclined walking. Unlike acceleration counts it is possible that *ODBA* can pick up finer changes in gait during inclined locomotion.

2.18.7 The effect of accelerometer placement

The majority of studies have used locations on the body that are either most convenient to the user during activities of daily living, such at the waist/hip attached to a belt (Freedson, Melanson, Sirard, 1998; Eston, Rowlands and Ingledew, 1998; Trost, et al., 1998; Hendelman, et al., 2000; Ott, et al., 2000; Howe, Staudenmayer and Freedson, 2009) or the limbs i.e. wrist, ankle etc. (Swartz, et al., 2000; Parkka, et al., 2007; Kim, et al., 2009), or most convenient to the scientist, such as the lower back (Ekelund, et al., 2002, Manohar, et al., 2011) as this most closely represents the centre of gravity and thus whole body movement. Yet, despite its potential significance in influencing the quality and application of the research, reviews on this topic are sparse and a single best placement is still yet to be obtained.

In general, in attempt to most closely represent the centre of gravity placements on the trunk or hips are preferred. Furthermore, differences between trunk locations including the upper and lower back and various hip placements are negligible. This is true when using the same type of accelerometer (Nilsson, et al., 2002; King, et al., 2004; Halsey, et al., 2008) and in some cases when using different devices (Welk, et al., 2000). For example, Nilsson, et al. (2002) considered the CSA at two different locations, the right hip and the lower back and reported no significant differences between total numbers of accelerometer counts when assessing activity levels of 16 children during all waking hours for 4 consecutive days. Furthermore, King, et al. (2004) mounted one of each of the CSA, BioTrainer-Pro, TriTrac-R3D and RT3 on the left hip and one on the right hip of 21 adults and found no significant differences between the two in terms of the *EE* readings for any of the devices during treadmill walking and jogging at 2, 3, 4, 5, 6, 7, and 8 mph. In support, Halsey, et al. (2008) also found no significant difference between three custom-made identical tri-axial accelerometers one on the neck, one on the upper back and one on the lower back in the ability to predict $\dot{V}O_2$ from *ODBA* in 10 adults.

Conversely, Yngve, et al. (2003) found small significant differences between CSA counts measured at the right hip and lower back on during self-paced walking and jogging on a treadmill and track (28 adults) although, this difference was not evident in a later field study (34 adults) where acceleration data was recorded for 7 consecutive days for the entire awake day.

When considering different devices, Welk, et al. (2000) assessed three placements around the hip (anterior axillary line, mid-axillary line, and an equal distance further posterior) with three accelerometers (TriTrac, BioTrainer, CSA) for locomotion of 3mph and reported no significant difference between acceleration values in the TriTrac and the BioTrainer however, small significant differences were present for the CSA. This is expected as the CSA is uni-axial device aligned in relation to the vertical plane and would therefore miss any medio-lateral or anterior-posterior movement associated with locomotion. It should be noted that although the BioTrainer is also uni-axial, it is tilted at a 45° angle and thus effectively acts as a bi-axial device.

More recently, limb placements are becoming more common and in particular more unusual placements such as trouser pockets and backpacks are being considered due to ease of long term use, such that it does not interfere with daily activities. However, where a larger variety of placements are considered the differences become more evident. For example, in a recent study, Manohar, et al. (2011) expressed concern regarding the lack of placement consideration in accelerometer based research as they found large variations in the coefficient of determination as well as slope and intercept of the regression equation between i-phone accelerometer readings at 7 different locations (Arm, Hand, Trouser Pocket, Backpack, Jack Side Pocket, Jacket Front Pocket, Handbag) and acceleration readings from a Physical Activity Monitoring System (PAMS) on the lower back during walking (r^2 = 0.65 – 0.91). Although, it is unclear whether placement also affects the ability of the device to predict *EE*. Although, this might be expected it is not always the case. For example, Bouten, et al. (1997) found that regardless of the substantial differences between acceleration data at 6 different locations on the body (head, trunk, lower back/foot, lower leg, lower arm/hand, upper arm, upper leg,) during walking at speeds of 3 – 7 kph, there was negligible influence on the correlations with *EE*. Conversely, it should be noted that the importance of these results are questionable due to the very small participant count (2 people).

Still, if trunk/hip placements are to be replaced with limb placements, then direct comparison of the ability to predict *EE* in these locations must be made. Several studies have investigated this but the results remain highly divergent with support both for (Parkka, et al., 2007) and against (Swartz, et al., 2000; King, et al., 2004) the use of limb placements over trunk/waist/hip placements and results showing limb and trunk/waist/hip placements are indifferent (Kim, et al., 2009). For example, Swartz, et al. (2000) assessed the relationship between accelerometer counts and METS in 70 adults and found poor coefficient of determination for wrist (r^2 = 0.181) compared to hip-mounted accelerometers (r^2 = 0.563) although both were statistically significant. Furthermore, King, et al. (2004) also indicated that limb mounted devices might be less reliable that hip mounted devices as the SenseWear Armband produced a gender and side (right and left side of body) interaction for individual axes counts, in comparison to four other hip mounted devices (Tri-Trac-R3D, RT3, BioTrainer-

Pro, CSA) where results where consistent. However, this difference became irrelevant when the *EE* readings where considered.

In opposition, Parkka, et al. (2007) reported that an ankle mounted in house tri-axial accelerometer gave the strongest relationship between predicted *EE* and measured *EE* (r^2 = 0.74) in comparison to wrist (r^2 = 0.67) and hip (r^2 = 0.64) mounted accelerometers. They suggest that this result could be due to the fact that most tasks involve majority foot work compared to hand movements. In addition, they also reported that wrist and hip accelerometers cannot accurately distinguish between activities other than running in terms of the predicted *METS*.

Additionally, Kim, et al. (2009) found no differences at all between Pearson correlations between acceleration data (expressed as the integral of each absolute signal) and *EE* at ankle, knee, wrist and upper back placements during submaximal treadmill exercise.

In conclusion, due to the largely variegated results when comparing limb and trunk/hip device locations, trunk/hip placements should be prioritised in studies not looking at placement effects. Furthermore, as the variances between trunk placements are on the whole indifferent, placement should be chosen due to practicality. For example, for humans during free living activity, attachment at the hip might be more sensible as the lower back device could get in the way/knocked during sitting activities. Conversely, during treadmill activity the lower back might be more sensible as the hip device could get knocked during arm swinging.

In conclusion, it is essential that detailed assessment of accelerometer placement using controlled variables i.e. the same acceleration and *EE* metrics is undertaken in future studies in order for the development of an accurate *EE* prediction equations.

2.18.8 The accuracy of device specific prediction equations for energy expenditure

The imperative aim of all accelerometer based research is to produce a valid prediction equations for *EE* that are can be applied across all activities and for specific populations. Currently, many studies find consistently high correlations between accelerometer metrics and *EE* measured via indirect calorimetry, particularly in locomotive activity. Subsequently, these data are used to produce prediction equations that are incorporated into accelerometers which allow the device to output *EE* values. Unfortunately, due to the large disparity between treadmill exercise and activities of daily living as well as additional complications of surface terrain, surface incline, upper body movement, isometric muscular contraction, lack of detail in the acceleration count metric and the possible effects of body anthropometrics and physiology (of which little research is available) the validity of most device prediction equations of *EE* are highly questionable. The large variety of commercially available accelerometers and corresponding *EE* prediction equations has caused an increasingly dispersed literature base with no clear conclusion. In addition, Lyden, et al. (2011) has reported considerable bias in the way in which new prediction equations are validated where models are tested using similar populations and activities under which they have been developed. Furthermore, many studies only assess a single device making comparison between devices very difficult.

It should be noted that for all studies discussed below the accelerometer devices were placed in similar locations i.e. waist/ hip. Hence, it is assumed that there is no effect of placement. The exception is the SenseWear Armband, however, as the results for this were similar to other devices placed at the waist, it has been included in the discussion.

In general, the literature indicates that the majority of devices overestimate locomotive activity (Welk, et al., 2000; King, et al., 2004; Crouter, et al., 2006a; Howe, Staudenmayer and Freedson, 2009) and underestimate other lifestyle/sporting activities (Welk, et al., 2000; Crouter et al., 2006a; Howe, Staudenmayer and Freedson, 2009).

Welk, et al. (2000) compared device based predicted *METS* (using manufacturer-based algorithms) to measured *METS* (via indirect calorimetry). The Tritrac and BioTrainer largely overestimated *EE* during treadmill exercise by an average of 112% and 128% respectively, although the CSA predicted the *METS* values within 3.3%. In addition, all three devices underestimated *EE* during combined lifestyle activities; CSA (53%), BioTrainer (52%) and Tritrac (57%). Similarly, King, et al. (2004) compared monitor predicted activity *EE* (total *EE* – *RMR EE* based on manufacturer's equations) with measured activity *EE* (via indirect calorimetry) for four waist mounted accelerometers (CSA, TriTrac- R3D, RT, BioTrainer-Pro) and one upper arm mounted accelerometer (SenseWear Armband) during treadmill walking and jogging (2, 3, 4, 5, 6, 7 and 8 mph). On the whole, all accelerometers over estimated activity *EE* ($p < 0.001$) at all speeds except the CSA which underestimated during very slow walking and jogging. Howe, Staudenmayer and Freedson, (2009) also reported a similar overestimation of activity *EE* for activities involving predominantly lower body movement i.e. including mainly locomotive activities (26.6-55%) and an underestimation of activity *EE* for activities with greater upper body movement (24.4-64.5%) using manufacturer based equations from a waist mounted RT3.

Further evidence of inconsistency can be found in a review by Crouter, et al. (2006a). These authors examined multiple previously published regression equations for three devices; CSA (later termed Actigraph) (15 equations), Actical (2 equations) and AMP-331 (manufacturer's equation). In general, the equations were denoted only valid for the activities they were established with. For example, the Actigraph equations developed via walking and jogging (e.g. Freedson, Melanson and Sirard, 1998 and Hendelman, et al., 2000) underestimated the most mixed activities. In addition, equations based on lifestyle activities (such as Swartz, et al., 2000) overestimated walking and light activity and underestimated mixed activities. The AMP-331 accurately predicted the *EE* for fast and slow walking but as with most of the above studies, it underestimated mixed activity. Unusually, the Actical was able to accurately predict sedentary activities but followed the general trend of underestimating mixed activities and overestimated walking.

In conclusion, no device has been found to accurately predict *EE*, with the highest intensities tending to give the least accurate results (Lyden, et al., 2011). For example, Welk, et al. (2000) reported that in general, the three waist mounted accelerometers (Tritrac, CSA, BioTrainer) were reasonably accurate in predicting *METS* at walking speeds of 3mph and 4mph, but produced greater error at the jogging speed of 6mph. Additionally, it has commonly been reported that the RT3, ActiGraph, and Actical are not accurate in predicting *EE* over a wide range of activities (Crouter, et al., 2006a; Lyden, et al., 2011) with difference even between different generations of the same device (Rothney, et al., 2008).

2.18.9 Conclusions regarding the validation of body acceleration against indirect calorimetry

The present seeks to assess the relationship between *DBA* and *EE* and specifically, to decipher whether *ODBA* or *VeDBA* is the best predictor of *EE*.

There were several options that were considered when designing the protocol including; population, activity type, type of relationship, type of accelerometer, epoch or averaging length, use of a gradient, accelerometer placement and use of prediction equations. These were based upon the literature review and are discussed in more detail below.

i) Population

In the present study, adults where the accessible population therefore subsequent decisions were based upon literature relating to adult populations.

ii) Locomotive activity or activities of daily living

The current literature reports a strong linear relationship between acceleration metrics and *EE* during locomotive activity in adults. This relationship is greatest when *DBA* is used as the acceleration metric.

DBA has not previously been used to predict *EE* during activities of daily living. Furthermore, other acceleration metrics such as acceleration counts have shown poor relationships with *EE* during activities of daily living in adults.

Thus, since the main aim was to access the differences between *ODBA* and *VeDBA*, a protocol involving locomotive activity only was chosen. This gives the opportunity to use previous research in which to draw comparisons and build conclusions. In addition, body position during locomotive activity is on the whole, upright. This simplifies the results when assessing the effect of device orientation.

iii) Linear versus quadratic relationship

There are mixed results regarding the appropriateness of using quadratic equations to describe the relationship between acceleration and *EE*. In addition, a large body of research shows reasonably strong linear relationships. Thus, the present study will assess the linear relationship between *DBA* and *EE*.

iv) Uni-axial versus tri-axial accelerometers

DBA is based upon tri-axial data therefore a tri-axial accelerometer must be used. Furthermore, on the whole, the literature reports stronger relationships between acceleration and *EE* with tri-axial devices.

v) Epoch or averaging length

A running mean of between 1s and 3s is common in *DBA* research. For this study, an averaging period of 2s was chosen based upon both the timing of the human gait cycle and the ability to compare between previous research.

vi) Inclined and declined terrain

The literature in relation to the effect of inclined and declined terrain on the ability of acceleration metrics to predict *EE* is scarce. However, from the studies that are available the following conclusions can be made. The use of regression equations

produced during level locomotion give largely inaccurate estimates of *EE* on graded terrain. Furthermore, development of regression equations on graded terrain has proven difficult using accelerometer count data due to the inability of acceleration counts to show substantial change on a gradient. *DBA* has proven much better at recognising gradients although poorer relationships between *DBA* and *EE* exist on an incline than on the flat. Due to the lack of research into graded terrain, the present study is based upon a flat gradient only.

vii) ***Accelerometer placement***

In general, trunk placements (neck, back, hip) have elicited the greatest relationships between acceleration metrics and *EE* and show little difference between them. Only one study to date has assessed the effect of trunk placements using *ODBA* and again shown no difference. However, the effect of placement on *VeDBA* has never been tested. Furthermore, *DBA* has already been shown to be a much more sensitive measure than any previous accelerometer metric therefore this study will seek to further evaluate the effect of different trunk placements. Placements near to the centre of gravity were chosen. The upper back was chosen due to ease of attachment and the hip due to potential for future use during activities of daily living.

viii) ***Device specific prediction equations***

The current plethora of prediction equations are specific to the population and protocol under which there were developed therefore the present study will use raw *DBA* and *EE* data to produce its own prediction equation.

Chapter 3

Methods

3.1 Human participants

The study consisted of twenty-one voluntary participants (seventeen males, four females) recruited via convenience sampling (mean age = 22.44 ± 3.28 years; height = 1.75 ± 0.07 m; weight = 70.66 ± 9.78 kg; *BMI* = 21.95 ± 2.41 $kg.m^{-2}$). Seventeen participants had a *body mass index* (*BMI*) equating to a normal body weight (*BMI* = 18.5-24.99 $kg.m^{-2}$) and four participants were considered overweight (*BMI* = 25.0-29.99 $kg.m^{-2}$). All participants were non-smokers.

The selection criteria included; i) aged between 18 and 50 years, ii) apparently healthy (i.e. free from chronic respiratory or cardiovascular problems, muscular disorders, metabolic disorders, central or peripheral nervous disorders, diabetes) and iii) not pregnant.

3.2 Experimental protocol

The experimental protocol involved two sessions of non-invasive physiological measurement; a body composition assessment (specifically fat mass and fat-free mass) and a maximal exercise test ($\dot{V}O_2$ max test) on a treadmill. Three body composition assessment techniques were used one after the other for comparison; air displacement plethysmography, bioelectrical impedance analysis and skinfolds. Ethical approval was granted by Swansea University Sports Science Ethics Committee. Prior to each session, written informed consent, a American Heart Association (AHA) /American College of Sports Medicine (ACSM) Health/Fitness Facility Pre-participation Screening Questionnaire and a 24 hour diet diary (including smoking status) were obtained.

3.3 Anthropometric measurements

3.3.1 Height and weight

Commencing each session, height was measured to the nearest 0.1 cm using a Holtain Stadiometer (Holtain Ltd, Crymych, Wales) and weight was measured to the nearest 0.1 kg using Seca 770 Digital Scales (Seca Ltd, Birmingham, UK) (Heyward

and Stolarczyk, 1996). Measurements were taken according to the International Standards for Anthropometric Assessment (2001), defined by the International Society for the Advancement in Kinathropometry as described in Heyward and Stolarczyk (1996) and Eston and Reilly (2001a).

3.3.2 Girths

Hip and waist girths (see Appendix 7.10 for descriptions) were measured using a Lufkin Executive Diameter Steel Tape Measure (Lufkin, Mexico) following the International Standards for Anthropometric Assessment (2001). The tape was positioned until there was no slack but it did not compress the skin. The zero end of the tape was held in the left hand and once wrapped around the girth, the overlapping tape was placed underneath the zero point (Heyward and Stolarczyk, 1996).

3.3.3 Lengths

Leg length was measured to the nearest 0.5 cm using a meter rule placed orthogonally to the floor. The trochanterion was considered the top of the leg (see Appendix 7.10 landmark description).

3.4 Body composition assessment

3.4.1 Pre-test requirements

It was requested that all participants adhere to the following stipulations prior to the body composition assessment; i) no eating 12 hours prior, ii) no exercise 12 hours prior, iii) no alcohol or caffeine 48 hours prior, iv) no diuretics 7 days prior, v) urinate and empty bowels within 30 minutes of testing, vi) consumption of at least 500ml water prior to testing and vii) remove all jewellery (Heyward and Stolarczyk, 1996; Hayward and Wagner, 2004; Bodystat Ltd, 2000).

3.5 Air displacement plethysmography

Air displacement plethysmography was performed using the *BODPOD* (Bod Pod 2000, A Body Composition System, Life Measurements Inc., California, USA). This system measures whole body density based on non-invasive measurement of body mass and body volume

3.5.1 Principle

The *BODPOD* is comprised of two chambers (a front test chamber and a rear reference chamber) parted with a computer controlled diaphragm system (Fig. 3.1). The diaphragm is oscillated during the test to create small changes in volume in each chamber. The changes in pressure are measured and subsequently used to determine volume. Initially, this procedure is used to establish volume of the empty test chamber and subsequently the volume when the subject is sat inside (Life Measurement Inc., 2000).

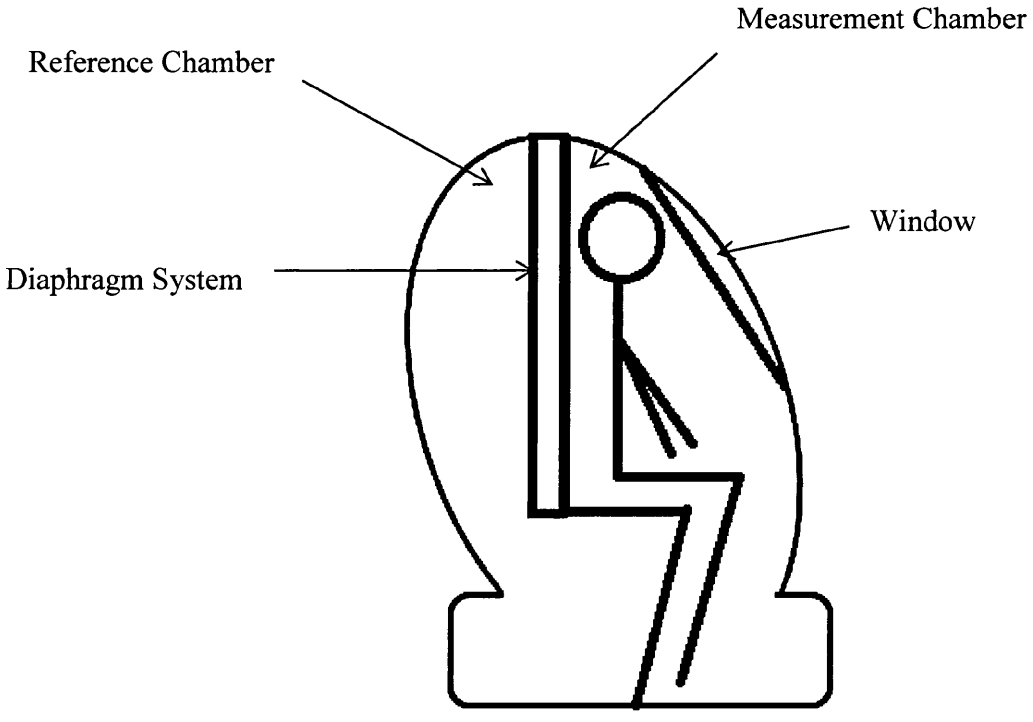


Figure 3.1. Schematic diagram of the BODPOD.

The volume of the chambers is calculated via the principle of Poisson's Law (Eq. 3.5), a variation of Boyles Law. Subsequently body volume, body density and percentage body fat can be calculated (Hayward and Wagner, 2004).

$$PV^{\lambda} = k \qquad (3.1)$$

P = pressure
V =volume
k = constant
λ = the ratio of the specific heat of the gas at a constant pressure to the specific heat of the gas at a constant volume

Poisson's Law describes the pressure-volume relationship in adiabatic conditions; conditions of no net heat flow i.e. where temperature varies throughout both chambers. Adiabatic conditions are created due to heat transfer from the body however, body hair, residual air in the lungs, clothing and skin surface area can create potential for isothermal conditions (constant air temperature). Air is much more compressible in isothermic conditions (40% more compressible compared to an adiabatic environment) and thus produces lower pressure signals for a given volume. Under these conditions, Boyle's law applies (Eq. 3.6).

$$PV = k \qquad (3.2)$$

P = pressure
V = volume
k = constant

(Higgins, et al., 2001)

The *BODPOD* has several circulation mechanisms to limit the presence of isothermal air including an air circulation mechanism and the oscillating diaphragm (Higgins, et al., 2001). In addition, the software adjusts for the effect of isothermal air around the skin surface area and in the lungs. The former adjustment (skin surface artefact), assumes minimal clothing and body hair, therefore all participants were asked to

enter the *BODPOD* in swimwear or underwear and a swim cap. With regard to the latter variable (the lungs), a nose clip is worn to reduce residual air in the respiratory tract (Hayward and Wagner, 2004). In addition, the *BODPOD* uses a predicted lung volume in its calculation of body volume.

Once body volume has been established the *BODPOD* calculates body density, fat mass and fat-free mass. First, body density is calculated using measured body volume and body weight.

$$Density(kg.m^{-3}) = \frac{Mass(kg)}{Volume(m^{-3})} \tag{3.3}$$

Percentage fat mass is then determined using a selection of pre-programmed equations. In this case the Siri (1956) equations were used (Eq. 3.2).

$$FatMass(\%) = \left(\frac{4.95}{Density(kg.m^{-3})} - 4.5 \right) \times 100 \tag{3.4}$$

Finally, percentage fat mass is converted to kilograms (Eq. 3.3) and fat-free mass (kg) calculated based upon the two compartment model of body mass i.e. fat-free mass and fat mass (Eq. 3.4).

$$FatMass(kg) = BodyMass(kg) \times \left(\frac{FatMass(\%)}{100} \right) \tag{3.5}$$

$$Fat\ Free\ Mass\ (kg) = Body\ Weight\ (kg) - Fat\ Mass\ (kg) \tag{3.6}$$

3.5.2 Calibration

The *BODPOD* was calibrated according to the manufacturer's instructions (Life Measurement Inc, 2000). The device was left to warm up for 30 minutes prior to testing. Next, a two-point calibration was performed; the empty chamber was measured to establish a zero baseline and then a metal cylinder of a known volume

(50.011L) was used as a second calibration value. Scales were calibrated using a 20kg weight and the reading was accepted within ± 0.01kg. The participant was weighed using the *BODPOD* scales and name, age and height details were entered into the system (Life Measurement Inc., 2000).

3.5.3 Protocol

The protocol was run according to the manufacturer's instructions (Life Measurement Inc., 2000). Upon entering the *BODPOD* the participant was instructed to sit upright, leaving a small gap between their back and the back surface of the chamber. It was requested that they keep still, quiet and breathe normally (relaxed tidal breathing). Two tests were performed, each lasting 50 s. The door was kept closed throughout each test but opened in between to allow mixing of air. Testing continued until two tests gave consistent values (usually within 2 tests) for body volume. The calculations for body density, fat mass and fat-free mass are then performed automatically.

3.6 Skinfolds analysis

3.6.1 Skinfolds

Biceps, triceps, subscapular and suprailliac skinfolds were taken using Harpenden skinfold callipers (British Indicators, West Sussex, UK) according to the International Standards for Anthropometric Assessment (2001).

All measurements took place in a warm room with the participant standing with shoulders and arms relaxed (Eston and Reilly, 2001a). Measurements were taken on the right hand side of the body and recorded to the nearest 0.1 mm (Heyward and Stolarczyk, 1996).

Landmarks and subsequent measurement sites (see Appendix 7.10 for descriptions) were marked by a small cross with a washable pen. For each measurement site the left thumb and forefinger was used to raise a fold of skin using a slight pulling and rolling action. The right hand was used to place the calliper pressure plates

perpendicular to the skinfold and 1cm below/right of the landmark. The callipers were held in position for approximately 2s before the measurement was taken. The fold was kept elevated throughout the measurement (Eston and Reilly, 2001a).

All measurements were taken once and then repeated in rotational order. If the two values were within ± 10% of each other an average value was used (Heyward and Stolarczyk, 1996). If not, a third measurement was taken and the median value used.

Body density was calculated using the regression equations developed by Durnin and Wormersley (1974) based upon the sum of four skinfolds, gender and age (Eq. 3.7 and Table 3.1).

$$BodyDensity\left(kg.m^{-3}\right) = (c - m) \times \log \sum biceps + triceps + subscapular + \sup railliac \tag{3.7}$$

c = see Table 3.1

m = see Table 3.1

Table 3.1. Values for c and m in the body density equations developed by Durnin and Wormersley (1974).

		Age (years)		
		17-19	20-29	30-39
Male	*c*	1.1620	1.1631	1.1422
	m	0.0630	0.0632	0.0544
Female	*c*	1.1549	1.1599	NA
	m	0.0678	0.0717	NA

Fat mass (%) was then calculated using the Siri equation (Eq. 3.2), converted to kilograms (Eq. 3) and the latter used to calculate fat-free mass (Eq. 3.4).

3.7 Bioelectrical impedance analysis

3.7.1 Principle

Bioelectrical impedance analysis (*BIA*) was performed using the BodyStat Quadscan 4000 (Stat Plus Electrical Impedance Dual Channel Analyser, UK). This sends a low level current through the body at a frequency of 50 kHz. The current passes through the body due to the presence of water and electrolytes and will follow the path that provides least resistance. Different body tissues contain varying of amounts of fluid and hence vary in there electrical conductivity. Fat is primarily anhydrous and so a poor electrical conductor (Heyward and Stolarczyk, 1996).

The Quadscan detects the voltage drop due to impedance which is caused by anhydrous body tissues. The electrical impedance value is used to calculate total body water and fat-free mass is subsequently calculated using an assumed hydration factor of lean tissue.

Estimates of total body water using bioelectrical impedance analysis are usually based upon the equation:

$$V = \frac{\rho S^2}{R} \tag{3.8}$$

V = conductive volume (represents total body water)
ρ= resistivity of the conductor
S = stature (assumed to be the length of the conductor)
R = whole body resistance

(Houtkooper, et al., 1996)

This equation assumes that the conductor cross sectional area and length are fixed, the conductor has a uniform composition and there is an equal current distribution. These do not hold true in the case of *Homo Sapiens;* the length of the conductive area does not equate to stature (see 3.7.3 for electrode placements) and p varies with

the composition and distribution of tissues (Heyward and Stolarczyk, 1996; Houtkooper, et al., 1996). However, clear statistical associations have been recognised between S^2/R and total body water in numerous study samples (Houtkooper, et al., 1996) thus manufacturer's regression equations have been developed to predict total body water and subsequently fat-free mass (using an assumed hydration factor of lean tissue) in relation to weight, height, gender and age.

3.7.2 Calibration

The *BIA* self-calibrates each time a measurement is taken, however to maximise the accuracy of measurement the device was turned one minute prior to testing as advised by the manufacturers (Bodystat Ltd, 2000).

3.7.3 Protocol

The protocol was implemented according to the manufacturer's instructions (Bodystat Ltd, 2000). Participants lay still and quiet in a supine position on a non-conductive bed in a room at ambient temperature (approximately 25 °C) (Heyward and Wagner, 2004). No parts of their body were touching i.e. a gap was left between the thighs and between the arms and trunk (Heyward and Stolarczyk, 1996). This state was assumed for 5 minutes prior to the test and throughout the measurement (Bodystat Ltd, 2000).

Four measurement sites were located along the right side of the body; the dorsal surface of the ankle and wrist, where the upper border of the electrode bisects the ulna/medial and lateral malleoli respectively, and the base of the second/third metacarpal/metatarsal-phalangeal joint on the hand and foot respectively. The sites were cleaned thoroughly with 70% alcohol wipes and electrodes placed onto the skin. A gap of at least 5 cm was left between the two electrodes on the hand and the two on the foot (Heyward and Stolarczyk, 1996). Leads were attached to the appropriate electrodes and participants details entered into the machine. The measurement period took 19-20 seconds. Percentage body fat values were recorded from the display.

3.8 Measurement of maximal oxygen uptake ($\dot{V}O_2$ max test)

3.8.1 Maximal oxygen uptake ($\dot{V}O_2$ max) pre-test requirements

Prior to the *maximal oxygen uptake test* ($\dot{V}O_2$ max test) it was requested that all participants adhere to the following stipulations; i) no eating 2/3 hours prior, ii) no exercise 12 hours prior, iii) no alcohol or caffeine 48 hours prior, iv) consumption of at least 500ml water prior to testing (Eston and Reilly, 2001b).

3.9 Heart rate monitoring

Participants were fitted with a Polar S610/S810 Heart Rate Monitor (Polar Electro, Kempele, Finland) (Fig. 3.2) in order to allow continual heart rate monitoring for both health and safety purposes and as part of the criteria for assessing $\dot{V}O_2$ max.

3.10 Respiratory analysis

A Jaeger Oxycon Pro Online Gas Analyser (Erich Jaeger GmbH, Hoechberg, Germany) was used for breath-by-breath measurement of oxygen (O_2) and (CO_2) concentration as well as volume of expired air throughout the $\dot{V}O_2$ max test.

The Jaeger Oxycon Pro consists of a silicon mask, digital Triple-V volume sensor (Fig. 3.2), twin gas tubes, a pressure transducer, an amplifier, O_2 and CO_2 gas analysers and a PC. The silicon mask was placed over the participant's mouth and nose and attached to adjustable strapping wrapped comfortably around the head (Fig. 3.3). The fit was modified until the mask created an air tight seal, allowing air flow solely through the volume sensor.

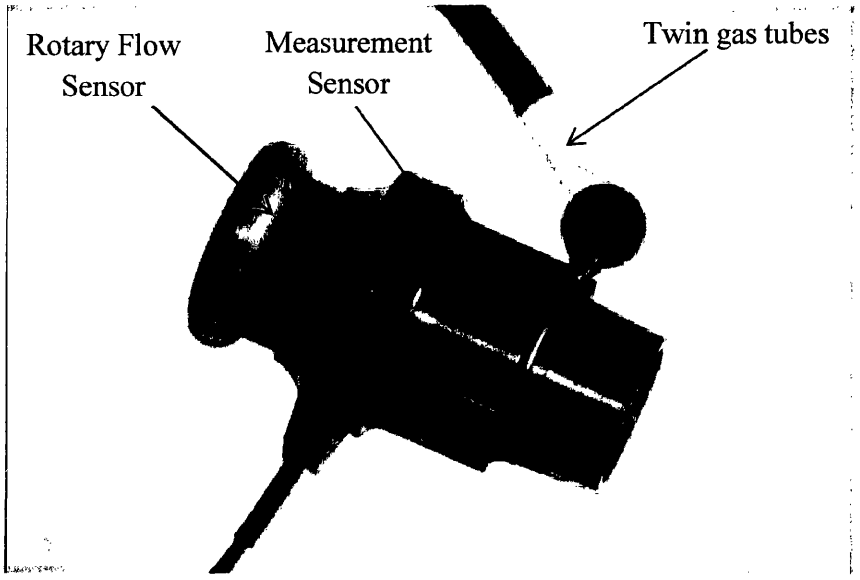


Figure 3.2. A schematic diagram of the Triple-V volume sensor.

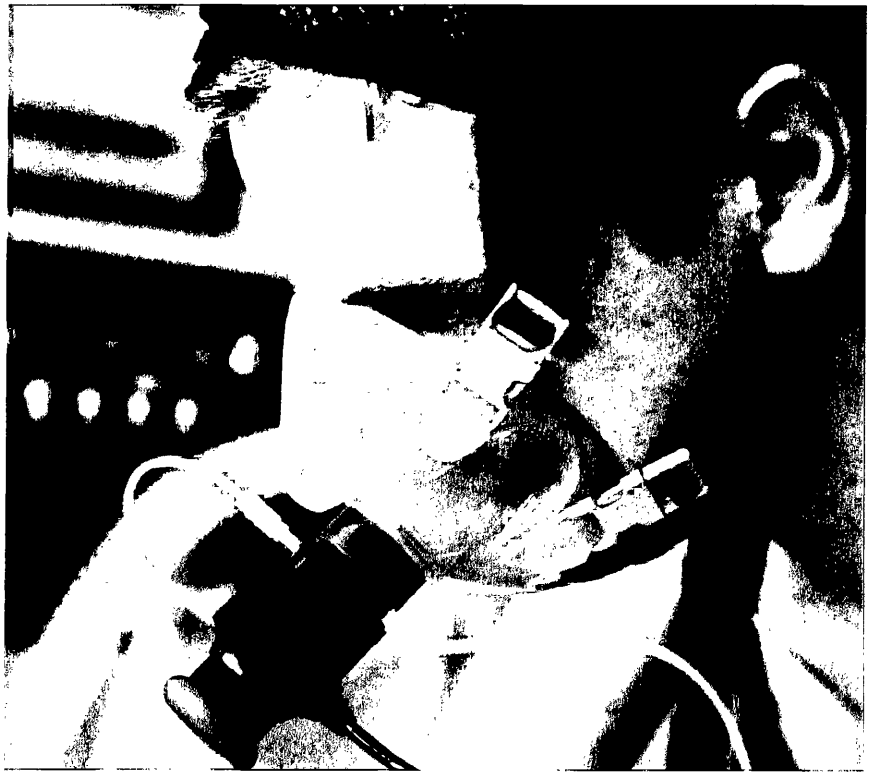


Figure 3.3. An example of the fitting of the silicon mask

3.10.1 Calibration

The Oxycon Pro was calibrated prior to each test using a three stage process; i) entry of ambient conditions, ii) manual volume calibration and iii) gas calibration according to the manufacturer's instructions (Erich Jaeger GmbH, 2002).

i) ***Ambient conditions***

Values for laboratory temperature, pressure, humidity and altitude were entered into the system to allow $\dot{V}_E$ (volume of expired air) to be converted from *ATPS* (ambient temperature and saturated vapour pressure) to *STPD* (standard temperature and dry vapour pressure) values (Eq. 11). This refers to dry gas i.e. containing no water vapour, at a temperature of 0°C and pressure of 760 mmHg. *STPD* values are necessary for inter-study comparisons.

$$\dot{V}_E STPD = \dot{V}_E ATPS \times \frac{(BP - SWVP)}{760} \times \frac{273}{273 + t} \quad (3.11)$$

(Eston and Reilly, 2001b)

ii) ***Manual volume calibration***

A 3L calibration pump was attached to the Triple-V volume sensor. Air was pumped at a constant speed until 5 accurate recordings were made. Values were excepted if the correction factors were within the manufactures guidelines, if not, the process was repeated (Erich Jaeger GmbH, 2002).

iii) ***Gas analyser calibration***

Verified concentrations of O_2 and CO_2 were used to calibrate the gas analyser. The calibration was accepted only if the correction factors were within the manufacturer's specifications (Erich Jaeger GmbH, 2002).

3.10.2 Check phase

This included a 3 minute period prior to the start of the $\dot{V}O_2$ max test in which the recording of the respiratory variables were visually checked to ensure the equipment is recording consistently and reliably.

3.10.3 Output

$\dot{V}O_2$ data was selected from the PC and exported as a csv file and subsequently converted into an Excel file.

3.10.4 Measurements and calculations

$\dot{V}O_2$ was calculated using the following formulae:

$$\dot{V}O_2 = (V_I \times F_IO_2) - (V_E \times F_EO_2) \quad (3.12)$$

$\dot{V}_I$ = Volume of inspired air
$\dot{V}_E$ = Volume of expired air
F_IO_2 = Concentration of inspired O_2
F_EO_2 = Concentration of expired CO_2

(Eston and Reilly, 2001b)

$\dot{V}_E$ *ATPS* is measured via the Triple-V volume sensor and converted to $\dot{V}_E$ *STPD* (Eq. 3.11). Concentration of inspired O_2 (F_IO_2) and CO_2 (F_ICO_2) are known i.e. 0.2093 and 0.003 respectively (Eston and Reilly, 2001b). Concentration of expired O_2 (F_EO_2) is measured via the O_2 and CO_2 gas analysers.

Volume of inspired air ($\dot{V}_I$) is calculated using the Haldane transformation. The Haldane transformation calculates $\dot{V}_I$ based on the concept that nitrogen (N_2) is essentially inert and so will have exactly the same number of molecules (mass) in inspired and expired air (Eq. 3.13). Assuming a constant mass, concentration of N_2

will vary directly with volume, therefore if the concentration/fraction of inspired N_2 (F_IN_2) and expired N_2 (F_EN_2) is known, $\dot{V}_I$ can be computed (Eq. 3.13–18) (Eston and Reilly, 2001b).

Mass of inspired N_2 = Mass of expired N_2 (3.13)

$$Concentration = \frac{Mass}{Volume} \quad (3.14)$$

Mass of $N_2 = V_I \times F_IN_2$ (3.15)

Mass of $N_2 = V_E \times F_EN_2$ (3.16)

$V_I \times F_IN_2 = V_E \times F_EN_2$ (3.17)

$$V_I = \frac{V_E \times F_EN_2}{F_IN_2} \quad (3.18)$$

(Eston and Reilly, 2001b, p. 147)

3.10.5 Hygiene

To avoid risk of infection, contaminated equipment i.e. the silicon mask and triple V sensor were disinfected via the disinfectants manufacturer's instructions and rinsed with distilled water after every participant.

3.11 Tri-axial accelerometers

Three tri-axial accelerometers were used (X6-1A USB; Gulf Coast Data Concepts, LLC, Waveland, USA; 16 bit resolution, recording range ± 6 g), each set to record at 80 Hz on each of the three orthogonal axes.

Each accelerometer weighs approximately 55g and is constructed of a printed circuit board, memory card, a USB connector, an on/off button, a removable microSD flash memory card enclosed in a semi-transparent blue plastic casing (Fig. 3.4 and 3.5). It is powered by a single 1.5V alkaline AA battery. The on/off button can be easily

accessed through a small hole in the casing and two LED's indicate system status. Accelerometer and 'logger' are used as equal terms from here on in.

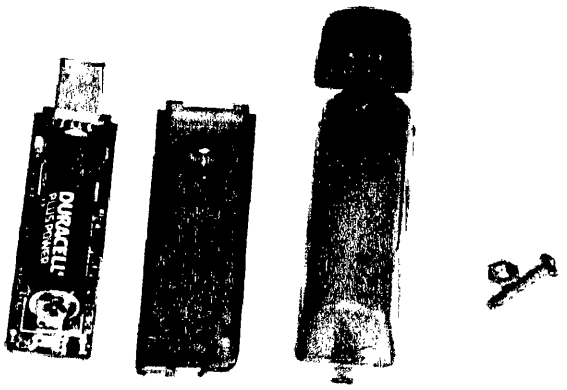


Figure 3.4. An X6-1A accelerometer.

Figure 3.5. A schematic diagram of a dismounted X6-1A accelerometer.

3.11.1 Placement

Two of the accelerometers were securely fastened in holding moulds cut into a polystyrene saddle (Fig. 3.6). One was held vertically in line with the main body axes (heave, surge and sway) and one displaced from by rotating the device by 30° about the yaw, roll and pitch (Fig. 3.7 and Fig. 3.8). The saddle was mounted on the mid-upper back between the scapulas and held tight to the skin using a specially made adjustable SilasticH harness (SilasticH P1 Base and Curing Agent, Thomson Bros Newcastle Ltd) which wrapped around the shoulders (Fig. 3.9). This kept the saddle in a stable locus even during vigorous movement. The structure and attachment of the saddle was optimised by trial and error during pilot studies so that it moved in

accordance with the participant's body. The third accelerometer was attached vertically (in agreement with the body's heave, surge and sway axes) to the mid-coronal plane of the right hip via an adjustable elasticated strap (Fig. 3.10).

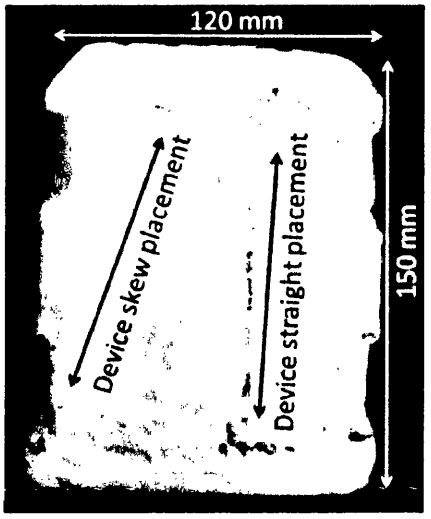


Figure 3.6. Polystyrene saddle showing the orientations of the holding moulds for the straight and skew mounted accelerometers.

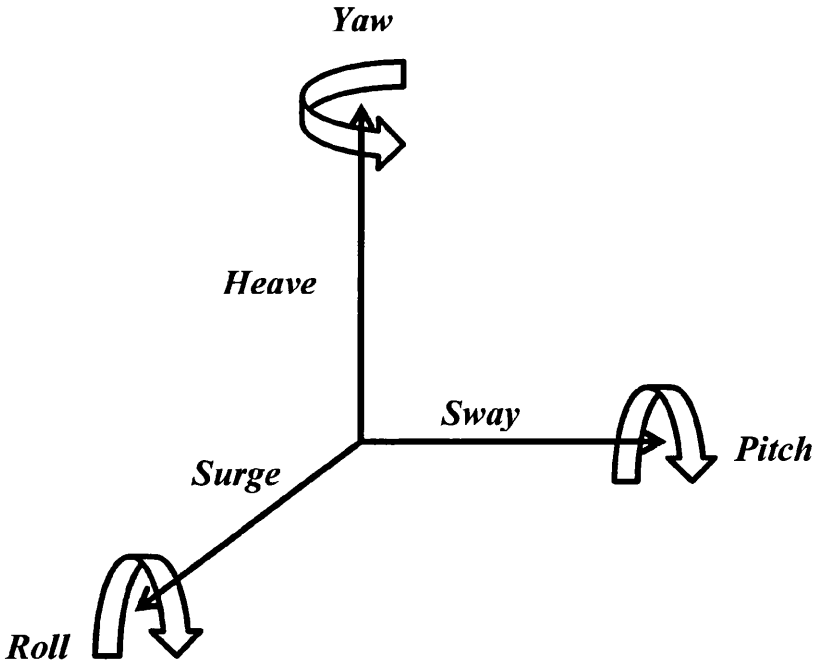


Figure 3.7. A diagrammatic representation of the axis upon which the accelerometers were orientated against.

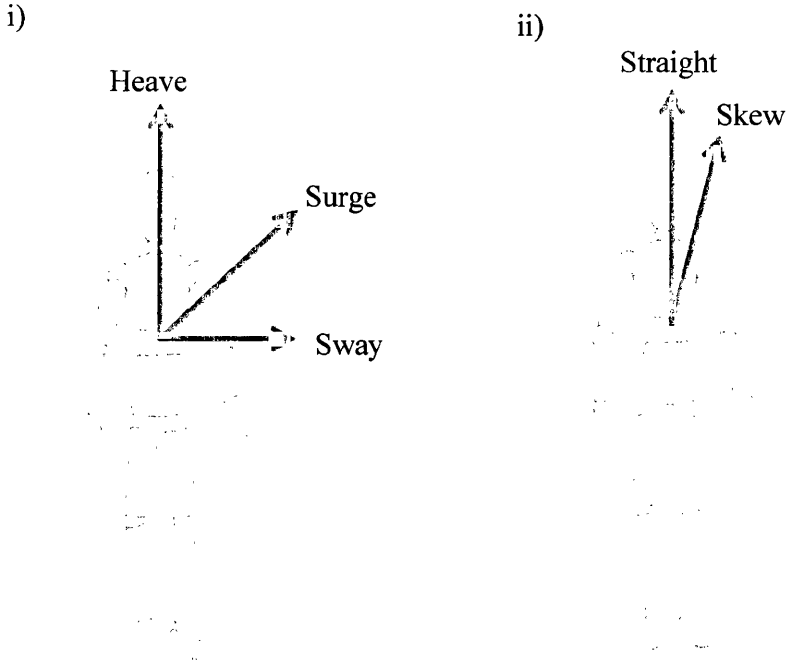


Figure 3.8. Diagram of i) the major axes of the body and (ii) the orientations of the 'straight' and 'skew' accelerometers.

Figure 3.9. Positioning of the saddle with SilasticH harness. The straps are in a figure of eight configuration.

Figure 3.10. Hip mounted logger attachment and positioning.

3.11.2 Calibration

After switching on the device, it was left stationary on a flat surface (heave axis parallel to the surface) for 10 seconds. From this position, three large consecutive back and forth movements were made firstly in the sway axis and secondly in the heave axis. The device was subsequently left to stand stationary on the table for a further 10 seconds. This calibration procedure left a clear trace in the output data and acted as the start point. Time was noted from the stop clock at the start of the calibration and again at the start of the $\dot{V}O_2$ max test.

3.11.3 Output

The logger archives data to comma delimited text files, which were subsequently opened in Microsoft Excel for data analysis as recommended by the manufacturers (Gulf Coast Data Concepts, 2010).

3.12 Rating of perceived exertion scale

Rating of perceived exertion was assessed using the Borg 15-point psychophysical ratio scale (Borg, 1982) recorded by holding a paper copy of the scale in front of the participant so that they could point to the perceived exertion rating (Appendix 7.2). This allowed continual psychophysical monitoring of the participant for health and safety purposes. Additionally, rating of perceived exertion was used as part of the criteria for assessing VO_2max.

3.13 Protocol for maximal oxygen uptake test ($\dot{V}O_2$max test)

A progressive, incremental maximal exercise test ($\dot{V}O_2$ max test) was performed on a motor driven treadmill (Woodway Ergo ELG 55 Treadmill, Woodway GmbH, Weil am Rhein, Germany). Treadmill speed started at 3 km.h^{-1} and increased by 1 km.h^{-1} increments every 3 minutes until volitional exhaustion. Treadmill gradient remained at 0% throughout the test due the effect that gradient might have on the relationship between acceleration and *energy expenditure* (*EE*) (see section 2.18.6).

It was requested that participants did not talk during the protocol unless necessary i.e. to ask questions regarding the protocol or to indicate exhaustion.

Breath-by-breath respiratory data, tri-axial body acceleration and heart rate from the Holter ECG were set to continuous recording throughout the test. Heart rate from the polar monitor and rating of perceived exertion were recorded manually in the last 10 seconds of each stage. Time was measured precisely using a stop clock.

The criteria used to confirm that participants had reached $\dot{V}O_2$ max included; i) a peak heart rate of ±10 beats of estimated age-related maximum, ii) rating of perceived exertion of 19 or 20 on the Borg exertion scale and iii) volitional exhaustion (Eston and Reilly, 2001b).

3.14 Methods of data processing

Respiratory data and acceleration data from the straight-mounted logger were obtained for all participants (N =21). Data from the skew-mounted logger and hip-mounted logger were obtained for 18 and 17 of the participants respectively.

3.14.1 Tri-acceleration data

The raw acceleration data was written in comma delimited text format with data lines containing readings from the x, y, z axes and of time. These files were converted to Excel files for analysis.

Raw data was registered as deadband counts. These units can be defined as an integer between 0 and 2048. At each sample point a new count will register if the value from any of the sensor axes exceeds that of the previous value by a deadband count. The deadband counts were converted into g using the manufacturer's calculations, which were based upon AD resolution (i.e. 16-bit) and gain (i.e. ± 6 g) (Eq.3.19).

$$g = \frac{DeadbandCounts}{5440} \tag{3.19}$$

Data from each axes were treated separately. Each channel was filtered using a running mean over 2 seconds. This reflects the static acceleration. *Dynamic body acceleration* (*DBA*) was calculated by subtracting the *static acceleration* from the *total body acceleration* (g) (Eq. 3.20).

$$DBA\ (g) = Total\ Body\ Acceleration\ (g) - Static\ Body\ Acceleration\ (g) \tag{3.20}$$

DBA for each axis was then converted into positive values and these values were either summed to provide *overall dynamic body acceleration* (*ODBA)* (Eq.3.21);

$$ODBA = |A_x| + |A_y| + |A_z| \tag{3.21}$$

where A_x, A_y and A_z are the derived dynamic accelerations at any point in time corresponding to the three orthogonal axes of the accelerometer, or used to produce the *vector of dynamic body acceleration* (*VeDBA*) (Eq. 3.22);

$$VeDBA = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{3.22}$$

3.14.2 $\dot{V}O_2$ data

Breath-by-breath $\dot{V}O_2$ data was extracted from the Jaeger Oxycon Pro in the form of Excel files and interpolated into 1 second intervals using MATLAB (R2011a version 712), a numerical computation, visualization and programming software.

3.15 Methods of averaging

3.15.1 Anthropometric data

Average weight (with equipment) and height over the two sessions were used in analysis. Weight (without equipment) was only measured for the $\dot{V}O_2$ max test.

3.15.2 Dynamic body acceleration and $\dot{V}O_2$ data

All data was visually scanned and plotted against time, prior to taking means. Means for *ODBA*, *VeDBA* and $\dot{V}O_2$ were derived for each running speed for each individual. Means for *ODBA* and *VeDBA* were commuted using data from the mid 2 minutes 30 seconds of each 3 minute speed in order to allow for settling of gait in the first 15 seconds, and eliminate the possible anticipated change in gait in the latter 15 seconds. Means for $\dot{V}O_2$ were derived from the 15 second period between 2.30-2.45 minutes during each stage.

Due to these techniques only complete 3 minute stages could be included in analysis. Reasons for an incomplete stage included either volatational exhaustion i.e. the end of the test or the accelerometer failing (in the case of *DBA* data only).

3.16 Calculation of the gas exchange threshold

Measurements of $\dot{V}O_2$ are most indicative of *EE* when metabolism is mainly aerobic. Thus, it was necessary to eliminate all data above the aerobic gas exchange threshold in order to acquire an accurate regression equation.

In order to determine aerobic gas exchange threshold, $\dot{V}O_2$ was plotted against $\dot{V}CO_2$; the *V*-slope method (Fig. 3.11). This plot typically shows two slopes corresponding to the way that $\dot{V}O_2$ changes with respect to $\dot{V}CO_2$. The point at which these two slopes intersect is considered to be the gas exchange threshold.

The slopes were initially visually divided into two straight lines. The points along each line were put into a Linest function in Excel. Some points where included in both lines where appropriate. If there was an obvious outlier, decided upon by visual inspection of the graph, the point was excluded from equations. The exact intersection (gas exchange threshold) is calculated using simultaneous equations and the lines on the graph were subsequently adjusted to represent the exact slopes (Fig. 3.12). The $\dot{V}O_2$ value is recorded at the point of intersection.

A speed *versus* $\dot{V}O_2$ graph was plotted and a trendline added that gave the highest r^2 value (polynomial order 6 for all participants; Fig.3.13). The speed below the speed that corresponded with the aerobic gas exchange threshold was used as the highest speed in which *ODBA*, *VeDBA* and $\dot{V}O_2$ data was used in regression analysis. This ensured that all data was representative of primarily aerobic metabolism, even in the event of small errors in aerobic gas exchange threshold calculations.

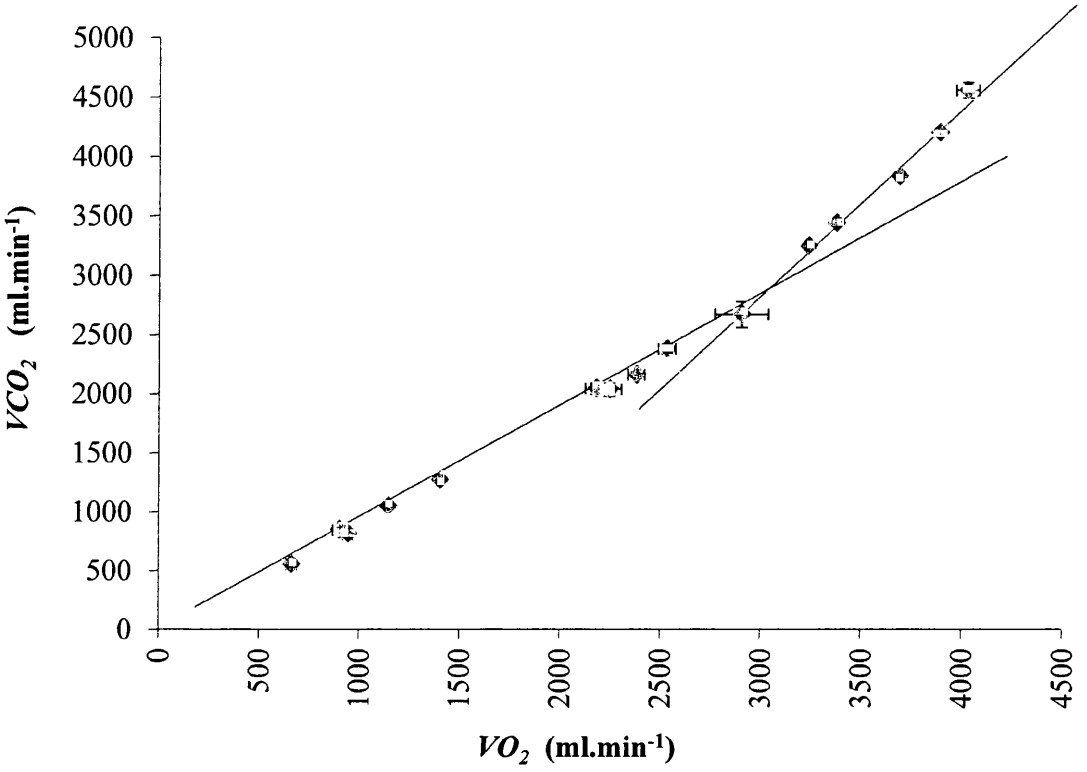


Figure 3.11. An example of a plot of $\dot{V}O_2$ against $\dot{V}CO_2$ for one participant with two visually drawn straight lines to indicate suspected gas exchange threshold.

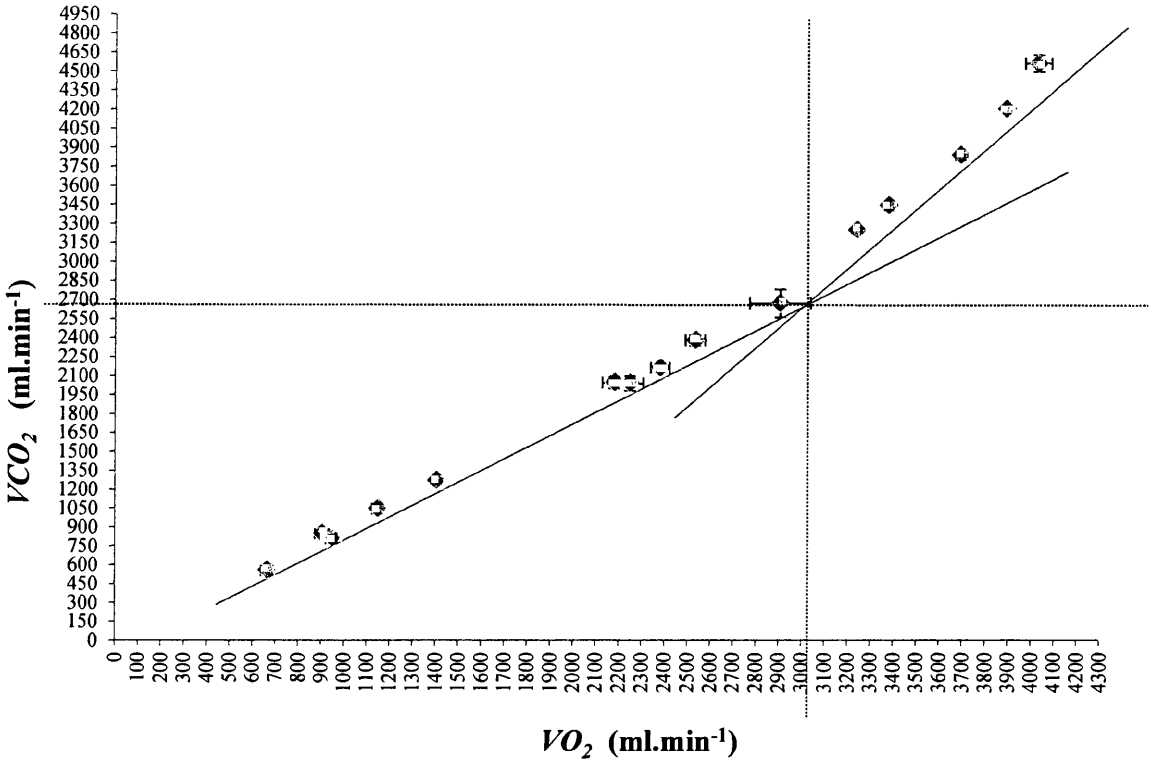


Figure 3.12. An example of a plot of $\dot{V}O_2$ against $\dot{V}CO_2$ for one participant with visually drawn straight lines adjusted for calculated intersection representing gas exchange threshold.

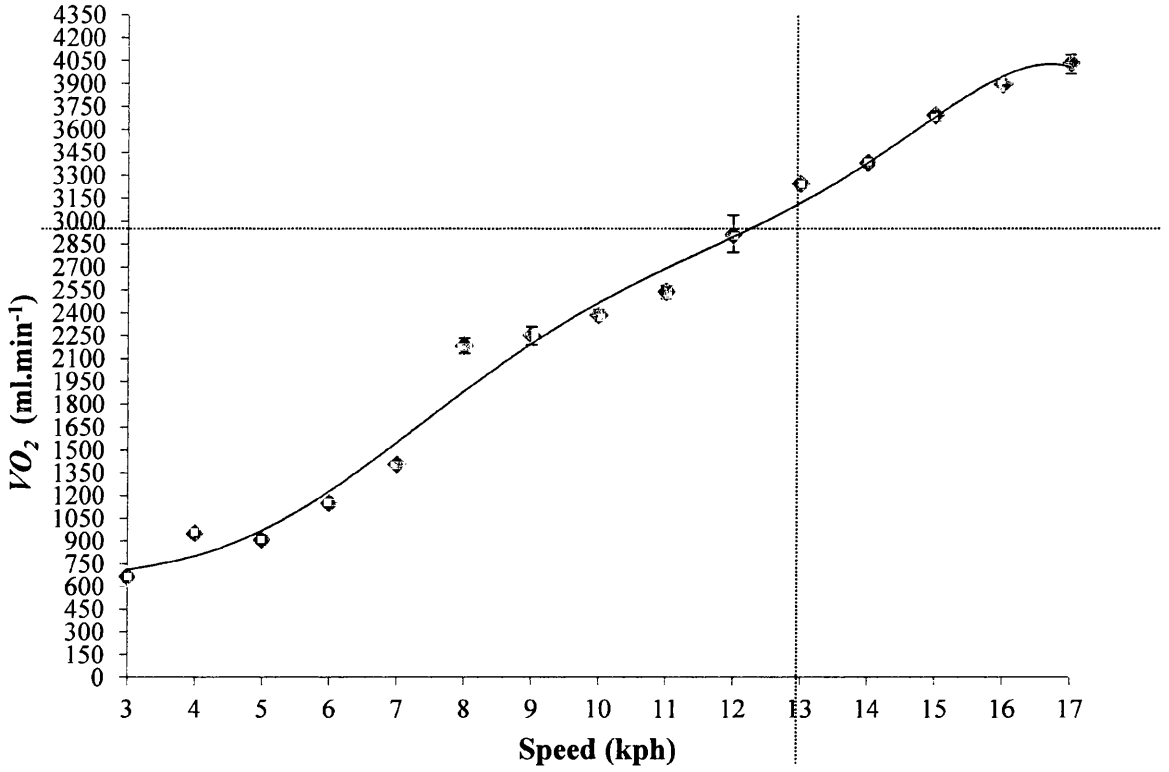


Figure 3.13. An example of a speed against $\dot{V}O_2$ graph with trend line for one participant. $\dot{V}O_2$ value at aerobic gas exchange threshold is marked along with corresponding speed.

3.17 Calculation of missing values

Missing values were present in some acceleration data due to occasions where a logger failed; the skew-mounted logger failed on 3 occasions and the hip-mounted logger failed on 4 occasions.

The strength of the relationship between $\dot{V}O_2$ and acceleration metrics can be more accurately defined with greater data points therefore simulation of these missing values was considered.

A number of techniques were used to calculate missing values including regression analysis, selected averaging and by automatic formulation using JMP.

3.17.1 Individual regression method (*IR*)

This method uses data from individual participants only and where possible, via logger mounting. Single linear regression graphs for speed against *DBA* were plotted via individual and logger mounting. The regression equations were used to calculate the missing values using speed as the known value. In cases where the number of existing data points for a particular participant and logger mounting was only two or less, then the entire existing data set for that individual (i.e. all logger-mountings) was used for regression.

3.17.2 Selected averaging method (*SA*)

This method uses the data from all participants and logger orientations/placements combined. The 'AVERAGEIFS' function in Excel is used to select all the *DBA* and related $\dot{V}O_2$ data pairs where the $\dot{V}O_2$ value is within 90-110% of the $\dot{V}O_2$ value associated with the missing *DBA* data point. An average of the *DBA* values associated with this $\dot{V}O_2$ range is then used to replace the missing *DBA* data point.

3.17.3 JMP method (*JMP*)

This method uses the data from all participants and logger orientations/placements combined. The JMP 'place missing values' function which inserts missing values based on sequential formulation using all existing data.

3.18 Statistical programmes used

Statistical analysis was performed using SPSS (IBM, Version 19) and JMP (Version 10). In all cases significance was set to $p < .05$. All results are shown as mean ± standard deviation.

3.19 Description of statistical techniques

3.19.1 Tests for normality

A normal (or Gaussian) distribution is represented by a 'bell-shaped' curve i.e. data is distribution symmetrically around the mean.

A non-normal distributions is often described by the 'skewness' or 'kurtosis', where skewness describes a distribution that slants sideways to the mean and kurtosis describes the 'peakedness' i.e. the width of the peak and length of the tails.

Normality was assessed using a combination of z-scores for kurtosis and skewness co-efficients, the Shapiro-Wilk test (denoted as W) and Q-Q plots (Appendix 7.4) as recommended by Razali and Wah, 2011.

Skewness and kurtosis values and their respective standard errors where gained from SPSS and converted to Z-scores using the following formula:

$$Z_{skewness} = \frac{SkewnessValue}{S\tan dardError} \qquad (3.23)$$

$$Z_{\text{kurtosis}} = \frac{KurtosisValue}{S\tan dardError} \quad (3.24)$$

Z-scores below 1.96 are non-significant and so represent a normal distribution.

The Shapiro-Wilk statistic was produced by SPSS where a non-significant result was indicative of a normal distribution.

Two types of Q-Q plots were also produced in SPSS; a normal Q-Q plot and a detrended normal Q-Q plot. The normal Q-Q plot displays the actual values of the sample against the expected values of the sample given a normal distribution i.e. the 'expected normal'. Normality is represented by a reasonably straight line. If the points are flatter or steeper than the straight line then kutosis is present and if the points form an arc or 'S' shape around the line, skewness is present. The detrended normal Q-Q plot displays the deviation of scores from the straight line. Normality is represented when most points are close to zero. The plots were visually inspected and used in parallel with the two other techniques to define the shape of the distribution.

Where distributions are non-normal nonparametric statistics should be used. However, as parametric tests have greater power and robustness both parametric and non-parametric equivalents were performed. If the results were the same, the parametric test was reported, if they differed the non-parametric test was described.

3.19.2 Simple linear regressions

For simple linear regressions two variables were plotted against one another and the straight line that gave the smallest sum of the squared residuals was fit through the data points. The residuals are the vertical distance between the measured value and the fitted line. The slope and the intercept of the line were then used to produce the coefficient of determination (r^2). This is a value ranging from 0 to 1 that describes how well the independent variable can predict the variability of the dependent variable; where the independent variable is the one that is the 'input' or 'possible cause'(i.e. *DBA*) and the dependent variable is the 'output' or 'effect' (i.e. $\dot{V}O_2$). The

closer the r^2 is to 1, the better the independent variable is as a predictor (Fields, 2009).

The coefficient of determination is calculated from the product-moment correlation coefficient. A product-moment correlation coefficient (r) measures the strength of the relationship (ranging from -1 to +1) between two measurement methods and will give a perfect correlation (-1 or +1) if any straight line is produced (Fields, 2009).

3.19.3 Wilcoxon's signed rank tests and paired samples *t*-tests

Both the Wilcoxon's signed rank tests and paired samples t-tests were used to determine whether there is a significant difference between two groups means. They compare related data sets i.e. 'repeated measures'; where in this case the same participants contribute to each data set. A significant result (i.e. $p< 0.05$) indicates a significant difference between the two groups (Fields, 2009).

For the Wilcoxon's signed rank tests both the z-score and the test statistic (T) is also reported. The z-score allows a significance value based on a normal distribution to be calculated and the test statistic T represents the sum of the negative ranks (Fields, 2009).

For the paired sample t-test the degrees of freedom (*df*), t statistic and the confidence intervals are also reported. The *df* represent the sample size minus 1, the t statistic represents the mean differences between the two data sets divided by the standard error of the differences (and is compared against known values based on *df* to assess significance) and the confidence intervals (*CI*) represents the limits within which the true mean is expected to lie (Fields, 2009).

3.19.4 Bland-Altman plots

To create a Bland-Altman plot the average of the two data sets were plotted against the difference between the two data sets. The mean difference between the two data sets ± 2 SD were then added to the graph. The mean difference represents the bias or level of 'agreement' (i.e. degree to which the two techniques are measuring the same

value) where a mean difference closer to 0 indicates a greater amount of agreement. The SD indicates the clinical practicality by highlighting minimum and maximum differences i.e. 'limits of agreement' (Bland and Altman, 1986).

For Bland-Altman plots, perfect agreement between method A and method B (two methods are measuring exactly the same values i.e. a mean difference of 0) will only occur if, when method A is plotted against method B, all points lie along the line of equality. For *r* a perfect correlation can occur along any straight line i.e. even when method A produces values twice as big as method B. In addition, *r* is affected by the range in the sample, with larger ranges giving higher correlations. This does not necessarily reflect the agreement (Bland and Altman, 1986).

3.19.5 One-way repeated measures analysis of variance (ANOVA)

An ANOVA tests for significant differences between group means when there are more than two groups. A significant result (i.e. $p<0.05$) indicates an overall experimental effect however it does not specify which groups where affected. Thus, a bonferroni *post hoc* test is used to find the groups affected (Fields, 2009).

There are several forms of ANOVA and 'post hoc' tests. A 'one-way' ANOVA was used in the present study as this analyses the effect of only one independent variable (e.g. measurement technique) on the dependent variable (e.g. body fat). A 'repeated measures' ANOVA was ascribed as the data in the three groups originate from the same participants (Fields, 2009).

A bonferroni *post hoc* test was allocated as this is very conservative i.e. reduces the type 1 error rate, in other words the chance of finding a significant difference when there is no difference (Fields, 2009).

3.19.6 Standard (Forced Entry) multiple regression with backward stepwise elimination

Multiple regression analysis allows construct of a model with several predictor variables. Hence, the r^2 value represents how well several independent variables (e.g. *DBA* and body fat) can explain the variability of the dependent variable (i.e. $\dot{V}O_2$).

Standard (Forced Entry) involves inclusion of all possible independent variables into the model. Firstly, variables are screened for collinearity and excluded if they met the removal criteria. The removal criteria are based upon test statistics such as Pearson's correlation coefficients and collinearity statistics. Next, variables that are not making a statistically significant contribution are removed one by one i.e. 'backward stepwise elimination'. After one variable has been removed the contribution of the remaining predictors are re-evaluated. Variables are eliminated until all make a significant contribution to the model (Fields, 2009).

3.20 Description of short hand terms used in statistical analysis

In Table 3.2 *ODBA* is used as an example however the same principles are applied to shorthand terms for *VeDBA*.

Table 3.2. Shorthand terms used in statistical analysis.

Shorthand term	Description
$\dot{V}O_2$	Mean $\dot{V}O_2$ for each speed
DBA	Refers to both *ODBA* and *VeDBA*
$ODBA_{all}$	Mean *ODBA* for each speed from all accelerometer data combined (straight, skew and hip)
$ODBA_{straight}$	Mean *ODBA* for each speed from the straight accelerometer
$ODBA_{skew}$	Mean *ODBA* for each speed from the skew accelerometer

$ODBA_{hip}$	Mean *ODBA* for each speed from the hip accelerometer
CV $ODBA_{all}$	Coefficient of variation of $ODBA_{all}$
r^2 ($\dot{V}O_2$ *versus* $ODBA_{all}$)	Coefficient of determination for the regression of $\dot{V}O_2$ against $ODBA_{all}$
IR $ODBA_{all}$	$ODBA_{all}$ – including values that have been allocated for missing data by the individual regression method
SA $ODBA_{all}$	$ODBA_{all}$ – including values that have been allocated for missing data by the selected averaging method
JMP $ODBA_{all}$	$ODBA_{all}$ – including values that have been allocated for missing data by *JMP*
FM	Fat mass
FFM	Fat-free mass
BODPOD	*FM* values gained from the BODPOD
SKF	*FM* values gained from skinfold assessment
BIA	*FM* values gained from bioelectrical impedance analysis
$ODBA_{subskew}$	Difference in *ODBA / VeDBA* when logger is subsequently skewed *(Figure 3.14: C-D)*
$VO_2ODBA_{subskew}$	Difference in $\dot{V}O_2$ when logger is subsequently skewed *(Figure 3.14: A-B)*
% $\dot{V}O_2$ $ODBA_{subskew}$	Percentage difference in $\dot{V}O_2$ when logger is subsequently skewed *(Figure 3.14: absolute value of* $\dot{V}O_2$ $ODBA_{subskew}$ */ A*100)*

3.21 Applications of statistical analysis

Statistical analysis was undertaken in order to assess which metric or combination of metrics best predicted $\dot{V}O_2$.

Specifically, analysis was assessed:

i) *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$.

ii) *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$in relation to device orientation (straight *versus* skew logger).

iii) *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$in relation to device placement (straight *versus* waist logger).

iv) The influence of body anthropometrics, body composition and aerobic capacity on the relationship between *DBA* and $\dot{V}O_2$.

In addition, statistical analysis was performed to help inform decisions regarding;

i) Assessment of the methods of imputing missing values

ii) Assessment of the most appropriate body composition measurement technique

3.21.1 *ODBA versus VeDBA* a proxy for $\dot{V}O_2$

Simple linear regressions were used to assess the relationship between *ODBA* and *VeDBA*, $\dot{V}O_2$ and *ODBA* as well as $\dot{V}O_2$ and *VeDBA* in order to assess the ability of both metrics to predict $\dot{V}O_2$.

A combination of *t*-tests and Wilcoxon's matched paired tests were used to highlight significant differences between *ODBA versus VeDBA* metrics, the coefficient of variation (*CV*) of *ODBA versus CV VeDBA* as well as between r^2 ($\dot{V}O_2$ *versus ODBA*) *versus* r^2 ($\dot{V}O_2$ *versus VeDBA*) in an attempt to ascertain which is the best predictor of VO_2.

3.21.2 *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$ in relation to device orientation (straight *versus* skew logger)

Simple linear regressions were used to assess the relationship between data produced by the straight-mounted logger *versus* data produced by the skew-mounted logger for *ODBA* and *VeDBA* as an indication of the amount of similarity in the data produced by the straight and skew devices.

A combination of *t*-tests and Wilcoxon's matched paired tests were used to highlight significant differences between the straight *versus* skew-mounted logger data for *ODBA*, *VeDBA*, *CV ODBA*, *CV VeDBA*, $\dot{V}O_2$ *versus ODBA* and $\dot{V}O_2$ *versus VeDBA.* This analysis was undertaken in an attempt to test the theory that the skewed device would be a poorer predictor of VO_2 than the straight device for the *ODBA* but not *VeDBA.*

In research on humans in free living situations, it is possible that even when the device is placed in a straight position it may get knocked and therefore skewed during in daily activities. To test for differences between *ODBA* and *VeDBA* in the effect on estimates of $\dot{V}O_2$ in the case of an initially straight-mounted logger subsequently becoming skewed, $\dot{V}O_2$ measured during speed 5 on the treadmill was compared to $\dot{V}O_2$ estimated from *ODBA* and *VeDBA* values recorded by the skew-mounted logger using the straight-mounted logger $\dot{V}O_2$ *versus ODBA* and $\dot{V}O_2$ *versus VeDBA* regression equations.

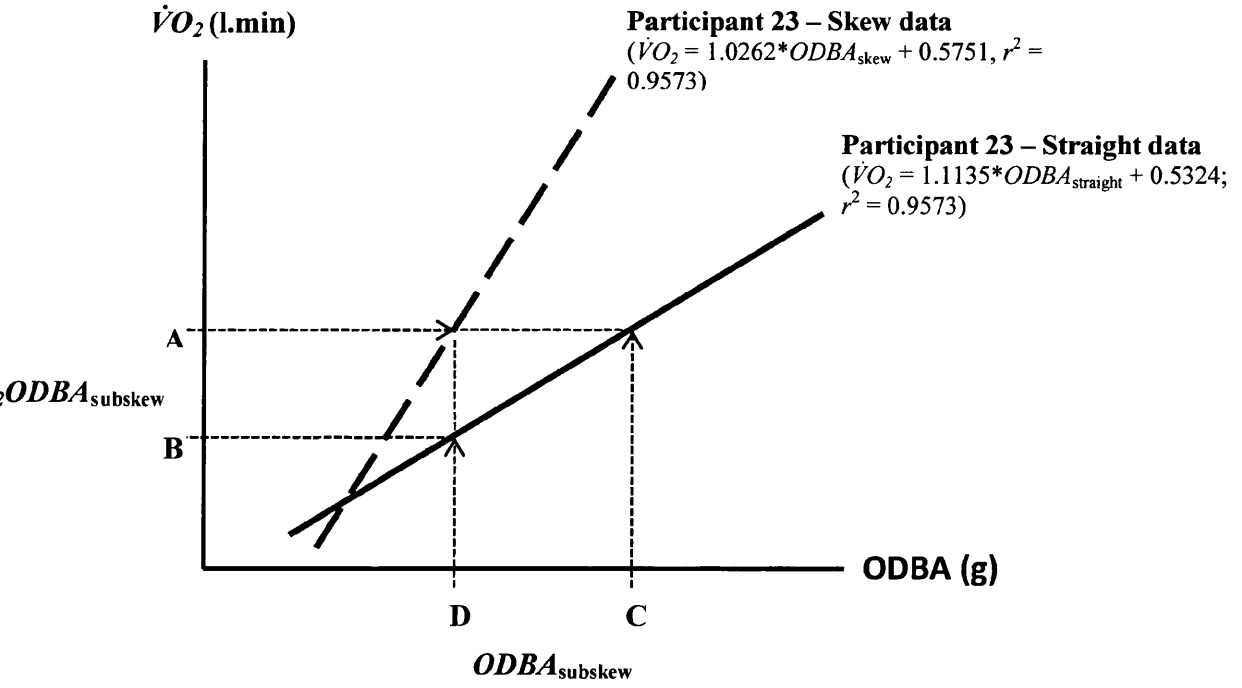


Figure 3.14. A diagrammatic representation of the error in ODBA and $\dot{V}O_2$ if a straight mounted logger subsequently skews. Participant 23 is used as an example. Similarly, ODBA is used as an example but exactly the same principle applies to VeDBA.

A = Estimated $\dot{V}O_2$ using straight logger

Estimated $\dot{V}O_2$ using participant 23 $ODBA_{straight}$ *versus* $\dot{V}O_2$ linear regression equation and average $ODBA_{straight}$ at speed 5 for all participant data combined

B = Estimated $\dot{V}O_2$ if logger subsequently skews

Estimated $\dot{V}O_2$ using $ODBA_{skew}$ estimate and participant 23 $ODBA_{straight}$ *versus* $\dot{V}O_2$ linear regression equation.

C = Average $ODBA_{straight}$

Average $ODBA_{straight}$ at speed 5 using all participant data combined

D = Estimated $ODBA_{skew}$

Estimated $ODBA_{skew}$ at speed 5 using estimated $\dot{V}O_2$ for $ODBA_{Skew}$ and participant 1 $ODBA_{straight}$ *versus* $\dot{V}O_2$ linear regression equation.

3.21.3 *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$ in relation to device placement (straight *versus* waist logger)

Simple linear regressions were used to assess the relationship between data produced by the straight-mounted logger *versus* data produced by the hip-mounted logger for *ODBA* and *VeDBA* as an indication of the amount of similarity in the data produced by the straight and hip devices.

A combination of *t*-tests and Wilcoxon's matched paired tests were used to highlight significant differences between the straight *versus* hip-mounted logger data for *ODBA*, *VeDBA*, *CV ODBA*, *CV VeDBA*, $\dot{V}O_2$ *versus ODBA* and $\dot{V}O_2$ *versus VeDBA*. This analysis was undertaken in an attempt to ascertain the effect that device placement would have on the ability of *ODBA* and *VeDBA* to predict $\dot{V}O_2$ and whether this deem one of them superior to the other.

2.21.4 Assessment of the methods of imputing missing values

Simple regressions were used to assess the relationship between all paired combinations of the three methods of imputed missing values (*IR*, *SA* and *JMP*) for both *ODBA* and *VeDBA* and Bland-Altman plots measured the level of agreement between the paired comparisons.

A one-way repeated measure *ANOVA* was used to assess differences between the *IR* $ODBA_{all}$, *SA* $ODBA_{all}$ and *JMP* $ODBA_{all}$ data sets in order to ascertain if there were any differences between the *ODBA* values produced by the three methods. The same procedure was repeated for *VeDBA*.

A one-way repeated measure *ANOVA* was also used to assess differences between r^2 ($\dot{V}O_2$ *plotted against IR* $ODBA_{all}$), r^2 ($\dot{V}O_2$ *plotted against SA* $ODBA_{all}$), r^2 ($\dot{V}O_2$ *plotted against JMP* $ODBA_{all}$) and r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{all}$) to ascertain if adding missing values improving the ability of *ODBA* to predict $\dot{V}O_2$ and if so which elicited the greatest improvement. The same procedure was repeated for *VeDBA*.

3.21.5 Assessment of the most appropriate body composition measurement technique

Three methods of body composition analysis were available to the study. Each technique has limitations so analysis was undertaken to ascertain which technique is most accurate for the present population.

Simple regressions were used to assess the relationship between all paired combinations of the three body composition techniques (*BODPOD plotted against BIA*; *BODPOD plotted against SKF* and *SKF plotted against BIA*) and Bland-Altman plots measured the level of agreement between the paired comparisons. A one-way repeated measure *ANOVA* with Bonferroni *posts hoc* analysis was used to assess differences between techniques.

The analysis was used to find the two techniques that most closely agreed with one another. The most appropriate technique between these two was then left to the literature.

3.21.6 The influence of body anthropometrics, body composition and aerobic capacity on the relationship between *DBA* and $\dot{V}O_2$

Standard (Forced Entry) multiple regressions with backward stepwise elimination were used to assess the effect of multiple independent variables on the ability to predict $\dot{V}O_2$.

Anthropometric, body composition and aerobic capacity variables including; *age* (years), *leg length* (m), *height* (m), *weight* (kg), *waist to hip ratio*, *fat-free mass* (kg), *fat mass* and $\dot{V}O_2$ *max* (ml.min^{-1}) were considered for the multiple regression model. Selected variables were entered into the model along with $ODBA_{hip}$, $ODBA_{straight}$, $VeDBA_{hip}$ and $VeDBA_{straight}$ separately, in order to produce models to predict $\dot{V}O_2$.

$ODBA_{hip}$ and $VeDBA_{hip}$ were used as they produced the highest coefficient of determination with $\dot{V}O_2$ in comparison to the other logger mountings respectively.

Furthermore, the hip mounting represents the most convenient placement for use in activities of daily living.

$ODBA_{straight}$ and $VeDBA_{straight}$ were used as they represent the ideal situation where the logger is kept secure and in line with the main axes of the body.

Only data for speeds 3-7 were used for this analysis to eliminate the bias created by the fact that some participants had a greater cardiovascular capacity than others and had therefore completed more stages of the $\dot{V}O_2$ max test i.e. more speeds.

Anthropometric and body composition data were available for 18 participants. $ODBA_{straight}$ data (speeds 3-7) was complete for all of these participants however $ODBA_{hip}$ data was only complete for 14 participants.

For each model, all variables were entered into a standard (Forced Entry) multiple regression equation. First, the variables were screened for collinearity and excluded if they met one or more of the following removal criteria:

i) Pearson's correlation coefficients > 0.7
ii) collinearity statistic, VIF > 10
iii) collinearity statistic, tolerance <0.2

(Tabachnick and Fidell, 1996; Field, 2009)

Next, backward stepwise elimination was used to remove one variable at a time until all variables in the model added significantly to the prediction of $\dot{V}O_2$.

Chapter 4

Results

4.1 Normality

All variables, except leg length (m), height (m), weight (kg), waist to hip ratio, fat-free mass (kg) and *maximal oxygen uptake* [$\dot{V}O_2$ max ($ml.min^{-1}$)] were non-normally distributed.

4.2 Raw data

The tri-acceleration data showed a very precise profile of gait for all participants during both walking and running (Fig. 4.1). Peaks in surge and heave were clear with each stride and smaller peaks in sway were also apparent (see Fig. 3.7 and Fig. 3.8 for heave, sway and surge diagram).

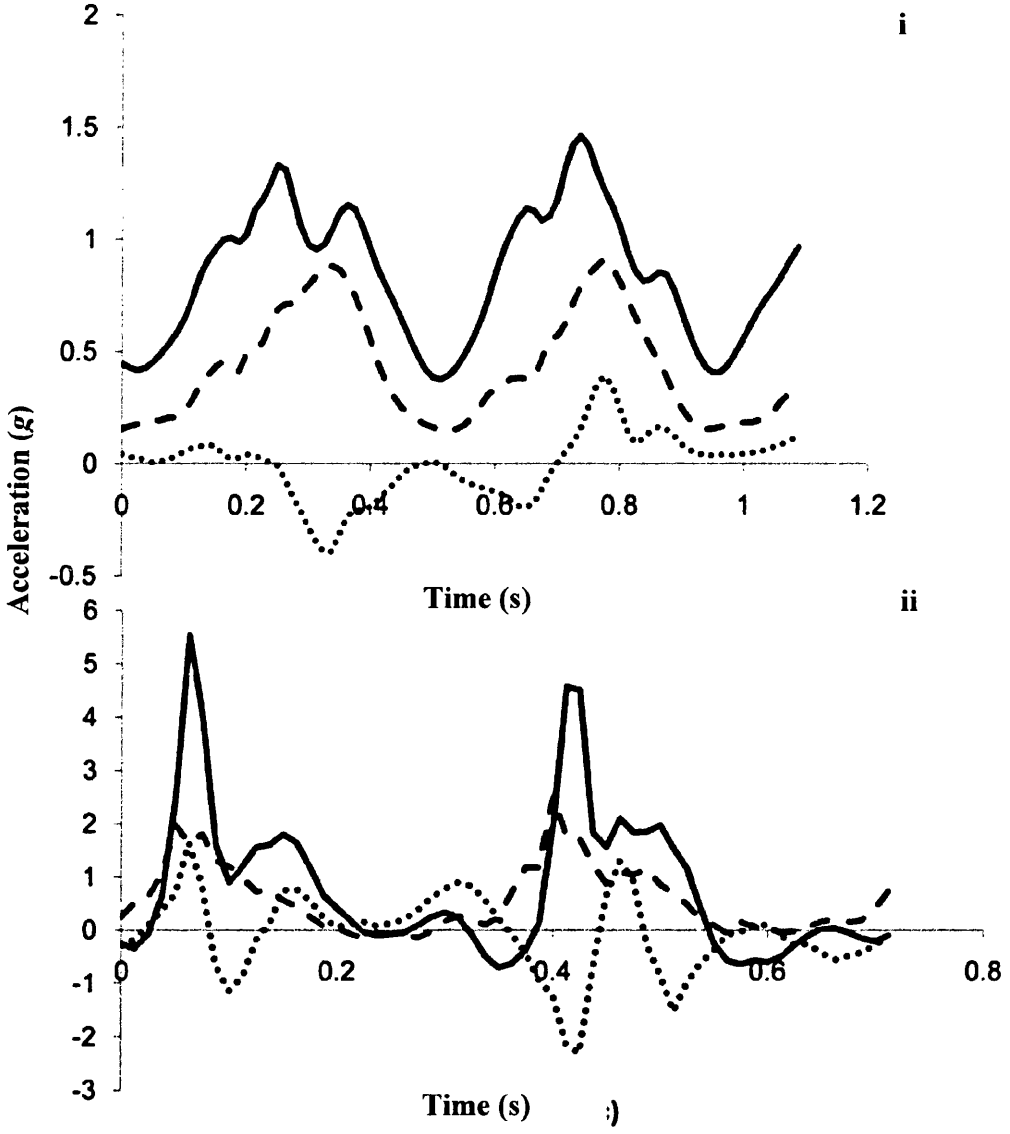


Figure 4.1. Tri-acceleration data over one stride from each leg during; i) walking and ii) running: heave (continuous line), sway (dotted line) and surge (dashed line).

4.3 *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$

The following set of results define the statistical relationship and differences between *overall dynamic body acceleration* (*ODBA*) and *vectorial dynamic body acceleration* (*VeDBA*) in an attempt to ascertain which is the best predictor of *volume of oxygen uptake* ($\dot{V}O_2$).

4.3.1 The relationship between *ODBA* and *VeDBA* metrics

ODBA and *VeDBA* were highly correlated with each other when data from all logger mountings was combined and for each logger mounting separately. For all scenario's, $p = 0.000$ (Table 4.1 and Fig. 4.2).

4.3.2 The difference between *ODBA* and *VeDBA* metrics

ODBA was significantly greater than *VeDBA* when data from all logger mountings was combined and for each logger mounting separately. In all cases, $p = 0.000$ (*t*-test, Table 4.2).

CV ODBA was significantly greater than *CV VeDBA* when data from all logger mountings were combined, for the straight-mounted logger alone ($p = 0.000$; Wilcoxon's test, Table 4.3) and for the skew-mounted logger ($p = 0.000$; *t*-test, Table 4.2)

CV VeDBA was significantly greater than *CV ODBA* for the hip-mounted logger ($p = 0.000$; Wilcoxon's test, Table 4.3).

4.3.3 The relationship between $\dot{V}O_2$ and *ODBA* & $\dot{V}O_2$ and *VeDBA*

Both *ODBA* and *VeDBA* were highly correlated with $\dot{V}O_2$ in all scenarios (data from all logger mounting combined and for each logger mounting separately). In all cases, $p = 0.000$ (Table 4.4 and Fig 4.3).

4.3.4 The difference between the coefficients of determination (r^2) for the relationships between $\dot{V}O_2$ and *ODBA* & $\dot{V}O_2$ and *VeDBA*

The coefficients of determination (r^2) for the relationship between $\dot{V}O_2$ and *ODBA* was significantly greater than r^2 for the relationship between $\dot{V}O_2$ and *VeDBA* for data from all logger mountings combined and for the skew-mounted logger (p = 0.002 and p = 0.020, respectively; t-test, Table 4.5).

The differences between r^2 for the relationship between $\dot{V}O_2$ and *ODBA* and r^2 for the relationship between $\dot{V}O_2$ and *VeDBA* were non significant for both the straight and the hip-mounted devices (p = 0.052 and p = 0.143, respectively; Wilcoxon's test, Table 4.6).

4.3.5 Analysis of confidence intervals

These results relate to the 95% confidence intervals for the difference between r^2 for the relationship between $\dot{V}O_2$ and *ODBA,* and r^2 for the relationship between $\dot{V}O_2$ and *VeDBA.*

For both the straight and skew-mounted loggers the 95% confidence intervals represent less than 1% of mean r^2 values for the relationships between: $\dot{V}O_2$ and $ODBA_{straight}$, $\dot{V}O_2$ and $VeDBA_{straight}$, $\dot{V}O_2$ and $ODBA_{skew}$ as well as $\dot{V}O_2$ and $VeDBA_{skew}$, respectively (Table 4.5 - 4.7). The 95% confidence interval for the hip-mounted logger represent less than 1.5% of mean r^2 values for the relationship both $\dot{V}O_2$ *versus* $ODBA_{hip}$ and $\dot{V}O_2$ *versus* $VeDBA_{hip}$ (Table 4.6 and Table 4.7).

Table 4.1. Coefficients of determination (r^2) and significance levels for the relationship between ODBA and VeDBA (all: n =21, straight: n = 21, skew: n = 20, hip: n = 20).

	r^2	P
$ODBA_{all}$ *plotted against* $VeDBA_{all}$	0.989	0.000
$ODBA_{straight}$ *plotted against* $VeDBA_{straight}$	0.998	0.000
$ODBA_{skew}$ *plotted against* $VeDBA_{skew}$	0.997	0.000
$ODBA_{hip}$ *plotted against* $VeDBA_{hip}$	0.997	0.000

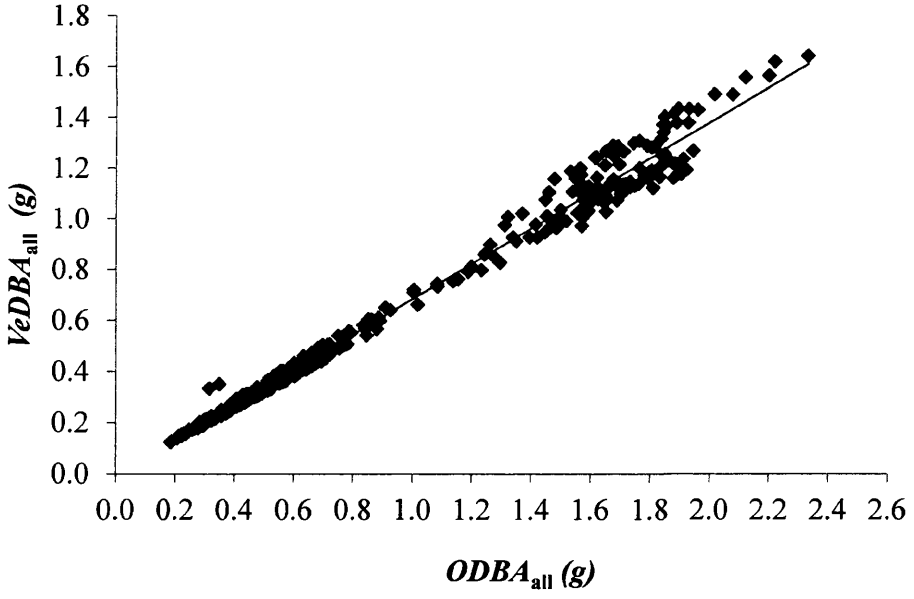


Figure 4.2. $ODBA_{all}$ plotted against $VeDBA_{all}$ (n = 21)

(ODBA = VeDBA 1.426 + 0.025, r^2 = 0.989, $p < 0.001$).*

Table 4.2. Results of paired samples t-tests between ODBA and VeDBA metrics & CV ODBA and CV VeDBA metrics (all: n =21, straight: n = 21, skew: n = 20, hip: n = 20).

CI = confidence interval of the difference, t = t-test statistic, df = degrees of freedom, p = significance level for a paired samples t-test statistic (significant at p > 0.05)

	Difference between the means (*g*)	95% CI		*t*	*df*	*p*
		Lower	Upper			
$ODBA_{all}$ *versus* $VeDBA_{all}$	0.27583	0.25797	0.29368	30.364	415	0.000
$ODBA_{straight}$ *versus* $VeDBA_{straight}$	0.27359	0.24402	0.30317	18.280	148	0.000
$ODBA_{skew}$ *versus* $VeDBA_{skew}$	0.29346	0.25738	0.32955	16.083	135	0.000
$ODBA_{hip}$ *versus* $VeDBA_{hip}$	0.26005	0.23328	0.28682	19.219	130	0.000
CV $ODBA_{skew}$ *versus CV* $VeDBA_{skew}$	0.01108	0.00666	0.01459	4.963	135	0.000

Table 4.3. Results of Wilcoxon's matched pairs tests between CV ODBA and CV VeDBA metrics (all: n =21, straight: n = 21, skew: n = 20, hip: n = 20).

T = lowest score from negative and positive ranks, z = z-score for the Wilcoxon statistic, p = significance level for t-test statistic (significant at p > 0.05)

	T	*z*	*p*
CV $ODBA_{all}$ *versus CV* $VeDBA_{all}$	162	-3.914	0.000
CV $ODBA_{straight}$ *versus CV* $VeDBA_{straight}$	42	-5.070	0.000
CV $ODBA_{hip}$ *versus CV* $VeDBA_{hip}$	44	-3.914	0.000

Table 4.4. Coefficients of determination (r^2) and significance levels for the relationship between $\dot{V}O_2$ and ODBA & $\dot{V}O_2$ and VeDBA (all: n =21, straight: n = 21, skew: n = 20, hip: n = 20).

	All logger mountings		Straight		Skewed		Hip	
	r^2	*p*	r^2	*p*	r^2	*p*	r^2	*p*
$\dot{V}O_2$ *plotted against ODBA*	0.789	0.000	0.790	0.000	0.777	0.000	0.822	0.000
$\dot{V}O_2$ *plotted against VeDBA*	0.780	0.000	0.797	0.000	0.782	0.000	0.825	0.000

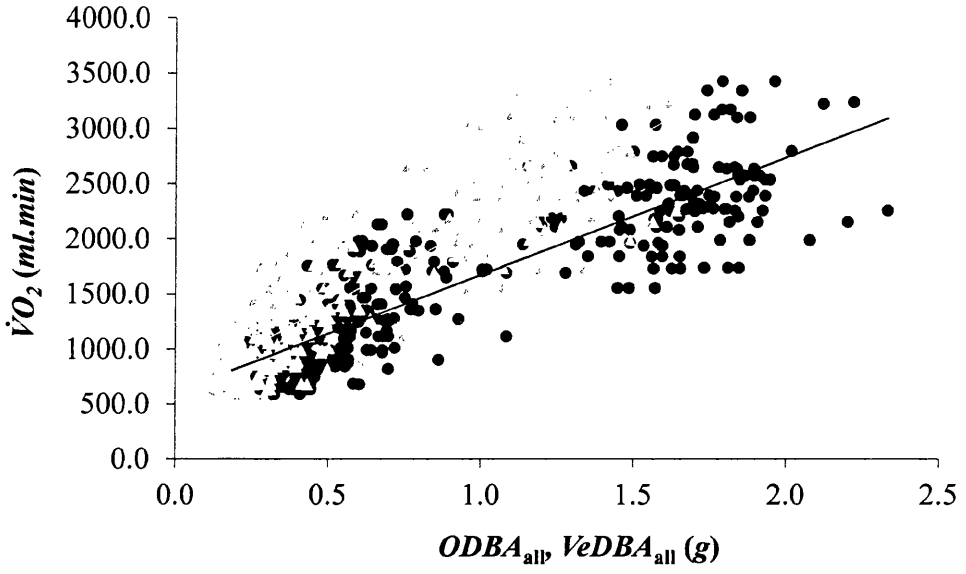


Figure 4.3. $\dot{V}O_2$ *plotted against* $ODBA_{all}$ *(black circles) and* $VeDBA_{all}$ *(grey triangles) (n = 21).*

($\dot{V}O_2 = 1063.778*ODBA + 607.82$, $r^2 = 0.789$, $p = 0.000$*)*

($\dot{V}O_2 = 1516.476*VeDBA + 633.680$, $r^2 = 0.780$, $p = 0.000$*)*

Table 4.5. Results of paired samples t-tests between the coefficient of determination (r^2) for the relationship between $\dot{V}O_2$ and ODBA & $\dot{V}O_2$ and VeDBA (all: n =21, straight: n = 21, skew: n = 18, hip: n = 18).

CI = confidence interval of the difference, t = t-test statistic, df = degrees of freedom, p = significance level for a paired samples t-test statistic (significant at p > 0.05)

	Difference between the means (*g*)	95% CI		*T*	*df*	*p*
		Lower	Upper			
r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{all}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{all}$)	0.0034	0.00133	0.00545	3.300	55	0.002
r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{skew}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{skew}$)	0.0028	0.00049	0.00507	2.557	17	0.020

Table 4.6. Results of Wilcoxon's matched pairs tests between the coefficient of determination (r^2) for the relationship between $\dot{V}O_2$ and ODBA & $\dot{V}O_2$ and VeDBA (all: n =21, straight: n = 21, skew: n = 18, hip: n = 18).
T = lowest score from negative and positive ranks, z = z-score for the Wilcoxon statistic, p = significance level for t-test statistic (significant at p > 0.05)

	T	*z*	*p*
r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{straight}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{straight}$)	2	-1.941	0.052
r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{hip}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{hip}$)	1	1.466	0.143

Table 4.7. Means of the coefficient of determination (r^2) for the relationship between $\dot{V}O_2$ and ODBA & $\dot{V}O_2$ and VeDBA regressions (all: n =21, straight: n = 21, skew: n = 18, hip: n = 18).

	Mean r^2
$\dot{V}O_2$ *plotted against* $ODBA_{straight}$	0.9467
$\dot{V}O_2$ *plotted against* $VeDBA_{straight}$	0.9433
$\dot{V}O_2$ *plotted against* $ODBA_{skew}$	0.9422
$\dot{V}O_2$ *plotted against* $VeDBA_{skew}$	0.9394
$\dot{V}O_2$ *plotted against* $ODBA_{hip}$	0.9559
$\dot{V}O_2$ *plotted against* $VeDBA_{hip}$	0.9518

4.4 *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$ in relation to device orientation (straight *versus* skew logger)

The following set of results define the statistical relationship and differences between the straight and skew-mounted logger data for *ODBA* and *VeDBA* in attempt to ascertain if device orientation affects which *DBA* metric is the best predictor of $\dot{V}O_2$.

4.4.1 The relationship between the straight-mounted and skew-mounted logger data

ODBA values from the straight-mounted devices were highly correlated with the *ODBA* values from the skew-mounted devices, as were *VeDBA* values from the straight- and skew-mounted devices. In both cases $p = 0.000$ (Figure 4.7).

4.4.2 The difference between the straight-mounted and skew-mounted logger

The skew-mounted logger produced significantly greater values than the straight-mounted logger for both *ODBA* and *VeDBA* ($p = 0.000$ and $p = 0.002$, respectively; *t*-test, Table 4.8).

There was no significant difference between the *CV* of the straight data compared to the skewed data for either *ODBA* or *VeDBA* metrics ($p = 0.666$ and $p = 0.306$, respectively; *t*-tests, Table 4.8).

4.4.3 The difference between the coefficients of determination (r^2) for the relationship between $\dot{V}O_2$ and data from the straight-mounted logger & $\dot{V}O_2$ and data from the skew-mounted logger

There were no significant differences between r^2 ($\dot{V}O_2$ *versus* $ODBA_{straight}$) and r^2 ($\dot{V}O_2$ *versus* $ODBA_{skew}$) as well as for r^2 ($\dot{V}O_2$ *versus* $VeDBA_{straight}$) and r^2 ($\dot{V}O_2$ *versus* $VeDBA_{skew}$). $p = 0.707$ and $p = 0.508$, respectively (*t*-test, Table 4.9).

4.4.4 The effect of the straight logger subsequently skewing

The differences between $ODBA_{subskew}$ and $VeDBA_{subskew}$, $\dot{V}O_2$ $ODBA_{subskew}$ and $\dot{V}O_2$ $VeDBA_{subskew}$ as well as % $\dot{V}O_2$ $ODBA_{subskew}$ and % $\dot{V}O_2$ $VeDBA_{subskew}$ were not significant (Table 4.10). This indicates that there is no difference between *ODBA* and *VeDBA* in terms of the error created if the straight-mounted logger subsequently skewed (i.e. *DBA* data from the skew-mounted logger was used to predict $\dot{V}O_2$ using the straight-mounted logger regression equation).

The percentage change in predicted $\dot{V}O_2$ created if the straight-mounted logger subsequently skewed was 1.4% for *ODBA* and 1.3% for *VeDBA*(% $\dot{V}O_2$ $ODBA_{subskew}$ and % $\dot{V}O_2$ $VeDBA_{subskew}$, respectively).

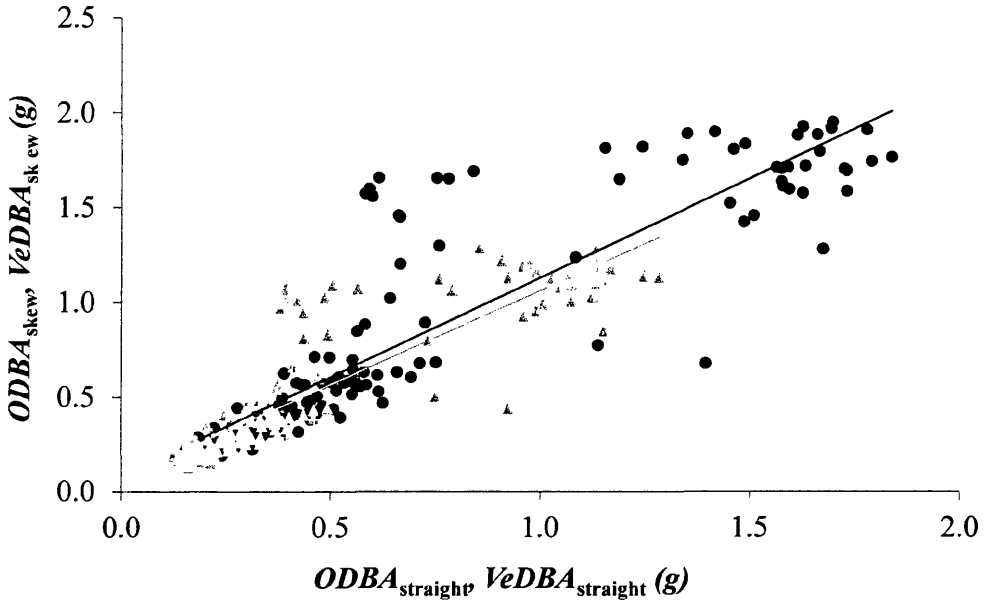


Figure 4.4. $ODBA_{straight}$ *plotted against* $ODBA_{skew}$ *(black circles) and* $VeDBA_{straight}$ *plotted against* $VeDBA_{skew}$ *(grey triangles) (n = 20).*

($ODBA_{straight} = 0.752*ODBA_{skew} + 0.093$, $r^2 = 0.787$, $p = 0.000$*)*

($VeDBA_{straight} = 0.791*VeDBA_{skew} + 0.049$, $r^2 = 0.783$, $p = 0.000$*)*

Table 4.8. Results of paired samples t-tests between straight-mounted and skew-mounted loggers for both ODBA and VeDBA & CV ODBA and CV VeDBA (n=20).

CI = confidence interval of the difference, t = t-test statistic, df = degrees of freedom, p = significance level for a paired samples t-test statistic (significant at p > 0.05).

	Difference between the means (*g*)	95% CI		*T*	*df*	*p*
		Lower	Upper			
$ODBA_{straight}$ *versus* $ODBA_{skew}$	-0.02631	-0.03517	-0.01746	-5.880	132	0.000
$VeDBA_{straight}$ *versus* $VeDBA_{skew}$	-0.00726	-0.01191	-0.00263	-3.096	132	0.002
CV $ODBA_{straight}$ *versus CV* $ODBA_{skew}$	-0.00126	-0.00701	0.00449	-0.432	132	0.666
CV $VeDBA_{straight}$ *versus CV* $VeDBA_{skew}$	0.00459	-0.00424	0.01341	1.028	132	0.306

Table 4.9. Results of paired samples t-tests between the coefficient of determination (r^2) for the relationship between $\dot{V}O_2$ and straight data & $\dot{V}O_2$ and skew data) for both ODBA and VeDBA metrics (n= 18).

CI = confidence interval of the difference, t = t-test statistic, df = degrees of freedom, p = significance level for a paired samples t-test statistic (significant at p > 0.05)

	Difference between the means (*g*)	95% CI		*T*	*df*	*p*
		Lower	Upper			
r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{straight}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{skew}$)	-0.0011	-0.00723	0.00501	-0.383	17	0.707
r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{straight}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{skew}$)	-0.0022	-0.00916	0.00472	-0.676	17	0.508

Table 4.10. Results of paired samples t-tests between ODBA and VeDBA metrics that represent the effect of the straight-mounted logger subsequently skewing (n=18).

CI = confidence interval of the difference, t = t-test statistic, df = degrees of freedom, p = significance level for a paired samples t-test statistic (significant at p > 0.05)

	Difference between the means (*g*)	95% CI		*t*	*df*	*p*
		Lower	Upper			
$ODBA_{subskew}$ *versus* $VeDBA_{subskew}$	-0.01131	-0.00729	0.00088	-1.653	17	0.117
$\dot{V}O_2$ $ODBA_{subskew}$ *versus* $\dot{V}O_2$ $VeDBA_{subskew}$	-0.02420	-0.00548	0.00486	-0.127	17	0.900
% $\dot{V}O_2$ $ODBA_{subskew}$ *versus* $\dot{V}O_2$ $VeDBA_{subskew}$	0.10622	-0.35522	0.56768	0.486	17	0.633

4.5 *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$ in relation to device placement (straight *versus* waist logger)

The following set of results define the statistical relationship and differences between the straight and hip-mounted logger data for *ODBA* and *VeDBA* in attempt to ascertain if device orientation affects which *DBA* metric is the best predictor of $\dot{V}O_2$.

4.5.1 The relationship between the straight-mounted and hip-mounted logger

ODBA values from the straight-mounted devices were highly correlated with the *ODBA* values from the hip-mounted devices, as were *VeDBA* values from the straight and hip-mounted devices. In both cases, $p = 0.000$ (Figure 4.5).

4.5.2 The difference between the straight-mounted and hip-mounted logger

The hip-mounted loggers produced significantly larger values than the straight-mounted loggers for both *ODBA* and *VeDBA*. For both metrics, $p = 0.000$ (*t*-test, Table 4.11).

The hip-mounted logger also produced significantly greater *CV* than the straight-mounted logger for both *ODBA* and *VeDBA*. For both metrics, $p = 0.000$ (*t*-test, Table 4.11).

4.5.3 The difference between the coefficients of determination (r^2) for the relationship between $\dot{V}O_2$ and data from the straight-mounted logger & $\dot{V}O_2$ and data from the hip-mounted logger

There were no significant difference between r^2 ($\dot{V}O_2$ *versus* $ODBA_{straight}$) and r^2 ($\dot{V}O_2$ *versus* $ODBA_{hip}$) as well as r^2 ($\dot{V}O_2$ *versus* $VeDBA_{straight}$) and r^2 ($\dot{V}O_2$ *versus* $VeDBA_{hip}$). $p = 0.273$ and $p = 0.328$, respectively (*t*-test, Table 4.12).

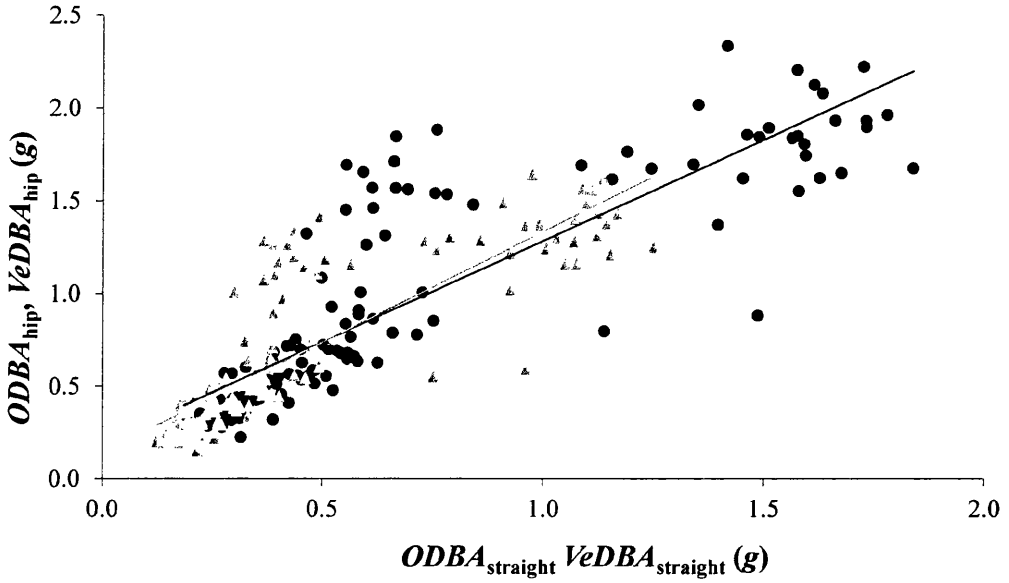


Figure 4.5. $ODBA_{straight}$ plotted against $ODBA_{hip}$ (black circles) and $VeDBA_{straight}$ plotted against $VeDBA_{hip}$ (grey triangles)(n = 20).

($ODBA_{straight} = 0.682*ODBA_{hip} + 0.044$, $r^2 = 0.744$, $p = 0.000$)

$VeDBA_{straight} = 0.612*VeDBA_{hip} + 0.037$, $r^2 = 0.739$, $p = 0.000$)

Table 4.11. Results of paired samples t-tests between the straight-mounted and hip-mounted logger data for both ODBA and VeBDA & CV ODBA and CV VeDBA (n=20).

CI = confidence interval of the difference, t = t-test statistic, df = degrees of freedom, p = significance level for a paired samples t-test statistic (significant at p > 0.05)

	Difference between the means (*g*)	95% CI		*t*	*df*	*p*
		Lower	Upper			
$ODBA_{straight}$ *versus* $ODBA_{hip}$	-0.09952	-0.11756	0.08148	10.921	122	0.000
$VeDBA_{straight}$ *versus* $VeDBA_{hip}$	-0.13285	-0.13285	-0.10692	-18.304	122	0.000
CV $ODBA_{straight}$ *versus CV* $ODBA_{hip}$	-0.06009	-0.08007	-0.04012	-5.956	122	0.000
CV $VeDBA_{straight}$ *versus CV* $VeDBA_{hip}$	-0.07318	-0.09408	-0.05228	-6.931	122	0.000

Table 4.12. Results of paired samples t-tests between the coefficient of determination (r^2) for the relationship between $\dot{V}O_2$ and straight data & $\dot{V}O_2$ and hip data for both ODBA and VeBDA metrics (n=17).

CI = confidence interval of the difference, t = t-test statistic, df = degrees of freedom, p = significance level for a paired samples t-test statistic (significant at p > 0.05)

	Difference between the means (g)	95% CI		*t*	*df*	*p*
		Lower	Upper			
r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{straight}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $ODBA_{hip}$)	-0.0106	-0.03037	0.00920	-1.134	16	0.273
r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{straight}$) *versus* r^2 ($\dot{V}O_2$ *plotted against* $VeDBA_{hip}$)	-0.0094	-0.02920	0.01037	-1.008	16	0.328

4.6 Assessment of the methods of imputing missing values

The following set of results define the statistical relationship and differences between the data sets produced using the three methods of computing missing values. In addition, the differences between the three methods of computing missing values and raw data in terms of the r^2 values obtained when plotting $\dot{V}O_2$ against $ODBA_{all}$ and $\dot{V}O_2$ against $VeDBA_{all}$ is shown. The aim is to ascertain whether using data sets with computed missing values improves the ability of *ODBA* and/or *VeDBA* to predict $\dot{V}O_2$ and, if this does occur, which method of commuting missing values elicits the greatest improvement.

Average values for each method of imputing missing values can be seen in Fig. 4.6. and 4.7.

4.6.1 The relationship between all paired combinations of the methods of imputing missing values

Regressions for all paired combinations of the methods of imputing missing values for both $ODBA_{all}$ and $VeDBA_{all}$ produced extremely high and significant coefficients of determination. For all combinations, $p = 0.000$ (Table 4.13 and Figures 4.8 – 4.13).

Bland and Altman plots showed that mean differences for all paired combinations for both $ODBA_{all}$ and $VeDBA_{all}$ were extremely close to zero (Table 4.14). However, on all six plots, 15 or more data points where outside of the 95% confident intervals (Figures 4.14 – 4.19).

For both $ODBA_{all}$ and $VeDBA_{all}$, *IR – SA* produced the smallest mean difference and *IR – JMP* produced the smallest confidence intervals (Table 4.14 and Figures 4.14 – 4.19).

4.6.2 The differences between *IR* DBA_{all}, *SA* DBA_{all} and *JMP* DBA_{all}

The results of the one-way repeated measure *ANOVA* show that there is no significant main effect of the methods of imputing missing values on the computed $ODBA_{all}$ and $VeBDA_{all}$ values for all participants (Table 4.15).

4.6.3 Differences in the coefficients of determination (r^2) between the relationship for $\dot{V}O_2$ and DBA_{all}, $\dot{V}O_2$ and *IR* DBA_{all}, $\dot{V}O_2$ and *SA* DBA_{all} & *JMP* $\dot{V}O_2$ and DBA_{all}

The results of the one-way repeated measure *ANOVA* show that there is no significant main effect of the methods of obtaining *DBA* (i.e. *IR*, *SA*, *JMP* and raw data) on the r^2 values for $\dot{V}O_2$ *versus* $ODBA_{all}$ and $\dot{V}O_2$ *versus* $VeDBA_{all}$ (Table 4.16).

However, both the *SA* and *JMP* method elicited a higher r^2 values than the raw data for $\dot{V}O_2$ *versus* $ODBA_{all}$ and $\dot{V}O_2$ *versus* $VeDBA_{all}$ (Table 4.17).

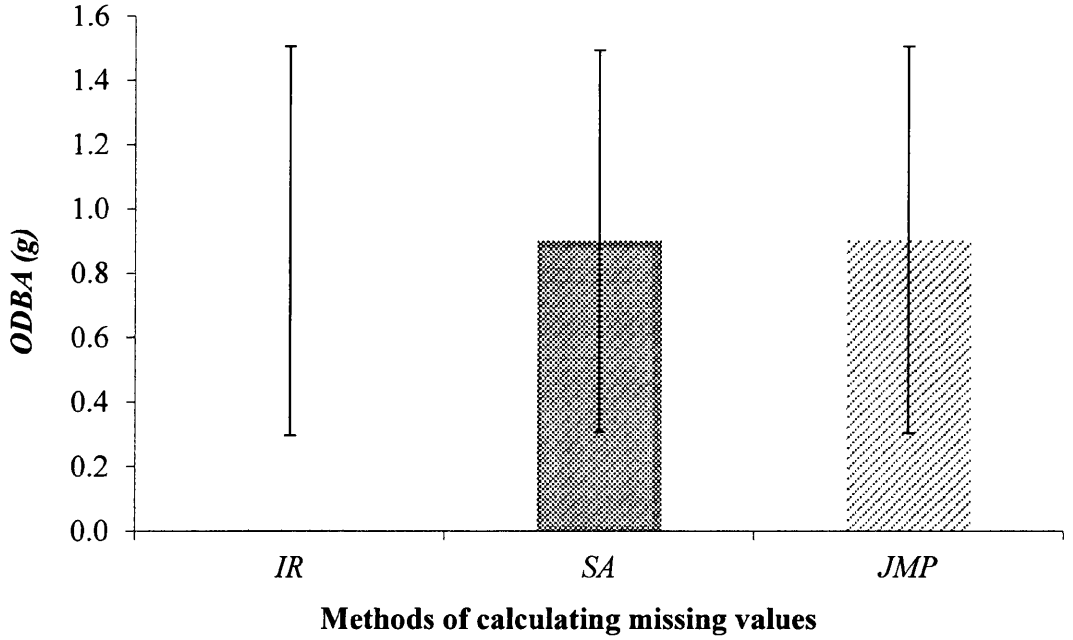


Figure 4.6. Average values ± standard deviation for each method of imputing missing values using $ODBA_{all}$ data.(n = 18).

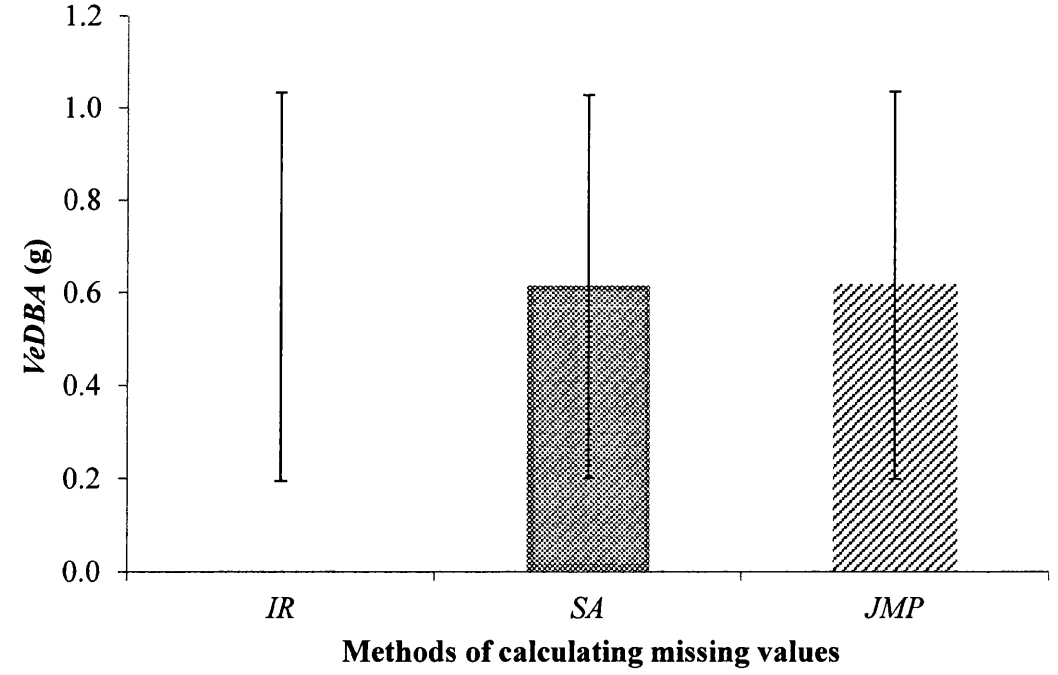


Figure 4.7. Average values ± standard deviation for each method of imputing missing values using $VeDBA_{all}$ data.(n = 18).

Table 4.13. Coefficients of determination and significance levels for all paired combinations of the methods of imputing missing values for $ODBA_{all}$ and $VeDBA_{all}$.

r^2 = coefficient of determination, p = significance level for regression equation (significant at $p > 0.05$)

All Data	r^2	P
$ODBA_{all}$ *IR plotted against* $ODBA_{all}$ *SA*	0.960	0.000
$ODBA_{all}$ *SA plotted against* $ODBA_{all}$ *JMP*	0.984	0.000
$ODBA_{all}$ *JMP plotted against* $ODBA_{all}$ *IR*	0.985	0.000
$VeDBA_{all}$ *IR plotted against* $VeDBA_{all}$ *SA*	0.965	0.000
$VeDBA_{all}$ *SA plotted against* $VeDBA_{all}$ *JMP*	0.985	0.000
$VeDBA_{all}$ *JMP plotted against* $VeDBA_{all}$ *IR*	0.986	0.000

Table 4.14. Bland and Altman variables; mean difference and limits of agreement (mean difference + 2sd and mean difference – 2sd) for all paired combinations of the three methods of imputing missing values.

	Mean Difference (g)	Mean Difference + 2sd (g)	Mean Difference – 2sd (g)
$ODBA_{all}$ *SA - ODBA*$_{all}$ *JMP*	-0.00431	0.14981	-0.15843
$ODBA_{all}$ *IR - ODBA*$_{all}$ *SA*	0.00068	0.24305	-0.24168
$ODBA_{all}$ *IR - ODBA*$_{all}$ *JMP*	-0.00363	0.14612	-0.15338
$VeDBA_{all}$ *SA -VeDBA*$_{all}$ *JMP*	-0.00292	0.09845	-0.10429
$VeDBA_{all}$ *IR - VeDBA*$_{all}$ *SA*	-0.00005	0.15690	-0.15701
$VeDBA_{all}$ *IR - VeDBA*$_{all}$ *JMP*	-0.00297	0.09461	-0.10056

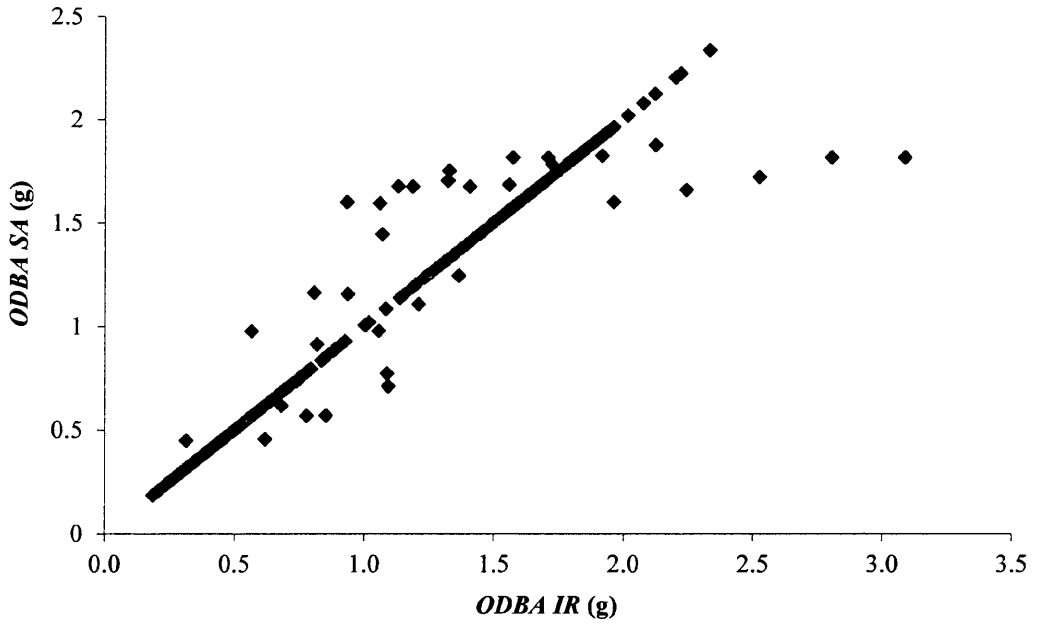


Figure 4.8. ODBA SA plotted against ODBA JMP (n = 18). The data points that follow the straight line represent the original values and data points that are scattered about the straight line represent predicted values.
*(ODBA SA = 0.978*ODBA JMP + 0.015, r^2 = 0.984, p =0.000)*

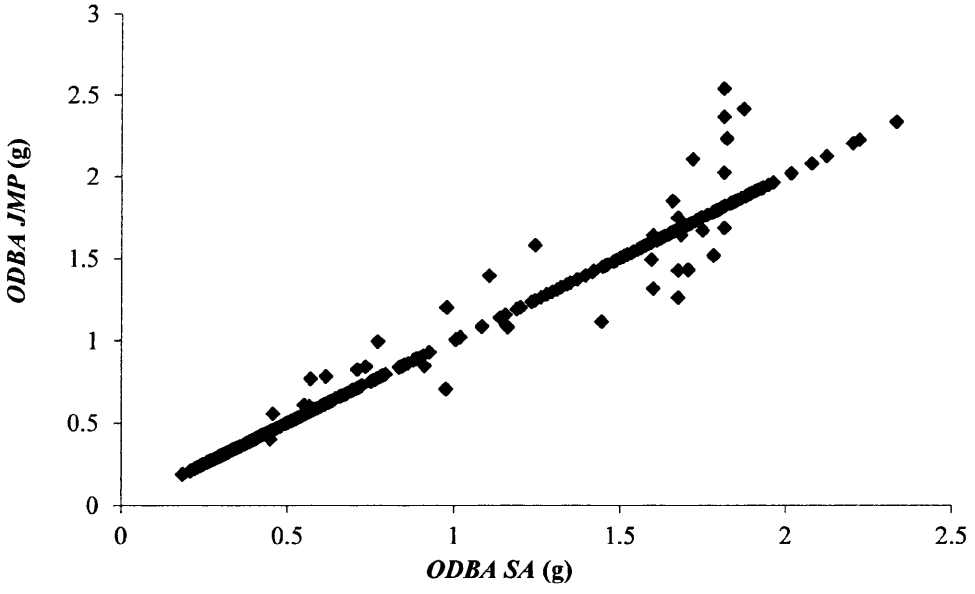


Figure 4.9. ODBA IR plotted against ODBA SA (n = 18). The data points that follow the straight line represent the original values and data points. that are scattered about the straight line represent predicted values.
*(ODBA IR = 0.999*ODBA SA + 0.001, r^2 = 0.960, p =0.000)*

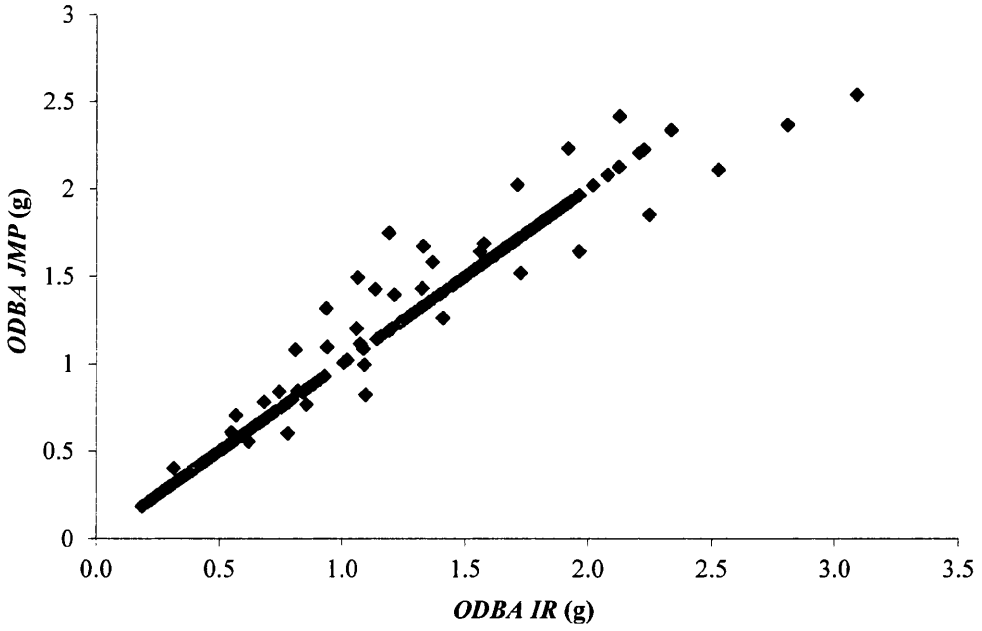


Figure 4.10. ODBA IR plotted against ODBA JMP (n = 18). The data points that follow the straight line represent the original values and data points that are scattered about the straight line represent predicted values.
*(ODBA JMP = 0.986*ODBA IR + 0.016, r^2 = 0.985, p =0.000)*

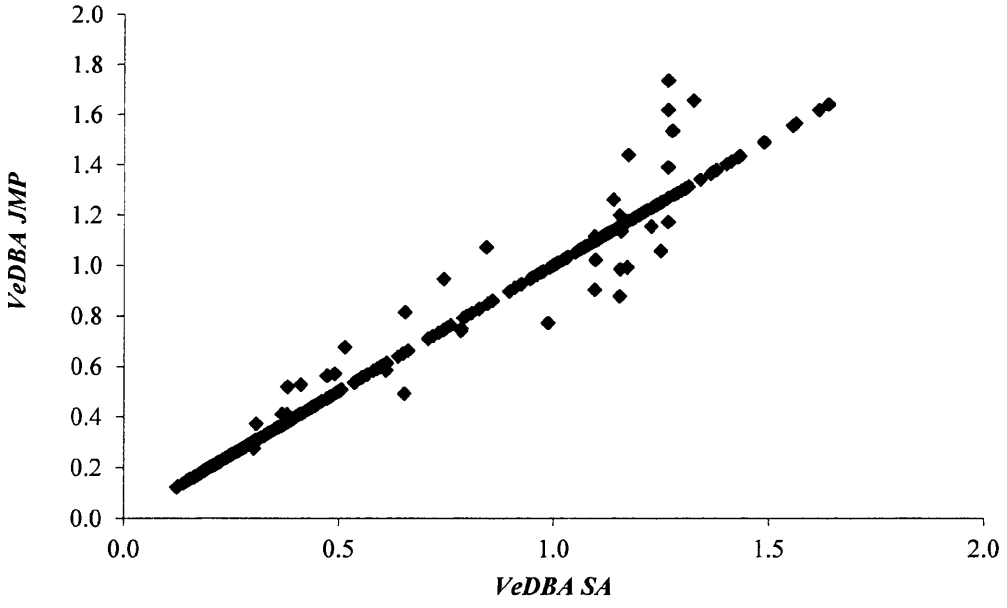


Figure 4.11. VeDBA SA versus VeDBA JMP (n = 18). The data points that follow the straight line represent the original values and data points that are scattered about the straight line represent predicted values.
*(VeDBA SA = 0.981*VeDBA JMP + 0.009, r^2 = 0.985, p =0.000).*

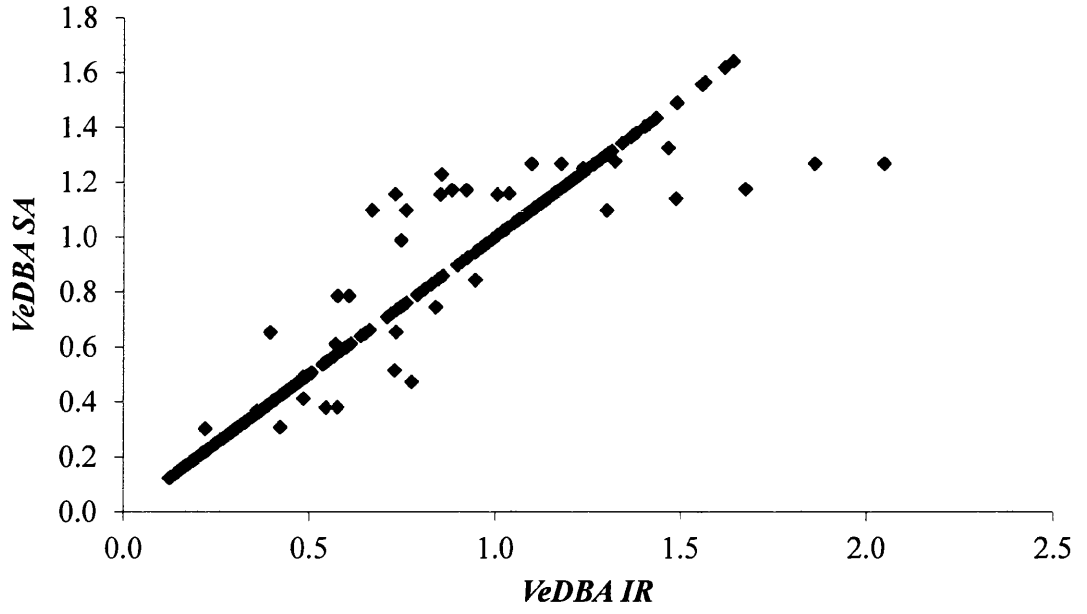


Figure 4.12. VeDBA IR versus VeDBA SA (n = 18). The data points that follow the straight line represent the original values and data points that are scattered about the straight line represent predicted values.
*(VeDBA IR = 0.996*VeDBA SA + 0.003, r^2 = 0.965, p =0.000)*

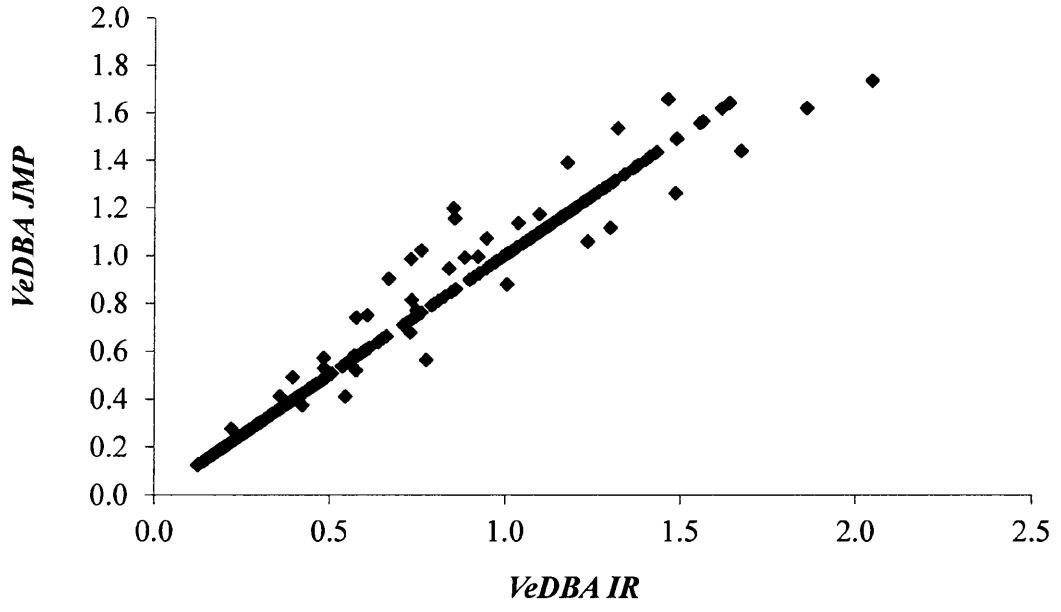


Figure 4.13. VeDBA IR versus VeDBA JMP (n = 18). The data points that follow the straight line represent the original values and data points that are scattered about the straight line represent predicted values.
*(VeDBA JMP = 0.991*VeDBA IR + 0.008, r^2 = 0.986, p =0.000)*

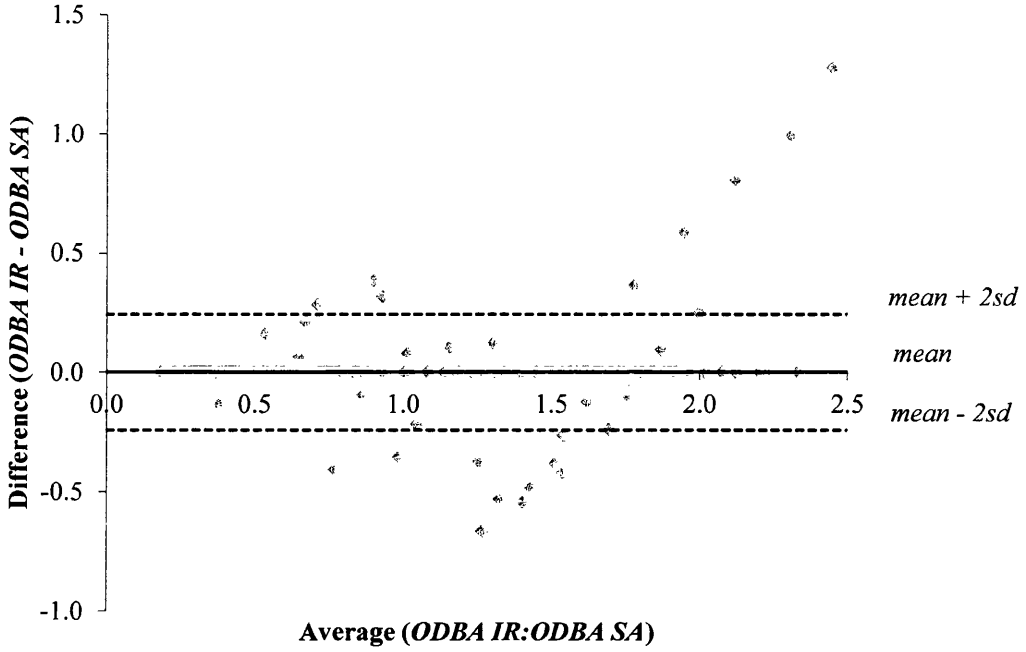


Figure 4.14. Bland and Altman Plot for ODBA IR and ODBA SA (n = 18).

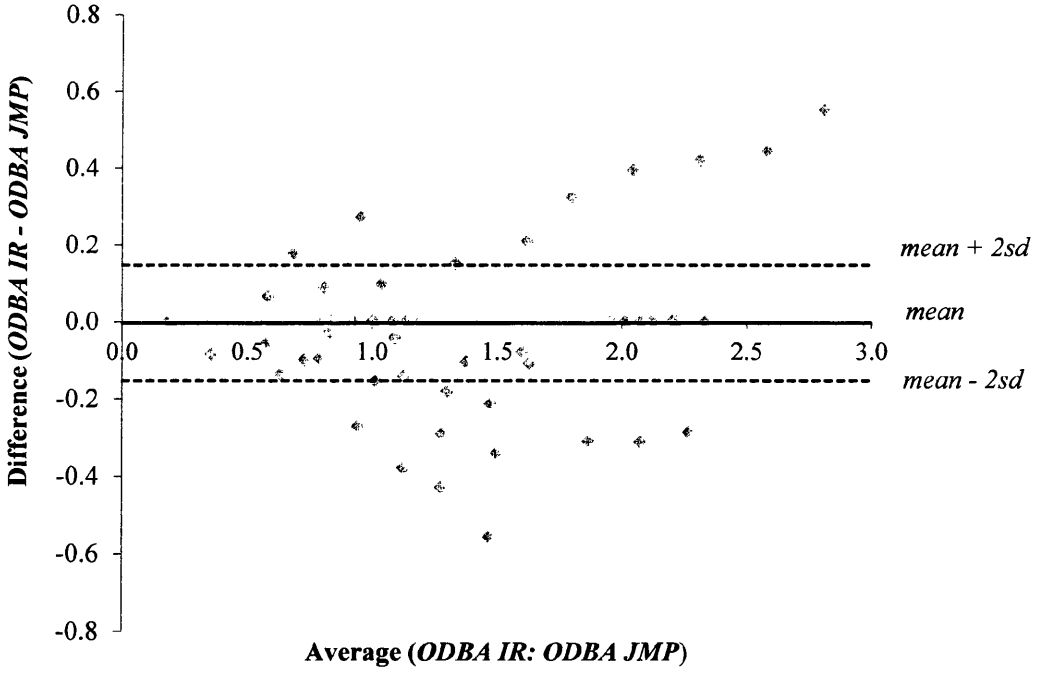


Figure 4.15. Bland and Altman Plot for ODBA IR and ODBA JMP (n = 18).

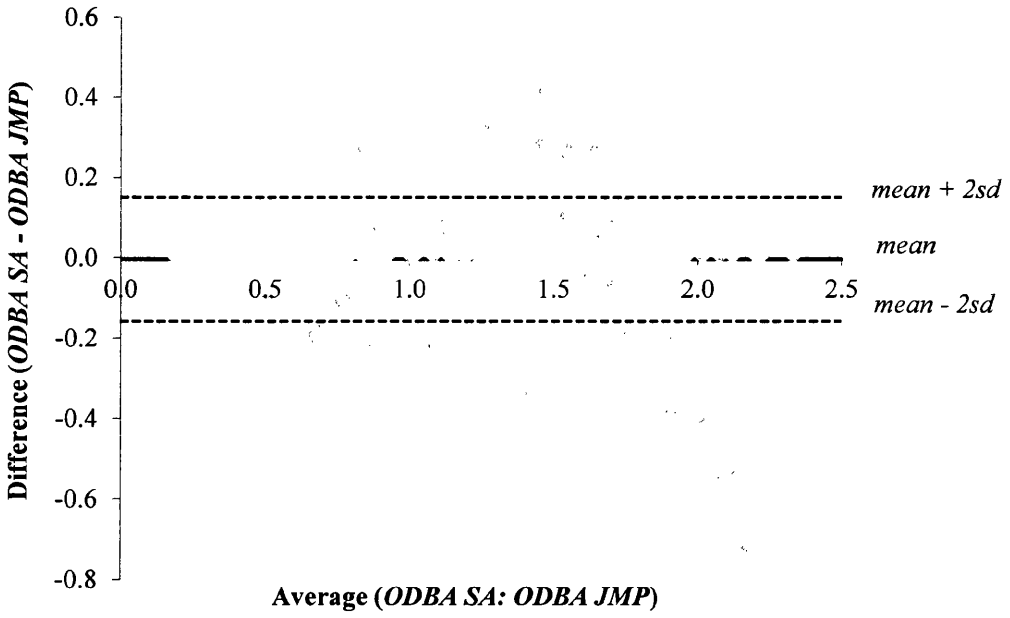


Figure 4.16. Bland and Altman Plot for ODBA SA and ODBA JMP (n = 18).

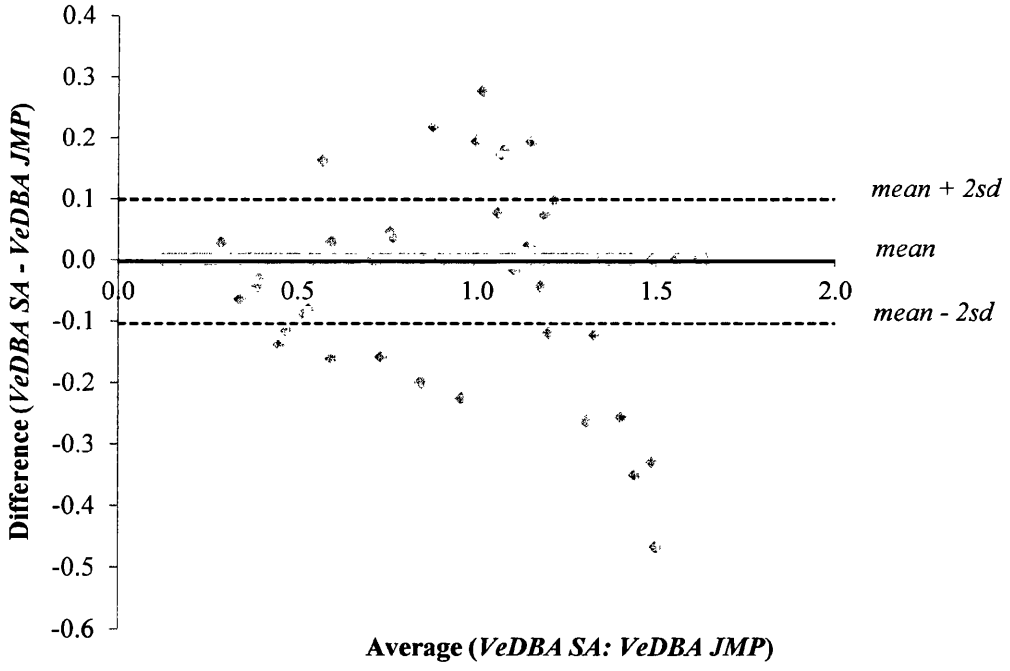


Figure 4.17. Bland and Altman Plot for VeDBA SA and VeDBA JMP (n = 18).

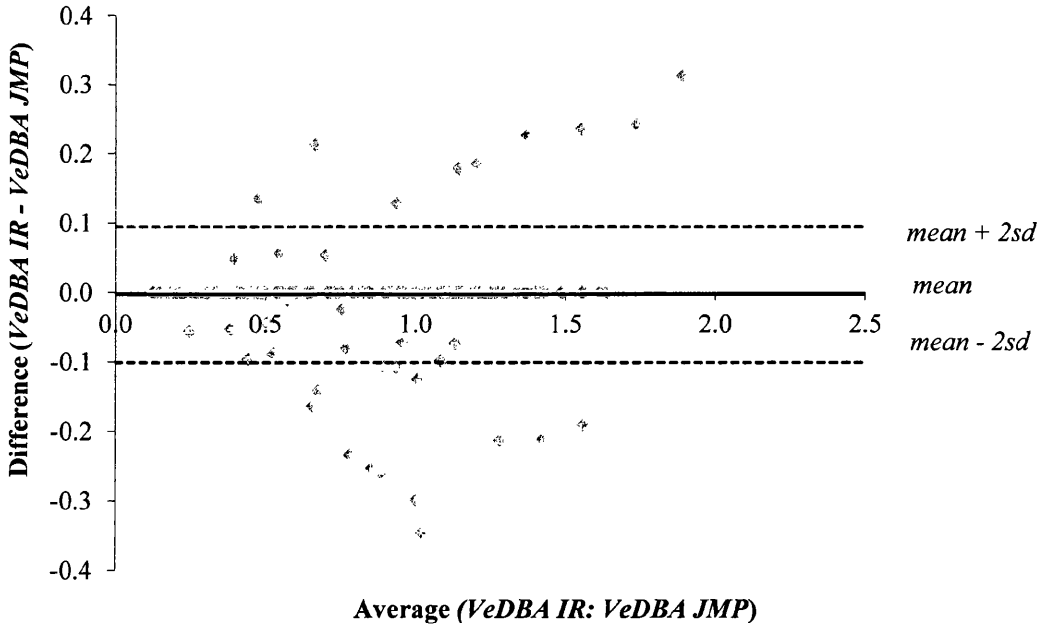


Figure 4.18. Bland and Altman Plot for VeDBA SA and VeDBA JMP (n = 18).

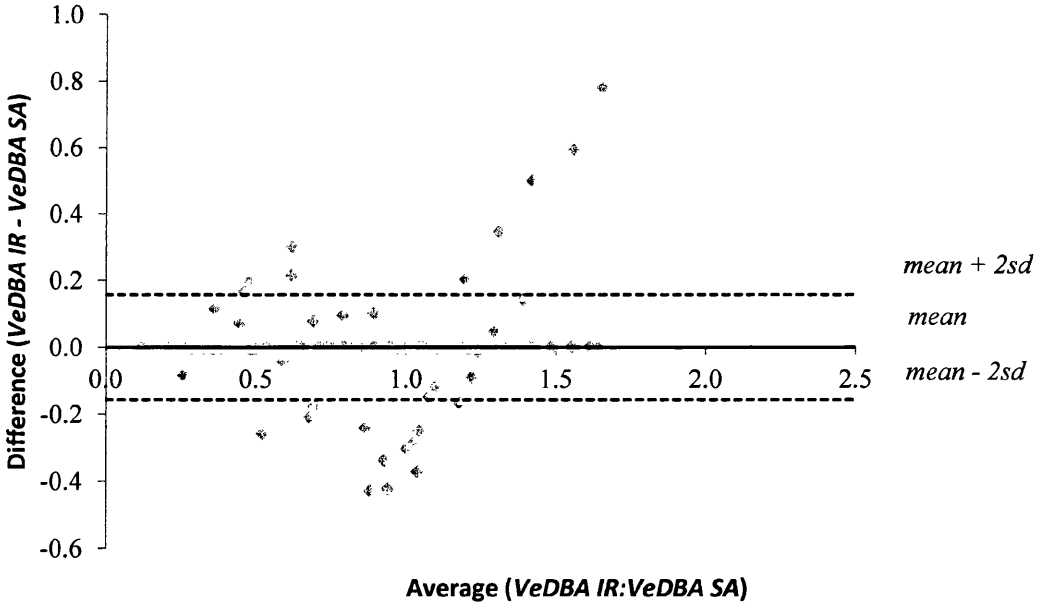


Figure 4.19. Bland and Altman Plot for VeDBA IR and VeDBA SA (n = 18).

Table 4.1.5 Results of a one way repeated measures ANOVA comparing DBA_{all} IR, DBA_{all} SA and DBA_{all} JMP data sets (n = 21).

df = degrees of freedom, F = statistic, p = significance level (significant at p > 0.05)

	Tests of Within-Subjects Effects		
	Sphericity Assumed		
	df	*F*	*p*
$ODBA_{all}$	2	0.555	0.574
$VeDBA_{all}$	2	0.706	0.494

Table 4.16. Results of a one way repeated measures ANOVA to compare the relationship between $\dot{V}O_2$ and DBA_{all} IR, $\dot{V}O_2$ and DBA_{all} SA & $\dot{V}O_2$ and DBA_{all} JMP.

W = Mauchly's W, df = degrees of freedom, F = statistic, p = significance level (significant at p > 0.05)

	Tests of Within-Subjects Effects		
	Sphericity Assumed		
	df	*F*	*p*
$\dot{V}O_2$ *versus* $ODBA_{all}$	3	1.632	0.191
$\dot{V}O_2$ *versus* $VeDBA_{all}$	3	0.833	0.481

Table 4.17. Regression equations for the relationship between $\dot{V}O_2$ and $ODBA_{all}$ & $\dot{V}O_2$ and $VeDBA_{all}$ for IR, SA, JMP and raw data (n =21).

	IR	*SA*	*JMP*	*raw data*
$ODBA_{all}$	$\dot{V}O_2 = 1067.871*VeDBA_{all} + 26.731$	$\dot{V}O_2 = 1104.690*ODBA_{all} + 25.828$	$\dot{V}O_2 = 1088.971*VeDBA_{all} + 25.568$	$\dot{V}O_2 = 1063.778*ODBA_{all} + 27.017$
	$r^2 = 0.781$	$r^2 = 0.803$	$r^2 = 0.801$	$r^2 = 0.789$
$VeDBA_{all}$	$\dot{V}O_2 = 1533.455*VeDBA_{all} + 39.036$	$\dot{V}O_2 = 1575.555*VeDBA_{all} + 37.669$	$\dot{V}O_2 = 1556.358*VeDBA_{all} + 37.368$	$\dot{V}O_2 = 1516.476*VeDBA_{all} + 39.583$
	$r^2 = 0.774$	$r^2 = 0.795$	$r^2 = 0.794$	$r^2 = 0.780$

4.7 Assessment of the most appropriate body composition measurement technique

The following set of results define the statistical relationship and differences between the data produced using the three techniques used to measure body composition in order to ascertain which two methods most closely agreed with one another. The choice between these will then be left to the literature.

Average values for each body composition technique can be seen in Figure 2.20.

4.7.1 The relationship between all paired combinations of body composition techniques

All combinations of paired regressions were significantly correlated (Table 4.18). The *BIA* and *SKF* produced an especially high r^2 value of 0.92).

The Bland and Altman plot graphed for *SKF versus BIA* gave the smallest 95% limits of agreement and mean difference (Table 4.19).

For *BODPOD versus BIA* and *BODPOD versus SKF* one data point lay outside the 95% limits of agreement. For *SKF versus BIA* all data points where within the limits of agreement (Figures 4.21-4.26).

4.7.2 The differences between body composition techniques

The results of the one-way repeated measures *ANOVA* show that percentage body fat is significantly affected by body composition assessment technique (p = 0.014, Table 4.20).

Bonferroni *Post hoc* analysis highlighted significant differences between the *BODPOD* and *BIA* (p = 0.041) but not between the *BODPOD* and *SKF* or *SKF* and *BIA* (Table 4.21). The *BODPOD* produced significantly larger values for percentage body fat than the *BIA*.

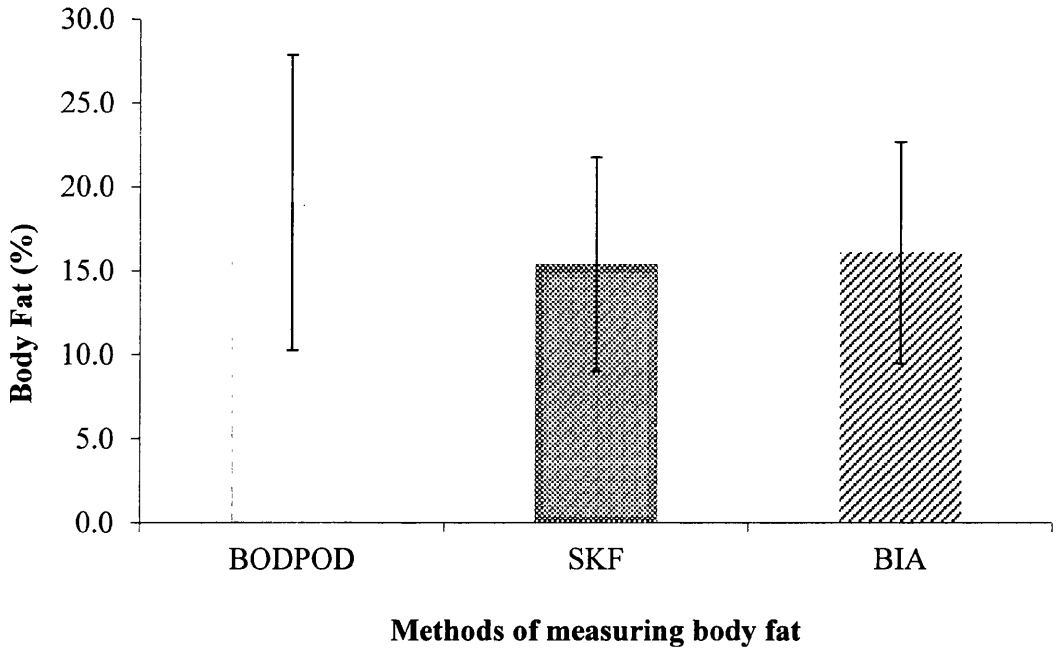


Figure 4.20. Average values ± standard deviation for each method of assessing percentage body fat (n = 18).

Table 4.18. Coefficients of determination and significance levels for all paired combinations of body composition assessment techniques.

All Data	r^2	*P*
BODPOD plotted against SKF	0.590	0.000
BODPOD plotted against BIA	0.736	0.000
SKF plotted against BIA	0.920	0.000

Table 4.19. Bland and Altman variables; mean difference and limits of agreement (mean difference + 2sd and mean difference – 2sd) for all paired combinations of body composition assessment techniques.

	Mean Difference (%)	Mean Difference + 2sd (%)	Mean Difference – 2sd (%)
BODPOD versus SKF	3.51	14.77	-7.76
BODPOD versus BIA	3.00	12.24	-6.24
SKF versus BIA	0.51	4.31	-3.29

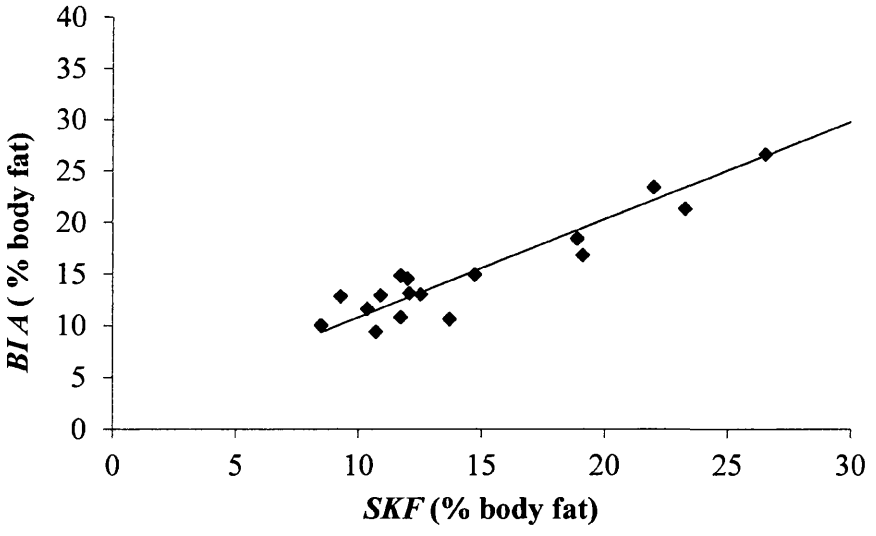


Figure 4.21. SKF versus BIA (n = 18).
*(SKF = 0.014 + BIA*0.968, r^2 = 0.92, p = 0.000)*

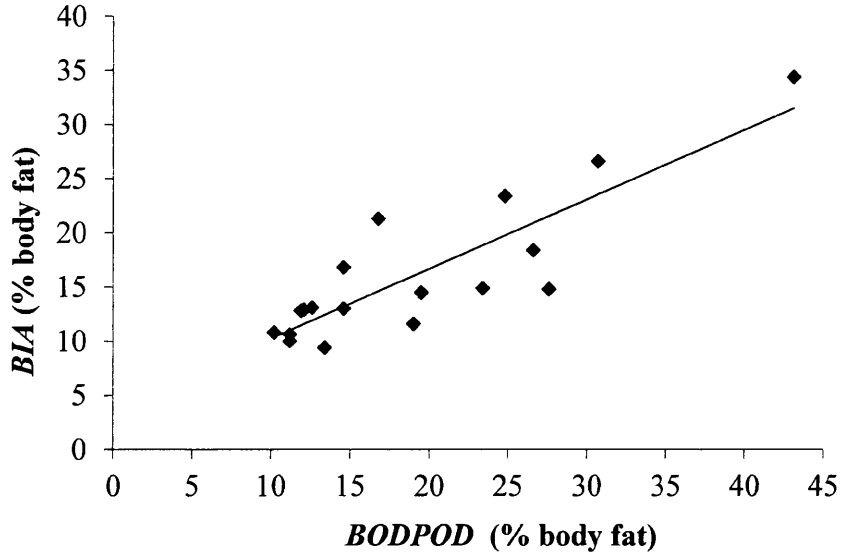


Figure 4.22. BODPOD versus BIA (n = 18).
*(BODPOD = 0.655 + 1.146*BIA, r^2 = 0.736, p = 0.000)*

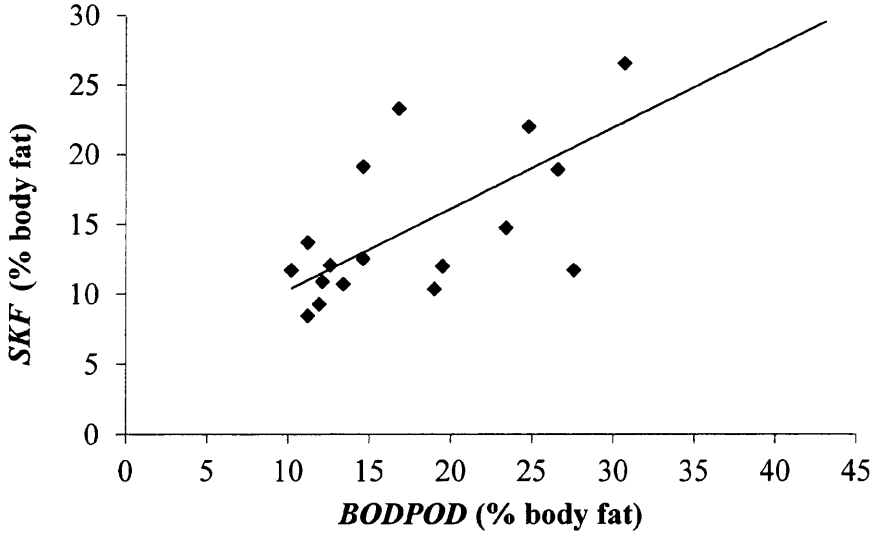


Figure 4.23. BODPOD versus SKF (n = 18).
*(BODPOD = 3.242 + SKF*1.017, r^2 = 0.590, p = 0.000)*

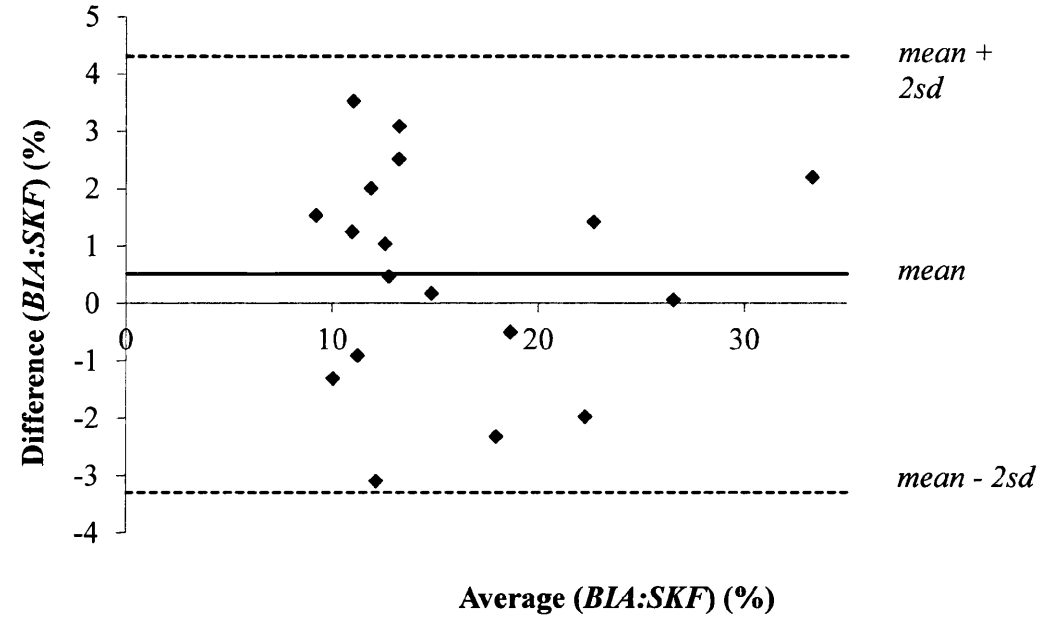


Figure 4.24. Bland and Altman Plot for BIA and SKF (n = 18).

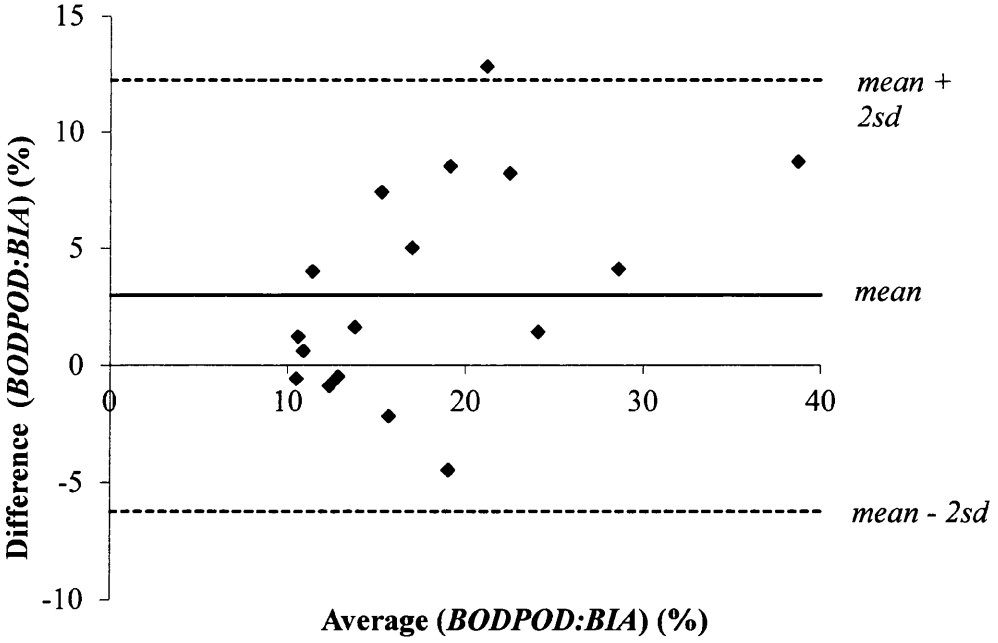


Figure 4.25. Bland and Altman Plot for BODPOD and BIA (n = 18).

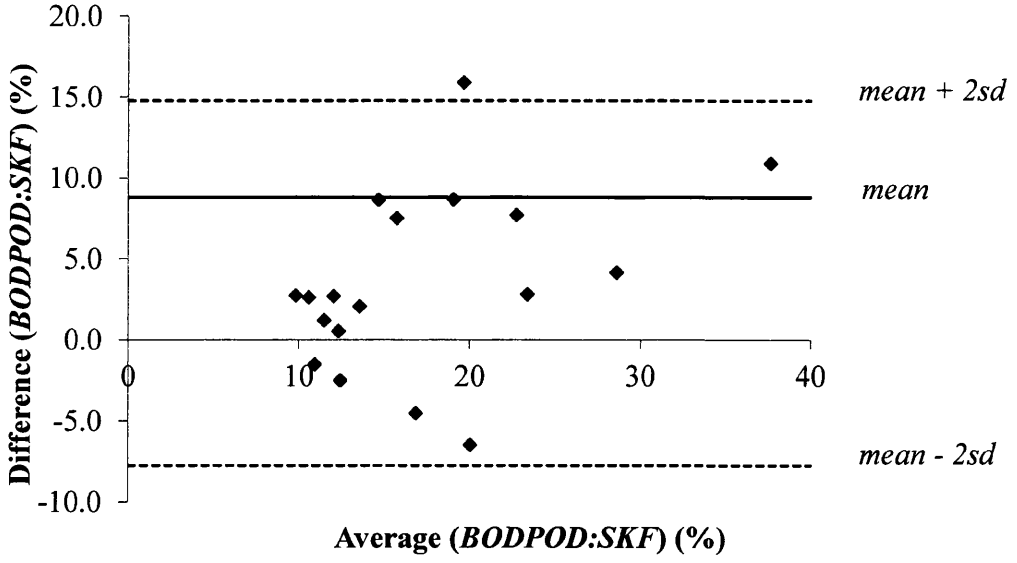


Figure 4.26. Bland and Altman Plot for BODPOD and SKF (n = 18).

Table 4.20. Results of a one way repeated measures ANOVA to comparing BODPOD, BIA and SKF.

W = Mauchly's W, df = degrees of freedom, F = statistic, p = significance level (significant at p > 0.05)

Mauchly's test of sphericity			Tests of Within-Subjects Effects		
			Greenhouse-Geisser		
W	*df*	*p*	*df*	*F*	*p*
0.243	2	0.000	1.138	6.842	0.014

Table 4.21. Results of the Bonferroni Post hoc analysis for the one way repeated measures ANOVA comparing BODPOD, BIA and SKF.

Factor1	Factor2	Mean Difference	*P*
BODPOD	*SKF*	3.506	0.052
SKF	*BIA*	-0.506	0.819
BIA	*BODPOD*	-3.000	0.041

4.8 The influence of body anthropometrics, body composition and aerobic capacity on the relationship between *DBA* and $\dot{V}O_2$

Note: In this section, ODBA has been used as an example however the conclusions were the same for VeDBA (see Appendix 7.11).

The influence of anthropometric, body composition and aerobic capacity variables on the linear regression equations for $\dot{V}O_2$ *versus* $ODBA_{straight}$ and $\dot{V}O_2$ *versus* $ODBA_{hip}$ were assessed in order to ascertain whether the addition of any of these variables would strengthen the ability of *ODBA* to predict $\dot{V}O_2$.

Fat mass was determined via the skinfold method. The skinfold method was chosen over the *BODPOD* and *BIA* using the following reasoning. The *BODPOD* was immediately eliminated as it had the highest standard deviation. Furthermore, when used in combination with the *BIA* and *SKF* lower r^2 values and higher mean differences were produced in comparison to *SKF* against *BIA* (see section 4.7).

The *BIA* was later eliminated due to the over reliance on anthropometric variables (Oates et al., 2006). Furthermore, there is a greater amount of pre-test requirements than *SKF*, making *SKF* a more practical method to implement for the present population.

Age (years), *leg length* (m), *height* (m), *weight* (kg), *waist to hip ratio*, *fat-free mass* (kg), *fat mass* and $\dot{V}O_2$ *max* ($ml.min^{-1}$) were considered in the models.

4.8.1 $\dot{V}O_2$ *versus* $ODBA_{straight}$

Weight was not included in the model as it is directly related to *FM* and *FFM. Height* was eliminated due to collinearity. All other variables were entered into the model and any variables that were not contributing significantly to the model were removed. This process occurred so that one variable was removed at a time and the model re-run each time a variable was eliminated. The variables were removed in order of the least significant contributor first; i) *Leg Length, ii)* $\dot{V}O_2$ *max and iii) Waist to Hip Ratio.*

$ODBA_{straight}$ ($p = 0.000$), *Age* ($p = 0.000$), *FFM* ($p = 0.000$) and *FM* ($p = 0.008$) were all significant predictors of $\dot{V}O_2$ (Table 4.22 and 4.23).

4.8.2 $\dot{V}O_2$ *versus* $ODBA_{hip}$

Weight was not included in the model as it is directly related to *FM* and *FFM. Height* and *Waist to Hip Ratio* were eliminated due to collinearity. All other variables were entered into the model and any variables that were not contributing significantly to the model were removed. This process occurred so that one variable was removed at a time and the model re-run each time a variable was eliminated. The variables were removed in order of the least significant contributor first; i) $\dot{V}O_2$ *max, ii) Leg Length.*

$ODBA_{straight}$ ($p = 0.000$), *Age* ($p = 0.001$), *FFM* ($p = 0.000$) and *FM* ($p = 0.004$) were all significant predictors of $\dot{V}O_2$ (Table 4.24 and 4.25).

Table 4.22. A model of all significant predictors of $\dot{V}O_2$ including $ODBA_{straight}$ data (n = 18).

Model	Unstandardised Coefficients B	Standardised Coefficients Beta	*P*
(Constant)	255.116		0.225
$ODBA_{straight}$	1273.352	0.775	0.000
Age	-36.696	-0.277	0.000
FFM	16.531	0.357	0.000
FM	11.726	0.148	0.008

Table 4.23. Regression equations for the relationship between $\dot{V}O_2$ and all significant predictors including $ODBA_{straight}$ (n = 18).

$\dot{V}O_2$ *versus* all significant predictors	$\dot{V}O_2$ *versus* $ODBA_{straight}$
$\dot{V}O_2 = 255.116 +$ $(ODBA_{straight}*1273.352) - (Age*36.696) +$ $(FFM*16.531) + (FM*11.726)$ $r^2 = 0.758, p = 0.000$	$\dot{V}O_2 =$ $1262.452*ODBA_{straight} + 523.639$ $r^2 = 0.590, p = 0.000$

Table 4.24. Model of all significant predictors of $\dot{V}O_2$ including $ODBA_{hip}$ data (n = 14).

Model	Unstandardised Coefficients B	Standardised Coefficients Beta	*p*
(Constant)	-178.403		-0.807
$ODBA_{hip}$	1194.570	0.825	0.000
Age	-25.338	-0.200	0.001
FFM	17.402	0.358	0.000
FM	11.986	0.168	0.004

Table 4.25. Regression equations for $\dot{V}O_2$ using all significant predictors including $ODBA_{hip}$ (n=18).

$\dot{V}O_2$ *versus* all significant predictors	$\dot{V}O_2$ *versus* $ODBA_{straight}$
$\dot{V}O_2$ = -178.403 + ($ODBA_{hip}$*1194.570) - (*Age**25.338) + (*FFM**17.402) + (*FM**11.986) $r^2 = 0.799, p = 0.000$	$\dot{V}O_2 = ODBA_{hip}$*117.086 + 374.377 $r^2 = 0.662, p = 0.000$

Chapter 5

Discussion

5.1 Dynamic body acceleration as a proxy for $\dot{V}O_2$

The use of *overall dynamic body acceleration* (*ODBA)* and *vectorial dynamic body acceleration* (*VeDBA*) in human research is relatively new, and subsequently there are very few studies in which direct comparisons can be drawn. Instead the main focus of this study was to attempt to quantify the value in using *ODBA* and/or *VeDBA* over traditional acceleration metrics such as accelerometer 'counts' and to postulate the exact difference between *ODBA* and *VeDBA* in terms of their ability to act as a proxy for *energy expenditure* (*EE*). Furthermore, the study sought to explore the influence of body anthropometrics, body composition and aerobic capacity on the relationship between *dynamic body acceleration* (*DBA*) and *EE*. The influence of anthropometric and physiological factors has rarely been considered alongside *DBA*.

Firstly, this study demonstrates that regardless of the metric used (*ODBA* or *VeBDA*), *DBA* has proven to be an excellent proxy for *volume of oxygen uptake* ($\dot{V}O_2$). For example, the coefficient of determination (r^2) for the relationship between mean $\dot{V}O_2$ and mean *ODBA* for all logger mountings (straight, skew and hip) was 0.79, for the upper back (straight only) was 0.79 and for the hip was 0.82. The coefficients of determination for the relationship between mean $\dot{V}O_2$ and mean *VeDBA* were also similar at 0.78, 0.80 and 0.83, respectively.

5.2 *ODBA* as a proxy for $\dot{V}O_2$

In the present study, although r^2 for the association between $\dot{V}O_2$ and *ODBA* for combined logger mountings were high (e.g. $r^2 = 0.79$), it is still considerably lower than a comparable study by Halsey, et al. (2008) where $r^2 = 0.90$ for the upper back, $r^2 = 0.92$ for the lower back and $r^2 = 0.91$ for the neck (single regressions, $n = 10$). This is despite exactly the same metrics, respiratory equipment, exercise protocol and very similar population characteristics between the two studies.

Moreover, regression equation for $\dot{V}O_2$ plotted against *ODBA* from a later paper by Halsey, et al. (2009) that re-used the acceleration data from the neck for 6 of the participants from Halsey, et al. (2008), was plotted in comparison to the present study. Clear differences in both the slope and intercept of the relationship between $\dot{V}O_2$ and

ODBA were visible (Fig.5.1). It is possible that this could be linked to aerobic fitness. McGregor, et al. (2009) found that trained individuals gave greater r^2 values between $\dot{V}O_2$ and *VeDBA* than untrained (r^2 = 0.96 to r^2 = 0.92). However, Halsey, et al. (2008) did not report $\dot{V}O_2$ max values therefore a conclusion can not be made. Additionally, it is possible that small differences in data processing techniques, such that the present study only used $\dot{V}O_2$ data under the gas exchange threshold (see section 2.15.2 for definition) and Halsey, et al. (2009) used the entire data set may further explain differences in slope and intercept between the studies, however, without more studies for comparison, norms cannot be established.

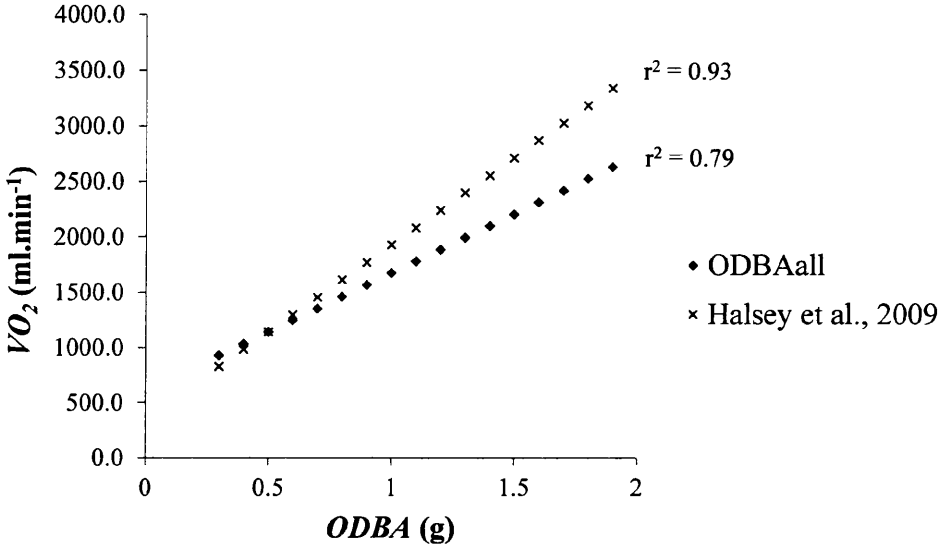


Figure 5.1 $\dot{V}O_2$ *(ml.min^{-1}) plotted against ODBA (g) using the regression equation from the present study (based on straight, skew and hip- mounted logger data combined i.e.* $ODBA_{all}$ *from 21 subjects) and the regression equation stated in Halsey, et al. (2009) (based on neck mounted logger data from 6 subjects). The* $\dot{V}O_2$ *and ODBA ranges are guidelines only and do not reflect the exact values in either study.*

$ODBA_{all}$: $\dot{V}O_2 = 1063.778 * ODBA_{all} + 607.082$, $r^2 = 0.79$, $p = 0.000$;

Halsey, et al. (2009): $\dot{V}O_2 = 1569 * ODBA + 355$, $r^2 = 0.93$

In addition, subsequent to the present research, a newly published study by Weippert, et al. (2012) has considered the relationship between $\dot{V}O_2$ and *ODBA* in humans. This study reports an r^2 value of 0.82 for the association between $\dot{V}O_2$ ($ml.kg^{-1}.min^{-1}$) and *ODBA* (*mG*) from an accelerometer placed on the chest during seven activities (supine, seated, seated mental arithmetic, seated writing, seated sorting books and walking at 4kph, walking at 6 kph and running at 8 kph on a treadmill). Direct comparison to the present study is not possible due to the differing metrics and activities. However the results do suggest that it might be possible to use only one single regression for $\dot{V}O_2$ plotted against *DBA* for activities of daily living (including those that require mainly upper body movement) and locomotive activity. This is unusual of studies using counts where combined activities have presented coefficients of determination of only 0.35 (Howe, Staudenmayer and Freedson, 2009) and 0.38 (Hendelman, et al., 2000).
In evaluation alongside other species, due to little evidence in humans, the coefficient of determination in the present study was not unusual but did fall in the lower range. For example, the coefficient of determination for $\dot{V}O_2$ plotted against *ODBA* for great cormorants was reported at 0.81 (Halsey, et al., 2009), bantam chickens at 0.82 (Halsey, et al., 2009), coypus at 0.91 (Halsey, et al., 2009) and cane toads at 0.74 (Halsey, et al., 2010).

When drawing a comparison to other metrics the association between $\dot{V}O_2$ and *ODBA* at the hip will be used (r^2= 0.82) as the majority of studies use this placement.

Unexpectedly, the present study shows that the r^2 for the $\dot{V}O_2$ and *ODBA* relationship for the hip mounted logger during locomotive activity is only slightly better than many comparable studies using accelerometer counts. This includes those using count data from an individual axis (Hendelman, et al., 2000, r^2 = 0.61; Welk, et al., 2000, r^2 = 0.77 and 0.72) or vector magnitude counts (Hendelman, et al., 2000, r^2 = 0.79; Howe, Staudenmayer and Freedson, 2009, r^2 = 0.64).

On the other hand, some studies still show acceleration counts are superior. For example, Welk, et al.(2000) reported an average r^2 of 0.86 between $\dot{V}O_2$ ($ml.kg^{-1}.min^{-1}$) and acceleration counts ($counts.min^{-1}$) for the TriTrac accelerometer over two treadmill walking/running trials with a highest speed similar to that of the present study.

Furthermore, Freedson, Melanson and Sirard, (1998) presented an r^2 of 0.88 between *METS* and acceleration counts; similar walking and jogging speeds to the present study.

5.3 *VeDBA* as a proxy for $\dot{V}O_2$

Similarly to *ODBA, VeDBA* has received little attention in terms of its use as a proxy for $\dot{V}O_2$ so few studies are available for comparison. McGregor, et al. (2009) used a microelectromechanical tri-axial accelerometer in order to assess running mechanics in relation to $\dot{V}O_2$, aerobic fitness and running speed and reported an r^2 value of 0.982 for $\dot{V}O_2$ plotted against *VeDBA,* considerably higher than the r^2 value of 0.79 in the present study.

Likewise to Halsey, et al. (2008), McGregor, et al. (2009) used the entire data set, up until $\dot{V}O_2$ max, which, as mentioned above, may cause small differences. Additionally, aerobic capacity was considerably higher in McGregor, et al. (2009) as 9 out of 18 participants were distance runners with an average $\dot{V}O_2$ max of 70.1± 6.2 $ml.kg^{-1}.min^{-1}$. In the present study, the average $\dot{V}O_2$ max of the fittest 9 participants was 57.0 ± 4.8 $ml.kg^{-1}.min^{-1}$.

Weippert, et al. (2012) reported a much closer r^2 value to the present study i.e. 0.81 for $\dot{V}O_2$ ($ml.kg^{-1}.min^{-1}$) plotted against *VeDBA* (*mG*) although as mentioned above this study includes both activities of daily living and treadmill activity so is not directly comparable.

When considering *VeDBA* in comparison to vector magnitude counts, the results are inconclusive. Reports show largely better (Mahohar, et al., 2011: $r^2 > 0.9$), similar (Hendelman, et al., 2000: $r^2 = 0.80$) and slightly weaker (Howe, et al., 2009: $r^2 = 0.64$) relationships between *EE* and vector magnitude counts.

But, large disparities are present between the studies in terms of the population characteristics, the range of locomotive speeds used and the analysis techniques including *EE* metrics in these studies. For example, locomotive speeds used in Mahohar, et al. (2011) are of slow walking pace only (maximum of 5.6 kph) which are more likely to elicit a strong association between *EE* and acceleration as locomotion is

highly aerobic. Furthermore, Howe, et al. (2009) also included both level and inclined walking, the latter which is known to produce weaker relationships between $\dot{V}O_2$ and *EE*.

5.4 *ODBA versus VeDBA* as a proxy for $\dot{V}O_2$

From a purely physical perspective, *ODBA* and *VeDBA* are derived using the same terms, yet the divergent formulation means that although larger *VeDBA* values will generally accompany larger *ODBA* values, *VeDBA* values will usually be lower than *ODBA*; in fact, *ODBA* can never be smaller than *VeDBA* (Qasem, et al., 2012).

With regard to the spread of data associated with each metric, *ODBA*, on the whole, tends to produce a higher coefficient of variation due to the greater range of values in which *ODBA* uses to represent acceleration in contrast to *VeDBA*. Also, due to the fact that even a small change in device orientation for a given acceleration will affect the values of *ODBA* while leaving *VeDBA* unchanged (see section 5.5).

This study found that for the hip device alone, *VeDBA* produces greater *CV*, which is particularly perplexing. A possible explanation is that hip logger was attached to an elasticated strap which could have shifted slightly particularly during the running stages of the protocol. This would effectively change the placement of the logger which could explain an increase in *CV* (see section 5.6) however this increase would be expected for both *ODBA* and *VeDBA*.

Exactly how much difference there is between *ODBA* and *VeDBA* is depicted by the type of motion, orientation and placement of the devices in relation to the main axes of the body and centre of mass, discussed in detail later in this chapter.

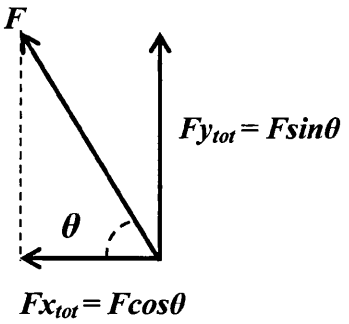
An important finding of this study is the extremely close relationship between *ODBA* and *VeDBA* metrics, with an r^2 of 0.989 for all participants and logger mountings (straight, skew and hip).

In terms of the coefficient of determination (r^2) value, the association between $\dot{V}O_2$ and *DBA* for the straight, skew and hip data separately, indicate *VeDBA* is a marginally

better predictor of $\dot{V}O_2$ (refer to Table 4.7). However, the combined data determines the opposite finding (refer to Table 4.7). In support, Weippert, et al. (2012) also shows *ODBA* is a marginally better predictor of $\dot{V}O_2$ than *VeDBA* ($r^2 = 0.823$ and $r^2 = 0.813$, respectively).

Statistical analysis revealed that based upon all logger mountings and for the skew data only, *ODBA* is a superior predictor of $\dot{V}O_2$ than *VeDBA*. Yet, that fact that no significant differences were found for the straight and hip mountings (the two placements likely to be used in future studies) makes a conclusion rather ominous.

Nevertheless, the general indication that *ODBA* is a stronger predictor has a largely plausible explanation in terms of the structure and function of muscles during movement. *VeDBA* describes movement arc of a single muscle contracting in the same plane as the movement. The theory behind *VeDBA* is based on a pure physics perspective and can be described using a simplified scenario of limb flexion i.e. 'movement of the bones towards each other at a joint by decreasing the angle' (Floyd, et al., 2012, p.387) in a two dimensional plane. For most levers in the body, the upper and lower limb bones are able to articulate with one another and muscles originating from the upper limb are inserted at various angles on the lower limb. In order for flexion to occur, the agonist muscles, the main contracting muscles that are involved in movement, pull the lower limb up toward the upper limb. Each muscle exerts a force which can be broken down into component vectors, force along the y-axis and force along the x-axis. The overall force along each axis can then be computed (Fy_{tot} and Fx_{tot}; Fig. 5.2).



Θ = angle of insertion

F = total muscular force

Figure 5.2. Resolution of force F into perpendicular force components Fx_{tot} and Fy_{tot}.

The following solution is used to describe Fy_{tot};

$$Fy_{tot} = \sum_{i=0}^{n} F_i \sin\theta_i \qquad (5.1)$$

'where the subscripts denote each of the specific muscles with their defined forces and angles of insertion relative to the y-axis of the lower limb' (Qasem, et al., 2012, p.5). The total force along the x-axis can be defined as;

$$Fx_{tot} = \sum_{i=\theta}^{n} F_i \cos\theta_i \qquad (5.2)$$

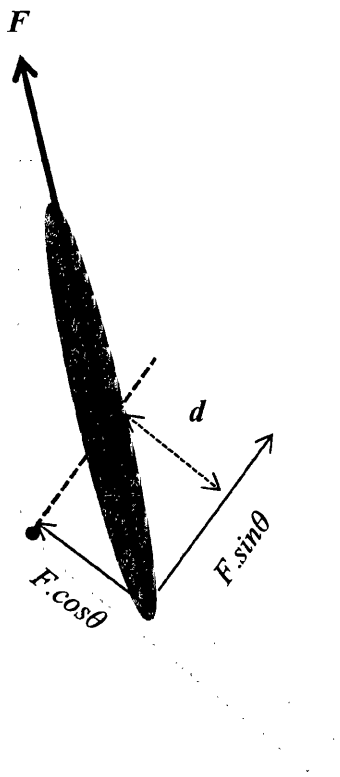


Figure 5.3 Diagrammatic representation of the components of torque; d = distance between fulcrum and muscle insertion, F = force applied along that axis by each muscle, θ = angle of rotation.

The relationship between the force applied by the muscles and the angular acceleration of the lower limb i.e. acceleration through the movement arc is directly related to the torque (τ) along the along the y-axis, defined as the tendency of the lower limb to rotate about the elbow joint toward the upper limb. The torque depends on the force applied along the y-axis by each muscle (Eq. 5.3) and the length of the lever (*d*), defined as 'the perpendicular distance between the line of action of the muscle force and the pivot point of the articulation' (Fig. 5.3; Qasem, et al., 2012);

$$\tau = F \times d \tag{5.3}$$

so that for Fx_{tot} represents the stabilising factor as the line of action is pointing toward the pivot point so;

$$d = 0 \tag{5.4}$$

and therefore;

$$F \text{ x } 0 = 0 \tag{5.5}$$

and Fy_{tot} is represented by;

$$\tau = \sum_{i=0}^{n} F_i d_i \sin\theta_i \tag{5.6}$$

Angular acceleration ($\propto$) and torque is associated via;

$$\alpha = \frac{\tau}{I} \tag{5.7}$$

where I is the moment of inertia, 'the resistance of an object to attempt to change its angular motion' (Watkins et al., 2007, p. 142).

However, the linear acceleration perceived by an accelerometer placed on the lower limb is related to the distance between the fulcrum i.e. joint and the device (r), therefore;

$$a = \frac{r\tau}{I} \tag{5.8}$$

Thus, 'linear acceleration observed from an accelerometer mounted in the y-axis and measuring in the plane of movement can be resolved by substituting equation' (Qasem, et al., 2012, p.5) 5.4 into equation 5.6. to produce;

$$a = \frac{r}{I} \sum_{i=0}^{n} F_i d_i \sin\theta_i \tag{5.9}$$

Still, the matter of concern to biologists with regard to energetics is not the total acceleration but how the *DBA* signal relates to rate of *EE*, and specifically the *EE*

utilised by the muscles involved. This is reflected by the work done (W) during muscular contraction to produce the forces needed for movement and can be denoted as;

$$W = F.\Delta D \tag{5.10}$$

where ΔD is the distance the muscle has contracted. The total amount of work done for all the muscles is;

$$W_{tot} = \sum_{i=0}^{n} F_i.\Delta D_i \tag{5.11}$$

a non-vectorial derivation, where the energy used equates directly with the O_2 utilised (Qasem, et al., 2012).

In the simplest of representations, *VeDBA* can be compared to a single muscle producing a movement arc of one limb by exerting an appropriate force and *ODBA* to that of two of more muscles with different insertion angles producing exactly the same force and thus vectorial solution as the single muscle. In both scenarios the amount of movement and physical work done is equal but in the latter scenario the forces are developed that are not equally manifest in the movement therefore O_2 consumed by the multiple muscles will surpass that of the single muscle (Qasem, et al., 2012).

Although, *VeDBA* is correct in terms of physical derivation of the acceleration vector it represents a muscular set up where each muscle force reflects proportionately in the overall force vector. This is obviously fallacious of biological organisms. Instead, each movement incorporates a combination of agonists (contracting muscles that flex the limbs) and antagonists (extensor muscles that extend until the limb is in its natural state), as well as synergists (muscles that assist in refining the movement of the agonists by stabilising joints) and neutralizers (muscles that counteract undesirable movement) (Floyd, et al., 2012). The 'inefficiencies' in terms of oxygen utilisation that result from this complex *intealia* of muscular embedment that contain partially opposing contracting muscles are, in fact, necessary both for limb stability and whole body balance (Qasem, et al., 2012).

The indication that *ODBA* may in fact be a better predictor of $\dot{V}O_2$ than *VeDBA* can be explained as *ODBA* accounts for the energy used for stability and balance.

5.5 *ODBA versus VeDBA* in relation to device orientation (straight *versus* skew logger)

Prior to any deduction as to which *DBA* metric holds the most truth in predicting *EE*, a specific concern over device orientation must be addressed; what happens when device orientation is not standardised?

By the very nature of the metric formulae, device alignment has the potential to lead to the greatest discrepancy between *ODBA* and *VeDBA* because for the same body acceleration, *ODBA* values will vary with device orientation yet *VeDBA* values will remain constant.

This study reports significant differences between straight and skew devices for both *ODBA* (0.026*g*) and *VeDBA* (mean 0.007*g*) metrics. However, only a small difference was found between the 'recorded $\dot{V}O_2$ at a speed of 5 $km.h^{-1}$ compared to $\dot{V}O_2$ estimated for the same speed from the data recorded by the skew-mounted logger using the calibrations obtained from the straight-mounted logger' (Qasem, et al., 2012, p.6). For example the difference with *ODBA* was 1.4% and with *VeBDA* 1.3%. Furthermore, no difference was established between *ODBA* and *VeDBA*, concluding that if a logger is deployed in the straight position but then subsequently skews (perhaps due to the intensity of the exercise), both *ODBA* and *VeDBA* are similarly powerful proxies for $\dot{V}O_2$. Contrary to what might be expected, *VeDBA* did not outperform *ODBA* (Qasem, et al., 2012).

The study determines that skewing the accelerometer by 30° in each of the major axes of the body (roll, pitch and yaw), is insufficient to elicit a marked difference in the way *ODBA* reacts to changes in orientation which gives rise to a further question; exactly how much 'skew' can occur before significant differences between the metrics arise?

The acceleration values recorded by a straight- mounted with respect to skew-mounted logger can be derived for any scenario using the relative rotations for each axis. This can be represented by an acceleration vector transformation matrix;

$$M = \begin{pmatrix} \cos\alpha\cos\beta & \cos\alpha\sin\beta\sin\gamma + \sin\alpha\cos\gamma & -\cos\alpha\sin\beta\cos\gamma + \sin\alpha\sin\gamma \\ -\sin\alpha\cos\beta & -\sin\alpha\sin\beta\sin\gamma + \cos\alpha\cos\gamma & \sin\alpha\sin\beta\cos\gamma + \cos\alpha\sin\gamma \\ \sin\beta & -\cos\beta\sin\gamma & \cos\beta\cos\gamma \end{pmatrix} \tag{5.10}$$

where α, β and γ signify the angles of roll, pitch and yaw (rotations carried out in this order) for the skew-mounted relative to the straight-mounted accelerometer. Hence, if the acceleration vector measured by the straight-mounted device is denoted as;

$$A_1 = (A1_x, A1_y, A1_z) \tag{5.11}$$

and the same acceleration vector in the skew-mounted position, is denoted;

$$A_2 = (A2_x, A2_y, A2_z) \tag{5.12}$$

then;

$$A_2 = (MA_1) \tag{5.13}$$

where the derived values for x, y and z vector components can be used to calculate *ODBA* and *VeDBA* (Qasem, et al., 2012).

The matrix formulations confirm that deviation in one or two axis in comparison to equal deviation in all three axis tends to produce larger a percentage change in *ODBA* between straight and skew devices (as shown in Fig. 5.4). This advocates that although this study found the difference between *ODBA* and *VeDBA* to be insignificant when device is skewed by 30° in all axes it may not be the case, if the skew was present in only one or two axes (Qasem, et al., 2012).

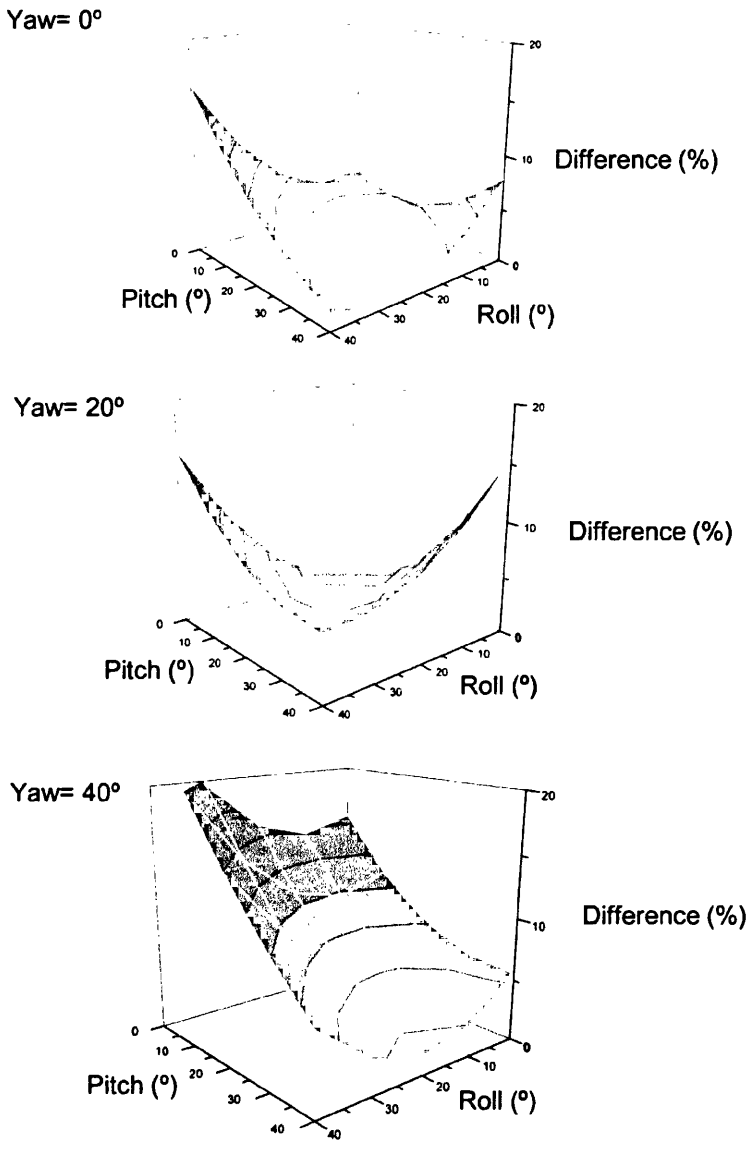


Figure 5.4. 'Predicted difference between straight and skew-mounted ODBA derived from recordings on a tri-axial accelerometer subjected to equal acceleration in the heave, surge and sway axes as a function of pitch, roll and yaw differences between straight and skew. Contour lines show 2.5% intervals.

The matrix indicates that deviations of up to 10° in any one or two axis produce only up to a ~1% change in *ODBA,* with three axes producing a ~ 0.03% change. Indeed, in order to reach a 5% difference in *ODBA* between the straight and skewed devices a 20° skew must occur in one or more axis. However, in any case, deviations much greater than 10° would tend to be visually obvious for most human studies therefore researchers can use *ODBA* without overly worrying about orientation. In the rare case that the devices are round and unmarked where the transducer alignment is unknown then it is advisable to use *VeDBA* (Qasem, et al., 2012).

Furthermore, it should be noted that when using this technology further afield, such as on other mammals in animal tracking studies, there are a number of obvious cases where it is imperative that *VeDBA* is used such as when tracking whales. Here devices are often attached via suction cups are consequently free to rotate (Hooker and Baird, 1999). In addition, in cases where devices are attached to animals and left for extended periods of time without monitoring, *VeDBA* should be considered if there is a risk of substantial skewing (Qasem, et al., 2012).

5.6 *ODBA versus VeDBA* in relation to device placement (straight *versus* waist logger)

The effect of placement has been aforementioned in many previous studies (Bouten, et al., 1994; Manohar, et al., 2011; Gleiss, et al., 2012). Gleiss, et al. (2012), speculated that substantial errors in any *DBA* metric would result from non-standardized positioning of an accelerometer relative to the body's centre of gravity, the theoretically 'correct' placement.

In the present study, unsurprisingly, clear differences were present between the straight and hip mounted devices for both *DBA* metrics, with the hip logger recording the highest acceleration. Larger acceleration values at the hip could imply either; i) the hip placement provides greater sensitively to whole body motion or ii) the hip logger produced greater error due to improper fixing of the device. The former can be explained as the proximity of the hip to the body's centre of gravity suggests that most of the acceleration of the limbs would manifest its self in acceleration at the hip. Equally, the latter stands to reason as the hip-mounted device produced a considerably

higher coefficient of variation (*CV*) than the straight-mounted device which could be explained as it was not secured and harnessed in the same way as the straight and skew loggers were.

Importantly, the difference between straight and hip devices become negligible when used as a proxy for *EE* ($\dot{V}O_2$), effectively deeming logger placement unimportant. Many studies report a similar occurrence in which differences are present between raw acceleration metrics but not when related to $\dot{V}O_2$ (Bouten, et al., 1997; Ynyge, et al., 2003). Furthermore, others support the final conclusion that placement is unimportant (Nilsson, et al., 2002; Ynyge, et al., 2003; Halsey, et al., 2008).

Nevertheless, this study highlights the effect of placement on the raw data can be demonstrated for even the smallest of placement alterations. For example, despite placing the straight and skew device as closely together as possible (in which they should effectively experience the same acceleration), *VeDBA* was marginally but significantly different (0.007g) in the two positions. Again, when the coefficients of determination were used for the relationship between $\dot{V}O_2$ and *VeDBA,* this difference became insignificant. However, the significant placement differences in the raw acceleration metrics for both straight *versus* skew and straight *versus* hip indicate that placement has the potential to influence $\dot{V}O_2$ (Qasem, et al, 2012).

5.7 The influence of body anthropometrics, body composition and aerobic capacity on the relationship between *DBA* and $\dot{V}O_2$

To date no studies have sought to determine whether body anthropometrics, body composition or aerobic capacity affects the relationship between $\dot{V}O_2$ and *DBA*, yet all are inter-related. The present study reports results only for *ODBA* as the overriding outcomes in terms of significance were the same for *VeDBA*.

The present study reports that *ODBA* accounts for ~79% of the variation in $\dot{V}O_2$ alone but that the addition of *fat-free mass*, *fat mass* and *age,* act as minor but significant additional variables to the model.

With the addition of these three variables 16.8% and 13.7% more of the variation in $\dot{V}O_2$ can be explained than when using $ODBA_{straight}$ or $ODBA_{hip}$ (respectively) as a single predictor.

5.7.1 Fat-free mass

The present results are in agreement with previous studies that report a significant effect of *fat-free mass* on activity *EE*, where an increase in *fat-free mass* produces an increase in *EE* (Liebel, Rosenbaum and Hirsch, 1995; Johnson, Russ and Goran, 1998). This is explained as in general, *fat-free mass* represents the metabolically active component of body mass so should directly relate to *EE*.

In the present study, *fat-free mass* was significantly related to $\dot{V}O_2$ when used as a single variable as well as in combination with *ODBA*, *age* and *fat mass*. *Fat-free mass* as a single variable explains ~9% of the variation in $\dot{V}O_2$. This is similar to that that reported by Johnson, Russ and Goran (1998) (i.e. 10%).

Furthermore, *fat-free mass* explained an additional ~12% of the variation in $\dot{V}O_2$ after inclusion of *ODBA*, *fat mass* and *age*.

5.7.2 Age

Age explained approximately 5% of the variation in $\dot{V}O_2$ after inclusion of *ODBA*, *fat-free mass* and *fat mass*.

The influence of *age* on $\dot{V}O_2$ where increasing *age* produces a decreasing $\dot{V}O_2$ is unexpected. as the *age* range in the present study is reasonably small i.e. 14 years, with 15 out of 18 participants aged between 19 and 24 years. Also, *age* was not significantly related to $\dot{V}O_2$ when used as a single variable. It is therefore unclear why *age* has a significant influence on $\dot{V}O_2$ in combination with *ODBA*, *fat-free mass* and *fat mass*.

It is well established that $\dot{V}O_2$ max ($l.min^{-1}$) declines with *age*. For example, a meta-analysis by Fitzgerald, et al. (1997) estimated that regardless of training status $\dot{V}O_2$max falls at a rate of around 10.0 to 10.9% per decade in women from the *age* of 25 years.

The link between age and submaximal $\dot{V}O_2$ is less clear and could be linked to numerous factors including $\dot{V}O_2$max and exercise economy (Jones and Carter, 2000).

5.7.3 Fat mass

Fat mass explained a small but significant additional amount of the variation in $\dot{V}O_2$ i.e. ~2% after inclusion of *ODBA*, *fat-free mass* and *age.*

There is only a small body of research that has previously considered the influence of *fat mass* on activity *EE* in adults, with most results showing no significant relationship between the two (Liebel, Rosenbaum and Hirsch, 1995; Goran, et al., 1997). However, there is also some evidence that fat mass is related to resting and basal metabolic rate (Nielson, et al., 2000; Johnstone, et al., 2005). Furthermore, *fat mass* has previously been reported to account for approximately 4% of 24-hour *EE* (Hallgren, et al., 1989 cited in Weinsier, Schutz and Bracco, 1992).

Unusually, the present study reported a significant influence of *fat mass* when the sample population displayed only a small range of fat mass values. For instance, all participants were within recommended levels of % body fat (low-high) based upon gender and age (Heyward and Wagner, 2004, p.6) with 14 out of 18 participants within 9-19% *fat mass*. In contrast, the sample population of Nielson, et al., (2000) ranged from a *BMI* of 'normal' to obese with *fat mass* values from 15-44%.

5.8 Conclusions

This study shows that *VeDBA* does not outperform *ODBA* as a proxy for $\dot{V}O_2$ and if anything *ODBA* is better (though the difference is minimal) as long as devices can be attached close to the major axes of the body. The choice between them should be based on (a) the value placed on representing the biology of muscle metabolism (b) the likelihood that device orientation could vary markedly (c) whether comparison with values in the literature is required. Critically, both *ODBA* and *VeDBA* are susceptible to variation in device positioning.

It is clear that the association between $\dot{V}O_2$ and *DBA* can be improved using additional variables. However, this study can only act as an indication as to which variables should be considered in future. The small sample size and lack of variety in anthropometric, body composition and aerobic capacity values limits the relevance of the conclusions considerably. Based upon the present results only *fat-free mass* has a large enough influence to recommend its use in future research. *Fat mass* and *age* require further assessment.

5.9 Limitations

5.9.1 Missing data values

Occasional faults in the accelerometers were a particular limitation of the study in the fact that it left missing results for some of the straight, skew and hip data sets. This study sought to ascertain the most appropriate way of deducing missing values using combined data from all logger mountings but found no significant differences between the predicted values construed by the three methods used (*IR*, *SA* and *JMP*) both in terms of DBA_{all} values and r^2 ($\dot{V}O_2$ plotted against DBA_{all}) values were used for both $ODBA_{all}$ and $VeDBA_{all}$ metrics (see Table 4.15 and 4.16).

Nonetheless, when the regression equations for $\dot{V}O_2$ against DBA_{all} were used, the *SA* and the *JMP* method showed improvements in r^2 values in comparison to the raw data for both $ODBA_{all}$ and $VeDBA_{all}$, with the *SA* method producing slightly higher r^2values than the *JMP* (see Table 4.17).

This advocates that the *SA* method of imputing missing values might be appropriate future studies using incremental locomotive activity in order to strengthen the conclusions of the investigation. However, it is important that this method is only implemented for group data and not on an individual basis.

Still, caution should be taken when applying these results to future studies as the influence of the methods of imputing missing values may change depending on the number of missing results. Furthermore, with larger data sets and fewer missing values

the accuracy of the imputed values is likely to increase with a small subsequent improvement in r^2.

Additionally, it should be noted that imputing missing values may not be appropriate for all protocols. The nature of the protocol in the present study particularly lends itself to calculating reasonably accurate values due to the following reasons; i) the incremental nature of the exercise creates a clear pattern in which to base subsequent predicted data and ii) there is no significant difference between the raw data set and data sets with imputed values.

5.9.2 Body composition data

The use of body composition data in the present study was highly limited in terms of the range of *fat mass* and *fat-free mass* in the sample population, although surprisingly both variables added significantly to the prediction of $\dot{V}O_2$. Still, due to the controversy that surrounds *fat mass* in particular, in terms of its influence on *EE*, it is imperative that this study is cross-validated with a sample with a larger *fat mass* range.

An additional drawback of the body composition data was use of the 2-compartment model of body density. This model is highly over simplified when related to *EE* as the fat-free mass component which is often considered as metabolically active includes both bone (non-metabolically active) and bone-free lean tissue (metabolically active). In the present study this model was necessary due to allow comparison between techniques. However, in order to be certain that *fat-free mass* and *fat-mass* are additional significant variables in the model of $\dot{V}O_2$ plotted against *DBA*, future studies should consider more detailed body composition data. For instance, the 3-compartment tissue-level model (body mass = fat + bone mineral + bone-free lean tissue) offers a more compound analysis and can be measured via dual-energy X-ray absorptiometry (Heyward and Wagner, 2004).

Additionally, as accelerometers measure activity *EE* specifically, researchers may wish to measure skeletal muscle mass alone which is approximated at 39% of *fat-free mass* (Weinsier, Schutz, and Bracco, 1992). This can be estimated using techniques such as the *BIA*.

5.9.3 Limited ability of accelerometers to predict activities of daily living

This study has established a strong relationship between $\dot{V}O_2$ and *DBA* during treadmill locomotive activity therefore the most imperative question leading on from this is can *DBA* accurately predict *EE* in free-living daily activities?

To decipher this, the regression equations developed in the present study must be validated using a large variety of daily activities and population characteristics (Lyden, et al., 2011).

Nevertheless, accelerometers as a whole have several possible limitations in terms of their application to daily activity which relate to the lack of ability to recognise; isometric muscular contraction, inclined/declined terrain (discussed in 2.18.6) and ground substrate. Isometric muscular contraction and ground substrate are discussed below along with suggestions on how these problems may be addressed in future studies (solutions).

i) Isometric muscular contraction

Isometric muscular contraction 'occurs when a muscle generates force and attempts to shorten but cannot overcome the external resistance' (McKardle, Katch and Katch, p.520) therefore energy is being utilised for muscular contraction but no movement occurs. This causes large problems in terms of the ability of an accelerometer to measure *EE* in situations particularly in situations where isometric muscular contractions are prolonged for example when carrying bags. In this case the accelerometer would almost certainly underestimate $\dot{V}O_2$ (Halsey, et al., 2011).

ii) Ground substrate

The effect of ground surface substrate is scarcely considered in research on use of acceleration signals as a proxy for *EE* in humans. Yet, clear differentiations in the energy cost of locomotion over a multitude of surfaces have been made. Lejeune, et al. (1998), reported 1.6-2.5 times more mechanical work and 2.1-2.7 times more *EE* is needed to walk on sand (speeds 0.5 – 2.5 $m.s^{-1}$) compared to walking at the same speed

on a hard surface. Similar, results were presented for running, with running on sand producing approximately 1.15 times more mechanical work and 1.6 times more *EE* than running on a hard surface (Lejeune, et al., 1998,). Likewise, Sassi, et al. (2011) found that running on natural grass or artificial turf elicits significantly higher energy costs than running on a hard surface (asphalted track) at the same speeds (2.22, 2.78, 3.33 $m.s^{-1}$).

The differences in energy cost between ground surface substrates are primarily due to reduced locomotive economy on softer surfaces. More specifically, augmented muscle-tendon work during walking and reduced muscle-tendon efficiency as well as a small increase in step frequency during running. Moreover, hard surfaces allow greater energy rebound where positive work done by the muscles to propel the body upwards is subsequently absorbed by the muscles when the centre of mass falls and in turn, part of this energy is then used again for the next step. Soft surfaces such as grass act as a dampener due to greater compression in comparison to a hard surface. Furthermore, on soft surfaces such as sand, the foot will move slightly during each step which further dissipates energy hence a much greater amount of work is done on the ground per step in comparison to a hard surface (Lejeune, et al., 1998).

Additionally, it should be noted that the effect of motorised exercise equipment such as the treadmill has been shown to produce substantial biomechanical differences in locomotion in comparison to over ground locomotion (Riley, et al., 2008). Correspondingly, Yngve et al., 2003, found significantly greater accelerometer counts were produced on a treadmill than on a running track for the same walking and jogging speeds although biomechanical factors were not assessed.

iii) Solutions

There are two main solutions that are currently appearing in the literature and need to be further investigated with the use of *ODBA* and *VeDBA* metrics; i) use of complex algorithms to decipher specific movements from acceleration patterns and allow subsequent adjustment of the acceleration *versus EE* regression equations, ii) use of acceleration values in combination within another device.

For instance, several studies have pursued techniques to decipher acceleration patterns such as artificial neural network analysis and time-frequency analysis to classify activity type (Staudenmayer, et al., 2009) and locomotion on graded terrain (Wang, et al., 2007) with relative success. For example, activity type has been correctly classified 88.8% of the time during locomotive, vigorous, household and low-level activities (Staudenmayer, et al., 2009).

Additionally, use of global positioning systems and barometers alongside accelerometers would allow changes in gradient and terrain to be registered. Yet both have major drawbacks including dependence on satellite signals and disturbance in readings due to metrological conditions.

Finally, measurement of heart rate (Brage, et al., 2005; Couder, et al., 2007; Halsey, et al., 2008) has shown promising results in increasing the accuracy of predicting $\dot{V}O_2$ and can help account for situations of isometric muscular contraction and graded walking. For example, *ODBA* and heart rate combined has been shown to be superior in predicting $\dot{V}O_2$ ($r^2 = 0.95$) than either heart rate ($r^2 = 0.86$) or *ODBA* ($r^2 = 0.60$) alone during inclined locomotion (Halsey et al., 2008). Furthermore, recent studies are considering the use of *HR* variability in the prediction of *EE*. *HR* variability gives much greater insight into the physiological response to exercise than *HR* alone as it measures beat-to-beat variation and therefore has the potential to improve the prediction of *EE* even further (Smolander, et al., in press).

5.10 Future recommendations

Based upon the results of the present study it is recommended that both *ODBA* and *VeDBA* are examined a proxies for $\dot{V}O_2$ in further detail in human studies including comparison in paediatric, adolescent, adult and elderly populations that widely vary in terms of *fat mass*, *fat-free mass* and anthropometric variables. Furthermore, due to the trend towards choosing accelerometer placements based upon the convenience of the user i.e. wrist, ankle etc. (Parkka, et al., 2007, Kim, et al., 2009) or use of i-phones to measure acceleration which are commonly placed in the trouser pocket or bag (Manohar, et al., 2011) the ability of *DBA* to predict *EE* at these placements must be tested to ensure long term application of the *DBA* metrics. Finally, it should be noted

that with any studies based upon *ODBA* the device should be kept within 10° of the major axis of the body at all times .

Chapter 6

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