# Physical Activity Measurement Using Novel Sensor Technologies in Unique Environments.

Gregory May, B.Sc.

~~

Name of Supervisor(s): Dr. Giles Warrington

School of: Health and Human Performance

Email: mayg2@mail.dcu.ie

Submitted: December 2012

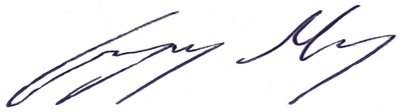
Voulmes: 1 of 1

~~

*This work is supported by Science Foundation Ireland under grant 07/CE/I1147, CLARITY: Centre for Sensor Web Technologies*

## Declaration

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

Signed:  (Candidate)

ID No.: 99369150

Date: 13/09/2013

# Dedication

*For my father Ciarán, who sadly died before I sat my PhD defence.*

*Thank you for supporting me all these years. I will miss you.*

# Abstract

***Author: Gregory May***

***Thesis Title: Physical Activity Measurement Using Novel Sensor Technologies in Unique Environments***

This thesis presents methods of estimating the physical activity, and energy expenditure during various activities in three unique environments using a low cost sensor platform, the GT3X ActiGraph accelerometer. The environments in this study included; simulated and real world horse riding, search and rescue operations, and ultra-endurance cycle racing.

GT3X ActiGraphs were deployed in each environment to measure the associated energy expenditure of specific activities. Where possible other validated energy expenditure estimation sensors were deployed in parallel with the GT3X ActiGraphs. However, due to the nature and duration of deployment in the environments, this was not always possible. In these cases assumptions were made based on the activity, the subject anthropometrics and the intensity of the motions observed in order to better estimate the energy expended.

Specific events were defined for each environment and the energy demands of these events were further investigated with the GT3X ActiGraphs. These included; the differences between simulated and outdoor horse riding at similar energy expenditure rates; the differences between sleeping environments on physical activity and sleep indices in search and rescue operators; and an analysis of the energy expended during cycling and rest periods during an ultra-endurance cycling race using proprietary and researcher developed algorithms.

However, the data presented from the propitiatory software may not be capable of estimating the physical activity expended during various activities certain environments as external factors may first need to be filtered out. This calls for a combined physiological and computer science approach to be taken in further research with these sensors.

# Acknowledgements

*I would like to thank my supervisor Dr Giles Warrington for helping me through this process.*

*Thank you, Pauline, for always reminding me I had a thesis hidden inside my head somewhere.*

*Thank you to all my friends and family for support and always enquiring when I'd finish.*

*Thank you anyone who reminded me that life is more than academia.*

*Thank you cycling for keeping me sane.*

# Table of Contents

## Glossary of terms

The following terms are used within the study and are explained below:

### *General*

- Energy expenditure: the total amount of energy expended by a body at any given time. See section 2.2.1.
- Physical activity: any bodily movement produced by the contraction of skeletal muscle that results in a substantial increase in the energy expended over resting energy expenditure.
- Uni-axial: Measuring along one plane of motion.
- Dual-axial:Measuring along two planes of motion.
- Tri-axial: Measuring along the three planes of motion; X (horizontal), Y (vertical) and Z (lateral).
- Actigraph: A piece of equipment utilising an accelerometer to measure movement or physical activity.
- Accelerometer: A sensor designed to measure acceleration due to gravity along a directional axis.
- GT3X/GT3X+: An accelerometer developed by ActiLife™ to measure physical activity and sleep.
- Sensewear™ Armband: A sensor used to measure physical activity, sleep and give energy expenditure estimation calculations.

### *Chapter 3: Trainee Jockeys Terminology*

- Equine simulator: A mechanical ergometer attempting to replicate the motion of a horse.

### *Chapter 4: Search and Rescue Operations Terminology*

- Tasking: A call out to which the SARC members must respond to.
- Sleep Duration: The amount of time spent sleeping, not differentiating between REM sleep and NREM sleep.
- Sleep efficiency: The percentage of time in a sleeping state during a sleeping period.
- Readiness period: The time between 1200 and 2100; 0730 and 1259 when the SARC are on 15 minute 'wheels up' ready state.
- Standby Readiness Period: The time between 2100 and 0730 when the SARC are on 45 minute 'wheels up' ready state of standby at home, on a SAR base, or at any other suitable accommodation.
- On-base: Being located within the SARC base situated at Dublin Airport.
- Off-base: Being located outside the SARC base situated at Dublin Airport.
- Flight duty Period: Official term for 24 hour shift employed by SARC members. Includes both 'readiness' and 'standby readiness'.

- Wheels up: Colloquial term used by SARC members to denote the aircraft being prepared for take off, flight plan logged and aircraft's minimum time to be airborne.

## *Chapter 5: Ultra-endurance Cycling Terminology*

- Ultra-endurance: A continual event lasting over 6 hours long, or of extended duration.
- Subject pair: A defined pair of cyclists during the Race Around Ireland
- On period: A period of time when a subject pair were actively racing and a single member of the pair was active; S1 + S2 – **S1 on**, S2 off.
- Off period: A period of time when a subject pair we actively racing and a single member of the pair was resting; S1 + S2 – **S1 off**, S2 on.

## List of Abbreviations

The following abbreviations are used within the studies and are explained below:

### *General*

- IMU: Inertial measurement unit
- PA: Physical Activity that results in motion
- EE: Energy expenditure
- TEEE:Total estimated energy expenditure
- TEF: Thermic effect of food
- BRM: Basal metabolic rate
- RMR: Resting metabolic rate
- MET: Metabolic equivalent
- kcal: Kilocalories
- $CO_2$: Carbon dioxide
- $O_2$: Oxygen
- SW: Sensewear armband
- VT: Vertical plane of motion
- AP: Horizontal plane of motion
- ML: Medial plane of motion
- GPS: Global positioning satellite
- UTC: Universal Time Constant

### *Chapter 3: Trainee Jockeys*

- RACE: Racing Academy and Centre of Excellence
- HRI: Horse Racing Ireland

### *Chapter 4: Search and Rescue Operations*

- SAR: Search and rescue
- $S_{eff}$: Sleep efficiency
- $S_{dur}$: Sleep duration

- GT: Group Total
- G1: Members of the SARC who sleep off-base
- G2: Members of the SARC who sleep on-base
- G3: Members of G2 while they sleep on-base
- EMF: Electromagnetic field
- GSR: Galvanic skin response

### *Chapter 5: Ultra-endurance Cycling*

- RAI: Race Around Ireland
- RAAM: Race Across America
- UCI: Union d'Cycliste International
- W: Watts
- MPT: Maximal performance trial
- RT: Resting time
- RPA: Resting physical activity
- TPA: Total physical activity
- CT: Cycling time
- CPA: Cycling physical activity
- PO: Power output, in Watts
- HR: Heart rate

# List of Publications

## 2012

May, Gregory and Warrington, Giles (2012) Sleep and activity measurement in search and rescue aircraft crews using novel sensing technologies. In: American College of Sports Medicine Annual Meeting 2012, 29 May - 2 June 2012, San Francisco.

May, Gregory and Warrington, Giles (2012) Assessment of Physical Activity in Search and Rescue Operations Using Accelerometer Based Technologies. In: Sensecam Symposium 2012, 2-3 Apr 2012, Oxford, UK.

## 2011

Conroy, Kenneth and May, Gregory and Roantree, Mark and Warrington, Giles and Cullen, Sarah Jane and McGoldrick, Adrian (2011) Knowledge acquisition from sensor data in an equine environment. In: Data Warehousing and Knowledge Discovery (DAWAK) 2011, 29 Aug - 2 Sept 2011, Toulouse, France.

Conroy, Kenneth and May, Gregory and Roantree, Mark and Warrington, Giles (2011) Expanding sensor networks to automate knowledge acquisition. In: British National Conference on Databases, 12-14th July 2011, Manchester, UK.

May, Gregory and Fitzpartick, Paula and Cullen, Sarah Jane and O'Hagan, Anna and Kelly, Lauren and Warrington, Giles(2011) An analysis of the impact of acute sleep deprivation on repeat cycling time trial performance. In: American College of Sports Medicine Anual Meeting 2011, 31st May - 4th June 2011, Denver.

## 2010

May, Gregory and Doherty, Aiden R. and Smeaton, Alan F. and Warrington, Giles (2010) Correlating multimodal physical sensor information with biological analysis in ultra endurance cycling. Sensors, 10 (8). pp. 7216-7235. ISSN 1424-8220

May, Gregory and Dolan, Eimear and Fitzpatrick, Paula A. and Doherty, Aiden R. and Smeaton, Alan F. and Warrington, Giles (2010) Physiological, haematological and performance characteristics of ultra endurance cyclists competing in the inaugural race

around Ireland. In: ACSM 2010 - 57th Annual Meeting of the American College of Sports Medicine - World Congress on Exercise is Medicine, 1-5 June, Baltimore, Maryland, USA .

Coyle, Shirley and Mitchell, Edmond and Ward, Tomas E. and May, Gregory and O'Connor, Noel E. and Diamond, Dermot(2010) Textile sensors for personalized feedback. In: IAPMA2010 - ECIR2010 workshop on information access for personal media archives, 28 March 2010, Milton Keynes, UK.

**2009**

May, Gregory and Warrington, Giles D. (2009) A comparison of the aerobic energy demands of two commercially available cycle ergometers in trained cyclists. In: ISBS 2009 - 27th International Society of Biomechanics in Sports Conference, 17-21 August 2009, Limerick, Ireland.

Connaghan, Damien and Hughes, Sarah and May, Gregory and Kelly, Philip and Ó Conaire, Ciarán and O'Connor, Noel E. and O'Gorman, Donal and Smeaton, Alan F. and Moyna, Niall (2009) A sensing platform for physiological and contextual feedback to tennis athletes. In: BSN 2009 - Body Sensor Networks , 3-5 June 2009, Berkeley, CA, USA. ISBN 978-0-7695-3644-6

May, Gregory and Dolan, Eimear and Fitzpatrick, Paula A. and Warrington, Giles D. (2009) A comparison of the physiological demands of two commercially available cycle ergometers in trained cyclists. In: American College of Sports Medicine Annual Meeting 2009, 27-30 May 2009, Seattle, Washington, USA.

# Index of Tables

# Illustration Index

## List of Limitations

The following limitations were seen within each of the studies and are declared below;

The primary limitations within this thesis are:

- Limited sample sizes
- Inability to deploy gold standard measurement techniques in all studies
- Loss of data due to sensor failure
- Effect of external motion overriding measurements taken from subjects

### *Chapter 3: Trainee Jockeys*

- The ability level of subjects only reflects that of trainee jockeys
- Possible overriding effect of the mount on measures of physical activity
- Loss of data due to sensor failure
- Addition of comparatively heavy monitoring equipment may have an effect on reliability and accuracy of estimated energy expenditure
- The unpredictable nature of the environment leading to artefacts in the data
- Emerging research environment with no readily available accelerometer data

### *Chapter 4: Search and Rescue Operations*

- A limited sample size from which to capture data
- Loss of data due to sensor failure
- Inability to deploy gold standard measurement techniques in the environment
- Estimated calculations for daily energy expenditure
- Unpredictable nature of the environment leading to loss of data due to a call out
- Unknown environment with no readily available comparative data

### *Chapter 5: Ultra-endurance Cycling*

- Limited sample size
- Inability to deploy gold standard measurement techniques
- Unpredictable nature of environment
- Lack of repeat cycle-bouts prior to event
- Loss of data in later stages of event

# Chapter 1: Introduction

## *1.1 Background Information and Justification*

In recent years the availability of low cost accelerometers has led to an explosion in the number of commercially available tools for the assessment of physical activity and estimation of energy expenditure. Many of these accelerometers are embedded into everyday objects such as mobile phones, laptops and other electronic equipment. With these sensors becoming more pervasive with each iteration of a technology, it stands to reason that attempts should be made to use these low cost accelerometers across a wide range of environments and activities in order to gather information. However, in many cases these accelerometers are not being used in an environment they were designed for, or, validated within. In many cases users are deploying these technologies and hoping that the resulting data that are captured is of some use. Users are avidly applying these technologies rather than performing theoretical, or laboratory based studies, and in many cases the data analysis that is performed is retrospective, rather than prospective. These users care not about the validity or repeatability of these technologies, only that they can generate meaningful data within their chosen environment that they can manipulate in some manner.

When it does occur, the scientific validation of many of these systems has predominantly occurred during activities associated with normal daily living, with only a few being tested under laboratory controlled conditions. The GT3X ActiGraph (ActiGraph, Pensacola, Florida, USA) is the most recent iteration of a research validated accelerometer platform designed to gather physical activity data. Containing a low cost tri-axial accelerometer, the GT3X ActiGraph provides a tool with low weight, size and cost that allows researchers to gather data within environments where it may not be possible to deploy traditional energy expenditure measurement systems. This sensor is suited to deployment in a myriad of environments due to its size and more recent waterproof versions. However, the hardware for this technology is being produced at a tremendous rate and is constantly superseding both the analysis software, and the validation studies performed on each iteration of the sensor platform. In this regard a 'record first, analyse later' approach to gather data, and adjust the analysis techniques post-event, may need to be taken when researchers are investigating unique environments.

The GT3X ActiGraph has been validated as a physical activity measurement tool during activities of daily living (Kozey-Keadle et al., 2011), specific activities such as walking and running (Sasaki et al., 2011; Santos-Lozano et al., 2012) and as a measure of sleep (Ancoli-Israel et al., 2003; Kripke et al., 2010). The GT3X is the most recent iteration of the successful GT1M accelerometer. It utilises a tri-axial accelerometer as opposed to the dual-axial design of the GT1M, and has an increased storage capacity. A shift from count based measures of physical activity towards measures based on raw acceleration values has led to a change in the methods by which physical activity and energy expenditure estimations are calculated (Howe et al., 2009; John et al., 2011; Sasaki et al., 2011). This move towards a raw data based estimation and assessment of physical activity and energy expenditure has opened the door to the possibility of differentiating specific actions within a data-set based on the acceleration profiles measured by the accelerometer. This in turn may allow for accurate information as to the activity a person was partaking in be it walking, cycling or swimming. Using traditional methods of measuring physical activity such as heart rate monitoring, or even via indirect calorimetry, it is not possible to say what activity a person was partaking in based on the data alone. The contextual data gathered from an accelerometer can act as ground truth for the intensity and type of physical activity occurring where it is not possible to directly observe, or measure, the events taking place. During long term deployments these systems may provide a method to measure a range of activities across a range of environments. However, in order to do so they must first be deployed in these environments under scientific conditions in order to gather appropriate data.

## *1.2 Purpose of the Research*

This thesis presents the deployment methods used, during three feasibility studies, to gather physical activity, and where appropriate energy expenditure, data within three unique environments where traditional systems may not be applicable; simulated and outdoor horse-riding, search and rescue operations and ultra-endurance cycling. Operational definitions for aspects of the thesis, as well as each study, have been included in the glossary of terms at the start of this thesis.

GT3X ActiGraphs were deployed in environments where activities varied based on exercise intensity, duration and the number of subjects studied. Some of the environments such as horse-riding and search and rescue operations have little information available on their specific physical activity demands. Although cycling has a large body of data it has relatively little physical activity data pertaining to ultra-endurance cycling due to the extended nature of the racing and data capture over such long periods. The GT3X ActiGraph provides an unobtrusive system that can be deployed for lengthy periods and requires no interaction from the user. The data is captured in a raw format, meaning that it may be used in conjunction with emerging research methods in activity recognition that are being developed for the GT3X platform. The data can then be analysed by researchers in order to compile information on the variables they are interested in, in this case physical activity and estimated energy expenditure.

The number of sensors used varied due to the activity environment, the duration and the inherit limitations of deploying sensors within the environment. Previous studies have focused on measuring physical activities with accelerometers located at the waist (Ancoli-Israel et al., 2003). However, at this location it may not always be possible to capture data that accurately portrays the true amount of physical activity occurring in an environment. As each environment studied involved motion at the extremities, many while the central mass remains relatively stable, a GT3X ActiGraph placed at the centre of mass may underestimate the amount of physical activity that is occurring, i.e. during activities such as cycling (Crouter et al., 2006).

By placing the GT3X ActiGraph at the ankle, it may be possible to gather physical activity data, as well as contextual data, to aid in defining specific events within each environment while accounting for activities that may not be accurately represented by a waist mounted accelerometer. These defined events may relate to different intensities of a similar activity being performed (horse riding at different velocities during training - e.g. trotting or cantering), differences due to changes in environmental conditions (search and rescue operations - e.g. sleeping on-base or off-base), or to periods of inactivity or activity (endurance cycling race - e.g. rest and recovery periods).

## *1.3 Research Aim and Objective*

The primary aim of this thesis is to determine the feasibility of using a low cost commercially available accelerometer platform, the GT3X ActiGraph, to estimate the energy expended during physical activity in three unique environments.

### *1.3.1 Overall Objectives*

To deploy an unobtrusive method of estimating the energy expended during physical activity, the GT3X ActiGraph, that can add to the currently limited body of physical activity knowledge available in three unique environments:

i. To estimate the energy expended, and, assess the physical activity undertaken by trainee jockeys, with a minimal weight penalty and no user interaction, during both indoor and outdoor training.
ii. To assess the differences in the energy expended during physical activity, as well as sleep variables such as sleep efficiency and sleep duration, between search and rescue operators who sleep on-base or off-base under normal working conditions.
iii. To assess the physical activity levels during an five day ultra-endurance cycling race which including individual cycle and rest periods using proprietary and non-proprietary measurement techniques.

## *1.4 Research Hypothesis*

That a single, ankle mounted, commercially available accelerometer platform will provide a representative estimate of the energy expended during physical activity in several distinct and varying environments.

## *1.5 Delimitations*

The following delimitations were present during each study:

- All sensors ran the same firmware to allow for accurate comparisons to be made between similar sensors.
- All data analysis for the GT3X and GT3X+ ActiGraphs was performed using the same software version to remove any variance due to algorithm calculated estimations of energy expenditure.
- All data analysis, sensor initiation and tests were administered by the author to reduce inter-test error.
- Subjects were considered for inclusion if they were free from any injury or conditions that may stop them performing in their environment. Subjects were not limited by age, ethnicity or habitual levels of physical activity.

The following delimitations were specific to each study:

### *1.5.1 Study 1: Trainee Jockeys*

- Subjects were restricted to trainee jockeys at RACE who were deemed competent horse-riders by staff at RACE.

### *1.5.2 Study 2: Search and Rescue Operations*

- Subjects were restricted to full time members of the SAR who had been employed for at least one year.

### *1.5.3 Study 3: Ultra-endurance Cycling*

- Subjects were restricted to cyclists who had held at least a category 2 Cycling Ireland race licence for at least one year.

## ***1.6 Limitations***

Limitations within this thesis include, but are not limited to:

- Loss of data due to sensor failure
- Unpredictable nature of the studied environments leading to artefacts in the data
- Emerging research environments with no readily comparable accelerometer data
- A limited sample size from which to capture data

### *1.6.1 Study 1: Trainee Jockeys*

- The ability level of subjects only reflects that of trainee jockeys.
- Possible overriding effect of the mount on measures of physical activity.
- Addition of comparatively heavy monitoring equipment may have an effect on reliability and accuracy of estimated physical activity.
- The unpredictable nature of the environment leading to artefacts in the data.
- Emerging research environment with no readily available accelerometer data.

### *1.6.2 Study 2: Search and Rescue Operations*

- Inability to deploy gold standard measurement techniques in the environment.
- Estimated calculations for daily energy expenditure.
- Unpredictable nature of the environment leading to loss of data due to tasking.

### *1.6.3 Study 3: Ultra-endurance Cycling*

- Limited sample size
- Inability to deploy gold standard measurement techniques
- Unpredictable nature of the race environment
- Lack of repeat cycling bouts prior to the race

# Chapter 2: Review of Literature

## 2.1 Introduction

The measurement of physical activity has been explored using many different technologies. In recent years the availability of low cost inertial measuring units (IMUs), or accelerometers, have allowed not only researchers, but the general public to explore previously uncharted activities and environments. This has led to an increase in the number of commercially available devices being used to assess physical activity (PA). Many of these novel technologies utilise accelerometers as their core measurement sensor. However, many of these technologies are being used in environments that they were neither designed for, nor are capable of measuring within. In order to have the capacity to measure physical activity in these environments technologies must either be; validated against gold standard measures, tested against technologies that are validated estimates of physical activity, or be deployed in a manner that helps with the development of algorithms to accurately estimate the physical activity data within that specific environment. The following chapter will provide a review of the current literature relating to development of energy expenditure and physical activity measuring techniques, the measurement of physical activity, as well as the use and application of one these technologies the GT3X ActiGraph.

This review will begin with a brief history of the development of devices for measuring physical activity. This will primarily be concerned with the measure of human physical activity through inertial measuring systems and the development of the first accelerometer based systems. Following this, a detailed description of the development of the gold standard techniques against which accelerometer based systems must be validated, energy expenditure measurement systems, and the limitations of these systems will be presented. This will include a review of several assessment systems that attempt to utilise multi-sensory systems and algorithms in order to better estimate the energy expended during physical activities. These however, do not directly measure the amount of energy expended.

Finally, a detailed overview of the development of accelerometer based physical activity measurement technologies will follow, as well as the current limitations to these fledgling systems. This will also include an in-depth review of the primary accelerometer used in the current research; the Actilife GT3X ActiGraph (Actilife, Pensacola, Fl, USA) and its evolution. This is intended to provide background to the three studies in three unique environments which were conducted as part of this thesis.

### *2.1.1 Availability of Sensor Driven Data*

Whether it be through written historical accounts or technology, humans constantly leave an evolving record of what has occurred. These datasets that were once handwritten, tangible items, have now migrated to the digital domain where they become something harder to manage, but much easier to manipulate. Cameras that once took images that needed to be processed from film now come as files; location annotated via GPS, timestamped and easy to distribute via social media. Through this combination of multiple sensors a user no longer has to remember when and where a photograph was taken, they only have to deal with the data that is the file. This technological change has allowed researchers to gather data and enrich it with contextual information without the involvement of the user from whom the date is being gathered.

Similar technological advances have allowed the development of smaller and more accurate sensing technologies that can be applied in every environment conceivable. A sensor is defined as '*a device that converts a physical measure into a signal that is read by an observer or instrument'* (Chen et al., 2012). Recently, previously cost prohibitive sensors have become widely available to the consumer generating a swell in their recreational use. Where ten years ago a 5 mega-pixel digital camera was the remit of a camera enthusiast or professional photographer, now modern low cost mobile phones have camera capabilities surpassing this. The rise of multi sensor integrated smart phones has placed multiple new sensor types into the hands of millions of users. These sensors are no longer relegated to the domain of the scientist or engineer; they are now in the hands of the general population who are attempting to measure and categorise all the activities they partake in with any sensing technologies available to them.

This availability of new sensing technologies has allowed researchers as well as the general public to better understand what is happening in a range of activities, environments and occupations. As these technologies proliferate into the public domain, the balance between the volume of measurements and the accuracy of measurement has changed. Users are not necessarily concerned with how valid or accurate a measurement tool is, just that it is reliably collecting the data they are interested in each time they use it. There is now a trade off between scientific accuracy and available data. Although scientists fall on the side of validity, accuracy and repeatability, most consumers fall on the side of cost, size and simplicity. Many consumers do not know what their heart rate, caloric expenditure or weight should be. Nor do they necessarily care. They simply wish to be able to track this data and share it with their friends at minimum cost. This has led to an increase in the volume of data being collected, but at the sake of accuracy and validity.

### *2.1.2 History of Physical Activity Measurement*

The earliest known attempt at measuring physical activity, using a simple form of motion as a measure, is accredited to Vitruvius (80-15BC). As an architect Vitruvius needed a method to measure the distance between points. This need resulted in the development of the first odometer, a machine for measuring distance. The odometer needed to be accurate, repeatable and standardised to a given, known, distance. This first odometer took the form of a rotating wheel which could be pushed by the user. As each rotation of the wheel was a distance known by its circumference, if the wheel was pushed between two points the distance would be known by the amount of turns taken by the wheel. Data was accounted for by small pebbles dropped into a basket through a hole in the side of the wheel. Each pebble was a data-point and the basket a data storage system for each measure taken. Thus the first standardised method of measuring a distance was born.

With both of these in place and assuming that simple rules were followed; straight lines and known angles at turns, it was possible to guarantee that the measurements taken were accurate and repeatable under similar circumstances. Although initially used for surveying purposes, the odometer was adopted by the Roman army in order to measure the distance its troops had to cover between cities. Retrospectively, it is possible to hypothesise that if the distance between two cities, the time taken to cover that distance, and the food a soldier needed to make said march was known, it would be possible to measure the amount of physical activity that was undertaken during the march. Thus, the first sensor for physical activity measurement may be attributed to the Romans.

### *2.1.3 Motion Based Measurement of Physical Activity*

As the odometer does not strictly measure human movement, it measures the displacement of a human, the first attempt at modelling human motion and measuring it is accredited to Leonardo Da Vinci in the 15th century. While designing a better odometer he drew an image of a pendulum attached to counting wheels similar to an odometer (Illustration 2.1). Da Vinci believed that the natural swing of a soldier's leg would cause a similar swing in the pendulum, thus allowing a measure of steps taken to be made. If the number of steps taken was known, and the distance of each step, Da Vinci surmised that he could know the distance covered.

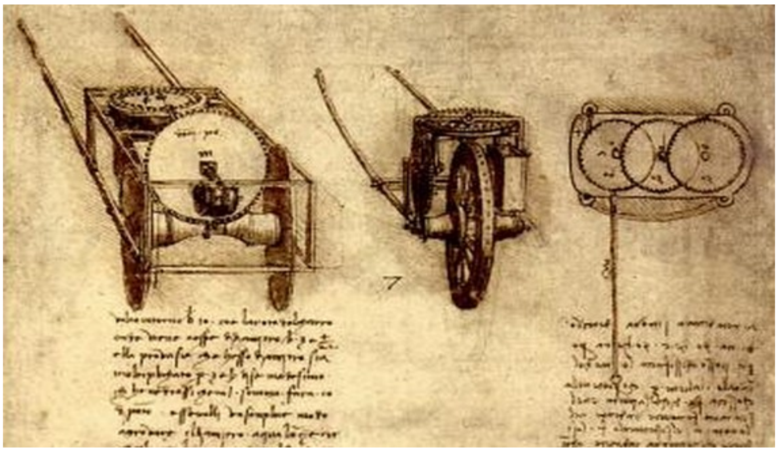


*Illustration 2.1: Leonardo's Pedometer, far right image.*

Unfortunately this was not the case. It is now known that most of the relative motion created during walking is in the vertical plane as opposed to the horizontal plane (Chen et al., 2012). This initial attempt at using the natural motion of a human to measure physical activity was something that was not further explored for many years. Da Vinci's work has led to the concept of a pedometer, the first inertial measurement unit that could be used to measure human locomotion.

### *2.1.4 Pedometer Development*

Further interest in the development of pedometers came in 1780 from a French clockmaker, Abraham-Louis Perrelet, who designed the first pedometers capable of measuring steps taken and estimating the distance travelled while walking. Perrelet is accredited with inventing the 'automatic' style watch which uses a weight on the end of a swing arm to wind the watch. It works on the premise that as the wearer's arm moves the swing arm within the watch also moves. The transfer of energy from the user's arm to the watch winds a spring which is used to operate the watch. Any acceleration along the axis of the swing-arm will allow the watch to be wound. By applying this same principle to the motion of a leg, Perrelet used this design to develop a pedometer.

### *2.1.5 Physics of Motion*

The pedometer works due to a simple principle of Newton's Laws of Motion, best thought of as pendulum undergoing a simple harmonic motion. At rest the pendulum hangs vertically with its weight at the base, its top attached to a fixed surface (Illustration 2.2, part A). That fixed surface in the case of a pedometer is its housing, which is in turn attached to the subject it is measuring. As the subject steps and accelerates, the housing moves forward, but the weight remains momentarily stationary. At this point (Illustration 2.2, part B) the pendulum has effectively experienced a negative displacement. As the subject finishes their steps and decelerates, the housing becomes stationary but the weight must experience a positive displacement. As the pendulum returns to rest it must once again pass the centre point. This period equates to one count, or one step in the case of a pedometer.

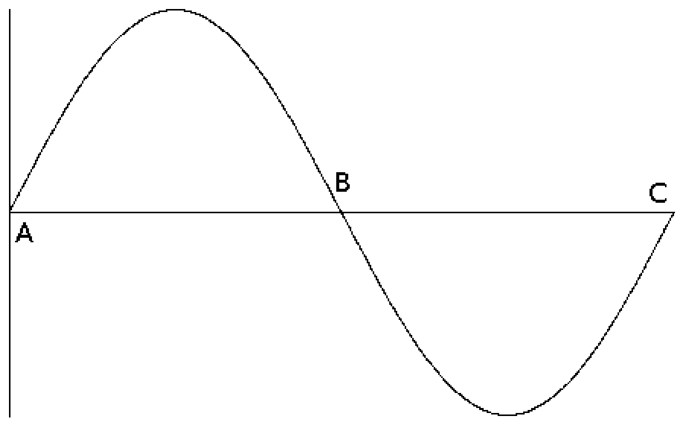



*Illustration 2.2: Single Step Sine Wave*

Due to this harmonic motion, a period can be measured if the amount of times the 'pendulum' reaches maximal displacement after is passes through the centre point is known. This can easily be visualised as a Sine wave where the point from A to B represents an acceleration, and B to C a deceleration. The total displacement of the pendulum is A to C which represents one step and the height of the wave, amplitude, represents the magnitude of the accelerations experienced. The line at the origin, X axis, represents zero accelerations being experienced.

If the imaginary subject did not stop, but continued to walk, it can be assumed that each step equates to a separate acceleration forcing the pendulum backwards, then forwards as that foot heel-strikes and decelerates. Each time this occurs an additional sine wave is added to the last one until a series of waves moves from A to A to A ad-nauseum. Each time it passes through C it instantly passes the centre point of the pendulum and starts a motion in the opposite direction (Illustration 2.3). Each of these waves can be counted, and thus generate a frequency of motion, steps per minute, or counts/min. This is the premise by which the pedometer has been adapted as a physical activity measure and on which initial measures in accelerometers were based (Chen et al., 2012).

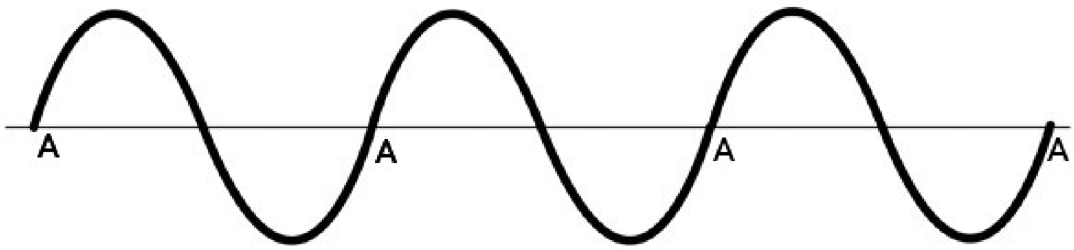



*Illustration 2.3: Repeat Steps Sine Wave*

This method is not an accurate representation of human motion, which is why Da Vinci's system did not work, however the principal is sound and is the basis on which accelerometers work. The difference however is not the method by which it is measured, but the plane of measurement. Whereas in this system it is assumed that the pedometer should measure accelerations along the horizontal axis, pedometers actually measure human locomotion best along the vertical axis (Butte et al., 2012). The measurement along a single vertical axis, or uni-axial, model places inherit limitations on measurements in pedometers which was one of the main reasons for the development of lightweight accelerometers for human physical activity measurement (Walter, 2007). In more recently developed pedometers, multi-axial accelerometers have been introduced. These simple systems still aim to only measure the amount of steps taken (Butte et al., 2012) and are generally only placed at the centre of mass. This is an inherent limitation to the use of pedometers in physical activity measurement as it is impossible to accurately measure any activity that does not register a step at the device's location, such as cycling.

### *2.1.6 Pedometer Evolution*

Pedometer systems initially worked by means of a flexible arm attached perpendicularly to a mounting plate. The pedometer arm has a known mass at its end which moves relative to the vertical forces applied to it and is referred to as a cantilever arm (Butte et al., 2012). Thus a pedometer can be thought of as a simple uni-axial accelerometer as it is capable of the measurement of accelerations along a single plane. With a known mass and a known arm length, the moment about the arm can be calculated and the magnitude of the acceleration resolved. Modern accelerometers have developed an electronic method of measuring this magnitude of displacement. This allows a digital measure of the amplitude of the signal generated and the frequency to be taken which allows for further interpretation of the data.

### *2.1.7 Accelerometer Development*

The cantilever arm measurement process was refined with the introduction of the AM7164, or CSA, accelerometer as used by ActiLife in their initial commercial accelerometer for physical activity measurement. The uni-axial AM7164 was widely used in the initial ventures into physical activity research during the 1990s and early 2000s until it was replaced by the ActiLife GT1M model (Sasaki, 2009; Freedson, 2011). The AM7164 system uses a bimorphic piezoelectric cantilever beam, similar to the mechanical version of a pedometer, but with lead zirconate titanate crystals acting as the mass at the end of the cantilever, as opposed to a simple metal mass (Freedson, 2012). In response to an acceleration, the seismic mass moves parallel to the direction of force as before, but it is now possible to measure these displacements through an electronic circuit. If a charge is running through the arm, a circuit can be fulfilled when it displaces towards either the upper or lower boundaries. Once this circuit opening and closing can be recorded, it is possible to do away with bulky mechanical systems and miniaturise the process of measurement.

The AM7164 generated an analogue signal which represented the accelerations occurring. The analogue signal could be transformed into a digital signal which could be captured and processed. This analogue signal was first filtered at a hardware level, digitised by an analogue-to-digital conversion system, and then underwent full wave rectification to be converted into absolute acceleration measures (Dinesh & Freedson, 2012). Each time a period was recorded an arbitrary unit, or count, was made (John et al., 2010). These counts enabled set boundaries to be defined for the description of the intensity of physical activities and toward estimates of energy expenditure (Troiano, 2006; Freedson et al., 2012). A further explanation of counts is given in section 2.5.1.

### *2.1.8 Uni-Axial Accelerometer Limitations*

Uni-axial accelerometers are not without their limitations. One of the inherit limitations of the uni-axial accelerometer comes from its simple design, that of the arm. The direction a force that is imparted onto the mass through the movement of the arm in response to an acceleration is not linear, but curvilinear. That is to say that the mass is not free to move directly parallel to the acceleration, but takes as curved path to its maximal displacement. Thus, if the plane of motion through which the arm moves is not linear, the device is not capable of measuring the direct force, but rather a vector of that force. This is one of the reasons that the development of piezoresistive accelerometers became important in the accurate measure of motion and the associated energy demands of the activity being undertaken (Chen et al., 2012).

In the uni-axial design there is the possibility for loss of energy in the system due to the rigidity in the arm that needs to be overcome when an acceleration is experienced. While this can be used to act as a mechanical form of a low pass filter, only allowing accelerations over a certain magnitudes to be registered, it also acts to lower the measured accelerations. Further limitations of these systems are as a result of the amount of displacement they can measure due to size and material constraints. If there is a limitation on the size of the unit that is to hold the cantilever, there will be a limit to the maximal acceleration it can measure. This is due to practical constraints on both the length of the cantilever arm and the mass at the end of the cantilever. While not necessarily limiting the size, the mass at the end of the cantilever does affect the range in which the accelerometer can operate (Welk et al., 2012). In a mechanical system these limitations are not necessarily a problem. If the direction of motion is simple, of a known direction and displacement, it is possible to work out the combined vector.

However, when trying to measure the motion of a non linear system such as a human, who moves in neither a linear nor in a constantly repetitive fashion, the limitations of a uni-axial measurement become apparent.

### *2.1.9 Capacitive and Piezoresistive Accelerometers*

Both capacitive and piezoresistive accelerometers work on a similar principal to that of a uni-axial cantilever accelerometer except that instead of acting like a pendulum, they act as though they were a mass suspended between two springs (Illustration 2.4). As a force is experienced the mass moves parallel and inversely to the direction of movement. This causes a deformation in the material that the accelerometer is manufactured from. When the semi conductor material that the accelerometer is made from experiences a change in its structure it expresses this as a change in its electrical resistance.

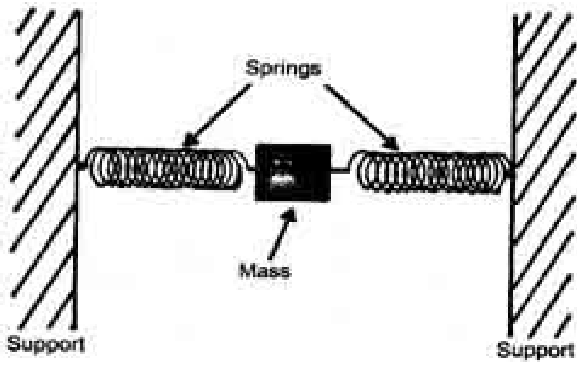



*Illustration 2.4: Accelerometer Simple Form*

If a current is placed through the material and a force (acceleration) acted upon it, a change in the voltage across the circuit will be experienced (Dinesh & Freedson, 2012). This change in voltage can be measured thus these accelerometers are refereed to as piezoresistive accelerometers as a change in resistance to a current is the method by which a signal is generated (Santos-Lozano et al., 2012; Chen et al., 2012). The piezoresistive accelerometer also has the added benefit of being able to measure static forces of acceleration, primarily that of gravity (Chen et al., 2012). The main advantages to piezoresistive accelerometers come from their ability to act as a measure in more than one direction (Chen et al., 2012). This has allowed for the development of single unit multi-axial accelerometers capable of measuring forces in multiple directions. If a mass is suspended on both sides along multiple axes, it is possible to design an accelerometer that is capable of measuring along two axes at the same time (X and Y). This acts as though the mass is suspended at the centre of a cube (Illustration 2.5, reproduced from Chen et al., 2012).

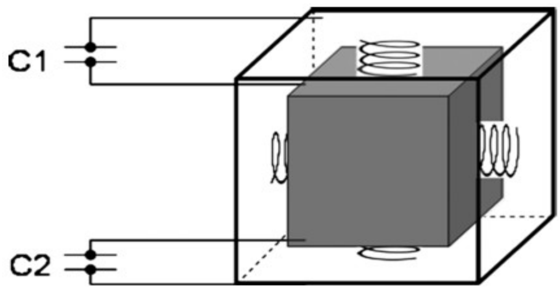



*Illustration 2.5: Dual-Axis Accelerometer*

When a force is exerted on the cube, an inverse measure of the force is measured by the accelerometer as before, however now it is capable of measurement of forces that are composites of more than one plane. These composite vector measures allow for a greater range of motions to be measured, as the measures are no longer limited to one plane of motion. This ability to measure vector accelerations has led to increasing interest in the use of tri-axial accelerometers in the measurement of physical activity. These units are capable of delivering acceleration data in three dimensions by adding measurement along the Z axis. This also allows for the first contextual source giving subject orientation in three dimensions in the form of an inclinometer (John & Freedson, 2012).

### *2.1.10 Synopsis*

The development of technologies that can quantify human motion through simple physics principles has made it possible to measure human motion, be this in the form of a simple analogue system that records distance travelled, or a more complex system that allow digital signals to be generated and captured. Although technology is now capable of measuring motion in multiple planes, the ability to estimate the energy cost of this motion necessitates the combination of this data with known methods of measuring energy expenditure and physical activity. These methods are discussed in section 2.2. The use and further development of multi-axial accelerometers in order to better measure the associated energy demands of certain activities are discussed in section 2.5.

## 2.2 Measures of Energy Expenditure

Methods and systems to measure human energy expenditure have undergone extensive research in the literature since the late 1800's (Jeukendrup & Wallis, 2005). While measurement of physiological variables such as energy expenditure are traditionally undertaken in a laboratory setting, there has been a recent move towards field based testing. Many of these systems operate by monitoring physiological parameters such as heart rate, respiration, oxygen consumption and body temperature (Howley et al., 1995). From these measured variables, each system attempts to measure the energy that is expended either at rest or during a specific activity. These methods provide different ways of measuring the energy expended, some more accurate or more portable than others. Due to these differences it is necessary to understand both when and where these systems should be applied and the limitations of each system.

### *2.2.1 Energy Expenditure Variables*

In order to measure the energy demands a human is experiencing it is necessary to first differentiate the variables that comprise the energy that is expended. At rest, total energy expenditure (TEE) is comprised of three aspects: the basal metabolic rate (BMR); the thermic effect of food (TEF); and the energy expenditure of activity, or physical activity (PA) (Levine, 2007; Butte et al., 2012). The TEE can be thought of as a gross measure, namely the total amount of energy expended over a period of time, whereas each of the other components can change affecting the TEE. Thus;

$$TEE = BMR + TEF + PA.$$

BMR is a measure of the energy expended at rest that is required for human function; respiration, brain function and cardiovascular function. When measurements of BMR are to be taken a subject must be in a pre-absorptive state, e.g. fasted and just awoken. It represents approximately 60% of energy expended at rest in sedentary populations and is highly predictable by lean body mass (Levine, 2007). TEF is a resultant of the increase in energy demanded to break down food and accounts for about 10% of TEE (Levine, 2007; Butte et al., 2012). PA is defined as '*any bodily movement produced by the contraction of skeletal muscles that results in a substantial increase over resting energy expenditure*' (ACSM, 2012). Thus the remaining 30% of TEE measured over a period is as a result of movements carried out during the period. At rest we would assume a very low percentage of energy is being expended, thus defining resting metabolic rate (RMR). The RMR lies approximately 10% above the BMR, the increase above the BMR predominantly due to the body being awake and other metabolic systems demanding energy (Butte et al., 2012). Similarly to BMR, RMR is measured with the subject at rest, lying in a supine position (Levine, 2007; Butte et al., 2012). In order to assess each of these energy expenditure components various methods have been developed to measure and predict how much energy will be expended under certain circumstances.

### *2.2.2 Direct Calorimetry Method of Energy Expenditure Measurement*

Direct calorimetry involves measuring the change in temperature of a body of air relative to a fixed point, after a subject has been introduced to a calorimeter. This was the basis by which the initial assessment of BMR and RMR were taken and is considered the gold standard of measurement of energy expenditure (Westerterp et al., 2004; Levine, 2007). Direct calorimetry works on a simple work-energy concept. As it takes a known amount of energy to increase a known volume of water by a degree Celsius, it is possible to calculate the amount of energy expended when a fraction of that temperature is increased. From this it is possible to calculate the TEE by a subject when they are placed in a sealed calorimeter for a known period of time. This method is expensive, complex and inherently in-situ due to the nature of the measures being taken (Levine, 2007). Although highly accurate, the complex nature of direct calorimetry does not lend itself well to many research departments. It is however the gold standard against which all other methods are gauged and thus all other systems are validated against it. Consequently, as this method is so cumbersome, indirect calorimetry was developed.

### *2.2.3 Energy Expenditure Measurement Standards*

In order to compare methods of energy expenditure it is necessary to have a standard unit of energy expenditure. This unit, the kilocalorie (kcal), represents the amount of energy needed to raise one kilogram of water by one degree Celsius at sea-level. This is the same basis used by the direct calorimeter and allows for a comparable unit to be used between any measure of energy expenditure, regardless of the system used to measure it. Another commonly used measure is that of the metabolic equivalent (MET). A MET is defined as 3.5ml/kg/min (Sasaki et al., 2011). The MET is the basis of the intensity ranges are represented for the ActiGraph accelerometer platforms described in the following sections. These physical activity measures can easily be converted into kcal or units of $VO_2$ should a researcher need to do so. The ActiGraph intensity ranges are set at <2.99 (Low), 3 – 5.99 (Moderate), 6-8.99 (Hard), and >9 (Very hard) (Sasaki et al., 2011). As each of these intensities relate to an equivalent associated energy expenditure, it is possible to estimate the amount of energy expended using an accelerometer that is capable of measuring intensity based on motion alone (Section 2.5).

### *2.2.4 Indirect Calorimetry Method of Energy Expenditure Measurement*

Indirect calorimetry involves the measurement of both inspired and expired carbon dioxide ($CO_2$) and oxygen ($O_2$) in order to calculate the amount of energy expended (Levine, 2007). The concentration of inspired air must be known and stable relative to the altitude and environmental conditions that are present at the time of testing. Thus, these systems are either calibrated to a known concentration of either or both gases, or they are calibrated to the relative air. As air is affected by environmental conditions such as altitude; changes in available oxygen, temperature and pressure; all of which change the viscosity of the air, it is necessary to use these environmental conditions in the calibration procedure. Every system on the market has its own method of calibration designed by the manufacturers which must be followed in order to be certain of a measure with the least amount of variance.

An indirect calorimeter works by measuring the change in concentration of expired gases relative to the gas that was inspired (Levine, 2007; Illustration 2.6). This is achieved through the use of carbon dioxide and oxygen sensors which can measure the amount of each gas expelled with each breath. As the intensity of an activity increases, i.e. cycling at increasing resistances, the amount of oxygen that the working muscle demands increases. As this demand for oxygen increases the body produces more carbon dioxide as a by-product. This increased demand for oxygen and increased production of carbon dioxide can be used to assess the fuel that is being utilised as well as defining metabolic events (Brooks, 2007; Jeukendrup & Wallis, 2005; Levine, 2007). As exercise intensity increases the bodies need for oxygen increases and carbon dioxide excretion increases exponentially until the subject is no longer able to maintain the required resistance due to an inability to deliver oxygen to the working muscle (Coyle et al., 1991).

*Illustration 2.6: Cosmed K4b$^2$ Portable Metabolic System*

These measures are then processed through a set of equations in order to calculate the amount of energy expended per breath, or over a given period of time. These use measures of the expired gases as well as anthropometric data to calculate the TEE from the sample, commonly using the Weir equations (Levine, 2007).

At rest this method can be used to assess the BMR and RMR of a subject without the need for a direct calorimeter. With this method it is also possible to measure the associated energy cost during physical activity and increases in the energy demands due to changes in intensity of the activity being undertaken. This is the common method by which most energy expenditure data is gathered in exercise laboratories, and recently during outdoor field testing.

### *2.2.5 Component Parts of Physical Activity*

In order to isolate various components of the total energy expended (TEE) when measured with an indirect calorimeter it is necessary to have a measure of the basal metabolic rate (BMR) and, if possible, the food ingested by the subject being investigated. If a known measure for the RMR of a subject is available and it is assumed that they have ingested no food it is possible to rearrange the equation from section 2.2.1 to read;

$$PA = TEE - RMR - TEF \text{ (where } TEF = 0\text{)}$$

### *2.2.5.1 Thermic Effect of Food (TEF)*

Although the thermic effect of food (TEF) is not negligible it is very difficult to measure without an accurate account of the food that the subject has eaten (Levine, 2007). Due to the associated changes in the body's temperature after the consumption of food, it has been suggested that a measure taken at the skin could prove an accurate measure for the thermic effect of food (Lanzola et al., 1990). Multi-sensory systems such as the SenseWear™ Armband (Section 2.3.6) have developed integrated thermistor-based algorithms into their hardware in an attempt to use this as a possible compensatory measure and to aid with the measurement of sleep periods (Liden et al., 2002; Sunseri et al., 2002; Jakicic et al., 2004). However, as of yet this has not been used to estimate times or the amount of food ingested.

### *2.2.5.2 Basal, and resting, Metabolic Rate (BMR & RMR)*

Once the BMR is known it is possible to estimate a value for the energy expended during the activity being measured, i.e. physical activity. If the RMR of the subject is not known, or there is not the time nor equipment to measure it, it is possible to estimate this value based on anthropometric data (Section 2.2.6). However, where possible it is better to have a measure for the BMR. Ideally this measure for BMR will also be representative of the activities the subjects are undertaking. Levine et al. (2007) note that the BMR should be measured first, followed by an RMR in the position in which the activity is being undertaken thus increasing the specificity of the measurement taken and ultimately reducing error in the physical activity measurement. However, if the activity is taking place in an environment where it is not possible to utilise direct measures of physical activity, estimations based on anthropometrics are the common way to estimate the subjects RMR.

## ***2.2.6 Calculated Estimates of Energy Expenditure***

Although less accurate, it is possible to calculate the RMR through non measurement based methods. The Harris Benedict equations are a method commonly used in nutritional assessment (Levine, 2007; Malavolti et al., 2007). However, these equations, that can be used for any age, ethnicity or weight tend to overestimate measured RMR by at least 5% (Frankenfield et al., 1998). Recent adaptations of these equations have not resulted in any greater accuracy and thus there is a need for better methods of measuring RMR without the use of BMR testing undertake in a laboratory setting (Malavolti et al., 2007). In recent years this has led to the development of new technologies that are capable measuring RMR from either single physiological measures such as heart rate, through direct measurement of work via power meters, or multi-sensory systems such as the SenseWear™ Armband.

### *2.2.7 Synopsis*

There are many methods of measuring and estimating the energy expenditure. However, the ability to objectively measure the amount of energy expended during a specific activity becomes more complex the greater the accuracy needed. For many people, the ability to estimate the amount of energy expended while they walk to work or cycle at the weekends is all they want and they are not worried about high levels of accuracy. However, these methods must still be capable of estimates that relate to the gold standards of energy expenditure measurement. Due to this need for information, more energy expenditure estimation tools are becoming available to researchers and the general public. These tools aim to estimate energy expenditure in different manners and are covered in the next section. Although they may be simple estimates of energy, their simplicity and relative low cost makes them an invaluable tool for research.

These systems, and other methods of physical activity measurement are discussed in the following section.

## 2.3 Tools for Estimating Physical Activity

In order to use any physical activity measurement system in a scientific research environment it first needs to undergo testing against the current gold standard for energy expenditure measurement. This allows researchers, athletes and users to monitor its performance using a tool that they know is valid. Currently there is a staggering uptake of simple technologies, such as accelerometer based pedometer systems, which claim to calculate daily energy expenditure as well as the energy expended during specific physical activities. These systems measure stride frequency and then extrapolate the distance a person walks based on the number of strides taken at an assumed, or user defined, distance per stride. Although in laboratory trials these systems can provide accurate measures (Bassett et al., 1996; Crouter et al., 2003), once taken into field testing where stride length and velocity is less constant, they tend to severely overestimate distance covered and energy expended (Crouter et al., 2003). However, for many users this is not an issue as they simply wish to measure what they are doing day-by-day.

### *2.3.1 Self Reporting Physical Activity*

With many different methods of estimating energy expenditure it can be problematical to measure physical activity with an appropriate level of precision or accuracy. In order to help users who do not have access to laboratory measures, or wish to estimate physical activity without technological intervention, the use of physical activity recall diaries has become commonplace. These involve a subject recording all the physical activity they perform over a period of time, either on their own, or with the help of a trained supervisor (Klesges et al., 1990) in order to asses the amount of energy expended. A clinician records the amount of time spent in various activities and calculates an estimate for the physical activity performed. The aggregation of laboratory standardised energy expenditure data for different activities has led to the creation of the 'Compendium of Physical Activities' (Ainsworth et al., 1993; Ainsworth et al., 2011). This contains a MET value for each activity, as well as a simple method of conversion from MET to kcal;

$$kcal = MET * mass(kg) * time\ (hours)$$

Once the total amount of time spent in each physical activity has been recorded, the clinician simply calculates the total estimated physical activity for the recorded period of time. The use of activity recall diaries is a standard process and many have been validated against standards such as doubly labelled water, which in turn are validated against direct calorimetry (Levine, 2007; Rush et al., 2008). Although there is a general agreement on the amount of energy that is expended during specific physical activities, and thus can be estimated via a written recording, there are multiple physical activity diaries and methods of gathering the data either with or without appropriate supervision. It is also not a particularly objective measure as the ability of the user, or assessor, affects the accuracy of the data collected (Levine, 2007). In the case of some recall diaries this data is significantly worse with subjects significantly underestimating sedentary activities and overestimating aerobic activities by over three hundred percent (Klesges et al., 1990). Thus, although easy to use and relatively accurate, due to the involvement of a human subject they may not always provide an objective measure of the physical activity undertaken. Due to this, it is becoming more common place to see these diaries used in conjunction with other methods of physical activity estimation such as the SenseWear™ Armband (Johannsen et al., 2010; Dolan et al., 2011) and various iterations of the ActiGraphs (Machado-Rodrigues et al., 2012; Martínez-Gómez et al., 2009; Patterson et al., 2002).

### *2.3.2 Validation of Sensor Platforms*

In order to evaluate a variable, the sensor system must be capable of reliably measuring that parameter in the first place and have a low test to test variance (Chen et al. 2012, Basset et al., 2008). Furthermore, if these sensors are to be deployed independently, they must be calibrated against the best measurement techniques in that area otherwise they may not measure what they claim to. Both incremental and ramped maximal exercise tests have been validated in the literature throughout the years for the measurement of physical activity undertaken during exercise testing. While it is not realistic to continually instrument people with metabolic carts as they go about their daily activities, any system that is to be used to estimate physical activity must ideally be trialled against these gold standard systems (Chen et al., 2012). Thus, it has become common practice to validate any new physical activity measurement device against these standard measurement systems. If the device overestimates the amount of energy expended, or the intensity of activity occurring, it will be necessary to take these measured variables and scale them so they can be used as accurate estimates (Welk et al., 2012). Furthermore, if a sensor is deployed in a location that is incapable of measuring the changes in physical activity occurring, it may be impossible to extrapolate any valid data from the device.

### *2.3.2 Heart Rate*

The ability to measure and display the response of the cardiovascular system to exercise has led to a revolution in the training methods of athletes over the past 20 years. This understanding has led the development of many portable systems capable of measuring heart rate. These systems have been popular since the early 1990's with Polar (www.polar.fi) and Garmin (www.garmin.com) becoming market leaders. Polar have multiple wireless heart rate systems which claim to measure to electro cardiograph (ECG) accuracy and allow for accurate estimation of the energy expended during any physical activity (Achten & Jeukendrup, 2003).

Like other methods of physical activity estimation, heart rate monitoring is relativity non invasive and, unlike direct and indirect calorimetry, the addition of a simple heart rate strap and watch do little to interfere with the activities being undertaken (Achten & Jeukendrup, 2003). The basis by which heart rate monitoring estimates physical activity is due to the associated response between heart rate and increasing oxygen demand with exercise (Capani et al., 1982; Achten & Jeukendrup, 2003). With an assumed, or measured, value for $VO_2$ entered into the unit, the changes in measured heart rate can be related to a set of median data for age and mass which is used to estimate the energy expended during any physical activity. This takes aspects of the user's anthropometric data and combines it with a gold standard measure in order to render a more accurate estimation of physical activity. This method of estimating physical activity has also been validated against indirect calorimetry (Capani et al., 1982). However, as heart rate changes in response to exercise, there is an associate lag and thus individual variation in the estimations (Firstbeat Technologies, 2007). Due to this, algorithms developed by Garmin in conjunction with Firstbeat technologies have allowed heart rate monitors to integrate VO2 data gathered during maximal incremental trials into their calculations.

This allows for the development of more accurate methods of estimating physical activity from heart rate measures, while using a gold standard measure as a method to make their algorithms more robust. Heart rate monitoring, although well established, still has some negative aspects. It is not always possible to gather a reliable signal from the user; even the introduction of electrolyte gel in order to increase conductivity can sometimes not be enough in hairy subjects. The use of a common 60Hz sample rate unfortunately places many heart rate monitoring devices in the same realm as commercial electrical appliances rendering them useless in some cases (Chen et al., 2012). With many modern heart rate systems moving away from proprietary transmission protocols and onto the ANT+ standard (www.thisisant.com) the ability to transfer multiple sets of data from multiple sensor sources to a single wrist based heart rate monitoring unit has become commonplace. However, this has now led to the necessity of rechargeable heart rate monitors with on board storage and very poor battery life.

### *2.3.4 Direct Measurement of Work*

Systems have been available to directly measure the mechanical work, or power output, of cyclists since the late 1800's and were used in the first measures of physical activity (Atkinson et al., 2003). Similarly, other sports have developed methods of directly measuring the amount of energy expended during their specific activity independent of metabolic carts or heart rate monitoring. In cycling, the ability to measure the physical capacity of a cyclist was traditionally restricted to laboratories on static ergometers (Section 2.3.4). While cycling, the cyclist would be measured via a metabolic cart and the energy expenditure for a bout of activity at a known resistance calculated. This was similar for many other sports and activities, with the subject using an ergometer designed for their activity. The recent commercial availability of portable power measuring technologies (Section 2.3.5) has led to a similar revolution in cycling as first experienced with low cost portable heart rate monitors in the sport of running. Recent technological advancements have allowed many traditionally laboratory restricted measurement techniques to proliferate into the commercial environment. This has allowed athletes and coaches to gather information about the specific energy demands of their sport in the field and with accuracy similar to that of a laboratory environment.

### *2.3.5 Direct Measurement of Physical Activity*

One such example of a static measure of physical activity is the Velotron Dynafit Pro (Racermate Inc., Seattle, U.S.A) a laboratory calibrated cycling ergometer designed for tests of performance during cycling ergometry. Through a simple calculation of the amount of work undertaken by the cyclist in Watts; 1W = 1.63kcal (assuming 100% efficiency) it is possible to estimate the amount of physical activity during that bout of cycling by converting into kcal. This equation is generally accepted as being a 1:1 ratio, 1W:1kcal, as much of the energy generated during cycling is disapated in the form of heat. This allows a cyclist to estimate how much energy an effort demands at a given power output, thus in longer cycling or triathlon events allow them to optimise racing and fuelling strategies based on energy demands (Atkinson et al., 2003).

### *2.3.6 Field Based Measurement of Physical Activity*

The SRM (Schoberer Rad Messtechnik, Welldorf, Germany) crank-set was one of the first portable power measuring tools available to the cycling community, albeit at a high price. The SRM system calculates power output from the torque and angular velocity generated at the bottom bracket of the bicycle (Faria et al., 2005a). This is achieved through a system of strain gauges located between the cranks and the chain-rings which measures the deformation between the two, a similar design to the first accelerometers used to estimate physical activity (Chen et al., 2012). The deformation in the strain gauge is proportional to the torque being generated during each pedal rotation and can be used to calculate the mechanical power, which in turn estimates the physical activity undertaken. Several studies have validated the crank-set and its test to test repeatability and it has been shown to be a valid system in both laboratory and field conditions (Gardner, 2004; Juekendrup, 2003; Duc et al., 2007). Variations of the crank-set now exist for both scientific measurement (accuracy + 0.5%, weight 827g), professional (accuracy ± 2.5%, weight 560g), and amateur (accuracy ± 5%, weight 640g).

This system combines measures of heart rate, power, cadence and speed in order to give a multi-sensory view of the physiological impact of cycling. The latest version of the PowerControl unit, the recording system for the SRM, has integrated wireless communication via the ANT+ protocol as well as an accelerometer which is currently only used to recognise when the unit is moving. Although the accelerometer apparently performs no use other than a simple marketing tool, this integration of an accelerometer into the unit shows how new sensing technologies are being adopted in order to prepare for future advances. It is quite possible that professional cycling teams are already working with this accelerometer data in order to assess aspects of cycling performance as yet unknown; however if this is so, the data has yet to be made available.

Athletes and coaches are now able to gather performance data during cycling and consequently can estimate the energy expended from a direct measure of the work performed by the cyclist in field conditions. These tools can be used to gather laboratory standard data in the field and are aiding in the development of other methods of estimating cycling performance in various field based environments (May et al., 2010; Conroy et al., 2011). By combing power measurement, GPS and heart rate capabilities it is possible to gather extensive data that can be better used to explore performance determinants of a given sport in detail.

### *2.3.7 Multi-Sensory Physical Activity Estimation Systems*

Although specific systems developed for a single sport are of importance, there is a need for objective measures of physical activity in all areas. The SenseWear™ Armband (Bodymedia, USA, Illustration 2.7) is one such system. It is a validated (Table 2.1), wireless body monitoring system that provides estimated data on energy expenditure in free-living conditions (Liden et al., 2002; Johannsen et al., 2010). The SenseWear™ Armband has undergone several form changes and has advanced significantly since the studies undertaken by Jakicic et al., 2004 that called for '*exercise-specific algorithms to the SenseWear™ Pro Armband*'. The most recent version, the SenseWear$^{Mini}$ incorporates wireless communications in order to transmit data to the users watch and smart-phone.

The armband employs a variety of sensors in order to estimate energy expenditure, measure physical activity and estimate sleep quality and quantity (Liden et al., 2002). It employs; a dual-axis accelerometer, a heat flux sensor, a galvanic skin response sensor, a thermistor-based skin temperature sensor and a final thermistor based near-body ambient temperature sensor (Liden et al., 2002). These sensors continuously gather data to estimate the energy expended, intensity of physical activity and temperature experienced by the user (Malavolti et al., 2007).

*Illustration 2.7: SenseWear™ Armband, Pro3 model*

Gender, age, weight and height are also incorporated into the unit in order to help with estimates of resting metabolic rate. Using this broad range of sensor data the SenseWear™ Armband is capable of estimating the total energy expenditure of its wearer both at rest and during exercise (King et al., 2004; Fruin & Rankin, 2004; Malavolti et al., 2006; Johannsen et al., 2010). However, it currently fails to fully capture short duration high intensity exercise (Drenowatz & Eisenmann, 2011; Koehler et al., 2011). As the SenseWear[Mini] has only recently become available in its new form, the high intensity issues may have been addressed with recent updates to the proprietary algorithms incorporated into their software.

*Table 2.1: SenseWear™ Validation Studies*

| Author | Year | Physical Activity Mode | Group Size | Duration | Intraclass correlation (R) |
|---|---|---|---|---|---|
| Brazeau et al. | 2011 | Ergo-cycling measured via indirect calorimetry (IC) | 31 (16 female, 15 male) | 45mins at 50% VO2peak | 0.81 |
| Drenowatz et al. | 2001 | Treadmill running measured via IC | 20 (10 female, 10 male) | Various from 10mins to 30mins | 0.71 |
| Koehler et al. | 2011 | Running and free-living | 14 males | 7 days | 0.73 |
| Jakicic et al. | 2004 | Walking, stepping, cycling and arm ergometers measured via IC | 40 | 20-30mins per mode | 0.39 - 0.77* |

The study from Jakicic et al. (2004) used a separate algorithm that they developed and applied to the SenseWearTM data which resulted in an intraclass correlation of 0.89. It is noted in this study that the change of intensities undertaken in the study were not picked up by the SenseWear™ armband due to its inability to measure rapid changes in intensity with its one minute sample rate. This study, undertaken with an early version of the sensor, called for a new version of the proprietary algorithms to be developed for any further releases of the SenseWearTM Armband. More recent iterations of the sensor from Bodymedia have provided a better tool with which to estimate energy expenditure and physical activity.

The SenseWear™ armband has been used in sleep studies where it has been shown as a used in the field of polysomnography, the measurement of sleep, which is generally undertaken within specifically designed sleep laboratories or retrospectively through the use of questionnaires (Sunseri et al., 2002). However, polysomnographic measurements are cumbersome, expensive and in the case of sleep lab studies, often affect the subject's natural sleep patterns (Sunseri et al., 2002). Previous studies have shown the SenseWear™ Armband to be a valid tool for the measurement of the time spent asleep and awake, as well as the quality of this sleep (Sunseri et al., 2002; Germain et al., 2006; Miwa, 2009). The addition of the dual-axial accelerometer allows for a measure of movement to be integrated into its calculations. This can also be used as a direct contextual tool as an indication of body position over a period of time, lying for example indicating sleep, however being only dual-axial this cannot act as a true inclinometer (Chen et al., 2012). This dual-axial accelerometer can also give a motion based assessment of physical activity independent of the other sensors if the information is extracted from the raw data.

### *2.3.8 Sleep Measurement*

From measured changes in the accelerometer of the SenseWear™ Armband, it is possible to calculate a score for sleep quality for a subject by measuring the number of wake periods during the night, the amount of movement and the duration of these periods (Miwa, 2009). By subtracting the duration of the wake periods from the time lying down it is possible to measure the time in sleep. Dividing this time by the duration spent lying down will gives a figure for the sleep quality as a percentage of overall time spent attempting to sleep. The actual algorithms developed by Bodymedia are not available to researchers so it is quite probable that other sensors are also being used to further refine the measurements. It is understood that core temperature varies in accordance with a person's circadian rhythm, or biological rhythms (Reilly, 1990). The integration of a thermal measurement allows for a more accurate approximation of the time spent sleeping, as well as cycles within that sleep, than estimates based solely on motion. However, the acceleration patterns that are produced during sleep allow for a layer of contextual information to be added to the captured data (Liden et al., 2002.; Ancoli-Israel et al., 2003; Kozey-Keadle et al., 2011).

The use of these small accelerometers, actigraphs, to log and measure movement is becoming more common place and more systems are starting to integrate this technology with other sensors to accurately measure sleep duration and quality (Bouten et al., 1994; Sunseri., 2002; Germain et al., 2006; van Wouwe et al., 2011). The advantage of these systems is that they can be used in any environment to measure sleep quantity and quality, as well as being used to investigate other aspects such as physical activity levels and patterns while the person undergoes activities of daily living (Sunseri et al., 2002).

### *2.3.9 Synopsis*

Measurement techniques are evolving at an exponential rate in agreement with Moore's law. Sensors are becoming more intricate and complex, utilising multiple streams of sensor data and using manufacturer driven proprietary algorithms in an attempt to mimic gold standard measures. Although these sensors are inherently tools of estimation, they are continually bridging the gap between estimation and measurement. Currently, the layer of accelerometer driven context is the basis on which the trend in physical activity measurement is based (Ravi et al., 2005; Butte et al., 2012). By taking the signals that are generated by these accelerometers, it is possible to know not just what activity is being undertaken; but also the intensity and duration of the activity, and furthermore to estimate the associated energy cost of the activity (Sasaki et al., 2011; Kozey et al., 2010; Kozey-Keadle et al., 2011). This current trend is being undertaken predominantly with tri-axial accelerometers with one of the most commonplace and widely accepted physical activity research units being that of the ActiGraph (Santos-Lozano et al., 2012).

## 2.4 ActiGraphs in Physical Activity Assessment

As technology has advanced, the sensors used to measure physical activity have become smaller, cheaper and more user friendly. Readily available electronic sensors are appearing that are capable of measuring any aspects of daily life. These systems embedded in phone, laptops and watches and are becoming pervasive in all electronic media. Although the objective monitoring of physical activity through the medium of accelerometers has been in practice since the 1980's (Dinesh & Freedson, 2012), it is only in recent years that these systems, and the methods to understand the data produced, have evolved to the point at which they are becoming more commonplace in physical activity research. The availability of low lost accelerometers has thus fuelled the development of smaller more portable physical activity measurement systems (Kozey-Keadle et al., 2011).

### *2.4.1 Limitations of Accelerometers in Physical Activity Assessment*

The use of the accelerometer based technologies in the assessment of physical activity has gathered more acceptance within the scientific community with tens of research papers emerging in the past few years. However, these systems are not without their limitations as they inherently measure only the motion occurring during physical activity, and thus, can only be used as estimates of one aspect of energy expenditure (Liden et al., 2002). With the increased interest in promoting physical activity, there is a necessity to validate these systems that are commercially available (Santos-Lozano et al., 2012), but also to do so in research and free-living conditions (Banda et al., 2010). Before using any system a researcher must be aware of its limitations and what it is capable of measuring. One of the most commonly used accelerometer based technologies in the literature is the ActiGraph, which has undergone many iterations in its development.

### *2.4.2 GT1M ActiGraph History*

As a result of the recent surge in interest in objective measures of physical activity, various assessment methods have been explored using accelerometers (Kozey-Keadle et al., 2011; Sasaki et al., 2011; Crouter et al., 2006). After the introduction of the AM7164 model in the early 1990s, ActiGraph introduced a new, superior, version called the GT1M uni-axial ActiGraph (Sasaki et al., 2011; Illustration 2.8). This model replaced the AM7164 with greater accuracy and higher range of measurement.

However, this system still worked on a simple count basis (Sasaki et al., 2011). This switch saw a change in the accelerometer used in the units from the AM7164 accelerometer to the ADXL220 accelerometer in the GT1M and from a cantilever based accelerometer, to a capacitive accelerometer (Dinesh & Freedson, 2012). A capacitive accelerometer works in a similar manner to a piezoresistive accelerometer, though it uses a different method to generate the signal needed to measure the accelerations. Recent studies have confirmed that valid comparisons can be made between the GT1M and with its predecessor the AM7164 resulting in the adoption of many of the physical activity measurement algorithms to the GT1M (Bassett et al., 2012; Staudenmayer et al., 2012). However, it must be noted that this only applies to count based data taken from the vertical plane (Dinish & Freedson, 2012; Santos-Lozano et al., 2012; Chen et al., 2012).

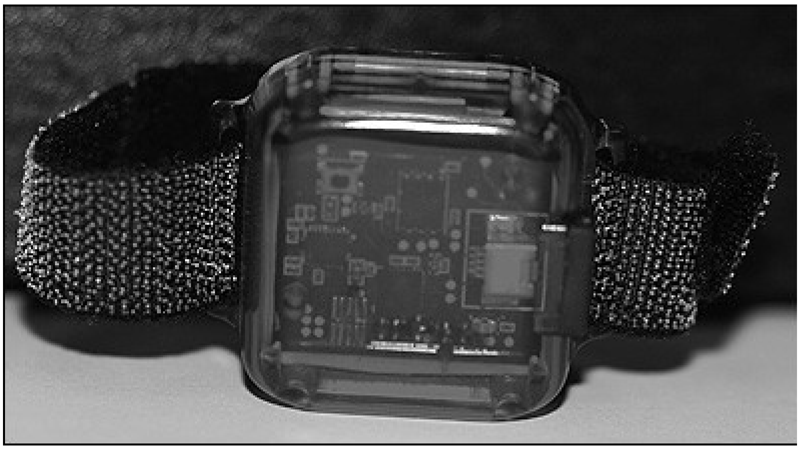


*Illustration 2.8: GT1M ActiGraph*

With the change to a capacitive accelerometer in 2008 ActiGraph enabled measurement on the second axis of the GT1M, thus allowing combined vector measures to be taken from the vertical and horizontal planes (Sasaki et al., 2011). The ability to measure vector forces, as opposed to accelerations along one or more axes independently, opened the door to a more accurate and descriptive measure of physical activity (Troiano, 2006). It was also the precursor to the tri-axial GT3X and GT3X+.

### *2.4.3 Composite Vector Forces*

With the introduction of vector measures on the GT1M, a new wave of possible uses emerged for the ActiGraph platform. Unlike its predecessor, the GT1M was now capable of measuring two axes independently and resolving a combined vector force, thus implying direction. Whereas previously research was conducted about the number of activity counts that were recorded on one plane of motion, the ability to resolve composite vector forces allows for the measurement of forces being experienced in all directions.

Composite Vector Measurement for multi-axial accelerometer:

Dual-axial: $VM2 = \sqrt{VT^2+AP^2}$

Tri-axial: $VM3 = \sqrt{ML^2+VT^2+AP^2}$

*Where, ML = medial plane, VT = vertical plane, AP = anterior-posterior plane (Sasaki et al., 2011).*

In theory the number of planes of measurement that could be used is infinite, but this will be limited by the design of the sensor, as well as the space that can be dedicated to it. It is possible that running several tri-axial accelerometers in different orientations to each other may allow for more planes to be added into these calculations. However, this adds another level of computation and error into systems that are already producing data far ahead of the analysis techniques for physical activity estimation that are available to most researchers.

### *2.4.4 GT1M Validity*

The GT1M was shown to be a valid measure of physical activity when related to 3 day physical activity recall diaries (Machado-Rodrigues et al., 2012) and more recently to agree with the more modern GT3X accelerometer under certain conditions (Vanhelst et al., 2012, Sasaki et al., 2011). Godfrey et al. (2008) note that the GT1M '*device can accurately measure activity counts, steps counts, calories and activity levels across a range of ages and clinical groups and test conditions*'. It is due to this that the GT1M has a large body of physical activity data with which to work, and on which most of the cut-points and algorithms used today are based (Godfrey et al., 2008; Dinesh &

Freedson, 2012). In 2009 ActiGraph released a new product, the GT3X accelerometer. Using a tri-axial design it has now superseded the GT1M as the current tool for objective physical activity measurement. Many of the techniques developed first on the AM7164 and transferred to the GT1M are still being used on the GT3X.

Of note however, are the differences that are experienced between measures along the horizontal plane in the GT1M and its successor the GT3X. It has been shown that direct comparisons can not be made between these units as differences do exist in combined vector measurements (Sasaki et al., 2011). It is possible that this is due to either firmware or hardware differences between the two units (Santos-Lozano et al., 2012; Freedson et al., 2012). Thus, any comparisons made should only be undertaken utilising data from the vertical plane alone. However, the benefit of this is that it allows comparisons of data to be made across all generations of the ActiGraph accelerometers for estimating physical activity once the count data from the vertical plane alone is used (Sasaki et al., 2011).

### *2.4.5 The GT3X ActiGraph Technical Specifications*

The GT3X ActiGraph accelerometer (ActiGraph, Pensacola, FL, USA; Illustration 2.9) is a lightweight (27g), compact (dimensions of 3.8 cm × 3.7 cm × 1.8 cm) and rechargeable unit (lithium polymer battery powered). It contains a solid state semiconductor piezoresistive tri-axial accelerometer capable of gathering data on the vertical (VT), horizontal (AP) and medial (ML) planes. It uses an ADXL335 accelerometer with an active range of ±3g (Sasaki et al., 2011). However, it only uses an active range of ~0.05g – 2.5g and a sample rate of 30Hz (Santos-Lozano et al., 2012). Other than changes in the accelerometer utilised in the GT3X, it is with all respects identical to the GT1M bar the capacity to record data on three axes of motion (Dinesh & Freedson, 2012).

*Illustration 2.9: GT3X ActiGraph*

Data from the GT3X however is expressed as raw accelerations rather than as count with the actual G forces sampled every 0.033s (John & Freedson, 2012). It must be noted that the raw acceleration data, although termed pre-filtered, is filtered at the level of the hardware with a low-band filter that is presented by the semiconductor material used in the accelerometer itself (personal communications with J. Dinesh). Hence, for sedate activities the GT3X may tend to underestimate the energy expended (Kozey-Keadle et al., 2011). This loss of data is also attenuated by a limitation of the unit itself known as the 'plateau effect'.

### *2.4.6 Plateau Effect*

The plateau effect is an artefact seen in the raw acceleration data. This inverted U shape is thought to be an effect due to the hardware filtering of the accelerometers within the GT1M and GT3X (Sasaki et al., 2011; Chen et al., 2012). This is seen as a levelling off of the accelerations measured and presents itself as a flat section at the top and bottom of a change of acceleration as shown in illustration 2.10 below. This effect shows itself at higher frequencies of motion and in studies performed by both Saskai et al. (2011) and Dinesh et al. (2012) they found that estimates of physical activity while running at treadmill velocities above 12km/hr were underestimating the energy expended significantly compared to other velocities. Sasaki et al. (2011) noted that the use of VM3 vector measures (Section 2.5.2) did not attenuate the loss in data when compared to data on the vertical axes alone. This suggests that the issues lie within the data capture at the vertical axis and is not an error created by transferring to a vector based measurement. It is also possible that this is down to a more simple issue, that of Nyquist's principle. This principle states that '*the sampling rate should be greater than or equal to twice that of the highest frequency contained within the signal*'. If the signal that is being measured is of a greater frequency than the device that can capture it, the time between signals may just swamp the sensor and a continual acceleration may be registered.

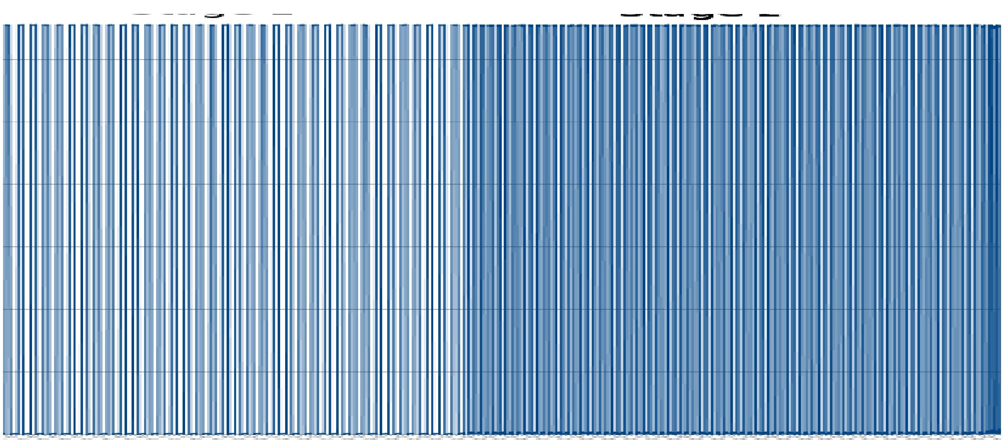


*Illustration 2.10: Plateau Effect*

### *2.4.7 Firmware and Hardware Issues*

The GT3X has undergone several firmware updates since its release in 2009. Firmware is defined as '*the programming code containing a set of instructions that enable communication between the hardware components of a device'* (Dinesh & Freedson, 2012). This firmware is located on the solid state memory of the GT3X and is updated as needed via the proprietary software package, ActiLife. This package also acts as the method for the user to initialise the units and perform data analysis. One of the advantages to this firmware based system is in that of the calibration of the units. It is possible that the calibration of these may drift over time, however this can be user reset by uploading a new set of firmware (Dinesh & Freedson, 2012). Unlike the GT1M which used a capacitive accelerometer, the GT3X uses a piezoresistive accelerometer. One of the worries with the GT1M model was that it would drift after a hard impact as capacitors are prone to impact damage. Dinesh et al. (2012) examined this and found that with drops from 2 metres onto a hard concrete floor that no noticeable drift occurred with the GT1M. Although it is possible that the GT3X may be susceptible to drift due to impact forces, it is not inherently part of the design of the accelerometer itself and more likely to be due to a catastrophic failure of the housing of the unit. The GT3X, much like the GT1M uses a proprietary connection to upload and download data and was not designed for water immersion although it was designated to be splash proof. The latest generation of the GT3X+ now incorporate a waterproof housing as well as a standardised micro USB connection making the unit easier to use and hopefully increasing the lifespan. The newest wGT3X+ also utilises wireless communication via the ANT+ protocol (www.thisisant.com) and only needs to be opened to recharge.

### *2.4.8 Validation of GT3X*

As mentioned in section 2.3 the question of the validity and accuracy of any system designed to measure, or estimate, physical activity must be investigated before it can be used for research purposes. It is at this point that the accuracy of these systems comes into question. However, the number of simple accelerometer based systems on sale today for personal measurement of physical activity is astounding. A simple search on the World Wide Web will give results from companies such as Motorola, Nike, Adidas and many more which have not been used in scientific trials although they claim to measure physical activity. With these systems the user may not be particularly concerned about the accuracy of the tracked variables, more the action of tracking said variables. The ability to capture data, share it with their social networks and look at personal trends has become more important than the validity and accuracy of the data itself.

This is not an acceptable standpoint to take in the scientific community and thus the ActiGraph accelerometers have become one of the prime systems in the measurement of physical activity via measured motion (Santos-Lozano et al., 2012; John & Freedson, 2012). Thus the GT3X has undergone extensive validation and accuracy trials presented below in table 2.2. Although these validity trials have also been carried out with respect to the older models of the ActiGraph, it is only recently that the newer GT3X model has undergone validations (Santos-Lozano et al., 2012). A study carried out by Santos-Lozano et al., (2012) using vibration plates at a known intensity and frequency, found high inter-reliability and intra-reliability testing between the GT3X units. That is to say they were both repeatable within a batch of independent units for the same measure, as well as against themselves over repeated measures (Santos-Lozano et al., 2012). This trial looked at activities between 0.5–5521 counts/min which related to activities from dish-washing (11 counts/min) to treadmill running at 2.23m/sec (7490 counts/min) (Santos-Lozano et al., 2012). This range was also explored by Sasaki et al., (2010) who used treadmill running at a range of velocities and found similar results. A summary of some of the validation trials on the GT3X platform is presented in table 2.2 below . Although validity and repeatability tests have been performed on the GT3X, it is worth noting that these have been undertaken in a laboratory environment and there is a consensus that there is a need to perform free-living repeatability and validity trials (Santos-Lozano et al., 2012; John & Freedson, 2012). Although the GT3X provides an excellent tool in the measurement of physical activity, it must still be recognised that it is still a new system and needs further validation.

*Table 2.2: GT3X Validation Studies*

| **Author** | **Year** | **Physical Activity Mode** | **Group Size** | **Duration** | **Intraclass correlation (R)** |
|---|---|---|---|---|---|
| Vanhelst et al. | 2012 | Free-living | 25 | 1 day | 0.99 |
| Santos-Lozano et al. | 2012 | Running (8 and 10 km·h-1), Walking 4 and 6 km·h-1 | 1 person, 8 units | Variable | 0.925 |
| Santos-Lozano et al. | 2012 | Mechanical oscillation | 10 units | 5mins | 0.97 |
| Davis et al. | 2013 | Free-living | 27 | 4 Days | 0.99 |
| Marshall et al. | 2013 | Free-living & sleep | 27 | 7 Days | 0.78 |

The GT3X ActiGraph has also been used in studies comparing physical activity questionnaires as measures of time spent in a sitting position in an occupational environment (Chau et al., 2011). The use of the GT3X ActiGraph as the objective measurement tool, rather than the written questionnaire, is a good indication of the acceptance of accelerometers within the research community. However, the fact that they are being used as a standard to validate other physical activity models before they themselves are validated in free-living conditions appears to be a slight oxymoron. Although it is likely that the GT3X will be as valid as its predecessor the GT1M in free-living conditions, assuming so is not ideal. But with the speed that the GT3X ActiGraph is being superseded by newer models, it may not be possible to have continually updated validity trials for the units themselves.

### *2.4.9 Accelerometer Placement*

The GT3X ActiGraphs have the capacity to record for extended periods of time and capture data on physical activity, and in recent years they have been used in the assessment of sleep and sleep disturbances (Ancoli-Israel et al., 2003; Kripke et al., 2010). Most studies adopt a waist mounted protocol as the waist is close to the centre of mass of the human body and are also widely accepted as a measurement of energy expenditure during certain physical activities and in free-living environments (Trost et al., 2012). However, a number of studies have highlighted the inability of waist placement to measure upper body movement and thus providing an inaccurate measure of energy expenditure in certain activities. Ankle mounted accelerometers have been shown to accurately reflect activity levels during gait related activities such as walking or running (Crouter et al., 2006; Sazonova et al., 2011; Godfrey et al., 2008).

### *2.4.10 Synopsis*

The GT3X ActiGraph is one of the primary systems in the assessment of physical activity through motion. The ability to continually record relatively high resolution data that can be analysed with previously validated algorithms allows for comparisons to be made with previously deployed sensors. With the development of new analysis techniques based on the tri-axial capacity of the GT3X platform it has become the 'go-to' tool for physical activity measurement and is being deployed in multiple environments in order to asses their needs.

## 2.5 Estimating Physical Activity from Accelerations

Physical activity is regarded as *'any body movement produced by the skeletal muscles resulting in energy expenditure'*. By measuring accelerations and decelerations of the body, accelerometers provide an objective measure of the movements occurring (Bouten et al., 1994). Studies have demonstrated a linear relationship between the accelerations experienced by a body and oxygen consumption during activity, thus validating the use of accelerometers to estimate physical activity when related to this data (Bouten et al., 1994; Trost et al., 2012). Although accelerometers can never provide a direct measure of energy expenditure, the combination of higher sample rates and refined methods of data analysis may eventually bridge the gap between measurement and estimation.

### *2.5.1 Counts*

In order to allow acceleration data to be expressed as physical activity variables they must be expressed in a unit that can be manipulated. Initially this was undertaken with an arbitrary unit, count, that is a summation of the absolute values of the changes in acceleration measured over a given time period (Santos-Lozano et al., 2012). When measures of count are taken on a piezoresistive accelerometer they are expressed as a measure of the change in the resistance (Gauss) in the accelerometer, with one count equating to 16.6miliGcs and sampled at 0.75Hz (Santos-Lozano et al., 2012). This is then summed over a given epoch, usually one second, in order to calculate a total count for that period. This derivative of this period then represents a quantitative measure of acceleration over time (dA/dT). This count has a linear relationship with the intensity of physical activity during a given time period and thus the total energy expended during any period of physical activity (Santos-Lozano et al., 2012). The ability to manipulate counts into energy expended is done through the use of specifically designed algorithms that utilise both count data and anthropometric data (Bassett, 2008). These algorithms can be both unit specific and count specific as the manner in which the count has been generated can affect the magnitude of the count recorded. Although it has been shown that count data from the AM7164, GT1M and GT3X are comparable, it must be noted that this is only for counts based off the vertical plane (Sasaki et al., 2011). The introduction of the horizontal plane measures in the GT1M model, although allowing the first two dimensional composite vector models (VM2) to be investigated, are not comparable to those of the GT3X (Sasaki et al., 2011; Santos-Lozano et al., 2012). This is thought to be due to the hardware and firmware differences between the accelerometers rather than the actual software used for analysis of the data. Sasaki et al., (2011) recommended that until conclusive evidence is given that changes in firmware do not cause differences in the energy estimations, that data should not be compared across firmware. This was also expressed by Dinish et al., (2012) who observed differences in counts measured on the anterior-posterior axis due to automatic firmware updates that resulted in data being excluded from use in their studies.

### *2.5.2 Cut-points & Algorithms*

In order to estimate the energy expended using the ActiGraph software cut-points have been developed that allow users the option of selecting from a number of algorithms with which to evaluate their data. Each choice uses a variety of cut-points, some of which can only be used by the older models due to the lack of vector models. It has been suggested by many researchers that a move away from count based algorithms towards acceleration based models should be the current direction of research (Sasaki et al., 2011; Freedson, 2012).

The following algorithms are options for use within the ActiGraph Actilife software and represent a single axis model (A) based on a summation of counts from the vertical axis alone, tri-axial model (B) based on a summation of counts above a threshold using acceleration values from all axes, and a combined model (C) using energy estimations from both algorithm A when below a count threshold and B when above a count threshold (2453 counts/min). The use of method C appears to allows for a better estimation of physical activity during both intense and sedate activities to be made and is known as the VM3 model:

*(A)* Work-Energy Theorem:
*kcals=Counts×0.0000191×Mass*

(B) Vector Magnitude:
*kcals = Scale×[(0.00097×VectorMagnitude(axis1,axis2,axis3))+(0.08793×Mass)]-5.01582 {for Counts>Scale×2453}*

(C) Vector Magnitude Combination:

*EEE = (kcals = (Scale×[(0.00097×VectorMagnitude(axis1,axis2,axis3))+(0.08793×Mass)]-5.01582) {for Counts>Scale×2453})*+ (kCals = (Counts×0.0000191×Mass) *{for Counts ≤ Scale×2453})*

*where; kcals=Total Calories for a Single Epoch, Counts=Count Level for a Single Epoch, Mass=User weight in Kg, Scale=(Epoch Period in Seconds÷60). Freedson et al., (2010)*

### *2.5.3 Counts or Vectors*

The ability to estimate physical activity from both the raw acceleration values and the count values provides two methods by which researchers may use these accelerometers. However, with more devices being made available and the low cost pervasive nature of tri-axial accelerometers, it is logical to use a vector based measurement technique rather than an arbitrary count based measure. It has been noted by Dinish et al. (2012) that this shift may itself cause issues due to the range of measurement of a given accelerometer. As the GT1M was superseded by the GT3X the effective range of measurement changed. Although the older GT1M accelerometer range of measurements of ±5g it was limited to ±2g range. If reverting to the raw accelerations in order to compare units, the GT3X with its lower absolute range of ±2.5g may underestimate the physical activity in calculations where both systems were used together. This necessitates caution when comparing raw accelerometer data to each other when they are from different units as the physical activity data may be erroneous due to the ability to measure activities above a certain acceleration threshold. This is further exacerbated by the plateau effect which the GT3X is already susceptible to (Section 2.4.6).

### *2.5.4 Future of Accelerometer Based Physical Activity Measurement*

The reliability of vector magnitudes measures to accurately describe intensities of physical activities is gaining acceptance. However, they are still in early days for the recognition of physical activities (Sasaki, et al., 2011; Chen et al., 2012). One of the areas undergoing extensive research is that of activity recognition and segmentation. This aims to automatically define activities based on the signal generated by the changes in the accelerations measured by the unit. Currently this is possible for certain activities with the ActiGraphs but is only possible using acceleration data from the vertical planes (Sasaki et al., 2011). Although limited, this opens the door for comparisons to be made between measures taken on the vertical plane and those taken with composite vector measurements (Chen et al., 2012; Sasaki et al., 2011). It is probable that these will be available in the future and will allow for automatic recognition and segmentation based on activity type. However, in order to do this it is necessary to gather data in these activities that is either gathered in parallel with gold standard techniques, or other validated methods of estimating physical activity.

Further work in the area of artificial neural networks is being undertaken by a number of research groups. This work aims to develop machine learning algorithms that can take contextualised raw accelerometer data and progressively 'learn' thus allowing for a smart program that understands what is occurring during a given set of data. These neural networks are showing promise in the automatic detection of events during specific activities such as activities of daily living (Trost et al., 2012), children's activity types (de Vries et al., 2011) and speed of motions (Song et al., 2007). This developing area is consequently bereft of data and an area for great research potential within the physical activity and computer science community.

## 2.6 Horse Racing Background and Research

The earliest records of horse-racing as a sport date back as far as 4500 BC. Within Ireland, the semi-state body Horse Racing Ireland (HRI) is responsible for the organisation and development of Irish horse-racing, while The Turf Club deals with the regulation of jockeys and race meetings with racing occurring most weekends throughout the year. Horse racing is one of the most popular spectator sports in Ireland drawing on average 3,682 people to individual race meetings over the year (HRI, 2011). Furthermore, it is also one of Ireland's greatest taxable income sources resulting in sums of over €97.5 million per year passing through on-course bookmakers (HRI, 2011).

### *2.6.1 Introduction*

Two types of competitive horse racing occur in Ireland governed by HRI and the Turf Club; flat racing – between 5-20 furlongs in distance - and jump, or National Hunt, racing – greater than 16 furlongs containing water, fence and ditch obstacles which the horse and jockey must clear (1 furlong = 201.16m) (Illustration 2.11). Current statistics show 510 registered and qualified jockeys in the country capable of riding either or both disciplines (HRI, 2011). In comparison, there are a registered 406 public trainers and 301 restricted license holders training the 5,030 registered thoroughbred horses in Ireland.


*Illustration 2.11: National Hunt Jockey (HRI, 2012)*

With so many horses and comparably few jockeys, a situation exists where jockeys race throughout the calendar year, sometimes with as many as 6 race meetings in one week and up to 5-7 races per day. With associated high levels of physical activity, it stands to reason that the ability to quantify the amount of physical activity undertaken by these weight category athletes is important. However, in a sport with very traditional views, the adoption of a specific training methodology for jockeys is a contentious issue as their training and preparation is deemed secondary to that of the horse.

### *2.6.2 The Professional Horse-Riding Environment*

In order to become a jockey in Ireland a candidate must pass standardised proficiency tests and take out a flat or jump licence. Many candidates who do not come from a horse racing background join the Racing Academy and Centre for Education (RACE) based at the Curragh, County Kildare and become trainee jockeys. This purpose built facility aims to provide the necessary skills for a candidate to eventually become a professional jockey. At the end of this course, and after placements within professional yards, the remaining students are assessed on site. After completion of their course trainees are free to take care of their own health and training and seek work within professional yards. It is at this point that many young apprentice jockeys are then exposed to the reality of life as a jockey and the traditional methods of preparing to make weight for races. In many sports the ability to track physiological workload during training allows athletes to take a periodised approach to weight loss (Faria et al., 2005b) allowing them to progressively drop weight over an extended duration. To date, this approach to performance monitoring has not occurred in horse-racing, partially due to lack of knowledge of such practices, but also due to an inability to measure the physiological demands on jockeys during training and racing. Without the ability to measure their responses to training and racing many apprentice jockeys mimic the training and weight loss practices of older jockeys when they enter the professional ranks. These practices, aimed at rapidly losing weight through a variety of practices involving fluid loss and dietary restriction, may be severely detrimental to a jockey's health and performance (Warrington et al., 2009; Dolan et al., 2011a).

### *2.6.3 Restricted Weight*

Horse-racing is a unique sport in that each race requires that a jockey race at a predetermined body mass, often appreciably below their habitual 'living' body mass. These weight handicappings are based on the ability of the horse itself and not the rider and strive for fairer racing. Prior to races, jockeys weigh in wearing their race clothing, boots, back protection and carrying their saddle (Illustration 2.12). In the unusual event that a jockey is below the minimum weight extra weight will be applied to the horse, via the saddle, to balance the total weights of each horse and rider. This classifying of races by weight means that jockeys are constantly trying to maintain an 'optimal riding weight'.

*Illustration 2.12: Jockeys Weighing In*

In reality, jockeys often reduce body mass rapidly in order to be at the stipulated weight for a given race. They do not have an 'optimal riding weight' that they aim to maintain, they do however have minimum and maximum weights. When this weight cycling takes place, it is common for jockeys to rapidly (~24 hours) reduce body mass (>4%) using extreme methods such as dehydration, exercise in sweat suits, vomiting or the use of laxatives (Dolan et al., 2011a). Although this weight cycling is common in other weight category sports, such as many combat sports, jockeys must weigh in before and after each ride thus giving little opportunity to replenish energy and fluid stores. With jockeys often riding several races during a day, and several race meetings each week, this can result in jockeys operating for extended periods in a negative energy balance (Dolan., 2011b) which may have a long term impact on health and physiological function

(Warrington et al., 2009). In a sport where many millions of Euro can be won or lost, the changing of traditional jockey preparation methods is often met with resistance. Thus, methods of optimising jockey weight cycling and its impact on performance has only undergone recent investigation.

### *2.6.4 Rider Skill*

Trowbridge et al. (1995) stated that "*horse-riding in National Hunt races requires two separate, but related, skills – horsemanship and jockeyship".* Where horsemanship can be considered to be pacing the horse to an effective finish and allowing it to use its full athletic potential, jockeyship is the act of affecting the horses performance as little as possible during the race by the riding skills and tactical ability of the jockey.

### *2.6.5 Horsemanship*

Recently it has become easier to quantify the first, horsemanship, in absolute values, as the physiological capacity of the horse can be assessed in similar manner to human subjects using maximal capacity tests (Eaton et al., 1995; Mukai et al., 2006; Gauvreau et al., 1995). Similarly the adaptations to training which have traditionally been measured using a stopwatch and the knowledge of trainers can now be assessed via heart rate monitoring and GPS systems specifically designed for the equine environment (Green et al., 2007; Kingston et al., 2006; Kusunose & Takahashi, 2003). One would expect that this is also undertaken with jockeys. However, it appears that this is not the case.

Some data on heart rate, lactate and respiratory responses to horse-riding have been reported in the literature (Trowbridge et al., 1995; Westerling, 1983; Devienne & Guezennec, 2000a). These however offer a very narrow view of what is occurring during horse-riding and give little insight into the act of horsemanship from the jockeys perspective. They give little applicable data that can be used by the jockeys themselves who appear to be unaware that it is possible to measure the demands of horse-riding on themselves. Thus, it is currently not possible to recommend jockeys a set amount of training based on energy expenditure rates during horse-riding as the specific energy demands remain yet to be determined. While there is an understanding among jockeys that there is an associated energy cost due to racing, many of them are unaware of how much, or little, they expend while riding. Trowbridge et al., (1995) noted an elevation in heart rate during concurrent races. It is possible that during the course of a race meeting, the effect of multiple races may continue to stack and demand greater levels of physical activity and thus more energy throughout the meeting. Furthermore, due to the weight classification of races, the ability to acquire data during actual races is even rarer as jockeys are neither comfortable wearing equipment during racing, nor willing to do so due to the inherent weight penalty (personal communication with jockeys).

### *2.6.6 Jockeyship*

The act of jockeyship has also undergone some investigation in the literature. It has been noted that "*successful riding depends on a harmony between rider and horse*" (Trowbridge et al., 1995). By placing themselves over the centre of gravity of their horse a jockey can hope to lessen their impact on the performance of the horse (Pfau et al., 2006). Trowbridge et al. (1995) also notes that the jockey must be capable of moving fore and aft on the horse in order to balance themselves during jumping and landing. Studies have also looked at the effect of rider experience on jumping and landing (Patterson et al., 2010) and the effect of different saddle positions and types (Latif et al., 2010). It stands to reason that the impact of the changes in gait of the horse will also call for a change in body position (Lovett et al., 2004). This movement, due to either a change in position, velocity or obstacle, will in turn increase the amount of muscle being recruited by the jockey. It would be expected that this would have an effect on the energy expenditure of the jockey especially in the lower limbs (Trowbridge et al., 1995). This aspect of jockeyship has not been looked at in-depth as most studies are once again concerned with the impact on the horse itself, not the rider. The commonly held belief that the physical conditioning of jockeys play no part in the eventual outcome of races is under threat as recent studies have shown that there is an impact on the horse due to the skill level of the jockey (Randle et al., 2010; Pfau et al., 2009; Schils et al., 1993; Symes & Ellis, 2009; Lovett et al., 2004). These studies have investigated how the skill level of the jockey affects the performance of the horse during racing. However many have not attempted to quantify the skill level of riders preferring to take a more subjective method of assigning riders to group.

Recently, the need to utilise a selection of different intensities during training has led to the development of indoor equine ergometers that can simulate the motion of a horse (Illustration 3.1). From a training perspective simulators of this type allow a coach to teach a trainee jockey to ride at different intensities, and from a jockey's perspective, it allows them to focus on aspects of their own physical and technical training. This is not always possible outdoors as the capability of the jockey, the nature of the horse and weather may not allow a jockey to undertake a training session. However, there are no readily available data on physical activity rates during equine ergometry in the literature, or any data about how they compare to on-horse riding as the level of intensity increases. In addition to training, horse racing ergometers can play a part in the rehabilitation of jockeys who have experienced an injury and are attempting to return to horse riding. By placing the jockey on the ergometer rather than a horse, it is possible that any further injury due to falling may be avoided. Ideally, after ergometer rehabilitation and training the jockey may return to racing with a minimal loss in fitness or technique.

### *2.6.7 Previous Jockey Research*

The physiological demands of flat and jump jockeys has received little attention within the scientific literature. Of the limited information available, much of the research has focused on the jockey's ventilatory response during different riding gaits (Westerling, 1983), the heart rate response during racing (Trowbridge et al., 1995) and the oxygen kinetics during horse riding (Devienne & Guezennec, 2000a). These studies used small cohorts and have only limited data on the physiological demands of horse-racing. Currently there are no studies focused on the individual energy demands of horse-riding at different velocities or running gaits. More recently, research has started to look in-depth at specific aspects of jockey health (Dolan et al., 2010), the impact of weight restriction and diet on long term health (Dolan et al., 2012), weight loss practices of jockeys (Dolan et al., 2011a) and the effects of chronic weight restriction on physiological function of jockeys (Warrington et al., 2009). However, this research is only starting to investigate some of the multiple issues associated with horse-racing. With high fall rates very common; 1 fall in every 240 during flat racing (Hitchens et al., 2010), 1 fall in every 19 during jump racing (Hitchens et al., 2011); the physical conditioning of jockeys may be paramount to their long term health. However, very little information on the strength and conditioning practices, if any, of jockeys is present in the literature.

### *2.6.8 Accelerometer Technologies in Equine Environment*

The use of accelerometers in the equine environment is not yet commonplace among jockeys, but has transferred on a smaller scale to the evaluation of equine performance. As a race-horse is not capable of taking charge of its own training, these technologies allow the trainer and owner to track the workload placed on their horses. Typically these systems combine GPS, heart rate measurement and accelerometers in order to detect changes in velocity, physiological response and gait characteristics (Green et al., 2007; Vermeulen & Evans, 2006; Gastin et al., 2008). Currently several commercial systems exist such as Gmax (Gmax Equine Ltd., Cambridge, UK), E-Trakka (E-Trakka, Booragoon, Australia) and Pegasus (Pegasus, Hertfordshire, UK). With a combination of physiological measures from heart rate and contextual data from GPS and accelerometers, these systems aim to act as tools to train horses in a periodised manner similar to human athletes. However, they remain cumbersome and the data often hard to interpret. Thus, many professional trainers are not fully committed to their use and rely on their own skills and interpretation of the horses actions.

### *2.6.9 Synopsis*

Currently there are no known studies that measure a jockey's physiological response to horse riding via accelerometery. Studies have investigated the effect of gait and velocity on the kinematics of the rider (Latif et al., 2010; Lovett et al., 2004; Powers & Harrison, 2002). Although dealing with show-jumping, one study by Patterson et al. (2010), has attempted to quantify the effects of jumping due to rider ability and experience during show-jumping. This is one of the only studies using accelerometers in an attempt to quantify a level of jockeyship as well as the impact of rider ability during jumping. However, many of these studies were focused on dressage, cross country and eventing riders not racing jockeys. Very few studies have specifically sought to measure the physical activity of a racing jockey during horse riding (Westerling, 1983; Trowbridge et al., 1995; Devienne & Guezennec, 2000b) and of those none have attempted to use accelerometers in their studies.

## 2.7 Search and Rescue Operations Research

To date, most aviation based research has focused on fixed wing commercial pilots with little information relating to helicopter pilots let alone search and rescue (SAR) operations (Illustration 2.13). What information is available is more focused on fixed wing civil aviation which cannot easily be compared to the environment of the SAR operators. Much of the limited information that is available are either studies of casualties and deployments (Grissom & Thomas, 2006), concerned with the helicopter and its effect on the crew (Kåsin et al., 2011; Balasubramanian et al., 2011), or the effect of the mildly hypoxic environment on aircrew (Hansen et al., 2012). Within these studies, none dealt with SAR operations environment and its impact on the operators or the physical demands of SAR duties.

*Illustration 2.13: Rescue 118; Dublin SAR Operators*

### *2.7.1 Introduction*

Although scheduled for a 24-hour operational day, SAR operator's actual periods of flight may vary from zero hours to upwards of 12 hours depending on the nature of the tasking. These flight operations may occur at any time of the day or night and thus SAR operators must be constantly ready to act. Previous research in athletic populations has suggested that the time of the day an athlete trains and competes may have an effect on sports performance (Carrier, 2000; Drust et al., 2005), this may have an impact on SAR operations. This need to respond to a tasking at any time of the day may have an effect on SAR operators performance levels due to diurnal variations, sleep deprivation and other psychological responses. Unlike commercial pilots who are limited to 13 hours of flying per day, including flight preparation, SAR pilots are not limited on a daily basis allowing crews to perform extended operations. However, this places pilots in a situation where they may be asked to perform in a sleep deprived state. Although SAR pilots are limited to 65 hours of flying within 28 days, the same as commercial pilots, during extended operations the choice about when to terminate an operation is made by the pilots themselves. The implications of a mentally or physically fatigued pilot making an error due to sleep deprivation or physical exhaustion could led not only to the loss of an asset, but that of the lives of the SAR operators and casualties they are tasked to assist. The ability to perform occupational tasks and make rational decisions while in a sleep deprived and fatigued state has been extensively researched in the literature, including clinical (Orzeł-Gryglewska, 2010), student (Martin et al., 2012) and athletic populations (Reilly & Edwards, 2007; Walters, 2002).

Current beliefs are that sleep deprivation affects physical health, leads to impaired decision making and in some cases may lead to visual disturbances (Falleti et al., 2003; Orzeł-Gryglewska, 2010) thus it is possible that one of the main roles of SAR operators, namely searching, not to mention flying the aircraft, may be further diminished. It is noted in the literature that the ability of trained SAR operators to locate casualties from the air is already quite poor and needs refinement through training (Croft et al., 2007). However, if a SAR operator is already excessively fatigued, no amount of extra training may be able to counteract this loss in performance. In a study performed on urban SAR teams (Jenkins et al., 2006), it was noted that the availability of pharmacological methods of inducing sleep may allow operators to sleep more. Although these methods do not appear to affect physiological function (Mougin et al., 2001), the introduction of these methods with aircrew may not offset the risk due to cognitive impairment (Orzeł-Gryglewska, 2010) they also impair their ability to competently handle the aircraft in the case of SAR pilots.

Previous studies suggest that a period of sleep deprivation of approximately 20 hours is comparable to a blood alcohol saturation of between 0.01 and 0.05% (Falleti et al., 2003). Unfortunately, it is much more difficult to accurately assess fatigue in the same manner as a blood alcohol test in order to gauge if a SAR operator should fly or not. Currently a SAR operator must make a subjective judgement call based on their levels of fatigue in order to decide if they are fit for duty. Without an objective method to measure the impact of operational duties and impact of sleep, or the lack thereof, it is unwise to assume that a SAR operator is capable of rationally making this decision.

### *2.7.2 Accelerometer Technologies in SAR Operations*

As there is a need to investigate SAR operations, the use of miniature lightweight accelerometer technologies may allow for in-depth research into the physical activity demands and impact of the different SAR sleeping environments. The use of accelerometers in the assessment of helicopter crews has primarily focused on the impact of aircraft vibration on the crew (de Oliveira & Nadal, 2005; Kåsin et al., 2011). To date, there have been no published studies evaluating physical activity or sleep indices in SAR operators using accelerometers.

The assessment of physical activity levels in normal-living is necessary in order to better understand an activity. This has become a major commercial venture with many companies designing tools that allow people to record aspects of daily life such as how far they walk, cycle or swim. As a result, various assessment methods have been explored including the use of lightweight accelerometers such as the ActiGraph (ActiGraph, Pensacola, USA) (Kozey-Keadle et al., 2011). These units have the capacity to record for extended periods of time, capturing data on physical activity and recently they have been used in the assessment of sleep and sleep disturbances (Ancoli-Israel et al., 2003). This follows a new trend in the use of accelerometers to measure motion during sleeping as a measure of sleep-wake cycles (Ancoli-Israel et al., 2003; Martin & Hakim 2011; Crespo & Aboy 2012). Much of this research is based on the premise that if a person moves frequently during sleep periods, the efficiency of their sleep declines (Ancoli-Israel et al., 2003). Although these units have never been used in SAR operations, their lightweight and waterproof housings provide the perfect tool for examining day-to-day and operational duties.

### *2.7.3 Synopsis*

Overall, the information that is available on the specific demands of SAR operators is limited and most research focuses on studies of casualties and deployments (Grissom & Thomas, 2006), the helicopter and its effect on the crew (Kåsin et al., 2011; Balasubramanian et al., 2011), or the effect of the mildly hypoxic environment on aircrew (Hansen et al., 2012). Little is known about the physiological demands of the SAR occupation and much of the basis for operational rosters are derived from anecdotal evidence, or adapted from other sources such as the civil airline industry or military operations. Most information that is available on SAR operations comes from ambulatory urban SAR operations or wilderness SAR operations such as mountain rescue teams, none of which is applicable to a helicopter based SAR team. Due to this, there is a need for in-depth research into the physiological and psychological demands of SAR operators as well as the impact of their sleeping habits and habitation.

## 2.8 Ultra-endurance Cycling

During ultra-endurance events the body is engaged in prolonged bouts of relatively intense exercise with relatively little sleep (Laursen et al., 2005; Scott et al., 2006; Orzeł-Gryglewska 2010). The natural circadian rhythm by which competitors are governed is ignored as they compete around the clock over extended durations. The longer the event the more important it becomes to understand how the athlete will be affected by the activity itself and the extended duration. This necessitates examination of the effects these events have on different aspects of physiological function. However, due to the prolonged nature of these events it is often difficult to continually measure what is occurring (Laursen et al., 2005). More recent advances in portable lightweight physiological monitoring devices many of which integrate multiple sensor types, such as heart rate, GPS and accelerometry, may not have the battery, or storage capacity, to record for the duration of many of longer duration events. This limits the ability of researchers, coaches and athletes alike to better understand the physiological responses that occur during these events.

### *2.8.1 Introduction*

The impact of ultra-endurance activity has been previously been studied across on a range of parameters including sleep deprivation (Scott & Mcnaughton, 2004; Scott et al., 2006; Orzeł-Gryglewska, 2010), muscle damage and fatigue (Laursen et al., 2005; Bessa et al., 2008; Macedo et al., 2008), physiological fatigue and cognitive capacity (Gianetti et al., 2008) and metabolic changes (Bessa et al., 2008). By increasing the understanding of the demands of participation in ultra-endurance events it may be possible to tailor training plans and other strategies important to effective preparation in order to minimise the effects of fatigue and optimise performance in these events. In order to achieve this, it is first necessary to establish a greater understanding of the specific demands of such events during both racing and periods of rest and recovery. Ultra-endurance cycling has grown in popularity over the past few years as cyclists look for more extreme challenges. However, ultra-endurance cycle events are not a recent phenomenon and have existed for over 100 years. Single, continual, 'point to point' events such as the Paris-Brest-Paris (PBP) cycle race have existed since 1891. With a distance of approximately 1,200km, and a cut off of 90 hours, the PBP is commonly considered the origin of ultra-endurance cycle racing and it is still used as an ultra-endurance test by many cyclists. The original guise of the Tour de France (1902) took the form of a 6 day race, covering 2,428km, with athletes cycling stages averaging 405km (Noakes, 2006; Sidwell, 2009). The eventual winner, Maurice Garin, crossed the line of the first Tour in a time of 94 hours and 33 minutes. This heralded the start of multi day ultra-endurance racing, albeit intermittent by nature, with the cyclists having the opportunities to rest between stages.

In recent times extreme athletes continue to expand the boundaries of ultra-endurance cycling by competing in multi day, non-stop cycling races such as the Race Across America (RAAM) and the Race Around Ireland (RAI). These events are contested as time trials as opposed to group races, either as solo riders or as teams of several cyclists. Ultra-endurance cycling has become recognised as a cycling discipline within its own right with World Cup events held by its governing body the Ultra Marathon Cycling Association (UMCA) (www.ultracycling.com). While solo ultra-endurance races can be considered to be continual moderate intensity events, team ultra-endurance races have been described as intermittent high intensity cycling events (Laursen, 1999).

### *2.8.2 Physiological Demands of Ultra-Endurance Racing*

Unlike traditional road racing, there is a dearth of information pertaining to the physiological attributes of elite ultra-endurance cyclists. However, many competitors who take part in ultra-endurance cycle races are from a road racing background. Successful road cyclists' specific physiological attributes include a high level of lactate tolerance for time trials, a high maximal power output for sprint finishes, and a high power to weight ratio for climbing (Farria, 2005). In solo ultra-endurance events however, the cyclist is generally never required to sprint and maximal power may not be a performance determining factor. In contrast, the team events are more akin to time trials as team members are allowed to rotate, allowing for periods of higher power output to be sustained by riders depending on the tactics adopted (Laursen et al., 2005).

It is possible that in order to perform within ultra-endurance cycling events athletes must be more akin to a time trial specialist as it is in this position they will spend most of the race (Illustration 2.14). Time trial specialists tend to be physically larger than road cyclists while retaining similar peak power to weight ratios (Faria et al., 2005). Padilla et al., (2001) noted that time trial riders were able to produce greater power output relative to body mass (W/kg) at both lactate threshold (LT1) and at onset of blood lactate accumulation (OBLA, LT2) than both uphill and all round cyclists. This is possibly due to a higher level of economy and a faster cadence than both road and hill climbers and also a possible change in muscle type towards type 1 fibres. Similar reductions can also occur due to a reduction in percentage body fat and body mass (Coyle, 2005). It is also probable that ultra-endurance cyclists have become more economical at working at the intensity demanded during a time trial which is close to OBLA for most cyclists (Faria et al., 2005).

In order to attain a highly aerodynamic position, time trial riders adopt a different set-up to road cyclists for steering and braking. Aero-bars are used to streamline the cyclist by bringing the arms ahead of the chest, but between the shoulders. This reduces frontal area, and aerodynamic drag, but impedes steering and braking. There is also an increased metabolic cost with this lower, more aerodynamic, position (Gnehm et al., 1997). This increased metabolic cost (increased heart rate, percentage $VO_2$max, and RER) necessitates increased training in the aerodynamic position to adapt to these demands.

*Illustration 2.14: Adapted Time Trial Position*

In the these ultra-endurance cycling events most cyclists use a lighter road bike that will also descend and climb better than a time trial bike and adopt a modified version of the aerodynamic position to be more versatile (Illustration 2.14). No previous studies have looked at the metabolic effect of racing in this adapted time trial position over the time durations experienced in these events. There appear to be no effect on a cyclist's ability to perform these high-intensity cycling bouts due to sleep deprivation in a laboratory environment while in this position (May et al., 2010). However, as this was performed with non repeat bouts of cycling, it cannot be said to hold true for the longer events such as the Race Across America and Race Around Ireland. This concept of a time trial specialist fits well with the team aspect of ultra-endurance racing and the specialised nature of the racing. The ideal rider for ultra endurance cycle racing is one who is capable of repeatedly working at a high power outputs, for relatively short durations. Quick recovery and being able to perform these intermittent bouts for extended durations may play a part in overall performance.

### *2.8.3 Accelerometer Technologies in Cycling Environment*

To date, the use of accelerometer technologies in the cycling environment is not common practice. Few attempts have been made to integrate accelerometer technologies into cycling hardware. Initial attempts to do so met with restrictions from the Union de Cycliste International (UCI), the world governing body of cycling, which have set strict guidelines on bicycle design and the technologies embedded in them. Purportedly, the GT Super-bike developed for team USA cycling team during the 1996 Atlanta Olympics had accelerometers integrated into it (Illustration 2.15). These were suggested to be capable of measuring lean angles, starting accelerations and other performance variables. However, after the '96 Olympics the UCI severely restricted the designs possible in these super-bikes and the project was dropped.


*Illustration 2.15: Team USA Atlanta Super-bike*

To date, the most commonplace use of accelerometers in cycling is not in the actual measurement of cycling itself, but in the classification of the event. This has been undertaken by many groups using single axial accelerometers (Long et al., 2009), dual-axial accelerometers (Brazeau et al., 2011) and tri-axial accelerometers (Crouter et al., 2006). Working in the domain of physical activity measurement, many of these groups only need to classify the act of cycling and care not about performance, but about how intense these cycling bouts are so they can relate them to MET scores in order to estimate energy expenditure.

However, without the ability to directly measure the amount of force being applied to the pedal by the cyclist these are, at best, an estimate as to what occurs. Recently ,cycle power meter companies such as Power2Max (Germany), Quarq (Spearfish, SD, USA) and Brim-Brothers (Bray, Co. Wicklow, Ireland) have made initial attempts to integrate accelerometers into their systems. The addition of these sensors is not for measurement of power, but as an addition to the algorithms that are used to calculate and measure cadence and give context to data-sets with start/finish times (Tuck, 2007). Such technological advances have been furthered by Garmin who integrate accelerometers into their GPS systems in an attempt to further refine algorithms for their GPS systems that suffer drop-outs while in built up, or wooded, areas. However, the value of these embedded accelerometers within power measurement systems has yet to be determined.

### *2.8.4 Synopsis*

Due to the extended duration, distance and intermittent nature of ultra-endurance cycle races such as the Race Around Ireland there is a need to investigate the physiological demands of these events. As the participants in these events spend more time off their bicycles resting and recovering there is also a need to measure the physical activity during both cycling and resting periods. The deployment of a lightweight, unobtrusive, accelerometer based platform that can continually record data about both the participant and the event may allow for data to be gathered within this unique environment.

## 2.9 Literature Review Summary

As with all technology, the systems available to measure physical activity are constantly evolving. Moore’s Law states that '*technology will continue to evolve at an exponential rate*', and in this regard the inertial measuring units capable of measuring physical activity are doing so. The concept of Moore's Law that a unit will have evolved at a rate that it out performs itself every 18 months is holding true within this niche research area. With the cost of production being driven down and storage size increasing, these systems are evolving at a tremendous rate, faster than that of the validation studies of the units. As researchers, it is no longer possible to take the time to ensure a system is a valid measure, data must now be captured and methods developed that can retrospectively analyse this data with the help of computer scientists.

During the process of this research study, the GT3X was superseded twice; once by the GT3X+ and more recently, by the wGT3X+ (wireless transmission and recording of heart rate). The GT3X+ is physically smaller and has a greater storage capacity (256MB vs. 16MB) than the GT3X. It has a capacity to measure a much higher range of accelerations ($\pm$6g) and is waterproof allowing research into water oriented activities. The evolution of the ActiGraph is far surpassing the 18 month barrier but is currently still using the same accelerometer platform to capture data.

These feasibility studies aim to look at this low cost accelerometer based platform in a number of unique environments. Within each environment, the potential for measuring different aspects of these activities with the same technology exists. However, in order to assess the applicability of these technologies in each area they need to be deployed alongside gold standard technologies (Chapter 3), compared to established estimation technologies (Chapter 4), or gather data that can be utilised to explore the environment measured in a retrospective analysis (Chapter 5). Each of these environments provided an environment to deploy these sensor platforms in feasibility studies. Ideally these would provide a base of knowledge for other researchers looking to attempt to utilise accelerometer based technologies in these environments.

# Chapter 3: Study 1; High Intensity Short Duration Activities – Jockeys

## 3.1 Introduction

### *3.1.1 Study Overview*

Depending on the sporting activity there are many different factors that can influence performance. These performance determinants can be physiological, psychological, technical, environmental and equipment specific. As they tend to be unique to the specific demands of the activity this has necessitated the deployment of specific sensing technologies within each sporting environment. However, some activities, such as horse-racing, buck this trend and data about its demands are not readily available. In a sport rooted in tradition, physiological monitoring systems have not been extensively explored due to the associated weight penalty of these devices. With little understood about the physiological demands of jockeys during horse-racing, the development of lightweight sensing platforms that may be integrated into current equipment would allow for the specific demands of this popular sport to be explored in greater detail. To date no accelerometer based system has been used in order to attempt to research any aspect of a jockeys physiology during horse-racing. The following chapter provides a feasibility study into the deployment, analysis and future use of the GT3X ActiGraph accelerometer platform in this environment.

The ability to accurately and reliably measure the daily physical activity levels of jockeys may be paramount to their performance and long term health and well being. As jockeys must reach a predetermined weight prior to racing, the additional weight of traditional physiological measurement systems is not something that many jockeys or trainers will tolerate. However, the use of lightweight accelerometer based technologies may provide a valid and unobtrusive solution to this challenge. As jockeys must utilise standard minimum equipment; saddle, helmet and body protection, it may be possible in the future to place accelerometers within these pieces of equipment in order to further assess their physiological response to horse riding. However, as these systems inherently measure motion, it may be that the motion of the horse itself may nullify the ability of these platforms to gather applicable data in their proprietary form. Only by deploying these sensors in this unique environment is it possible to say whether or not they are applicable to research in this area.

This study aims to assess the applicability of an accelerometer based technology in its proprietary form during simulated and outdoor horse-riding in the assessment of physical activity during horse-riding. However, due to the unique nature of horse-riding, it may be necessary to develop sports specific algorithms, post capture, to manipulate the data that is recorded with these systems.

### *3.1.2 Aim*

The primary aim of this study was to assess the feasibility of an unobtrusive method of assessing the physical activity undertaken by trainee jockeys, with a minimal weight penalty and no user interaction during both indoor and outdoor training.

### *3.1.3Objectives*

i. To estimate the amount energy expended while training on an equine simulator and during outdoor horse-riding.

ii. To compare the amount of physical activity undertaken on an equine simulator versus outdoor trials at similar rates of energy expenditure.

iii. To evaluate feasibility an accelerometer based technology in estimating the energy expended during physical activity undertaken while horse riding.

### *3.1.4 Hypothesis*

That a commercially available accelerometer platform is capable of estimating physical activity during simulated and on-horse horse-riding in its proprietary form.

### *3.1.5 Environment Studied*

The environment studied was that of professional horse riding and the training environments adopted for trainee jockeys. Subjects were in full time employment and were training to become jockeys. The environment is defined by subjects training indoors on an equine simulator and outdoors on live horses. This provided the context by which data was segregated for analysis. Subsequently, training periods defined by similar measured and estimated intensities were compared.

## 3.2 Methodology

The following section describes the methods used during the study as well as information pertaining to the subject selection used within the study.

### *3.2.1 Subjects*

Ten subjects were recruited for the study. These were trainee jockeys based at the Racing Academy and Centre for Education (RACE) located at the Curragh in County Kildare, Ireland. Subjects volunteered for inclusion in the study after being informed of the study via a group meeting. RACE consists of both male and female trainees all of whom were considered in the study. The data was not split on this basis. Subjects were included if they were free from any injury or condition that would stop them performing their day-to-day duties. Age was not considered to be a restricting factor, nor ethnicity, nor daily levels of physical activity. Subjects were to be considered proficient horse riders by their instructors for inclusion in on-horse testing and the overall study.

Prior to commencement of the study subjects filled out a general health questionnaire, read the study plain language statement and if they agreed to take part in the study, filled out an informed consent form. This was witnessed by another researcher independent of the primary researcher if any of the subjects were under 18 years of age. Parents and guardians of the under-age subjects were directly informed of the study and invited to ask questions, or to remove the subject from the testing pool if they so wished. Parental or custodial consent was then gathered. All subjects were residents at RACE, training full time as part of their jockey qualification. The study was approved by the Dublin City University (DCU) Research Ethics Committee. When the above inclusion and exclusion criteria were utilised on the data, only ten male subjects out of twenty one subjects remained for analysis.

### *3.2.2 Environmental instructions*

Subjects were advised to maintain their normal daily and nightly routine during all testing including the food they consumed. However, this was not recorded nor enforced as provision of daily food and exercise were determined by the staff at RACE. As trainees were not at the same level of proficiency as professional jockeys, the instructors based at RACE were utilised so only trainees with a minimum level of riding proficiency were tested. This limited the subject pool size but ensured a high level of competency and comparability between subjects.

Two separate conditions were used for training and comparison between subjects: simulated riding indoors on an equine ergometer, and outdoor on-horse riding on retired racing horses. Most training performed by trainees on the equine ergometer was done in the evenings. On this basis, and limited availability of the trainees, testing on the ergometer was performed during the trainees evening schedule, 18:00–20:00 hours. As subjects rode out horses each morning, 06:30–10:00 hours, this was used as the basis for the on-horse testing. Maximal aerobic capacity testing was undertaken during the evening, at the same time as scheduled for the simulator testing.

### *3.2.3 Equipment and Sensor Configuration*

Each subject was instrumented in the same manner over the course of the study. All sensors started recording data 5 minutes prior to test commencement and were calibrated to the universal time constant (UTC) for comparability between sensors. For on-horse testing, subjects were instrumented with an additional sensor in the form of a Garmin 405 GPS sensor (Garmin Ltd., Olathe, KS, USA) in order to gather data on the horses velocity during each gait adopted. Subjects were not instrumented with the GT3X ActiGraphs during the maximal aerobic capacity testing session (Section 3.2.4.2).

#### *3.2.3.1 Cosmed K4b$^2$*

Calibration of the system was undertaken in accordance with the manufacturers specifications with a calibrated 3 litre syringe and known sample of carbon dioxide. Anthropometric data recorded prior to each session was entered into the system to account for age, mass and height. Environmental data recorded at each session was entered into the system to account for temperature, altitude and barometric pressure. The battery pack, sensor cells and transmitter/receiver unit were located on the trainee’s back (Illustrations 3.1 & 3.2) and worn outside their back protectors during riding trials. Although jockeys wear helmets while riding, the face mask from the Cosmed was tested to make sure it did not interfere with either the safety or vision of the jockeys during riding prior to its use in data collection.

### 3.2.3.2 GT3X

The following data was required to initiate the GT3X ActiGraphs (Section 2.4.5) and was input by researchers in the proprietary software, ActiLife version 5.2.2: date of birth, age, mass, height, ethnicity, dominant side and location of sensor. Physical activity measures were calculated based on the Combined Freedson Vector Magnitude calculations demonstrated by Sasaki et al. (2011) that are embedded in the ActiLife software. This allowed for a count based measure of physical activity to be made during all activities. As it was understood that the GT3X ActiGraphs may suffer from the effects of the Plateau Effect (section 2.4.7) data was not processed in a raw format. However, it is possible to extract this data for future analysis.

All accelerometers were set to record, tri-axial mode. The inclinometer was set to record. The sample rate was set at 30Hz. Data was logged in 1 second epochs. All sensors ran firmware version 4.2.0. Where possible, subjects wore the same units as utilised in previous testing so as to avoid any differences due to unit-to-unit calibration. The ActiGraphs were kept in the same orientation for each test and attached via a soft Velcro strap which allowed for minimal movement of the sensor, but remained comfortable enough for long deployments. In the case of the GT3X ActiGraphs deployed at the chest and waist, the sensors were worn underneath their body protection to minimise movement of the accelerometers.


*Illustration 3.1: Instrumented Trainee Jockey on Equine Simulator*

A GT3X ActiGraph was placed (Illustration 3.1): 1) On the waist of each subject at the lower back (junction of L5-S1). 2) On the bottom of the sternum below the xyphoid process. 3) On the right wrist (posterior aspect). 4) On the right ankle of the subject {lateral aspect}. 5) On the pommel of the saddle in front of the subject.

#### *3.2.3.3 Polar S725i Heart rate Monitor*

Heart rate was measured continuously using a wireless Polar heart rate monitor (Polar S725i, Polar Electro, Finland). A heart rate monitor strap was placed on the athlete to facilitate easy measurement of heart rate through the Polar heart rate monitor located on the ergometer or wrist of the subject.

### *3.2.4 Experimental Trials:*

Subjects performed an initial test session at RACE to assess maximal aerobic capacity (Section 3.2.4.2) followed by two testing periods, one in each test environment: simulated riding on an equine ergometer (Section 3.2.4.4) and on-horse at the training arena (Section 3.2.4.5). Data from the maximal aerobic capacity session were used as physiological descriptors and as a basis to determine the percentage of maximal intensity the subjects performed the simulator and on-horse trials at.

#### *3.2.4.1 Descriptive and Anthropometric Data*

Subject's date of birth, height and body mass were recorded at the start of the study. Subject's body mass was assessed again while in their riding equipment with boots and helmet. This data was used in the set up procedures of the GT3X ActiGraphs and Cosmed $Kb4^2$. Saddles were not utilised in this mass assessment unlike during racing conditions. Subjects' mass was recorded before each sensor deployment. If a change was observed, the sensors were adjusted to the new value.

#### *3.2.4.2 Maximal Aerobic Capacity*

The participants' initial visit involved a maximal incremental exercise test performed on a factory calibrated Wattbike cycle ergometer (Wattbike, Wattbike Ltd., Nottingham, UK; Illustration 3.2). Maximal aerobic capacity was assessed during an incremental exercise test using a Cosmed $Kb4^2$ portable metabolic system (Cosmed, Rome, Italy).

The Wattbike ergometer allowed for the measurement of: power output (W), cadence (RPM, pedal turnover rate per minute) and heart rate (BPM, via a Polar wireless chest mounted transmitter). As subjects regularly train on indoor cycle ergometers whilst attempting to maintain their weight they were deemed habituated to the nature of the test. Previous research has also used indoor cycle ergometers for assessment of maximal aerobic capacity in jockeys (Westerling 1983; Devienne & Guezennec 2000b; Dolan 2011). Currently there are no methods in the literature of undertaking maximal and sub-maximal assessment of jockeys in a sports specific environment.

*Illustration 3.2: Maximal Aerobic Capacity Testing*

Participants initially cycled at a resistance of 60W which increased in 35W stages every 3 minutes until volitional failure. Due to the nature of the ergometer, a combined air and magnetic braking system, subjects had to modify their pedalling cadence as the resistance was altered. These changes were related verbally to the subjects by the researchers. In the last minute of each stage the following parameters were recorded: Heart rate via a Polar heart rate monitor; Blood lactate using a Lactate Pro hand held lactate analyser; Inspired and expired oxygen, carbon dioxide, respiration rate and respiration volume were measured in real time via the Cosmed Kb4[2] portable metabolic system (Cosmed, Rome, Italy).

#### *3.2.4.3 Specific Riding Trials*

Testing was undertaken during both simulated and on-horse riding. During simulated testing the intensity was defined by the motion of the ergometer which aims to simulate a horse riding at different velocities (Section 3.2.4.4). However, it is not possible to objectively state what velocity each of the stages on the ergometers equate to. When subjects were deemed competent enough by RACE trainers, they undertook an outdoor on-horse testing session during which intensity was defined by the gait, and subsequently the velocity, adopted by the horse (Section 3.2.4.5). It was not possible to utilise a random order between the indoor and outdoor testing periods as many of the trainee jockeys were not yet deemed competent enough during on-horse riding for the duration required for data capture. The total duration of test segregation was one week between the maximal aerobic capacity trial and indoor testing; and six weeks between indoor and outdoor test sessions.

#### *3.2.4.4 Simulated Horse Riding - Equine Ergometer*

The ergometer (Racehorse Simulator MK1; Racewood, Cheshire, UK) used for the study was capable of five different stages of intensity. The ergometer moved the "horse" section by means of a cam and push-rod arrangement powered by a motor. In order to increase the "intensity" of the stage the motor spins the cam at an increased speed. This in turn moves the ergometer via the push-rod to its furthest forward and rearward positions. Thus, the total displacement of the ergometer does not change at each relative intensity as it is limited by the cam and length of the push-rod. In order to increase the intensity of each stage the frequency of displacement increases as the motor simply rotates faster. This assumes that at higher rates of displacement, the jockey's metabolic response will increase.

The manufacturer's technical specification outlines that at the highest stage the equine ergometer equates to the velocity of a horse at full gallop and estimated it to be around 30kph. This is significantly lower than the maximum speed racehorses are capable of, but similar to that of a horse while cantering. The ergometer also does not mimic the motion of a horse as it transfers between running gaits (Gastin et al., 2008). Thus, the jockey can stay in the same position for all stages and not have to adopt different stances as they would during outdoor riding, i.e. rising trot vs. crouch.

#### *3.2.4.5 On-Horse Riding*

A group of ex-racehorses were provided by RACE for use in the study. It was not always possible to use the same horse, or for trainees to be capable of riding the same horse. Due to this a difference in stride rate and distance per stride was present depending on which horse was being ridden. However, the pattern adopted by horses is similar in each of the different gaits. Ideally data would be captured utilising the same horse in all conditions. Although all data was taken in the same arena and outdoor area, unavoidable inconsistencies will be present due to changes in the environmental conditions. Where possible testing was carried out in the same weather conditions in an attempt to minimise the affect of environmental changes on the riding surface.

### 3.2.5 Testing During Simulated Horse Riding

Testing was undertaken with the portable metabolic system in order to assess the energy expended during each stage while training on an equine ergometer (Section 3.2.4.4). Subjects also wore the GT3x ActiGraphs in order to estimate the physical activity undertaken during each stage. Subjects performed four minute stages at each intensity as dictated by the equine ergometer during which they adopted a racing position (Illustration 3.3).

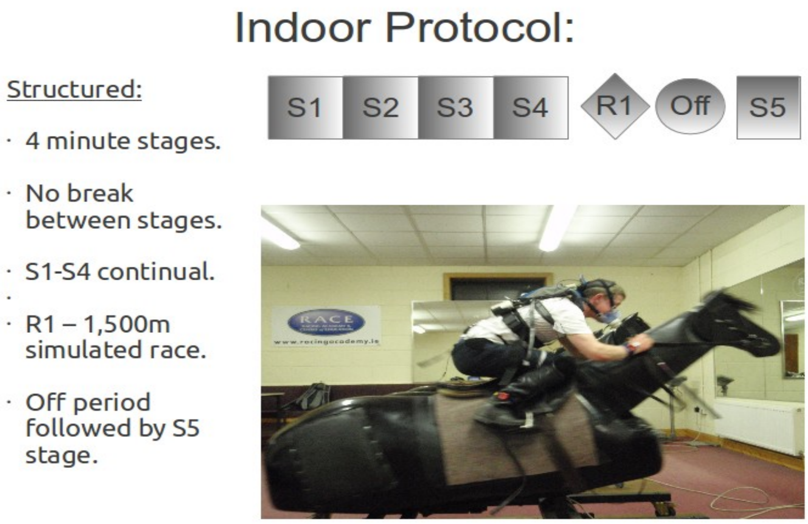



*Illustration 3.3: Equine Ergometer Protocol*

Stages one through four were completed with no break between each stage. Each stage related to a specific speed setting on the equine ergometer predetermined by the manufacturer. A five minute rest period was taken after stage four before a 1,500m simulated race. This was followed by another five minute recovery period and a final four minute stage at the highest intensity stage five. Data was recorded continually on all sensors throughout the test and was analysed for each stage using the last minute of data. Data from the rest periods and the 1,500m race were not analysed as they formed part of a separate research study.

### *3.2.6 Testing During On- Horse Riding*

Testing was undertaken with the portable metabolic system in order to assess the energy expended during each stage during on-horse outdoor training. Subjects also wore the GT3x ActiGraphs in order to estimate the physical activity undertaken during each stage. This utilised a semi-structured protocol in which subjects were asked to ride their horses at several intensities as governed by the gait adopted by the horse (Illustration 3.4). Subjects were instrumented at RACE and walked into the yard to prepare their horse. Subjects then mounted their horse and walked it around the indoor yard (1). Following this warm-up for the horse it was then walked to the circular gallop (2), trotted around the gallop (3) and then cantered (4). Periods 1, 3 and 4 were used to define walk (1), trot (3) and canter (4) periods of intensity.

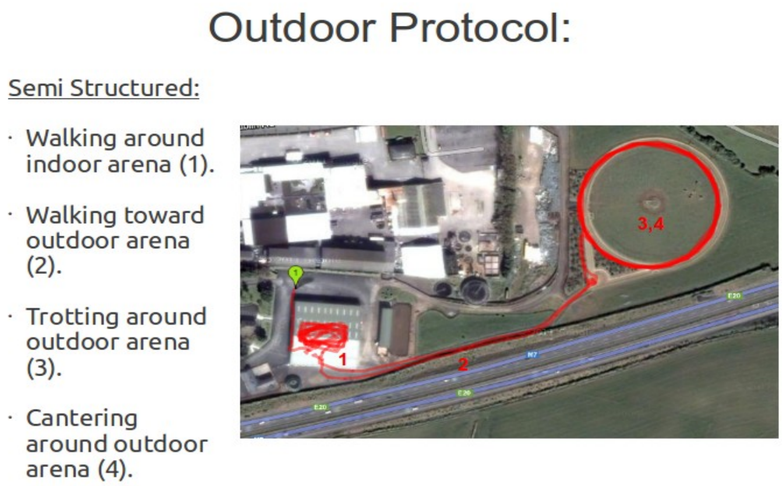



*Illustration 3.4: Horse Based Protocol (GPS Trace)*

Data was recorded continually throughout the test and was analysed for each stage, each period had to last at least 4 minutes and the final minute of data was used in analysis. Subjects were additionally instrumented with a Garmin 405 GPS (Garmin, Kansas City, USA) unit in order to assess the velocity adopted during each gait. This GPS unit was capable of measuring through the plastic and light aluminium roof of the indoor arena. It was not possible to account for the accuracy of the GPS satellites. However, a minimum of six satellites were needed for the unit to initiate. Traditionally the velocity of the horse is calculated by the trainer using a known distance and a stopwatch. By utilising a GPS to estimate the velocities travelled during each of the gaits it was possible that a level of error was inferred to the data. However, the velocities that were recorded during outdoor testing are similar to those found by other researchers (Latif et al., 2010; Kusunose & Takahashi 2003; Vermeulen & Evans 2006; Kingston et al., 2006).

### *3.2.7 Data Exclusion Criteria*

Data were excluded from statistical analysis for the following reasons;

- Data sets were discarded if the sensors were worn for less than 95% of the allotted duration of the sample window. (n=0)
- Data sets were excluded from the study if the subjects were not of proficient enough at horse riding. This decision was made by the instructors based at RACE. (n=6)
- Data sets were excluded if an incomplete capture was made on any, or all sensors. (n=4)
- Unaccountable failure of sensors occasionally occurred which resulted in partial or damaged data files. It was not possible to recover, or utilise, this data. (n=1)

In total 11 subject data sets were excluded from the study resulting in a final 10 subjects used in the study.

### *3.2.8 Data analysis*

Data from the Cosmed $K4b^2$ was downloaded via their proprietary software (CPET suite versions 9.1) and exported to LibreOffice (The Document Foundation) for analysis. Data from the GT3X ActiGraphs was downloaded via ActiLife version 5.8.3 and analysed in version 6.1.2. Data from the Garmin 405 was downloaded via Garmin Training Centre version 3.6.5 and analysed in WKO+ version 3.0 (Cycling Peaks Group). All statistical analysis was undertaken using SPSS (PASW Statistics 18).

Independent samples T-tests were carried out to examine mean differences between variables on the same systems between indoor and outdoor conditions (objective 2 and 3). Paired T-tests were carried out to see if significant differences existed between variables from each of the sensors (objective 3).

### *3.2.9 Synopsis*

During training and racing it is not practical to instrument jockeys with metabolic systems such as the Cosmed $K4b^2$ in order to evaluate their physiological performance on a day-to-day basis. Thus, a small, lightweight system capable of long deployment periods that can gather data to assess the associated energy costs of horse-riding in any environment may be of benefit. However, as none of these systems have been deployed in the horse-racing environment, this study provides a feasibility study into their use in this area.

## 3.3 Results

The following are the descriptive results pertaining to the subjects as well as the data analysis undertaken.

### *3.3.1 Subjects*

Ten subjects completed all three tests out of an initial group of twenty one: 1) Maximal aerobic capacity ($VO_2max$), 2) Horse Racing Simulator and 3) On-horse testing. The results from each test are presented in the following sections.

No differences in subjects' mass were observed between test sessions. Descriptive and anthropometric data are presented below in Table 3.1;

*Table 3.1: Descriptive and Anthropometric Data (n=10)*

| Variable | Value + SD |
|---|---|
| Age (*yrs*) | 16 $\pm$ 1 |
| Mass (*kg*) | 54.82 $\pm$ 6.58 |
| Height (*m*) | 1.66 $\pm$ 0.71 |
| BMI ($kg/m^2$) | 19.84 $\pm$ 1.61 |

Data presented as mean $\pm$ SD

### *3.3.2 Descriptive Baseline Physiological Test Data*

$VO_2peak$ was defined as the mean of the 3 highest consecutive recorded $VO_2$ values measured over 20 seconds, once an RQ of higher than 1.1 and 95% of age predicted heart rate maximum had been reached. Baseline physiological test data are presented below in Table 3.2;

*Table 3.2: Descriptive Baseline Physiological Test Data (n=10)*

| Variable | Value + SD |
|---|---|
| $VO_{2peak}$ (*ml/kg/min*) | 57.96 $\pm$ 5.57 |
| $HR_{peak}$ (*BPM*) | 196 $\pm$ 2 |

Data presented as mean $\pm$ SD

### *3.3.3 Estimated Energy Expenditure*

Energy expenditure rates were compared across all stages during simulated and on-horse riding using the Cosmed Kb4[2].

#### *3.3.3.1 Estimated Energy Expenditure During Simulated Horse-Racing*

Significant differences were seen in energy expenditure measured via the Cosmed Kb4[2] between each stage ($p$<0.01), bar between S3 and S4 where a significant difference of p<0.05 was observed (Table 3.3). This indicates that as each stage increased there was a corresponding increase in the rate of energy expenditure as would be expected.

*Table 3.3: Mean Energy Expenditure Simulated Horse-Riding (n=10)*

| Stage | Value |
|---|---|
| S2 (*kcal/min*) | 4.1 ± 0.7** |
| S3 (*kcal/min*) | 4.8 ± 0.9 * |
| S4 (*kcal/min*) | 5.2 ± 0.8* |
| S5 (*kcal/min*) | 6.5 ± 0.7** |

Data presented as mean ± SD

**$p$<0.01; *$p$<0.05

#### *3.3.3.2 Estimated Energy Expenditure During Each Outdoor Gait:*

Significant differences were observed between Walk and Trot ($p$<0.01), Walk and Canter ($p$<0.01). No significant difference was observed for energy expenditure between Trot and Canter implying that there was no difference in energy expenditure rates between the two dissimilar gaits (Table 3.4).

*Table 3.4: Mean Energy Expenditure – On-horse (n=10)*

| Gait | Value |
|---|---|
| Walk (*kcal/min*) | 3.3 ± 1.4** |
| Trot (*kcal/min*) | 6.0 ± 1.3 |
| Canter (*kcal/min*) | 6.0 ± 1.5 |

Data presented as mean ± SD

**$p$<0.01; *$p$<0.05

### 3.3.3.3 *Graphical Representation of Energy Expenditure*

The following graph (illustration 3.5) depicts the rates of energy expenditure as measured on the Cosmed Kb42 during each stage of equine ergometry (red points) and outdoor gaits (blue points) with increasing stage intensity or gait.

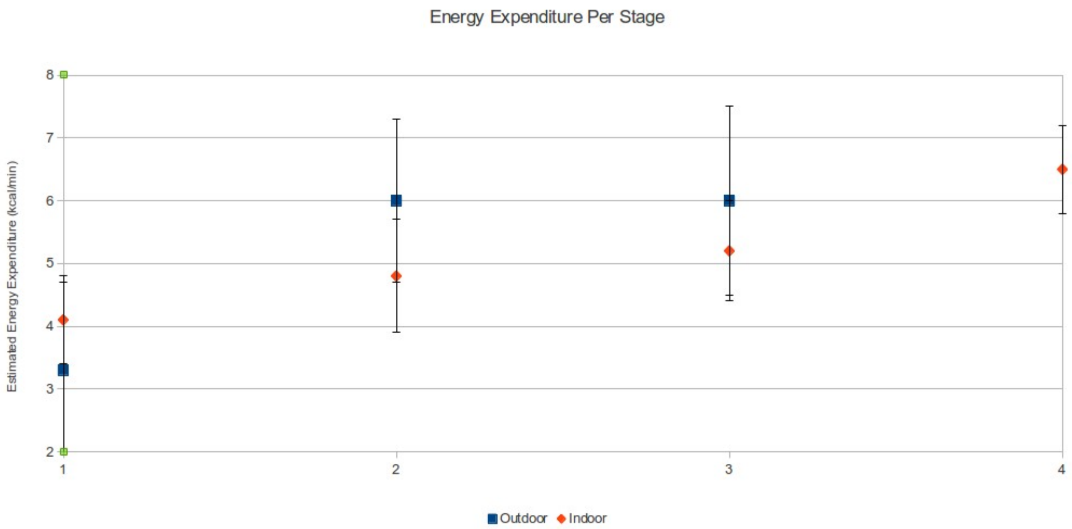



*Illustration 3.5: Estimated Energy Expenditure Per Stage (Indoor and Outdoor)*

## *3.3.4 Physical Activity*

Physical activity data was compared across all data sets during simulated and on-horse riding using the GT3X ActiGraphs. In all bar one case (Stage 2, ankle mounted GT3X ActiGraph) each sensor was shown to be statistically different to the Cosmed Kb4$^2$.

### *3.3.4.1 Mean Physical Activity During Each Indoor Stage*

Differences in physical activity were observed between some GT3X ActiGraphs during each stage (Table 3.5). Individual differences for each sensor location are outlined stage by stage in the following sections and the associated *p* value presented in separate tables; 1) *Section 3.3.4.2* Table 3.6 – S2, 2) *Section 3.3.4.3* Table 3.7 – S3, 3) *Section 3.3.4.4* Table 3.8 – S4, 4) *Section 3.3.4.5* Table 3.8 – S5.

*Table 3.5: Mean Physical Activity During Simulated Horse-riding (n=10)*

| Stage | Ankle | Saddle | Waist | Wrist | Chest |
|---|---|---|---|---|---|
| S2 (*kcal/min*) | 6.0 ± 6.5 | 4.6 ± 3.1 | 6.5 ± 2.4 | 7.8 ± 1.7 | 7.2 ± 1.6 |
| S3 (*kcal/min*) | 7.8 ± 2.6 | 7.8 ± 3.3 | 7.7 ± 1.9 | 8.8 ± 2.6 | 8.5 ± 1.9 |
| S4 (*kcal/min*) | 10.9 ± 3.9 | 11 ± 3.5 | 10.6 ± 3.1 | 11.5 ± 3.4 | 10.7 ± 3.4 |
| S5 (*kcal/min*) | 10.3 ± 1.4 | 10 ± 1.1 | 10.1 ± 1.0 | 10.6 ± 0.9 | 10.1 ± 1.3 |

Data presented as mean ± SD

### *3.3.4.2 Physical Activity Comparison Stage 2*

All GT3X ActiGraphs bar the saddle mounted were statistically different to the Cosmed Kb4[2]. Differences were observed between several GT3X ActiGraphs as outlined below (Table 3.6).

*Table 3.6: Stage 2 Statistical Differences All Sensors (n=10)*

| Location | Ankle | Saddle | Waist | Wrist | Chest | Cosmed |
|---|---|---|---|---|---|---|
| Ankle | N/A | 0.11 | 0.21 | 0.01** | 0.09 | 0.02* |
| Saddle | | N/A | 0.05 | 0.01** | 0.02* | 0.55 |
| Waist | | | N/A | 0.05 | 0.31 | 0.01** |
| Wrist | | | | N/A | 0.23 | 0.01** |
| Chest | | | | | N/A | 0.01** |
| Cosmed | | | | | | N/A |

Data presented as mean ± SD

**$p$<0.01; *$p$<0.05

### *3.3.4.3 Physical Activity Comparison Stage 3*

All GT3X ActiGraphs were statistically different from the Cosmed (**$p$<0.01) while never being statistically different from each other during this stage. This implies that all the GT3X ActiGraphs were measuring similar rates of energy expenditure during this stage (Table 3.7).

*Table 3.7: Stage 3 Statistical Differences All Sensors (n=10)*

| Location | Ankle | Saddle | Waist | Wrist | Chest | Cosmed |
|---|---|---|---|---|---|---|
| Ankle | N/A | 0.14 | 0.17 | 0.79 | 0.96 | 0.01** |
| Saddle | | N/A | 0.85 | 0.46 | 0.51 | 0.01** |
| Waist | | | N/A | 0.09 | 0.07 | 0.01** |
| Wrist | | | | N/A | 0.47 | 0.01** |
| Chest | | | | | N/A | 0.01** |
| Cosmed | | | | | | N/A |

Data presented as mean ± SD

**$p$<0.01; *$p$<0.05

### *3.3.4.4 Physical Activity Comparison Stage 4*

All GT3X ActiGraphs were statistically different to the Cosmed (**$p$<0.01). Significant differences were observed between GT3X ActiGraphs as outlined below implying that in some cases they agreed on the rate of energy expenditure, and in others did not (Table 3.8).

*Table 3.8: Stage 4 Statistical Differences All Sensors (n=10)*

| Location | Ankle | Saddle | Waist | Wrist | Chest | Cosmed |
|---|---|---|---|---|---|---|
| Ankle | N/A | 0.89 | 0.7 | 0.18 | 0.68 | 0.01** |
| Saddle | | N/A | 0.56 | 0.25 | 0.73 | 0.01** |
| Waist | | | N/A | 0.02* | 0.03* | 0.01** |
| Wrist | | | | N/A | 0.03* | 0.01** |
| Chest | | | | | N/A | 0.01** |
| Cosmed | | | | | | N/A |

Data presented as mean ± SD

**$p$<0.01; *$p$<0.05

### *3.3.4.5 Physical Activity Comparison Stage 5*

All GT3X ActiGraphs were statistically different to the Cosmed (**$p$<0.01). A significant differences was only observed between GT3X ActiGraph located at the saddle and wrist during this stage (Table 3.9).

*Table 3.9: Stage 5 Statistical Differences All Sensors (n=10)*

| Location | Ankle | Saddle | Waist | Wrist | Chest | Cosmed |
|---|---|---|---|---|---|---|
| Ankle | N/A | 0.22 | 0.23 | 0.43 | 0.64 | 0.01** |
| Saddle | | N/A | 0.6 | 0.01** | 0.59 | 0.01** |
| Waist | | | N/A | 0.08 | 0.09 | 0.01** |
| Wrist | | | | N/A | 0.09 | 0.01** |
| Chest | | | | | N/A | 0.01** |
| Cosmed | | | | | | N/A |

Data presented as mean ± SD

**$p$<0.01; *$p$<0.05

### *3.3.4.6 Mean Physical Activity During Each Outdoor Gait*

Significant differences in physical activity were observed between some GT3X ActiGraphs during each stage (Table 3.10). Individual differences for each sensor location are outlined stage by stage in the following sections and the associated $p$ value presented in separate tables 1) *Section 3.3.4.7* Table 3.11 – Walk, 2) *Section 3.3.4.8* Table 3.12 – Trot, 3) *Section 3.3.4.9* Table 3.13 – Canter.

Table 3.10: Mean Physical Activity – On-horse (n=10)

| Stage | Ankle | Saddle | Waist | Wrist | Chest |
|---|---|---|---|---|---|
| Walk (*kcal/min*) | 9.0 ± 2.1 | 8.8 ± 2.2 | 9.4 ± 1.3 | 9.4 ± 1.3 | 8.9 ± 1.5 |
| Trot (*kcal/min*) | 13.5 ± 3.5 | 13.4 ± 3.5 | 13.0 ± 3.4 | 13.4 ± 3.5 | 12.5 ± 3.1 |
| Canter (*kcal/min*) | 12.7 ± 2.9 | 12.5 ± 2.8 | 12.3 ± 2.7 | 12.6 ± 2.8 | 11.5 ± 2.2 |

Data presented as mean ± SD

### *3.3.4.7 Physical Activity Comparison Walk*

All GT3X ActiGraphs were statistically different to the Cosmed (**$p$<0.01). Significant differences were observed between GT3X ActiGraphs as outlined below with the chest mounted GT3X ActiGraph being dissimilar to all other locations (Table 3.11).

*Table 3.11: Walk Statistical Differences All Sensors (n=10)*

| Location | Ankle | Saddle | Waist | Wrist | Chest | Cosmed |
|---|---|---|---|---|---|---|
| Ankle | N/A | 0.13 | 0.01** | 0.11 | 0.01** | 0.01** |
| Saddle | | N/A | 0.14 | 0.74 | 0.01** | 0.01** |
| Waist | | | N/A | 0.03* | 0.01** | 0.01** |
| Wrist | | | | N/A | 0.01** | 0.01** |
| Chest | | | | | N/A | 0.01** |
| Cosmed | | | | | | N/A |

Data presented as mean ± SD

**$p$<0.01; *$p$<0.05

### *3.3.4.8 Physical Activity Comparison Trot*

All GT3X ActiGraphs were statistically different to the Cosmed (**$p$<0.01). Significant differences were observed between GT3X ActiGraphs as outlined below with the chest mounted GT3X ActiGraph being dissimilar to all other locations (Table 3.12).

*Table 3.12: Trot Statistical Differences All Sensors (n=10)*

| Location | Ankle | Saddle | Waist | Wrist | Chest | Cosmed |
|---|---|---|---|---|---|---|
| Ankle | N/A | 0.3 | 0.01** | 0.09 | 0.01** | 0.01** |
| Saddle | | N/A | 0.2 | 0.52 | 0.01** | 0.01** |
| Waist | | | N/A | 0.02* | 0.02** | 0.01** |
| Wrist | | | | N/A | 0.01** | 0.01** |
| Chest | | | | | N/A | 0.01** |
| Cosmed | | | | | | N/A |

Data presented as mean ± SD

***p<0.01; *p<0.05*

### *3.3.4.9 Physical Activity Comparison Canter*

All GT3X ActiGraphs were statistically different from the Cosmed (**$p$<0.01). Significant differences were observed between GT3X ActiGraphs as outlined below implying that in some cases they agreed on the rate of energy expenditure, and in others did not (Table 3.13).

*Table 3.13: Canter Statistical Differences All Sensors (n=10)*

| Location | Ankle | Saddle | Waist | Wrist | Chest | Cosmed |
|---|---|---|---|---|---|---|
| Ankle | N/A | 0.19 | 0.27 | 0.45 | 0.85 | 0.01** |
| Saddle | | N/A | 0.16 | 0.32 | 0.84 | 0.01** |
| Waist | | | N/A | 0.97 | 0.02* | 0.01** |
| Wrist | | | | N/A | 0.02* | 0.01** |
| Chest | | | | | N/A | 0.01** |
| Cosmed | | | | | | N/A |

Data presented as mean $\pm$ SD

**$p$<0.01; *$p$<0.05

## *3.3.5 Indoor and Outdoor Comparisons Based on Energy Expenditure*

Significant difference were observed for estimated energy expenditure between each of the stages to each other,and between walking relative to trotting and cantering. A comparison was undertaken between indoor stages and outdoor gaits where no significant differences in estimated energy expenditure measured with the Cosmed occurred.

### *3.3.5.1 Stage 3 vs. Trot*

No significant differences were observed for estimated energy expenditure measured with the Cosmed. Significant differences in physical activity were observed for each GT3X ActiGraphs at each site: Ankle $p$<0.01, waist $p$<0.01, chest $p$<0.01, wrist $p$<0.01 and saddle $p$<0.01.

### *3.3.5.2 Stage 3 vs. Canter*

No significant differences were observed for estimated energy expenditure measured with the Cosmed. Significant differences in physical activity were observed for each GT3X ActiGraphs at each site: Ankle $p$<0.01, waist $p$<0.01, chest $p$<0.01, wrist $p$<0.01 and saddle $p$<0.01.

### *3.3.5.3 Stage 4 vs. Canter*

No significant differences were observed for estimated energy expenditure measured with the Cosmed. No significant differences in physical activity were observed for any ActiGraphs at any site.

#### *3.3.5.4 Stage 5 vs. Trot*

No significant differences were observed for estimated energy expenditure measured with the Cosmed. Significant differences in physical activity were observed for each GT3X ActiGraphs at each site: Ankle $p<0.01$, waist $p<0.05$, chest $p<0.05$, wrist $p<0.05$ and saddle $p<0.01$.

### *3.3.6 Velocity Calculations*

Velocity data were measured for each gait with the Garmin GPS. The following were the mean velocities measured for each gait pattern using data from all subjects and horses used in the study (Table 3.14).

*Table 3.14: Velocity Estimations Outdoor (GPS) (n=10)*

| Gait | Value |
|---|---|
| Walk (*kph*) | 5.58 $\pm$ 0.79 |
| Trot (*kph*) | 12.58 $\pm$ 1.51 |
| Canter (*kph*) | 28.08 $\pm$ 2.19 |

Data presented as mean $\pm$ SD

Velocity was estimated for the indoor condition using a simple algorithm, the Ergocal method Appendix section 8.1. These velocities were not used for comparative purpose in this study as they are not validated, results however are presented in Appendix section 8.1. **Note:** Stage 1 (S1) was not used as part of the testing protocol as the subjects never use this setting during their own training.

### *3.3.7 Synopsis*

With significant differences between physical activity measures from the metabolic system (Cosmed Kb4[2]) and the GT3X ActiGraph in all but one case, these sensors may not provide accurate measures in the field with the data analysed in its proprietary form. Although the jockey absorbs much of the motion of the horse, increasing their physical activity, it is likely that any measured movement is as a result of the horse, not the rider. Thus, any measures estimated for physical activity may be skewed if taken from the accelerometer alone. This is most likely due to the Plateau effect within the accelerometers themselves and may be partially mitigated by the use of a count-based approach to measurement over the raw data. However, comparisons made based on similar energy expenditure rates between ergometery and outdoor riding show little agreement in physical activity rates between the GT3X ActiGraphs when compared at the same site. It is probable that specific algorithms may need to be developed in order to account for the movement of the horse and its effect on the measurement of the GT3X ActiGraphs. This would require the post-event processing of the data acquired in this feasibility study by those trained in signal processing to remove the effect of the horse.

## 3.4 Discussion

Based on the findings of the current study, there appear to be problems associated with measuring physical activity during horse riding via accelerometery. These are primarily due to the interaction between rider and horse as it is not possible to be wholly certain that the data captured is solely due to the movement of the jockey. Thus, inferring any physical activity measures based on an increase in movement are flawed unless they can be proven to come from the jockey alone. To accurately assess physical activity in this environment, reliable methods of energy expenditure estimation must be used in parallel with physical activity measures taken from accelerometers. During this feasibility study, this was undertaken during simulated and outdoor horse-riding in order to assess the similarities between the two, and assess the applicability of the GT3X ActiGraph in both of these environments. From this study it may be possible to refine algorithms that can measure physical activity more accurately from the GT3X ActiGraph.

### *3.4.1 Subjects*

The subjects used in this study were trainee jockeys undergoing training at RACE. These subjects, although riding full-time, were not as well trained or technically proficient as their professional counterparts. Despite this, the subjects had similar height, mass and BMI as professional jockeys previously reported in the literature (Dolan 2010; Dolan et al., 2011; Warrington et al., 2009) as well as measures of maximal aerobic capacity (Westerling, 1983; Trowbridge et al., 1995; Devienne & Guezennec, 2000). From this it is reasonable to assume that, whilst the trainee jockeys used in the current study may not have the technical or tactical skills of professional jockeys, they are similarly matched for physiological work capacity.

As there is a lack of scientific literature examining the energy demands of horse-riding during different gaits, it is difficult to be certain that the recorded data for energy expenditure are in line with reported data. Data from Westerling et al. (1983) reported a mean peak value for $VO_2$ during horse-riding of 55 ml/kg/min. This data is similar to that found in the current study which reported a mean peak value for $VO_2$ of 57.3 ml/kg/min. However, Westerling et al. (1983) did not report any data for energy expenditure. Similarly more recent studies from Trowbridge et al. (1995) have only reported the heart rate response, whereas a study by Devienne et al. (2000) reported $VO_2$ responses during each gait and jumping, but again presented no data for energy expenditure. In the case of Devienne et al. (2000), the subjects used were not jockeys, but rather dressage riders thus, the data may also not be fully comparable. Furthermore these studies also suffer from small sample sizes; Westerling et al., (1983) n=3; Trowbridge et al., (1995) n=7; Devienne et al., (2000) n=5). Although data in this study pertains to a sample size of 10 subjects, $VO_2$ data was captured for 21 subjects in total and the results were similar to those presented, {n=21} $VO_2$peak = 55.7 $\pm$ 5.6 ml/kg/min ($\pm$ SD). Subjects were only included in this study if they completed both indoor and outdoor riding trials.

### *3.4.2 Environmental Differences*

The current study dealt with data in the two environments in which jockeys train; indoors on equine ergometers that simulate horse-riding and outdoors on-horse. The purpose of any training ergometer is to mimic the motion of the physical activity pattern and thus simulate the physiological systems in a similar manner. Using an indoor ergometer comes with limitations such as an inability to control for environmental factors such as wind resistance generated during riding, the thermic effect of the horse itself, as well as only working in two relative planes of motion. Anecdotally, the jockeys used in the study believed that riding indoors on the ergometer was harder than riding outdoors on a horse (personal communication with study participants). In order to accurately assess how comparable indoor and outdoor riding are using accelerometry, it would be necessary to compare the instantaneous velocity and acceleration profiles of the ergometer settings to those of a real horse for a range velocities. Although they may never be identical (as the ergometer is only moving in two axes) comparisons could be made by looking at peak velocity and acceleration values and/or at integrals of both values. This would then need to be performed for various sub-sections of full movement cycles, i.e. fast trot vs. slow trot, in order to better approximate the ergometer to outdoors. With the low acceleration range of the GT3X ActiGraphs, these sorts of calculations are not be possible and more accurate units would be needed to facilitate these calculations. Due to this, comparisons were made based on energy expenditure rates measured via a portable metabolic system in order to assess the GT3X ActiGraphs performance in these two environments and the feasibility of future use in this environment.

It has been noted in cyclists that increases in core temperature during stationary training led to changes in the energy cost of cycling at a fixed resistance, as well as changes in cardiac output and gross efficiency (Hettinga et al., 2007). While riding on the simulator the jockeys have zero net forward motion in comparison to relative wind speeds of up to 60kph outdoors. Due to lack of external cooling, this may result in an increased body temperature as the heart pumps more blood to surface tissue in an attempt to cool itself. Consequently, this increase in temperature may lead to changes in the energy demand during simulated horse-riding similar to those experienced by cyclists during indoor ergometry. If this is occurring in jockeys, it may in part explain the perception of ergometer training as harder. However, it must be noted that during outdoor horse-riding jockeys are sitting on an animal that is attempting to do exactly as they are, dissipate heat. In all likelihood, the thermic effect of the horse on the jockey may be similar to that of riding indoors thus negating the above supposition, but exacerbating it during indoor riding. However, as this has not been investigated in this study, nor in the existing literature, it warrants further investigation. This may also be due to the limited motion of the simulator itself as it only travels in two planes of motion. This is discussed in the following section.

### *3.4.3 Energy Expenditure Differences*

In order to investigate the differences between the indoor and outdoor riding, data were first compared based on the estimated energy expenditure as measured on the Cosmed $Kb4^2$ portable metabolic system. Studies have noted that there is an increase in the dynamic motion of the lower legs during the final, more intense, stages of racing (Trowbridge et al., 1995). It is also understood that the upper limbs play a part in balancing the jockey over the horse's centre of mass (Pfau et al., 2006). Thus, it is expected that this increase in the horse's motion leads to an increase in the energy demands of the jockey as it changes gait in order to run faster. The associated metabolic costs of the changes in gait on the jockey were investigated by Devienne et al., (2000) who noted a difference in the $VO_2$ cost between walking, trotting, cantering and jumping in dressage riders. Unfortunately, no measures for the energy expended during each gait were reported in their study thus direct comparisons to this thesis data cannot be made.

Based on the findings of the current study, there was no significant differences in the energy expended during trotting and cantering while using direct measures of energy expenditure (Table 3.4) which is counter-intuitive and dissimilar to the results in the Devinnes et al. study. This may in part be due to differences in the type of rider used in the respective studies (trainee jockeys versus recreational dressage riders). It is possible that the trainee jockeys may have become adept at riding at these specific intensities and thus expend less energy. Interestingly, during the simulated horse-riding each increase in intensity produced a significant rise in the energy expended as would be expected from the ergometer (Table 3.3).

### *3.4.4 Physical Activity Analysis*

By placing GT3X ActiGraphs at multiple locations on the subjects it was hoped that physical activity could be assessed and compared to energy expenditure measurements across several sites. The sites chosen were not based on previous accelerometer based research studies in this environment as none exist. Thus, the most commonly used sites from the literature were chosen and multiple sensors deployed. This was done in order to assess the feasibility of the sensors to operate in this environment, and, to aid in choosing the most appropriate location for measurement in future studies. An additional sensor was placed on the pommel of the saddle on the horse, or simulator, in order to assess the impact of the mount on the rider. The addition of this mount based GT3X also allowed for a simple measure of the “physical activity” that was being produced by the mount itself. It was expected that the movement of the mount may swamp the data that was being recorded by the GT3X ActiGraphs. However, by placing a sensor at this location is was hoped that in future research it may be possible to extract the signal of the mount from the data of the jockey and thus give a better measure of the physical activity of the jockey. As it currently stands, the GT3X platform may not have the granularity in its count-based data analysis, but it may be possible with future raw acceleration based physical activity analysis.

As expected, when compared within the same stage or gait, the physical activity measured by the GT3X ActiGraphs varied significantly from each other at most locations (*Simulated riding*: Tables 3.5 – 3.9; *On-horse*: Tables 3.10-3.13). In contrast, the ankle and saddle sites proved to be similar to each other in all cases. This raised the question of whether or not these were measures of the physical activity of the rider, or the motion of the horse, or simulator, itself. It is possible that the measured changes in physical activity are not due to the increased lower leg activation noted by Trowbridge et al., (1995) but due simply to an increasing frequency of motion being registered as increased physical activity by the sensor. This was also observed between the saddle and the waist mounted GT3X ActiGraph during all trials, as well as the saddle and the wrist during outdoor trials. It may be possible with specific filtering applied to the data to eliminate, or at least account for, the effect of the mounts movement on the physical activity of the rider. However, in its current form it is not advisable to assume that physical activity data taken from the ankle, waist or wrist is an accurate representation of the energy being expended by the jockey during horse-riding, simulated or otherwise.

### *3.4.5 Energy Expenditure Based Comparison of Physical Activity*

Where no significant differences in the rate of energy expenditure, as measured by the Cosmed K4b$^2$, were observed between a gait and stage on the ergometer, data were compared between the two conditions. This was performed in order to assess if simulated horse-riding and on-horse riding, when matched for a similar rate of energy expenditure, produced similar similarities in physical activity via the GT3X ActiGraphs. This resulted in the comparison of four sets of coupled data for a simulator intensity and on-horse gait (Table 3.14). While it was expected that cantering, as defined by on-horse data from the Cosmed K4b$^2$, would logically follow a more intense stage on the ergometer than trotting, it was unexpected that trotting would be similar to the 'harder' intensity of stage 5. A possible explanation for the disassociation of intensity levels on the ergometer and that of the horse, is due to the nature of the motion of the ergometer.

As the ergometer only moves in the horizontal and vertical planes, there is no need for the jockey to compensate for the lateral motion that would normally occur as a horse is cornering or moving as it sees fit. Thus, it is possible that while riding on the simulator a jockey may adopt a less aggressive position during later stages thus reducing the amount of physical activity undertaken. With the recent availability of equine ergometers with 3 degrees of freedom it may be possible to compare a standard ergometer and a newer model in order to assess this. As the ergometer is not capable of independent decision making like a horse, the more harmonic and predetermined motion of the ergometer may, coupled with the possibility of a reduced adrenalin response from being on a ergometer versus a live horse, partially explain the reduction in both physical activity and energy expenditure in the latter stage of the simulated trials. It is possible that the ability of the jockey to relax while riding a simulator may allow them to expend less energy.

Data were compared at each site, based on the coupled energy expenditure pairs, in order to assess the difference in physical activity rates between ergometry and on-horse riding. This was undertaken across each of the accelerometer locations. During stage 3 (cantering and trotting) and stage 5 (trotting), differences were noted at each location implying that there were no similarities in the physical activity rates being measured. This was unexpected as the energy expenditure data would imply that there were no differences between these intensities in each environment. It is not clear why this occurred, it is possible that the plateau effect noted by Sasaki et al. (2011) and Chen at al. (2012) may play a part (Section 2.4.6). This levelling off of the rate of acceleration measurement due to the frequency and amplitude of motion may cause the units to over or underestimate the amount of motion that is occurring. This is similar to findings from Dinish et al. (2011) who found that at running velocities over 12km/hr energy expenditure rates were underestimated. This artefact is due to the hardware of the GT3X itself and the older GT1M legacy algorithms for estimating physical activity rates. However, during stage 4 and cantering, no differences in physical activity were observed at any location implying that the GT3X ActiGraphs were measuring similar rates of physical activity at the same location. It is possible that these intensities represent a zone where the frequencies and amplitude of motion of the jockey are not large enough to instigate the plateau effect. With the introduction of the newer GT3X+ models with a higher sample rate and measurement range, it may be possible to mitigate this effect and allow for a larger range of measurement.

While the plateau effect is not something that can be currently addressed, due to it being a hardware issues, it is possible to address it somewhat by the manner of analysis used. By approaching the analysis with a count-based method, as undertaken in this study, it is possible to at least know when a jockey has changed from one speed to another as the number of counts per minute changes in accordance with the rate of change of velocity during either ergometry or gait. This, combined with known values of energy expenditure as measured by a system such as the Cosmed, would allow for post processing of the data and an estimate of the energy expended based on time in each stage or gait to be made. This would necessitate the pre-deployment of a Cosmed style system in order to gather these readings, however with a large enough sample size across a range of velocities it may be possible to define energy expenditure rates for indoor and outdoor horse-riding. If data were to be analysed in this manner it would require the collaboration of both sports and computer scientists in the development of the appropriate software to do such analysis.

### *3.4.6 Sensor Feasibility*

In a sport where weight saving is at a premium, the additional weight of any physiological monitoring system is difficult to justify. In this study, the feasibility of deploying lightweight, unobtrusive accelerometer based technologies to measure physical activity were presented. With little information about the energy demands of jockeys during horse-riding this research adds to the small body of data with a unique method of investigation. These systems can be deployed for extended periods of time, gather data without the interaction of the user and have proved to be capable of recording similar data across a variety of intensities and gaits. As this study used two different environments it was necessary to deploy sensors at several different locations on the jockey in order to assess which would be the most applicable for use. By gathering both energy expenditure data from the Cosmed $K4b^2$ and physical activity data from the GT3X ActiGraphs a comparison could be made based on the energy expended during exercise. When the data were analysed, none of the GT3X ActiGraphs agreed with the data from the Cosmed $K4b^2$ either during indoor or outdoor conditions. From this it would be easy to surmise that the GT3X ActiGraphs are not applicable in this environment no matter where they are located. However, as the Cosmed is acting as a direct measure of the energy expended and not solely estimating based on the motion of the jockey, this is not surprising.

The use of multiple GT3X ActiGraphs placed on both the jockey and saddle did allow for the investigation into most applicable location and their impact on physical activity measurement. This in itself was confounded in most instances as there was little agreement between the sensors whilst trying to measure the same variable within each stage or gait. The effect of the motion of the mount possibly overriding the physical activity measures cannot be ignored and may need to be addressed before gathering additional physical activity data. In order to do so it would be necessary to dig into the raw data and extract the acceleration profiles for each gait and stage for both the jockey and mount or ergometer. This would require a much more accurate and higher ranged accelerometer than the GT3X ActiGraph which is currently limited to a small acceleration range.

Overall, in their current form the GT3X ActiGraph is not capable of gathering appropriate physical activity data, but this data does not necessarily relate to estimates of energy expenditure as the data is swamped by the motion of the horse or ergometer. In order to align the physical activity data from the GT3X ActiGraphs to the Cosmed $K4b^2$ energy expenditure data would necessitate a computer science approach, and the removal of the raw acceleration data from the mount itself. This outside the scope of this thesis but would make for interesting future research.

### *3.4.7 Research Implications*

Due to the lack of agreement between the gold standard measurement techniques and the GT3X ActiGraphs it is not possible to say that they accurate measures of physical activity in this environment in their proprietary form. In order to further utilise these lightweight systems in this environment it will be necessary to capture specific data at a range of velocities and gait patterns to develop specific filters that can be applied to the data during post processing. This has been undertaken by other groups for various other activities. Overall this research provides a unique data set with both physiological and contextual data.  This can then be utilised to develop an activity specific method of measuring physical activity during horse-riding.

### *3.4.8 Population and environmental limitations*

Limitations within this study include, but are not limited to:

- The ability level of subjects only reflects that of trainee jockeys.

- Overriding effect of the mount on measures of physical activity.
- Loss of data due to sensor failure.
- Addition of comparatively heavy monitoring equipment may have an effect on reliability and accuracy of estimated energy expenditure.
- The unpredictable nature of the environment leading to artefacts in the data.
- Emerging research environment with no readily available accelerometer data.

## 3.5 Summary

Based on this study it can be concluded that traditional methods of estimating energy expenditure are possible during simulated and actual horse-riding. This is in agreement with existing research in the literature. The feasibility of the GT3X ActiGraphs as a method of physical activity assessment is unlikely. Without environment specific algorithms these sensors cannot be used in their proprietary form to estimate physical activity during simulated or outdoor on-horse riding.

When matched for energy expenditure rates, simulated horse-riding and on-horse riding produce significantly different physical activity rates when measured via the GT3X ActiGraphs. In many cases the sensors mounted on the jockey agreed with the saddle mounted sensors. This implies that the motion of the mount overrides the activity of the jockey and potentially renders the sensors useless if the the proprietary software is utilised. In reality, the effect of the horse cannot be mitigated only measured and adapted into any further calculations. This problem necessitates the combined efforts of sports and computer scientists in order to develop event specific algorithms that may be capable of removing the effect of the mount on the jockey. As it stands, it is not recommended to use the GT3X ActiGraphs in this environment in their proprietary form.

In conclusion, there is potential for the use of accelerometer based measurement techniques in the field of horse-racing in order to measure the demands of horse racing on jockeys. However, current techniques and software do not allow for the accurate measurement of physical activity. It may be possible with future research, to develop specific algorithms that can adapt to changes in a horses gait as a jockey races and trains. This would give a valuable tool to jockeys for measurement of their own training and possibly help in long term weight management strategies.

# Chapter 4: Study 2; Evaluating Physical Activity and Sleep Indices During Daily Search and Rescue Operations

# 4.1 Introduction

### *4.1.1 Study Overview*

Helicopter search and rescue (SAR) crews operate on a 24-hour shift with operators either sleeping on-base or off-base depending on proximity of their homes to the base. This may led to possible variations in the amount of physical activity undertaken, sleep efficiency, sleep duration and total estimated energy expended between members of the SAR dependant on their sleeping location  during their shift.

Ireland is served by four search and rescue bases located at Dublin, Sligo, Waterford and Shannon crewed 24-hours a day, 365 days of the year. These bases have four person search and rescue (SAR) teams based on site at all times. SAR operators form part of the Irish Cost Guard and are tasked with giving '*aid to persons who are, or are believed to be, in imminent danger of loss of life'* (Irish National Maritime Search And Rescue Framework, 2010). This contract is currently held by Canadian Holding Company (CHC) who supply helicopter rescue services through out the world. CHCs deployed assets currently consist of six Sikorsky S-61 'sea-king' helicopters that are on lease to the government as part of the contract to fulfil operational duties. Similar contracts are held by CHC in Spain and Sweden. The SAR operational area covers the Irish Flight Information Region covering up to 50km off the southern coast and 325km off the western coast of the Republic of Ireland (Illustration 4.1).

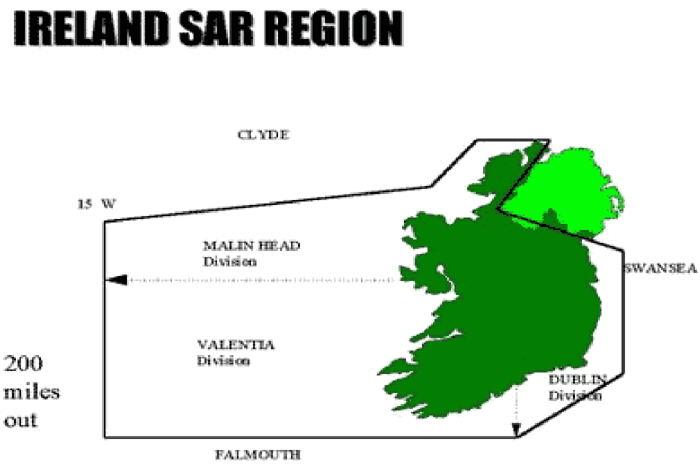
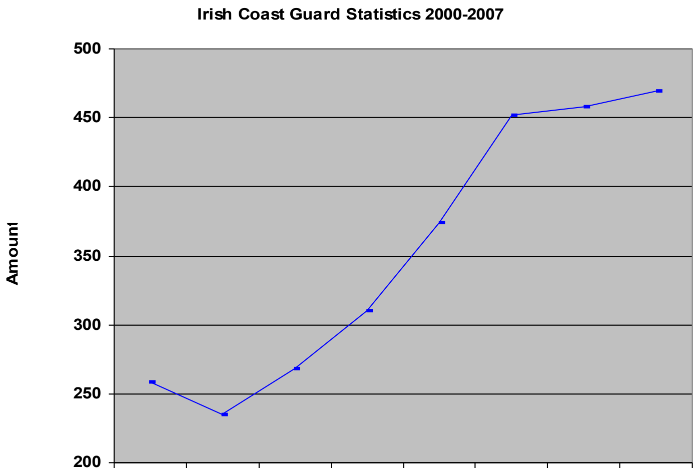



*Illustration 4.1: SAR Operational Region, 2011*

With increases in shipping traffic, commercial fishing and the number of offshore oil and gas platforms, the number of SAR operations in Ireland has increased appreciably in recent years (Illustration 4.2). As a rescue service, SAR operations do not have to adhere to international boundaries during a tasking and this has resulted in Irish SAR operators being involved in prolonged operations as far north as the Shetland Islands, 400km north of the Scottish coast. While providing primarily offshore rescue capabilities that are otherwise unavailable, SAR assets also perform operations inland in situations where it is otherwise impossible to remove or access casualties using another rescue service. Currently the Health Service Executive (HSE) may also utilise SAR assets when needed for medical emergencies or patient transport.




| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|---|---|---|
| S61N | 259 | 235 | 268 | 310 | 374 | 452 | 458 | 469 |

*Illustration 4.2: Total Irish SAR taskings for S-61*

### *4.1.2 SAR Operations*

During each duty period, two pilots and two members of the winch-crew are on duty. Pilots are recruited from ex-Gardai, military pilots, or civilians who have attained commercial helicopter pilot licences. The winch-crew is comprised of a winch-operator and a winch-man who also act as spotters during casualty approaches. The winch-crew perform interchangeable rolls and provide medical support to casualties who are rescued. The winch-crew are comprised of ex-HSE employees; paramedics, nurses or other medical personnel. If the winch-crew are incapable of delivering the necessary treatment to stabilise a casualty for transfer to ground based emergency services, the aircraft is flown to a HSE medical centre capable of receiving airlifted casualties.

Irish SAR crews start to log their 24 hour operational duty period at 13:00 hours. Between the hours of 13:00-21:00 and 07:30-13:00, SAR crew operate in a 15 minute state of readiness requiring them to be in the air within 15 minutes of a tasking being called in. This time is considered the 'normal' working day for SAR operators and they must be present on-base and capable of flight duties. Between 21:00 and 07:30 hours SAR operators are on a 45 minute state of readiness, allowing members who reside within 20 minutes travel of the base to remain on-call off-base at home or in any other suitable accommodation. Those who reside further than 20 minutes travel from the base must sleep on-base. During the standby readiness period (21:00-07:30 hours) subjects are effectively off work, on standby, and free to perform whatever recreational activities they wish once they are capable of meeting the 45 minute readiness clause.

Current regulations state that on-base standby readiness accounts for 100% of the duty period meaning that each hour of standby duty spent on-base accounts for one full work hour. However, standby readiness off-base only accounts for 25% of the working hours. This is derived from a belief that the physical demands of SAR operators who remain on-base are greater than those off-base. With a maximal of 2,000 duty hours per annum, members who spend their standby readiness period off-base will take longer to reach this limit, however they will have effectively worked more hours than those residing on-base.

With such prolonged working hours and variable working conditions, there is a need to better understand the physical demands of this unique environment. It is difficult to deploy any form of traditional physiological measurement techniques in this environment due to the prolonged nature of deployment and the inherently difficult environmental constraints. This study provided a chance to perform a feasibility study with the GT3X ActiGraph platform as the central sensor in an attempt to assess the amount of physical activity undertaken in this environment as well as other sleep indices that may impact performance in this occupation. This also allowed an in-depth look to be taken into the effect of sleeping location on members of the SAR crew. This formed part of a research study requested by SAR operators themselves who were unsure of the effect of sleeping on or off base on their performance.

### *4.1.3 Aim*

The aim of this study was to investigate if differences exist in the amount of physical activity undertaken, sleep efficiency and sleep duration between members of the SAR who sleep on-base or off-base under normal working conditions. This was to be undertake with a simple commercially available accelerometer platform the GT3X ActiGraph which was to be compared to another validated measure of physical activity and sleep measurement.

### *4.1.4 Objectives*

i. To estimate the amount of physical activity undertaken by search and rescue operators in both operational environments.
ii. To estimate the amount of energy expended by search and rescue operators in both operational environments.
iii. To assess and compare the amount of sleep accrued by search and rescue operators in both operational environments.
iv. To assess and compare the efficiency of the sleep accrued by search and rescue operators in both operational environments.
v. To investigate if a change in sleeping environment has an effect on the above variables.

### *4.1.4 Environment Studied*

The environment studied was that of the normal activities of daily living of search and rescue crew members located at Dublin airport during operational duties. Subjects operate on a 24 hour shift and can be required to respond to a tasking at any time of day. The environment is defined by subjects who sleep on-base and off-base. This provided the context by which subject groups were segregated for analysis. Subsequently, subjects whose normal sleeping condition was that of off-base, slept on-base providing data in both a habitual and abnormal sleeping condition.

### ***4.1.2 Synopsis***

As there is a need to investigate physiological impact of SAR operations the use of lightweight accelerometer based technologies may allow for in-depth research into the physiological demands and impact of the different SAR sleeping environments. The use of accelerometers in the assessment of helicopter crews has primarily focused on the impact of aircraft vibration on the crew (de Oliveira & Nadal, 2005; Kåsin et al., 2011). To date, there have been no published studies evaluating physical activity or sleep indices in SAR operators using accelerometers. The use of these technologies may objectively assess if there is a difference in the physiological demands placed on SAR operators based solely on their sleeping location.

## 4.2 Methodology

The following section describes the methods used during the study as well as information pertaining to the subjects.

### *4.2.1 Subjects*

Participants were recruited from members of the Dublin SAR base, were employed for a minimum of one year and deemed habituated to the occupational environment. Ten subjects (41 ± 5.4 years) volunteered to participate in the study after being informed of the purpose of the research. This represented 63% of the total crew of the Dublin SAR team. It was not a requirement that all SAR operators on-base take part in the study. Subjects were considered for inclusion if they were free from any injury or conditions that may stop them performing their day-to-day duties. Age, ethnicity and habitual levels of physical activity were not considered exclusion criteria. Subjects were given opportunities to ask questions and, after being informed of the requirements and content of the study via a plain language statement, consented to being in the study. Informed consent was then gathered from all participants as well as a general health questionnaire (Section 8.3.1). The study was approved by the Dublin City University's (DCU) Research Ethics Committee.

### *4.2.2 Subject Grouping*

A SAR aircraft consists of both pilots and winch-crew all of whom were considered for inclusion in the study. The data were not split on the basis of their role in the aircraft as this would further reduce the power of the data, thus all crew members were pooled as one data-set. Multiple sets of data were gathered for subjects where possible. The total number of subjects was defined as group total (GT, n=10) which resulted in 27 sets of total data. The subjects were further categorised based on their normal sleeping environment: habitual on-base sleepers were defined as group one (G1, n = 4), 8 total sets of data, and habitual off-base sleepers group two (G2, n = 6), 12 total sets of data.

In the second part of the study, members of G2 acted as self controls by sleeping on-base in an abnormal condition defined as group 3 (G3, n = 4), 7 total sets of data. This allowed for a direct comparison to be made as to whether a difference existed due to sleeping location. These subjects had all slept on-base several times in the past year and were deemed accustomed to sleeping on-base. This data was not used when assessing SAR operators in the on-base, G1 condition. Summary of study groups:

- GT – All subjects (n=10) {27 total sets}
- G1 – Habitual on-base sleepers (n=4) {8 total sets}
- G2 – Habitual off-base sleepers (n=6) {12 total sets}
- G3 – Habitual off-base sleepers sleeping on-base (n=4){7 total sets}

### *4.2.3 Environmental instructions*

Subjects were advised to maintain their normal daily and nightly routine during all testing and record it in an activity diary (Section 8.3.2). The data from the activities diary was not used to assess daily physical activity or dietary intake and acted as a written ground truth for data collected by the sensors. Facilities at the SAR base allowed the crew to exercise during operational duties, thus subjects were asked to keep a record of any exercise they undertook and repeat this in future testing. Subjects recorded the timing of meals but not specific nutritional intake. Training flights and their duration were recorded in the activity diary. Subjects were not advised when they should go to sleep or for how long. Subjects were free to sleep whenever they saw fit and recorded it in the activity diary. These self reported sleep periods were used to assess the sleep data from the sensors deployed. In order to do so, these periods were manually entered into the appropriate software to set start and finish boundaries for sleep periods.

Subjects were asked to note any day on which a tasking occurred. It was felt that the response to a tasking may impact on normal sleep patterns, and due to the infrequency of tasked flight operations, the likelihood of each operator undergoing a similar tasking is remote thus lowering the comparability of the data. Thus, any day on which a tasking occurred was removed from the data set and stored for future use.

SAR operators must attempt to fly every day as part of the agreed contract between the Irish government and CHC. This acts as a way of training the crew in different situations and weather conditions. If a tasking has not occurred, or is not liable to due to weather conditions, SAR operators will fly for between two and three hours. As pilots and winch-crew do not swap rolls it was assumed that once training flights of similar duration occurred between data captures that the energy expended would be similar. However, this was not assessed in-depth.

### *4.2.4 Equipment and Sensor Configuration*

All sensors started recording data 5 minutes prior to testing commencement of the flight duty at 13:00 hours and were calibrated to the universal time constant (UTC) for comparability between sensors. Each subject was instrumented in the same manner over the course of the study, with the same sensors where possible (Illustration 4.3). Due to the duration of deployment and the nature of the environment the SAR operate within, it was not possible to utilise technologies such as radio-telemetry based heart rate monitoring systems. Prior to data collection an electromagnetic field (EMF) test was under taken by SAR engineers and these systems showed possible interference with the aircraft's RADAR system. Due to any possible interference with the aircraft systems, the use of any radio-telemetry based systems was deemed unsuitable for the environment and thus they were not used. As SAR operators must wear helmets with integrated communication systems during all operations it was not possible to use a portable metabolic gas analysis systems in this environment.

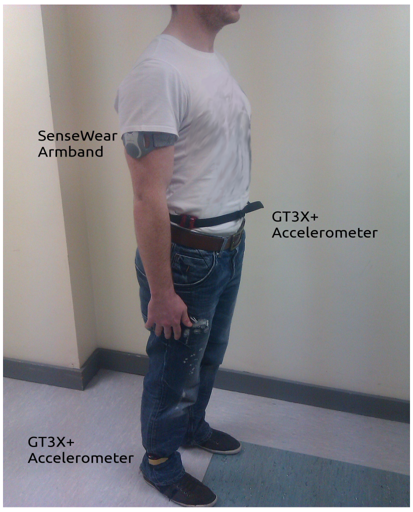



*Illustration 4.3: Placement of Sensors*

#### *4.2.4.1 GT3X+ ActiGraph:*

The following data was required to initiate the GT3X+ ActiGraphs (Section 2.4.5) and was input by researchers in the proprietary software, ActiLife version 5.2.2; date of birth, age, mass, height, ethnicity, dominant side and location of sensor. Physical activity measures were calculated based on the Combined Freedson Vector Magnitude calculations demonstrated by Sasaki et al. (2011) that are embedded in the ActiLife software. All accelerometers were set to record in tri-axial mode. The inclinometer was set to record. The sample rate was set at 100Hz. Data was logged in 1 second epochs. All sensors ran firmware version 2.2.0. Where possible, subjects wore the same units as utilised in previous testing so as to avoid any differences due to unit-to-unit calibration. The ActiGraphs were kept in the same orientation for each test and attached via a soft Velcro strap which allowed for minimal movement of the sensor, but remained comfortable enough for long deployments. A GT3X+ ActiGraph was placed around the waist of each subject on the right hip. A second GT3X+ ActiGraph was placed on the right ankle of the subject (Illustration 4.3).

#### *4.2.4.2 SenseWear™ Armband*

The following data was required to gather initiate the SenseWear™ Armband (Section 2.3.6) and was input by researchers into the propitiatory professional software, version 7.0; date of birth, age, mass, height, smoking status and dominant side. Accelerometers on the vertical and horizontal plane were set to record (dual-axial). The inclinometer, external thermistor, skin thermistor and galvanic skin response (GSR) sensor were set to record. The sample rate was set at 15Hz and data was logged every minute. All sensors ran firmware version 8.1.2. Where possible, subjects wore the same units as utilised in previous testing so as to avoid any differences due to unit-to-unit calibration. The SenseWear™ Armband was placed on the upper right arm of the subject on the triceps (Illustration 4.3). This enabled the armband to be worn at all times without interference to the immersion suit, flight suit or normal daily activities. This has a standard orientation and was maintained for each subject.

#### *4.2.4.3 Total Estimated Energy Expenditure Measures*

In order to estimate the total energy expenditure (TEEE) with the GT3X+ ActiGraphs it was first necessary to calculate an estimate for the daily energy expenditure for each subject. This was performed using the Harris Benedict equation (1919) which although overestimating resting energy expenditure by up to 5%, has not been improved on by any more recent estimation algorithms (Malavolti et al., 2007). This equation takes into account anthropometric data from subjects; age, height; and weight, to estimate a value for daily energy expenditure. This is then scaled for a relative value of the mean intensities of the activities performed by the subject; 1.1 – 1.5 {sedate – high activity}.

Data from the GT3X+ ActiGraphs were used to assess the mean intensity of SAR operations, a method previously use in other studies in order to classify the intensity of activities of daily living (Crouter et al., 2006; Carr & Mahar, 2012; Sasaki et al., 2011). The value chosen to scale the Harris Benedict equation for SAR operations was that of Moderate – 1.3.

By combing the TEEE calculated from the Harris Benedict equation with measures of physical activity taken from the GT3X+ ActiGraphs, values were estimated for the total daily energy expenditure of each subject without the need for indirect calorimetry measures (Tables 4.2, 4.4 & 4.5). Although not as accurate as a direct measure of resting energy expenditure (REE) this is non invasive method of combining physical activity and REE and is a commonly adopted method in clinical settings and nutritional assessment (Malavolti et al., 2007). Therefore, the method by which the TEEE is estimated is the dependant on the accuracy of the method by which the physical activity measures are made.

#### *4.2.4.4 Sleep Efficiency Estimation*

Accelerometer based sensing technologies allow for a measures of movement to be taken during sleeping and also an indication of body orientation, e.g. lying down. From measured changes in the accelerometer it is possible to calculate a sleep efficiency score by measuring the number of wake periods during the night and the duration of these periods based on the motion of a subject. By subtracting the duration of the wake periods from the time lying down motionless it is possible to estimate the time spent sleeping. Dividing this time by the duration spent lying down will give an estimate for the sleep efficiency as a percentage of overall time spent attempting to sleep. This results in the sleep efficiency being a direct derivative of the duration of sleep. The additional use of a near body thermistor in the SenseWear™ Armband allows for changes in body temperature to be taken into account as a subjects body temperature fluctuates throughout the night. This multi-sensory approach may allow for more accurate estimation of sleep duration than can be calculated from an accelerometer only based system (van Wouwe et al., 2011). Unfortunately, due to the nature of the software provided by both ActiLife and SenseWear™ , it is not possible to access the proprietary algorithms that they use to perform their calculations at this time.

#### *4.2.4.5 Additional Instructions to Subjects*

Subjects were instructed to remove the SenseWear™ Armband while showering as the unit is not waterproof unlike the GT3X+ ActiGraphs. Most subjects opted to remove all sensors while showering. Subjects were instructed to replace the sensors as soon as possible and made aware that a data capture with less than 95% wear time was considered invalid. Sensors were otherwise continually worn for the test period.

### *4.2.5 Experimental Trials*

Subjects were not instructed to perform any specific protocols as this study was performed in free-living conditions. Subjects performed their normal SAR operational duties as outlined in section 4.1.1. Data capture followed the normal daily schedule for the SAR operators. Subjects were instrumented at 12:30 hours when they arrived on-base prior to their 24-hour flight duty period commencing at 13:00 hours. The SAR operators regularly arrived early to hand over shifts, thus subjects often left early. In order to compensate for this, data is only considered for 23 hours of the working day: 13:00-12:00 hours.

#### *4.2.5.1 Anthropometric data collection*

Subjects' height and body mass were recorded at the start of the study. This data was used in the set up procedures of the GT3X+ ActiGraphs and the SenseWear™ Armband. Subjects' body mass was recorded again before each sensor deployment, if a change was observed, the new value was noted and the sensors were adjusted to the new value.

#### *4.2.5.2 Sensor Applicability Pilot Study*

A pilot study involving 4 subjects was undertaken to gather preliminary data and establish if all of the sensors deployed worked in the environment as well as excluding any sensors that caused interference during an EMF test. The data taken during the pilot study was excluded from the final analysis. Following the applicability study, the methods by which sensors were deployed are described in the following sections.

#### *4.2.5.3 SAR Study*

The primary data collection period spanned four months gathering data from all groups. Subjects wore the GT3X+ ActiGraphs and SenseWear™ Armband for a 48-hour period, followed by a second 24-hour period several days later (Illustration 4.4). The first 24 hours were during operational duties and the second 24 hours during non-operational duties. This was followed by another 24-hour operation duties capture several days later. Where possible data captures were performed with minimal time between the first and second captures. However, this was not always possible due to flight limitations placed on SAR operators, subject availability and rosters. Once members of the G2 group had provided two sets of data in their 'normal' condition they were asked to provide a set of data in an 'abnormal' G3 condition. This followed the same time schedule as a standard data capture, except subjects slept on-base.

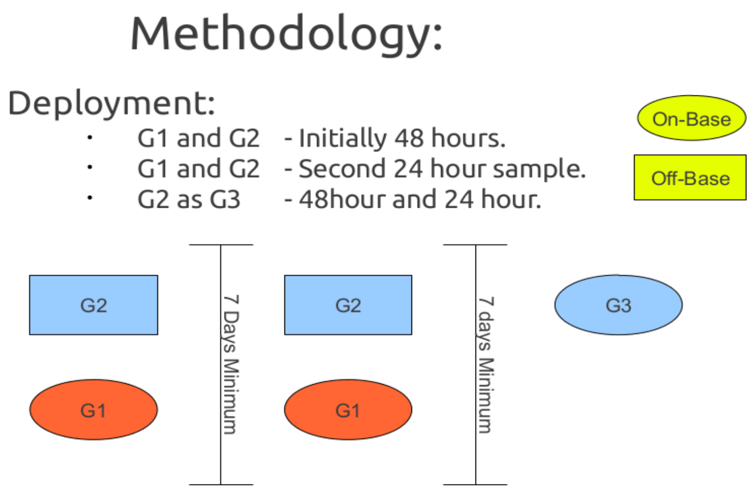



*Illustration 4.4: Schematic of Search and Rescue Deployment Periods*

### *4.2.6 Data Exclusion Criteria*

Subjects were excluded from this study if they met the following criteria:

- *Study Exclusion:* Subjects were unable to carry out day-to-day SAR operational duties due to injury or sickness.
- *G3 Exclusion:* Subjects who normally sleep off-base and who had never slept on-base before.
- *Data Exclusion:* Data were excluded from this study if they met the following criterion;
- Data sets were discarded if the sensors were worn for less than 95% of the allotted sample window (24-hours), (n=2).
- Data sets that involved a tasking were excluded from the study as this was seen as an artefact to the 'normal' sleep patterns of the subjects, (n=2).
- Unaccountable failure of sensors which resulted in partial or damaged data files. It was not possible to recover, or utilise, this data, (n=4).

- Data sets were excluded if a subject undertook excessive amounts of physical activity during a data capture that was not repeated in further testing, (n=0).

### *4.2.7 Data analysis*

Data from the SenseWear™ armbands was downloaded via the professional version of SenseWear™ 7.0. Data from the GT3X+ accelerometers was download via Actilife version 5.8.3 and analysed in version 6.1.2.

All statistical analysis was undertaken using SPSS (PASW Statistics 18). Significance was accepted at $p<0.05$. An independent samples T-test was carried out to evaluate differences between groups for each variables (objectives 3, 4 and 5). Paired T-tests were also carried out to see if there were significant difference for each variables between the three pieces of equipment (objectives 1,2,3 and 4).

### *4.2.8 Synopsis*

During operational duties it is not possible to instrument SAR operators with traditional laboratory base methods of measuring physical activity or sleep indices. The deployment of low cost accelerometer based technologies may allow for the investigation of the physiological demands of SAR operators. Two such systems were deployed under free-living conditions to investigate aspects of SAR operators physical activity as well as sleeping habitation. The following section presents the results from the data collected.

## 4.3 Results

The following are the descriptive results pertaining to the subjects as well as the data analysis undertaken.

### *4.3.1 Subjects and Descriptive Data*

The following were the mean values for all subjects (n=10) and in each of their respective groups. No significant differences in anthropometric variables were observed between subjects allocated to either of the groups from each other, or from the group as a total entity. The n value represents the number of subjects per group, the number of data sets utilised is also presented below (Table 4.1).

*Table 4.1: Subject Descriptive and Anthropometric Data (n varies)*

| Variable | GT (n=10) | G1 (n=4) | G2 (n=6) | G3 (n=4) |
|---|---|---|---|---|
| Age (*yrs*) | 41 ± 5.4 | 39.3 ± 6.9 | 42.2 ± 4.4 | 43.6 ± 2.8 |
| Mass (*kg*) | 87.7 ± 12.9 | 83.3 ± 8 | 90.6 ± 15.3 | 83.3 ± 1.1 |
| Height (*m*) | 176.1 ± 5.6 | 176.6 ± 5.2 | 175.7 ± 6.3 | 174.4 ± 2.4 |
| Datasets | 27 | 8 | 12 | 7 |

Data presented as mean ± SD

### *4.3.2 Group Measures*

Data were analysed for all members of GT in order to asses if differences in total estimated energy expenditure (TEEE) and total physical activity (PA) per day (*kcal/day*) existed due to the sensors used and their respective location.

Analysis of the TEEE data revealed significant differences between the ankle mounted GT3X+ ActiGraph ($GT3X+^{ank}$) and the SenseWear™ Armband (** $p<0.01$) and waist-mounted GT3X+ ActiGraph ($GT3X+^{wai}$) (** $p<0.01$) (Table 4.2).

Analysis of the PA data revealed significant differences between each of the systems; the ankle-mounted GT3X+ ActiGraph and the SenseWear™ Armband (** $p<0.01$); the waist-mounted and ankle-mounted GT3X+ ActiGraphs (¥ $p<0.01$); and the waist-mounted GT3X+ ActiGraph and the SenseWear™ Armband (¤ $p<0.05$) (Table 4.2). These differences reflect the methods of estimating energy expenditure between the two sensor platforms as well as the location of the GT3X+ ActiGraphs themselves.

*Table 4.2: Group Activity Differences (n=10)*

| Variable | GT3X+$^{ank}$ | GT3X+$^{wai}$ | Sensewear$^{TM}$ |
|---|---|---|---|
| TEEE (*kcal/day*)<br>PA (*kcal/day*) | $3510.5 \pm 452.2^{**,¥}$<br>$1113.7 \pm 380.2^{**,¥}$ | $2960.2 \pm 403.6^{¥}$<br>$563.5 \pm 230.5^{¥,¤}$ | $2905.6 \pm 438.2^{**}$<br>$724.6 \pm 473.8^{**,¤}$ |

Data presented as mean + SD

**,¥ $p$<0.01; ¤ $p$<0.05

Data were analysed for all members of GT in order to asses if differences in sleep duration ($S_{dur}$) and sleep efficiency ($S_{eff}$) existed due to the sensors used and their respective location. Analysis of the $S_{dur}$ data revealed significant differences between both GT3X+ ActiGraph systems and the SenseWear™ Armband (**,¥ $p$<0.01) but not each other (Table 4.3).

Analysis of the $S_{eff}$ data revealed significant differences between each of the systems; the ankle-mounted GT3X+ ActiGraph and the SenseWear™ Armband (** $p$<0.01); the waist-mounted and ankle-mounted GT3X+ ActiGraphs (¥ $p$<0.01); and the waist-mounted GT3X+ ActiGraph and the SenseWear™ Armband (¤ $p$<0.05) (Table 4.3). These differences reflect the methods of calculating sleep indices between the two sensor platforms as well as the location of the GT3X+ ActiGraphs themselves.

*Table 4.3: Group Sleep Differences (n=10)*

| Variable | GT3X+$^{ank}$ | GT3X+$^{wai}$ | Sensewear$^{TM}$ |
|---|---|---|---|
| $S_{dur}$ (*min*)<br>$S_{eff}$ (%) | $405.7 \pm 44^{**}$<br>$97.3 \pm 1.9^{**,¥}$ | $409.3 \pm 47.9^{¥}$<br>$98.2 \pm 1.5^{¥,¤}$ | $316 \pm 78^{**,¥}$<br>$76.6 \pm 13.4^{**,¤}$ |

Data presented as mean + SD

**,¥ $p$<0.01; ¤ $p$<0.05

### *4.3.3 Activity Analysis*

Analysis of the total estimated energy expenditure (TEEE) and physical activity (PA) data was undertaken in the following conditions.

#### *4.3.3.1 On-base vs. Off-base (G1 vs. G2)*

No significant differences in total estimated energy expenditure (TEEE) were observed on any device (Table 4.4). Significant differences in physical activity (PA) ($p$<0.05) were observed at the GT3X+ located at the waist.

*Table 4.4: Activity Differences On-base vs. Off-base (G1 vs. G2)*

| Variable | G1 (n=4) | G2 (n=6) | Difference (%) |
|---|---|---|---|
| TEEE GT3X+$^{ank}$ (*kcal/day*) | 3350.2 $\pm$ 414.7 | 3636.9 $\pm$ 443.5 | -8 |
| TEEE GT3X+$^{wai}$ (*kcal/day*) | 2752.6 $\pm$ 373.5 | 3117.7 $\pm$ 462.5 | -13 |
| TEEE Sensewear™ (*kcal/day*) | 3021 $\pm$ 578.7 | 2932.6 $\pm$ 376.3 | 3 |
| PA GT3X+$^{ank}$ (*kcal/day*) | 1016.2 $\pm$ 258.9 | 1159 $\pm$ 375.7 | 14 |
| PA GT3X+$^{wai}$ (*kcal/day*) | 418.7 $\pm$ 197.8* | 640.4 $\pm$ 273 | 53 |
| PA Sensewear™ (*kcal/day*) | 829.2 $\pm$ 554 | 696.4 $\pm$ 497.4 | 16 |

Data presented as mean + SD

***p*<0.01; **p*<0.05

### *4.3.3.2 Off-base vs. On-base Abnormal Condition (G2 vs. G3)*

No significant differences in total estimated energy expenditure (TEEE) were observed on any device (Table 4.5). No significant differences in physical activity (PA) were observed on any device.

*Table 4.5: Activity Differences Off-base vs. On-base Abnormal Condition (G2 vs. G3)*

| Variable | G2 (n=6) | G3 (n=4) | Difference (%) |
|---|---|---|---|
| TEEE GT3X+$^{ank}$ (*kcal/day*) | 3636.9 $\pm$ 443.5 | 3477.9 $\pm$ 507.5 | 5 |
| TEEE GT3X+$^{wai}$ (*kcal/day*) | 3117.7 $\pm$ 462.5 | 2927.5 $\pm$ 206.2 | 7 |
| TEEE Sensewear™ (*kcal/day*) | 2932.6 $\pm$ 376.3 | 2727.3 $\pm$ 354.2 | 6 |
| PA GT3X+$^{ank}$ (*kcal/day*) | 1115.9 $\pm$ 375.7 | 1113.3 $\pm$ 520.7 | 1 |
| PA GT3X+$^{wai}$ (*kcal/day*) | 640.4 $\pm$ 273 | 596.9 $\pm$ 200.1 | 7 |
| PA Sensewear™ (*kcal/day*) | 696.4 $\pm$ 497.4 | 653.4 $\pm$ 372.8 | 4 |

Data presented as mean + SD

***p*<0.01; **p*<0.05

## *4.3.4 Sleep Analysis*

Analysis of the sleep duration ($S_{dur}$) and sleep efficiency ($S_{eff}$) data was undertaken in the following conditions.

### *4.3.4.1 On-base vs. Off-base (G1 vs. G2)*

Significant differences were observed ($p$<0.01) for sleep duration ($S_{dur}$) measured with the GT3X+ located at the ankle and waist (Table 4.6). There was also a significant difference observed for sleep efficiency ($S_{eff}$) measured with the SenseWear™ Armband ($p$<0.01) .

*Table 4.6: Sleep Differences On-base vs. Off-base (G1 vs. G2)*

| Variable | G1 (n=4) | G2 (n=6) | Difference (%) |
|---|---|---|---|
| $S_{dur}$ GT3X+$^{ank}$ (*mins*) | 439.1 ± 49.2** | 381.5 ± 19.4 | 14 |
| $S_{dur}$ GT3X+$^{wai}$ (*mins*) | 443.9 ± 59.6** | 385.2 ± 15.3 | 14 |
| $S_{dur}$ Sensewear$^{TM}$ (*mins*) | 276.1 ± 97.3 | 311.5 ± 69.9 | -12 |
| | | | |
| $S_{eff}$ GT3X+$^{ank}$ (*%*) | 97.9 ± 1.6 | 96.6 ± 2.3 | 1 |
| $S_{eff}$ GT3X+$^{wai}$ (*%*) | 97.6 ± 1.9 | 98.5 ± 1.5 | -1 |
| $S_{eff}$ Sensewear$^{TM}$(*%*) | 61.7 ± 10.8** | 81.1 ± 9.9 | -32 |

Data presented as mean + SD

**$p$<0.01; *$p$<0.05

### *4.3.4.2 Off-base vs. On-base Abnormal Condition (G2 vs. G3)*

No significant differences were observed for sleep duration ($S_{dur}$) or sleep efficiency ($S_{eff}$) for any device (Table 4.7).

*Table 4.7: Sleep Differences Off-base vs. On-base Abnormal Condition (G2 vs. G3)*

| Variable | G2 (n=6) | G3 (n=4) | Difference (%) |
|---|---|---|---|
| $S_{dur}$ GT3X+$^{ank}$ (*mins*) | 381.5 ± 19.4 | 409 ± 48.9 | -7 |
| $S_{dur}$ GT3X+$^{wai}$ (*mins*) | 385.2 ± 15.3 | 411 ± 50.9 | -6 |
| $S_{dur}$ Sensewear$^{TM}$ (*mins*) | 311.5 ± 69.9 | 369.1 ± 29.5 | -18 |
| | | | |
| $S_{eff}$ GT3X+$^{ank}$ (*%*) | 96.6 ± 2.3 | 98.1 ± 1.3 | -1 |
| $S_{eff}$ GT3X+$^{wai}$ (*%*) | 98.5 ± 1.5 | 98.7 ± 0.5 | 0 |
| $S_{eff}$ Sensewear$^{TM}$ (*%*) | 81.1 ± 9.9 | 86 ± 4.6 | 6 |

Data presented as mean + SD

**$p$<0.01; *$p$<0.05

## ***4.3.5 Other select data***

Data was also analysed for the following conditions even though they were not part of the research hypotheses.

### *4.3.5.1 On-base vs. Off-base in Abnormal Condition (G1 vs. G3)*

Significant differences were observed for both sleep duration ($S_{dur}$) ($p$<0.05) and sleep efficiency ($S_{eff}$) ($p$<0.01) when measured with the SenseWear™ Armband (Table 4.8).

*Table 4.8: Sleep Differences*

| Variable | G1 (n=4) | G3 (n=4) | Difference (%) |
|---|---|---|---|
| $S_{dur}$ GT3X+$^{ank}$ (*mins*) | 439.1 $\pm$ 49.2 | 409 $\pm$ 48.9 | 7 |
| $S_{dur}$ GT3X+$^{wai}$ (*mins*) | 443.9 $\pm$ 59.6 | 411 $\pm$ 50.9 | 7 |
| $S_{dur}$ Sensewear$^{TM*}$ (*mins*) | 276.1 $\pm$ 97.3 | 369.1 $\pm$ 29.5 | -26 |
| | | | |
| $S_{eff}$ GT3X+$^{ank}$ (*%*) | 97.9 $\pm$ 1.6 | 98.1 $\pm$ 1.3 | 0 |
| $S_{eff}$ GT3X+$^{wai}$ (*%*) | 97.6 $\pm$ 1.9 | 98.7 $\pm$ 0.5 | 0 |
| $S_{eff}$ Sensewear$^{TM**}$ (*%*) | 61.7 $\pm$ 10.8 | 86 $\pm$ 4.6 | -29 |

Data presented as mean + SD

**$p<0.01$; *$p<0.05$

### *4.3.6 Synopsis*

As expected, significant differences were observed between systems while measuring the same variable based primarily on their location, but also due to their sensor type which is to be expected due to the sensors they use to estimate the various variables. However, the data shows no apparent difference in the levels of physical activity, total energy expended, sleep duration or sleep efficiency for the same group of SAR operators based on their environment alone when compared with any sensor against itself (Tables 4.5 and 4.7). This implies that their environment during the standby readiness period may not effect their energy or sleep demands and thus no differentiation should be made between staff rostering or working hours based on this alone. Overall the GT3X+ ActiGraphs is capable of recording the required variables in the SAR environment, but further validation studies will be required in order to be certain of its accuracy. Due to their single sensor nature the GT3X ActiGraphs never agreed with the SenseWear™ Armband multi-sensory platform across all variables, for all participants, in all conditions . It is possible that the GT3X+ ActiGraphs may provide the data necessary to investigate this unique environment however further investigation of the sensor location on operators as well as specific data analysis may be required.

## 4.4 Discussion

Due to environmental restrictions it was not possible to deploy traditional methods of energy expenditure estimation in the SAR environment. Safety and communications equipment worn by SAR operators during flights makes it impossible to deploy breath by breath metabolic systems and instruments within the aircraft itself prevent the deployment of any radio telemetry based system such as heart rate monitors. In order to investigate the demands of the SAR environment, a validated system of estimating energy expenditure and sleep indices, the SenseWear™ Armband, was deployed in conjunction with two GT3X+ ActiGraphs. As these systems had never been deployed in this environment it was unknown if they would prove to be accurate or reliable. Thus, this study is best viewed as a feasibility study in the ability of accelerometer based technologies in the measurement of physical activity and other performance variables in the SAR environment. Despite this, these systems give the first opportunity to look at the physiological demands of the SAR environment.

The purpose of this study was to investigate if a difference exists in levels of physical activity, sleep efficiency and sleep duration between SAR operators based on their sleeping location. This study was conducted under free living operational conditions during the standby period of a typical 24-hour shift.

### *4.4.1 Subjects*

Although few in number (n=16), members of the Dublin SAR form a very unique group. This study utilised 63% of the total SAR crew employed at the Dublin base (n=10) and represents an appropriate sample for the group studied. Multiple data sets were generated for each subject over an extended period in order to give a better indication of the physiological demands of this environment. Each dataset was treated as an individual set, and a bias towards any single subject was avoided by taking multiple sets from each subject. No significant anthropometric differences were observed between subjects allocated to any of the groups. With no anthropometric data represented in the literature it is not possible to say whether the observed measures are representative of a well trained or unfit SAR population. The only readily available data comes from Balasubramanian et al., (2011) who looked at the impact of small aircraft vibration on twenty military pilots. This study reported mean data (value ± SD; age 36.5 ± 3.5 years and BMI 24.4 ± 0.8). Attempts were made to find data from combat helicopter pilots and crew as a comparison however this was not found. Data presented in this thesis show SAR operators are older and have higher BMI's than those in the Balasubramanian et al. study (2011). This is possibility representative of the ex-military nature of many of the pilots and less active lifestyle experience during SAR operations over military duties. No reported data was found for total estimated energy expenditure, physical activity rates, or sleep indices within SAR operations or any other helicopter aircrew environment. It is possible that this data has been collected via military studies, however if so this data has not been made available to the public.

### *4.4.2 Environmental Differences*

The purpose of this study was to establish whether differences existed between the on-base and off-base environment of SAR operators during the standby readiness period. If a difference did exist it was hypothesised that this would express itself as a difference in physical activity, sleep quality or sleep duration. During the standby readiness period most SAR operators engage in low intensity sedentary activities such as watching television, reading or doing paperwork. This environment of activities of daily living have been researched extensively through the generations of ActiGraph systems as well as the SenseWear™ armband. As subjects from both G1 and G2 undertake the same activities during the standby readiness period any differences during this period may be due to the environment itself.

Initially the primary environmental difference appeared to be that of noise levels as some subjects moved from their normal sleeping environment to that of a port-a-cabin located under a flightpath of a major international airport. Although they may live near the airport, the proximity of aircraft and frequency of air-traffic would be expected to be lower at their home environment. Anecdotally, subjects noted that they '*no longer hear the planes passing overhead*' (personal communications with subjects). While this may effect a non SAR operators ability to sleep in the on-base environment, the SAR operators may have been habituated to this environmental factor unbeknownst to themselves. While it was not undertaken in this thesis, it may be possible to measure the amount of ambient noise between a subjects normal sleeping environment at home, versus the habitual environment they spend their standby readiness period sleeping in. This would allow for investigation into the effect of the ambient noise experienced on-base versus at home for member of G3.

Data was collected from members in their habitual sleeping environment during the standby readiness period; on-base (G1) and off-base (G2) and off-base sleepers were asked to sleep on-base (G3). Subjects were instructed to, as much as possible, maintain a ‘normal’ sleeping routine as if sleeping off-base. If the standby readiness environment had an effect on the studied variables this should be visible if the same sample group were exposed to this abnormal environment. Unfortunately, it was not possible for those who habitually sleep on-base to sleep off-base as they live outside the designated 20 minute travel area. As they are still subject to the 45 minutes readiness period, subjects who were off-base tended to stay at home and perform similar activities to those on-base. Several members of G2 had young families and it was expected that this may be reflected in the results with subjects sleeping longer or better while on-base. However, when data were compared no significant differences were observed for physical activity or total estimated energy expenditure between G2 and G3. This implies that sleeping on-base did not have a positive or negative effect on habitual off-base sleeping habits. In order to further this research it would be necessary to gather more data from members on each base under both environmental constraints. This would allow for a larger data set that could be analysed further.

Anecdotally, SAR operators often sleep off-base in hotels while located at other SAR bases around the country and did not think it had an effect on their sleep or activity patterns. These subjects are not only outside a habitual sleeping environment, but are also exposed to a different operational environment. This may have an effect on the sleeping or activity patterns of subjects but was outside the remit of this thesis. However, the methodology utilised in this thesis could be expanded to encompass such a study by forming a G4 group where subjects sleep off-base but in a different operational environment, i.e. Dublin SAR operators based at the Waterford SAR base.

### *4.4.3 Activity Analysis*

The estimation of energy expenditure has previously been explored using different methods including the use of lightweight accelerometers (Kozey-Keadle et al., 2011).

By using a multi-sensory approach the SenseWear™ Armband estimates energy expenditure data comparable to that of an indirect calorimetry system (Sunseri et al., 2008). There are however associated issues with the SenseWear™ Armband , primarily the inability to provide an accurate measure of energy expenditure at high intensities or during short events (Drenowatz & Eisenmann 2011). During this study it appears that many of the day-to-day activities of the SAR operators did not involve the levels of intensity that were seen in the Drenowatz & Eisenmann study. However, it is possible that such activities were missing from the SenseWear™ Armband data and may explain some of the observed differences.

The GT3X+ ActiGraph bases all its estimations off its tri-axial accelerometers and data is assessed post-hoc using a series of algorithms built into the Actilife software. For this study the Combined Freedson Vector Magnitude calculations demonstrated by Sasaki et al., (2011) were used. These take into account not only the number of movements recorded over a period of time but, the intensity and direction of these motions. Doing so allows for a more representative measure of energy expenditure as it assesses motion as a composite vector, rather than three separate one-dimensional planes. Recent literature has suggested that a move towards vector based analysis may allow for more accurate energy expenditure estimations as well as the integration of automatic activity categorisation (Dinesh & Freedson, 2012).

#### *4.4.3.1 Physical Activity Measures*

Inherently there are differences in estimations of physical activity between dual-axial and tri-axial accelerometer systems due to the number of planes on which data is being captured (Vanhelst et al., 2012; Howe et al., 2009; Dinesh & P. Freedson, 2012). Due to this, it was anticipated that the physical activity measures of the dual-axial SenseWear™ armband would differ to that of the two GT3X+ systems. However, differences were observed between each of the systems relative to each other, irrespective of accelerometer type, with the waist mounted GT3X+ ActiGraph having a mean value closer to the SenseWear™ Armband (Table 4.2). As each of the sensors were deployed at different locations about the body it is unwise to do any direct comparison between them. With the GT3X+ located at the waist giving the lowest mean values; followed by the SenseWear™ Armband on the triceps; then the GT3X+ at the ankle, a trend exists whereby the sensors located at the extremities record higher levels of movement thus greater rates of physical activity. As ankle mounted accelerometers have been shown to accurately reflect activity levels during gait related activities such as walking or running (Crouter et al., 2006; Sazonova et al., 2011; Godfrey et al., 2008), it may be the case that an ankle mounted GT3X+ ActiGraph could give a more accurate representation of what is happening during SAR operations.

When G1 (on-base) were compared to G2 (off-base) a significant difference in physical activity measures taken at the waist were observed (Table 4.4). It is possible that this specific location did not accurately portray the amount of activity the subjects undertook in this situation as neither of the sensors located at the extremities showed any statistical differences. With the centre of mass remaining relatively motionless during activities such as controlling the flight of the helicopter, this constantly requires both the pilots arms and legs to move, it is possible that the activities that are specific to SAR operators may not be measured at the waist site. However, when the total estimated energy expended was calculated at the same site by adding the estimated resting energy expenditure (REE), calculated from the Harris Benedict equation, a statistical difference no longer existed (Table 4.4). Without further contextual data it is hard to definitively state whether these differences were due to one group being more active than the other or due to the location of the GT3X+ as it was not shown on any other device.

When the subjects in the G2 group subsequently slept on-base as G3, there were no significant differences in physical activity measured on any of the sensors (Table 4.5). Thus, it may be reasonable to assume that the subjects levels of physical activity did not change dependant solely on the environment they were sleeping in. Similarly, there were no significant differences in total estimated energy expenditure between any group with the only observed differences due to the location of the sensor.

### *4.4.4 Sleep Analysis*

During the study data was captured for both sleep efficiency and sleep duration. As these systems had never been deployed in this environment it was not known if the systems would gather reliable data. As the investigation of SAR operators through polysomnography was not possible due to its primarily laboratory based use and size of the monitoring equipment, the SenseWear™ Armband was selected in order to measure sleep indices. Previous research has suggested that by using a broad range of sensor data the SenseWear™ Armband is capable of accurately measuring sleep duration (Germain et al., 2006; Miwa, 2009; Sunseri et al., 2008; van Wouwe, et al., 2011).

The GT3X+ ActiGraph has not been used extensively in the area of sleep measurement. However, a roll for actigraphy has been seen in polysomonography in regards to accurate sleep wake cycle measures and sleep logging and it has started to be utilised more (Ancoli-Israel et al., 2003; Shambroom et al., 2011) and many new ActiGraph systems are focusing on the wrist as a point of measurement for sleep (Martin & Hakim, 2011; Montgomery-Downs et al., 2011; van Wouwe et al., 2011). However, as the GT3X+ had already been deployed on two sites on the subjects, and while trying to keep the technology as unobtrusive as possible, no further sensors were deployed. The location of the sensor being used for calculations can be taken into account within the Actilife software itself and data was calculated with respect to deployment location in this manner. However, in order to do so it is necessary to know when subjects went to sleep. This may have led to additional error in the estimation of these sleep indices and demands a non subjective method of assessing the start and finish time for overall sleep cycles.

When subjects from G1 were compared to G2, significant differences in sleep duration were noted on both the GT3X+ systems ($p$<0.01, Table 4.6). It is possible that due to the user recalling when they went to sleep and woke up for analysis, that the time points used for data analysis were not as accurate. This is probable as the automated SenseWear™ Armband showed no difference in sleep duration. It would be expected that this would also show in the G2 vs. G3 group (Table 4.7). However, as they were comprised of the same subjects it is possible that they self reported as accurately, or inaccurately, in both instances thus nullifying the effect. These difference showed that members of G1 had a greater sleep duration ($S_{dur}$) than those in G2 from data based on the GT3X+ ActiGraphs (Table 4.6).

The G1 and G2 groups also showed significant differences in sleep efficiency based on the SenseWear$^{TM}$ Armband ($p$<0.01) with G1 subjects sleeping 20% less efficiently than those in G2 (Table 4.6). Initially it was believed that this difference may be due to the sleeping location. This acted as the spur to record data from the G2 group sleeping in abnormal conditions on-base, the G3 group. When the data were analysed, no statistical differences were seen for G2 sleeping in a G3 mode for either sleep duration or sleep efficiency on any system. This was a surprising find as many of the SAR operators had young families and were expected to sleep better, and longer, while on-base. However this was not the case, subjects did sleep on average 37 minutes longer while on-base, but not long enough to cause a statistical difference despite a 6 to 8% increase in sleep duration and up to 6% difference in sleep efficiency depending on the sensor used (Table 4.7). This is further supported by the data showing that on average G1 subjects slept 58 minutes more than G2 subjects, and 30 minutes more than  G3 subjects. Thus, it is logical to conclude that there is a difference in the amount of sleep a SAR operator experiences based solely on the environment where they are sleeping. However, this appears to contradict the SAR standby readiness hours policy currently in-place which is based on the belief that subjects who sleep off-base sleep more than those on-base which appears not to be the case.

### *4.4.5 Sensor Applicability*

Daily SAR operational duties noted in the activity diary gathered during this study were similar to normal sedate working populations with most of their time spent undertaking office-work. However, while in the aircraft much of the motion of pilots and winch-crew were undertaken by their extremities. Thus, due to the nature of the operations undertaken by SAR crew, sensors were deployed at the centre of mass; upper extremities; and lower extremity. As subjects were both pilots and winch operators there may have been a difference due to the role they perform in the aircraft. However, with this relatively small sample size it may require a larger cohort, possibly from other SAR bases, to assess if the subject's role in the aircraft had an effect on the studied variables.

While the SenseWear™ Armband was capable of capturing the data necessary to analyse specific aspects of SAR operations, the GT3X+ ActiGraphs also provided relatively high resolution data. Tables 4.2 and 4.3 show comparisons made between sensor platforms for each variable irrespective of sleeping environment. As expected, data from the GT3X+ ActiGraphs and SenseWear™ Armband were statistically different to each other and were not comparable due to the their data capture methods. However, measures for physical activity and sleep efficiency for the GT3X+ ActiGraphs were also statistically different from each other based on their location. Thus, comparisons must be made not only between the same sensor system, but also at the same location if reliable physical activity or sleep efficiency data are to be collected. However, it is possible to argue that the location of the sensors at the extremities may also be inaccurate. Within the same group of subjects (G2 and G3), while sleeping in either environment, none of the systems were shown to be different from themselves. Thus, by the data provided, a user could select any system and once they only compared it to itself, at the same location, for the same group of people, they could be confident in that data being comparable to itself. But, as these sensors are being applied in this study as a feasibility study, it would be necessary to deploy them in parallel with their relevant gold standards to be certain. However, this is not possible in the SAR operational environment.

During the study itself the GT3X+ ActiGraphs proved to be highly reliable with only one data set being lost due to an incorrect activation time input by the researcher. No hardware issues were experienced throughout the study. Several of the SenseWear™ Armband failed during initial pilot testing when a higher sample rate was used. Although a higher granularity of data was being captured, this data filled the memory capacity of the unit to a point where it was impossible to retrieve data. As a consequence the sample rate was reduced during the main data collection to compensate for this, allowing longer deployments, albeit at a lower granularity. This had not been reported in the literature and it is possible that most researchers are simply using the basic, lower sample rates. This has limitations associated with it as the rate at which data is captured, once per minute, may not provide a fine enough granularity to capture shorter more intense efforts. This was investigated by Drenowatz & Eisenmann (2011) who showed that the SenseWear™ Armband is not capable of discerning the effect of short and intense bouts of running, thus underestimating the overall energy expended. This limitation may mean that in the SAR operational environment where rescues are often short and intense, this sensor platform may not be applicable.

A similar trade-off was made with the GT3X+ ActiGraphs. By utilising a lower sample rate the sensors ran no risk of running out of battery or storage. However, it was still possible that at lower sample rates the data being captured was not fine enough. A major advantage of the newer GT3X+ ActiGraphs over the older GT3X model are their capability to record motion in a raw acceleration format. This facilitates future sample recognition techniques that can be applied to older sets of data gathered with these systems. It also allows for a much higher sample rate to be utilised. Currently, captured data is post processed by the researcher at a 1 second sample rate and the propitiatory algorithms that have been developed for the calculation of physical activity or sleep indices are applied. Furthermore, data for sleep indices are calculated at a 60 second epoch meaning that wake cycles of less than 1 minute may not be taken into account. These sample rates at which the algorithms are calculated act as to smooth the reported data, making it less reliable when looking at shorter duration activities.

As a result data from these propitiatory algorithms may give an understanding of the energy expenditure and sleep indices of SAR operators, but without the development of further analysis techniques it may not give relevant data about specific activities within their day. Work in the development of vector acceleration models that can detect specific activities is under-way with research groups attempting to develop such analysis techniques specifically for the GT3X ActiGraph platform (Sasaki et al., 2011; Kozey-Keadle et al., 2011; Dinesh et al., 2012). However, these models are currently only capable of recognising the most basic activities of daily living, walking and other gross movements. In order to analyse aspects of SAR operation it would be necessary to bypass these epoch generated figures and work with the raw data itself to develop further algorithms specific to this occupation and its demands. With a higher sample rate, capability to record raw values, as well as the addition of a waterproof housing, the GT3X+ ActiGraph is a very applicable sensor for use in the SAR environment.

### *4.4.6 Other Select Data*

This section covers data that were not part of the objectives of the study, but provide extra information about the subjects themselves.

#### *4.4.6.1 On-base (G1) vs. Off-base abnormal sleeping (G3)*

As an extra comparison, G1 subjects were compared to G3 to investigate if a difference existed between groups solely due to sleeping on-base (Table 4.8). While no differences were observed in physical activity or total estimated energy expenditure, significant differences in sleep duration ($p<0.01$) and efficiency ($p<0.05$) were observed between G1 vs. G3 with measures taken via SenseWear™ Armband. This is dissimilar to the observed non-statistical difference between G1 and G2 (Table 4.6) and implies that G2 subjects sleep efficiency may have been altered due to the environmental change. This increase in sleep duration was large enough to prove statistically different between the two different groups sleeping in the same location (G1 vs. G3). However, it was not large enough to cause a statistical difference to occur between the same group off-base and on-base. This further supports the findings that the two groups of subjects may have natural differences in their sleep duration and efficiency.

### *4.4.7 Research Implications*

Much of the data presented is from a relatively small, but unique, group of people. With only 16 SAR operators on base a sample size of 10 gave a large picture of the subjects in the base. By generating multiple sets of data for each operator, up to a total of 27 sets of data in total, it was possible to increase the power of any statistical calculations. However, these statistics are based on a limited study size and would need to be expanded in order to draw any firm conclusions from the study. Thus, the percentage and descriptive data is presented as such. In order to further this study ideally all subjects within the Dublin SAR base would have been used, however many of them were unwilling to be part of the research. It is unclear if a sample from another airport, with less air traffic and thus less ambient noise, would be applicable in this study in order to bulk out the study. However, if the data from other airports around the country could be collected it would allow for a greater picture to be generated as well as a comparison between bases to be made. In order to further each the data set for the Dublin base ideally the data would be gathered over a more prolonged period, 2-3 years, with new recruits being taken into the data collection as they start.

As previously discussed, it is difficult to deploy any form of traditional energy expenditure measurement techniques in the SAR environment. Although these results are of benefit in an area with little information, there is a need to look at specific aspects of the environment and how they affect subjects over longer periods. One of the major issues within the study, namely context of activities undertaken, was partially addressed by the use of a physical activity diary. Much of the physical activity data gathered from the GT3X+ ActiGraphs is useless without the ability to understand what events are occurring at any given time. In order to further research in this area, activity specific algorithms need to be developed that can target the specific demands of SAR operators. During SAR operations, the two pilots remain relatively inactive while piloting the aircraft, whereas the winch-crew tend to move about the cabin more often. During winching operations the winch-man may experience even higher levels of exertion while being lowered and raised. However, this aspect of the SAR operations is nearly impossible to currently account for. With no contextual information as to what exactly is occurring it is impossible to differentiate between a winch-man sitting in the aircraft's hull, or being lowered onto the deck of a trawler. It is possible that with signal recognition software it may be possible to define these events, but this would require data to be gathered in a myriad of situations that the SAR crew may operate in. By combining physical activity diaries, accelerometer based data captures and other visual capture technologies such as the Microsoft Sensecam it may be possible to define these specific SAR activities and research them more in-depth.

### *4.4.8 Population and environmental limitations*

Although the dataset presented is representative of a large percentage of the overall population of the SAR base in Dublin, 63%, it is still a relatively small sample size, albeit from a very specialised occupation. In order to gather more robust data, continuation of the study across the other three SAR bases in Ireland would allow a larger data set to be gathered. If this were the case it would also be possible to look at any potential differences between the SAR bases due to their geographical location, number of operations per year, type and duration of operations.

One of the other noted aspects of the SenseWear™ Armband during training flights was that of temperature changes (Section 8, Illustration 8.2). Several sets of data from the pilot study were generating abnormal values for TEEE. At further investigation it was seen that during training flights there was a large change in the measured temperature on the armband. It is possible that these large changes in heat flux may have been caused by the subjects wearing their immersion suits during winter training operations which may have effected the TEEE calculations as they are partially based on the data from the thermistors in the unit. However, without access to the SenseWear™ Armbands proprietary algorithms, this is impossible to ascertain.

Estimated calculations for daily energy expenditure for the GT3X+ ActiGraphs themselves are not without their limitations. As the GT3X platform bases all its calculations on movement alone it is not possible to be totally confident that the use of the Harris Benedict equation in order to estimate the TEEE was the most appropriate method. In order to better these estimations it would be more appropriate to perform resting metabolic tests (Section 2.2.1) for each subject.

Finally, as the SAR operational environment is one with with no readily available comparative data it is impossible to be certain that the data reported in this thesis is an accurate portrayal of the SAR operational environment or the differences that may occur between on-base or off-base SAR operators.

## 4.5 Summary

During this thesis the GT3X+ ActiGraph sensor platform provided a reliable system in order to assess the activity levels and sleep indices of SAR operators. Based on this study it is possible to conclude that there are natural differences between members of the Dublin based SAR who sleep on-base and off-base when investigates via the GT3X+ ActiGraph sensor platform. However, when the same subjects slept both on-base and off-base there were no observed differences due to the environment they slept in.

No differences in the amount of physical activity undertaken, sleep efficiency and sleep duration between SAR operators who sleep on-base or off-base existed under normal working conditions when the same subjects slept in both locations. Thus, should the necessity occur for a SAR operator who habitually sleeps off-base to sleep on-base this should be no effect on their normal operations based on their normal sleeping patterns and levels of physical activity assuming they had previously been habituated to sleeping on-base. When investigated using a validated sensor system this difference was seen to occur primarily in the sleep efficiency between environments. However, this difference also existed between members of the habitual on-base group and the habitual off-base group when they slept in an abnormal condition. From this it is possible to conclude that any difference that existed in sleep efficiency may not be due to the location the subjects slept in, but rather inherent differences between the subject groups themselves. However, these differences in sleep efficiency did not occur when measured with the

GT3X+ ActiGraph. Therefore, it is possible that this purely movement based system was not able to accurately measure sleep periods as it relies on the user noting the boundaries of their sleep and wake periods. As this system is only recently being developed for sleep measurement it is probable that the algorithms that are currently in use may may be further developed and validity studies against gold standards such as polysomonography may be undertaken.

Differences were observed between habitual on-base SAR operators and off-base members for levels of physical activity measured at the waist using the GT3X+ ActiGraphs with the G1 subjects being less active than those of the G2 group. When this data was expanded to include an estimation of daily energy expenditure this became a non-significant difference between the groups. Without further contextual data it is hard to objectively say if this difference in physical activity was due to one group being more active than the other as it was not shown on any other device.

Overall, these previously validated sensor systems for the measurement PA, TEEE, $S_{eff}$, and $S_{dur}$ proved to be applicable in this environment as they did not interfere with SAR operations. However, the relative bulk of the SenseWear™ Armband when compared to the GT3X+ ActiGraph, as well as more data failures on this system and shorter possible deployment time, resulted in its applicability in the environment being questioned. The GT3X+ ActiGraphs provided high granularity data, low weight and waterproof housing resulted in it being possibility more applicable in this environment. With the potential for longer deployment this sensor provides an ability to track SAR operators of prolonged periods and perhaps look at the effects of cumulative fatigue.

However, results for the measurement of TEEE suggest that when compared to a previously validated sensor, in this environment, the ankle-mounted GT3X+ ActiGraph is not as accurate a measure as a waist-based sensor for the estimation of energy expenditure. Although it overestimated the amount of physical activities performed, and hence calculation for TEEE, it did this consistently. This may be an inherent issue with the location of the sensor, or it could be a more accurate portrayal of the environment due to its ability to measure high intensity activities. In this regard the application of a scaling algorithm for this location may allow for its deployment at this location in this environment. At the same time, while the measures for sleep duration and sleep efficiency were significantly different from the SenseWear™ Armband, they were the same for both the waist and ankle-mounted GT3X+ ActiGraphs across all conditions.

In conclusion, the GT3X+ is capable of being deployed in this area and giving reliable measures for sleep indices, physical activity and an estimation of total energy expenditure. The location the GT3X+ ActiGraph is deployed in appears to greatly affect the amount of physical activity measured, and hence the estimation for energy expended, so caution must be taken when choosing a location for deployment.

# Chapter 5: Study 3; Repeat High-intensity Ultra-Endurance Cycle Racing: The Race Around Ireland

## 5.1 Introduction

### *5.1.1 Study Overview*

Ultra-endurance cycling events, such as the Race Around Ireland (RAI), involve competitors performing periods of intermittent high intensity cycling for extended durations. The ability to maintain a consistently high mean power output whilst in a sleep deprived state is a critical factor in optimising performance during these events. Minimising excessive energy expenditure during resting periods may led to improved performance in these events. However, a simple, low-cost method of gathering data during these extended durations has not been possible until recently. The use of accelerometers in this environment, combined with event specific data assessment methods, may allow for further insight into these events.

Over the past 30 years ultra-endurance events have undergone a major rise in popularity with an increasing number of ultra-endurance races spanning a wide variety of sports including running, cycling, swimming, and triathlon (Fallon et al., 1999; Zaryski & Smith, 2005; Noakes, 2006; Knechtle et al., 2009). These ultra-endurance events, classified as any event over 6 hours in duration, are becoming more commonplace and are attracting an increasing number of participants each year (Zaryski & Smith 2005). In many of these events it is not possible to measure variables which may impact performance in these environments. The developing trend for accelerometer based measurement platforms may give researchers and participants the ability to gather data in these extended duration events where traditional measurement systems may not be applicable. This chapter investigates the practical application of an accelerometer based platform in order to estimate potential performance variables within an ultra-endurance cycling race. The data gathered from this event may allow for future hypothesis based research in the area with more extensive data capture and a greater number of subjects.

### *5.1.2 The Race Around Ireland*

The Race Around Ireland (RAI) is an ultra-endurance cycling race and is one of the few races that are part of the Ultra Marathon Cycling Association (UMCA) World Cup. The event is a time trial where teams of cyclists and solo riders aim to complete a 2,170 km circuit of Ireland in as short a time as possible (Illustration 5.1). Solo participants have a maximum allotted time of 120 hours, whereas teams have 96 hours in which to complete the circuit. Competitors are continually followed by a support car to indicate their position on the road to other road users and to allow for illumination of the rider during night-time hours, 7 pm – 7 am (Illustration 5.1).


*Illustration 5.1: Race Around Ireland 2009 Competition Route*

To date there is a dearth of available general scientific information investigating the demands of these ultra-endurance events including cycling. Few studies were found relating to larger sample groups (>20 subjects). Published studies are either single subject case studies (Gianetti et al., 2008; Iglesias et al., 2012), on groups of solo participants (Callard et al., 2001; Wirnitzer et al., 2008), or teams of rotating riders (Laursen 1999; Hulton et al., 2010). These studies are focused on describing the events and their effects on the subjects rather than the overall measure of subjects' performance during the race. In many cases the low sample sizes are due to the high attrition rates of these races and reflect the low number of entrants and finishers.

This study investigated a 4 person team who had entered the RAI and subsequently agreed to take part in the research study. The members of the team rotated cycle-bouts to maximise the performance of the team based on a pre-determined race strategy. This strategy was determined prior to the RAI during physiological test procedures as described in the following sections. An accelerometer based platform was deployed as part of a feasibility study in order to investigate its applicability in this environment.

### *5.1.3 Aim*

The aim of this study was to deploy an unobtrusive method of measuring physical activity during a five day ultra-endurance cycling race which was capable of measuring individual cycle and rest periods and their associated energy cost.

### *5.1.4 Objectives*

i. To describe the profile of physical activity undertaken during a high intensity ultra-endurance cycling event on participants taking into account time spent racing and resting.
ii. To estimate the amount of physical activity undertaken during the cycle portions of the event.
iii. To estimate the amount of physical activity undertaken during the resting portions of the event.
iv. To compare two forms of activity analysis on the data gathered during the Race Around Ireland.

### *5.1.5 Hypothesis*

That a single ankle mounted accelerometer can be utilised to accurately measure physical activity undertaken during an ultra-endurance cycling race.

### *5.1.6 Environment Studied*

The environment studied was that of a competitive ultra-endurance cycling race. Subjects partook in alternating high intensity cycling bouts as a pair while the other pair rested. This continued until race completion. The environment is defined by subjects either racing or resting provided the context by which data was segregated for analysis. Subsequently, this was segregated into defined '*on periods*' and '*off periods*' for each pair of subjects during racing periods. While one subject was on, the alternate member of the pair was off. However, both members were actively racing.

### *5.1.8* ***Synopsis***

The purpose of this study was to deploy a low-cost, unobtrusive accelerometer based technology that could be used to gather both physical activity and contextual data during a 96 hour, continual, ultra-endurance cycle race. The data gathered was then used to explore the physical activity rates, pacing strategies and variations in performance of the subjects during the inaugural Race Around Ireland. This study was to act as a feasibility study for future hypothesis based research in this area with accelerometer based sensor platforms.

## 5.2 Methodology

The following section describes the methods used during the study and information pertaining to the subject selection used within the study.

### *5.2.1 Subjects*

Due to the nature of multi day ultra-endurance races, low participation levels and high attrition rates typically make it difficult to guarantee a large sample size. A decision was therefore taken to focus data collection on a small select group of subjects who were most likely to finish the event. Four male subjects were recruited from a team already entered into the RAI and inclusion was on a voluntary basis. All members of the four-man team selected came from an extensive racing and training background (road racing, triathlon and adventure racing). Although subjects had not raced a specific ultra-endurance road race of this duration, or distance, they were considered well trained endurance cyclists who were likely to finish the event as well as be competitive in the overall results.

Subjects were considered for inclusion if they were free from any injury or condition that may have precluded them from participating or completing the race. All subjects were given opportunities to ask questions and, after being informed of the requirements and content of the study via a plain language statement (Section 8), consented to being in the study. Informed consent was then gathered from all participants as well as a general health questionnaire (Section 8.3.1). All subjects were required to have held a minimum of a senior 2 racing licence from Cycling Ireland for one year. Age was not considered to be a restricting factor, nor ethnicity. The study was approved by the Dublin City University (DCU) Research Ethics Committee prior to the commencement of the study.

### *5.2.2 Descriptive and Anthropometric Data*

Subjects' age, height and body mass were recorded at the start of the study. Each subjects' body mass was assessed while in their cycling clothing, without shoes, prior to each performance test. This data was used in the initialisation of the GT3X actigraphs and standard protocols of the Innocor metabolic cart. Subjects' mass was recorded every 24 hours during the RAI. If a significant change in mass was observed, $\pm$ 5% difference, the time was noted and the sensors were to be adjusted post event to the new value during analysis.

### 5.2.3 Equipment and Sensor Configuration

All sensors were aligned to the universal time constant (UTC) for ease of comparison post event. The sensors and equipment were configured for the following parameters in the following manner:

#### 5.2.3.1 Innocor$^{TM}$

Calibration of the system was undertaken in accordance with the manufacturer's specifications with a calibrated 3 litre syringe, ambient air and known sample of carbon dioxide. Anthropometric data recorded prior to each session was entered into the system to account for age, mass and height. Environmental data recorded at each session was entered into the system to account for temperature and barometric pressure.

#### 5.2.3.2 Lactate Pro

The Lactate Pro (Arkay, Japan) is a portable hand held analyser which can be used to measure blood lactate in field situations. Only a small amount of blood is needed to get a blood lactate measure. A calibration strip provided by the manufacturer with each new packet of reagent strips was used to calibrate the analyser prior to each session. Lactate measurement was conducted on the side of the body closest to the metabolic cart. The earlobe was first sterilised with a sterile wipe, then pricked with a lancet (Accu Check Softclix Pro Lancet, Accu Check, Australia) to promote blood flow. The first blood sample was wiped clean and a fresh sample used to take a measurement with the Lactate Pro analyser.

#### 5.2.3.3 Polar S725i Heart rate Monitor

Heart rate was measured continuously using a wireless Polar heart rate monitor (Polar S725i, Polar Electro, Finland). A heart rate monitor strap was placed on the athlete to facilitate easy measurement of heart rate through the Polar heart rate monitor located on the ergometer or wrist of the subject.

#### 5.2.3.4 GT3X ActiGraph

The following data was required to initiate the GT3X ActiGraph (Section 2.4.5) and was input by researchers in the proprietary software, ActiLife version 5.2.2; date of birth, age, mass, height, ethnicity, dominant side and location of sensor. Physical activity measures were calculated based on the Combined Freedson Vector Magnitude calculations demonstrated by Sasaki et al. (2011) that are embedded in the ActiLife software. All accelerometers were set to record, tri-axial mode. The inclinometer was set to record. The sample rate was set at 30Hz. Data was logged in 1 second epochs. All sensors ran firmware version 4.2.0. Where possible, subjects wore the same units as in previous testing to avoid any differences due to unit-to-unit calibration. The ActiGraphs were kept in the same orientation for each test and attached to the right ankle, lateral aspect (Illustration 5.2), via a soft Velcro strap which allowed for minimal movement of the sensor and remained comfortable enough for long deployments.


*Illustration 5.2: Sensor Location*

### *5.2.4 Test Ordering*

Physiological and performance tests were undertaken in the human performance laboratories at DCU in order to assess physiological capacity and to compare the subjects to the reported literature. This involved three test sessions in the three weeks before the RAI (Illustration 5.3). Any data gathering prior to the event which required repeat testing was carried at the same time of day for each repeat test to reduce any physiological variation. Data from the maximal aerobic test was used to assess the physiological capacity of the subjects and is not directly related to the aims and provides primarily descriptive data. Data from the maximal performance tests were used to estimate the amount of power that was expended during each cycle-bout. Without the data from the maximal performance tests it would not have been possible to undertake the Ultracal analysis in the method it was performed.

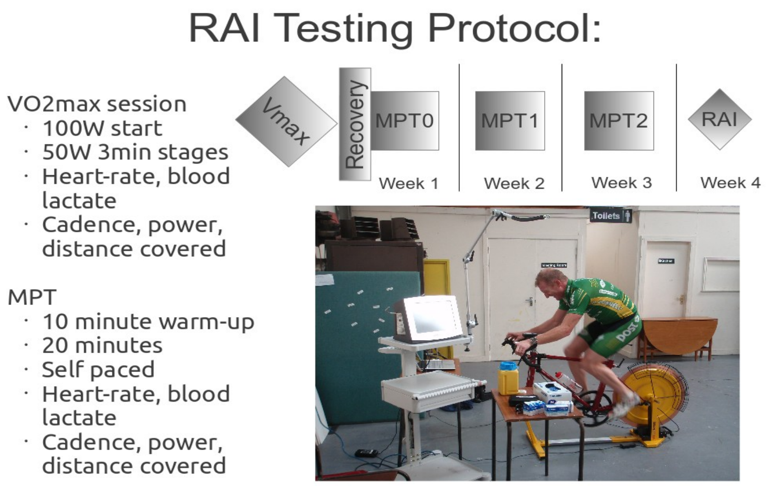



*Illustration 5.3: Schematic of Experimental Protocol*

Subjects were advised to maintain their pre-race routine during all testing prior to the RAI including training, diet and sleep routines. However, this was not monitored by researchers during the study. Data from testing prior to the RAI was used to develop a team order for the team's race strategy, based on a 20 minute maximal performance test (MPT).

### *5.2.5 Session 1, Part 1: Baseline data & Maximal Aerobic Capacity*

Baseline anthropometric data was taken for each subject (Section 5.2.2). Subjects then performed a maximal aerobic capacity test to assess $VO_2max$ and other sub-maximal performance variables. This test was performed on a calibrated cycle ergometer (Velotron Dynafit Pro, Racermate, US). $VO_2max$ was assessed during the maximal incremental exercise test using an Innocor™ metabolic cart (Innocor, Denmark). The Velotron ergometer allowed for the manipulation and measurement of: power output (W), cadence (RPM, pedal turnover rate per minute), heart rate (BPM, via a Polar wireless chest mounted transmitter), speed (Km/h), and distance covered (Km). In the last minute of each stage the following parameters were recorded: Heart rate via a Polar heart rate monitor; Blood lactate using a Lactate Pro hand held lactate analyser; Inspired and expired oxygen, carbon dioxide, respiration rate and respiration volume measured in real time via the Innocor™ metabolic cart. Participants initially cycled at a resistance of 100W which increased in 50W stages every 3 minutes until volitional failure. Resistance was generated by an electromagnetic load generator which allowed for a variation in resistance through a propitiatory PC program.

### *5.2.6 Session 1, Part 2: Maximal Performance Test (MPT)*

After a one hour recovery period, during which they were free to eat and drink as they saw fit, subjects performed a habituation 20 minute maximal performance trial (MPT). This habituation trial was not used in the analysis of performance during the RAI. During the MPT participants were given 20 minutes to cover as much distance as possible on a simulated course. The course was divided into kilometre long sections of increasing gradient, inter-spaced by kilometre long flat sections continuing ad infinitum. Subjects were instructed to give a best effort performance and to treat it as a race effort. No further verbal encouragement was given during the test.

Data for power output, velocity, cadence, distance and heart rate were continually measured during the 20 minute effort from the ergometer itself and recorded to a PC for later analysis. This data was later used to define the mean power output that each subject could maintain at a given intensity and integrated into the Ultracal analysis method. Subjects were free to drink ad-libitum during the test, they refrained from eating during the test. Subjects were cooled by two fans during the test in an attempt to minimise any changes in gross efficiency due to increasing core temperature (Hettinga et al., 2007). Subjects were not instrumented with the Innocor™ metabolic cart. However, they wore a GT3X ActiGraph during the habituation and each subsequent MPT.

### *5.2.7 Session 2: Maximal Performance Test 1*

Seven days after the first session subjects performed a 10 minute self paced warm up on the cycle ergometer followed by a best effort MPT (Section 5.2.6). This MTP was used as part of the final data analysis.

### *5.2.8 Session 3: Maximal Performance Test 2*

Seven days after the second session subjects performed a 10 minute self paced warm up on the cycle ergometer followed by a best effort MPT (Section 5.2.6). The best effort MTP between session 2 and 3 was used as part of the final data analysis.

### *5.2.9 Race Around Ireland*

Seven days after the final MPT the RAI began and subjects' activities were continually recorded via the ankle mounted GT3X ActiGraph. During the RAI subjects were not instructed as to how they should perform, rest or carry out any recovery. In this regard, the experimental data from the RAI itself was carried out under free-living conditions. The race strategy adopted by the team was noted at the start of the race, as was the order in which each pair rode at the start of each cycle period. Subjects are represented in the study as: Mean Data – Team (N=4) and Individual Datasets – S1, S2, S3, S4.

### *5.2.10 Additional Data*

GPS data was continually recorded from a support vehicle following the active cyclist at all times (Illustration 5.4). This instrumented van was provided by the National University of Ireland, Maynooth (NUIM, Strategic Research in Advanced Geotechnologies group - StratAG). This, combined with video footage was captured so as to support post-race data analysis allowing for a continual ground truth with which to review any abnormalities as suggested by accelerometer data. Video was captured from the follow vehicle and was either visible spectrum video (daytime) or video from an infra-red camera with infra-red floodlights mounted on the roof of the follow van for night-time cycling. The RAI provided the initial outing for this purpose built vehicle and acted as a trial run for further research undertaken by the NUIM group.

*Illustration 5.4: Follow Vehicle*

As race rules stated that the racing rider must be continually followed by a vehicle for safety reasons, researchers attempted to utilise this in order to map the route taken by the team during the race (Illustration 5.1). As the follow vehicle would be independent of separate riders, it would require only one GPS unit in order to measure the entire race. With many of the checkpoints located at petrol stations along the race route, it was possible for the vehicle to refuel at checkpoints where a second, sleep vehicle followed the riders for a short period. By insuring that the follow vehicle took the race route back to the team a continual GPS trace was gathered. However, this was not used in analysis of the data during this thesis.

### *5.2.11 Known Artefacts*

As the study was carried out in free-living conditions it was not possible to account for environmental changes during the race, changes in cycling equipment during the race (i.e. a change in bicycle), or any nutritional aspects. As the GT3X Actigraph had never been deployed in this environment it was not possible to know if it was capable of functioning in this environment. Thus this study presents itself as a feasibility study.

### *5.2.12 Data Exclusion Criteria*

Data were excluded from statistical analysis for the following reasons;

- Data sets were discarded if the sensors were worn for less than 95% of the allotted duration of the sample window. In total this resulted in 1 dataset being discarded from aspects of the study (25%).
- Unaccountable failure of sensors occasionally occurred which resulted in partial or damaged data files. It was not possible to recover, or utilise, this data. In total this resulted in 1 dataset being discarded from aspects of the study (25%).

### *5.2.13 Data analysis*

Data from the Innocor were downloaded and imported into LibreOffice (The Document Foundation) for analysis. Data from the GT3X ActiGraph were download via ActiLife version 5.8.3 and analysed in version 6.1.2. All statistical analysis was undertaken using SPSS (PASW Statistics 18).

A linear regression analysis was undertaken on data calculated with the Ultracal method in order to estimate the effect of cycle bout length (Section 5.3.6.2), and estimated power output during these bouts, (Section 5.3.6.3) on overall performance.

### *5.2.14 Advanced Analysis Estimate Method – Ultracal*

Data from the GT3X ActiGraphs were used to estimate aspects of the subjects' performance during the RAI using a specific method dubbed Ultracal. This method used data gathered during and prior to the RAI in order to assess total physical activity (TPA), cycling time (CT), resting time (RT), cycling physical activity (CPA) and resting physical activity (RPA). This analysis was undertaken using a method that was based on the MPTs undertaken prior to the race as well as assumed race tactics adopted during the RAI. However, by basing this model on tests conducted under laboratory conditions the accelerometer data that was gathered did not account for any forward motion during cycling. Due to this, all calculations were based on the data from the power-metre situated within the ergometer, rather than on the count based data from the accelerometer itself. In future testing, it would be recommended that data from a 20 minute MPT be taken under real world conditions such as within an indoor velodrome where surface conditions and environmental conditions could be accounted for. As these were not available to the researcher during this study, it was not possible to do so. This method of estimating multiple variables within the ultra-endurance race is presented as a proposed method of data analysis and has not undergone any validation trials. Due to this, it would be recommended that future studies look to refine this method with the aid of computer scientists.

The Ultracal detection method was designed to recognise bouts of activity from data gathered by the GT3X ActiGraph, take these periods and estimate an intensity for each bout. Using this intensity in conjunction with user defined parameters from the MPT performed under laboratory conditions, Ultracal calculated other variables as defined by the user. The data that remained were assumed to relate to inactive periods and were used in separate calculations in order to estimate the amount of time spent resting. The estimated physical activity data were calculated based on the amount of time participants were active and used a combined vector magnitude score. This used the Freedson V3 cut-points which have shown a better correlation with measures of energy expenditure than traditional cut-point methods (Howe et al., 2009; Sasaki et al., 2011, Section 2.5.2).

The analysis was undertaken via a macro written in Microsoft Excel which was designed to manipulate the data from the GT3X units as output via the proprietory software ActiLife. This data is a summation of the activity data measured by the GT3X ActiGraph and is used within ActiLife to perform its own calculations and is presented in a count based format. The Ultracal method effectively replaces the propitiatory calculations performed by ActiLife and allows researchers to use their own set of calculations which they can manipulate. This macro was designed by members of the CLARITY: Centre for Sensor Web Technologies and was undertaken by computer scientists within the centre.

The macro segmented the data into individual bouts in the following manner:

1. A weighting was calculated for each sample based on its relative intensity. This was undertaken on a per-subject basis. This was then summed into periods of activity and inactivity based on its relative intensity.
2. With each sample having a known sample rate, it was possible to calculate the amount of time elapsed during each activity-bout (Time Per Cycle Bout).
3. A minimal time of 10 minutes was defined for each cycling bout. This definition was based on the tactics that were to be adopted during the RAI and may have led to data loss during the final 4 hours (Section 5.4.6).
4. This data was then scaled base on the mean recorded power output for the 20 minute MPT carried out prior to the RAI. This allowed an estimated mean power-output for each bout of physical activity to be calculated (Power Output Per Cycle Bout).
5. A lower boundary was set below which physical activity levels were assumed to be at rest. This was set at 40% of the peak recorded activity during the 20 minute MPT prior the RAI, equivalent to that of the top end of moderate with Freedson V3 cut-point measures.
6. This boundary in turn defined resting time (RT) as any time below this boundary and resting physical activity (RPA) the amount of activity during that period.

### *5.2.15 Actigraph vs. Ultracal Method*

Analysis was undertaken for variables that could be measured and compared using the GT3X with traditional methods of analysis via the ActiLife proprietary software and the Ultracal method. These variables were: total physical activity (TPA), cycling time (CT) and resting time (RT). It was not possible to perform analysis on the physical activity during cycling (CPA) and resting physical activity (RPA) as these cannot be measured via the AcitLife software. Subject S2 was excluded from these comparisons as they were missing 20+ hours of data from the second half of the race due to a sensor failure. However, some data is presented for this subject.

### *5.2.16 Synopsis*

During ultra-endurance cycle events it is not possible to instrument riders with traditional measures of physiological capacity due to the limited recording capacity of these units. Thus, a small, light weight accelerometer based system capable of long deployment periods that can gather data associated energy costs of cycling as well as contextual data about the environment and race strategies may be of benefit. During this study, the GT3X ActiGraphs were deployed in order to test their feasibility in providing appropriate data within an ultra-endurance race that may aid in estimating performance during these prolonged events.

## 5.3 Results

The following are the descriptive results pertaining to the subjects as well as the data analysis undertaken. Where sensor failure occurred data is not for subject S2.

### *5.3.1 Subject Descriptive and Anthropometric Data*

The subjects' descriptive and anthropometric data are presented in table 5.1. From the subjects used in the study the following were the mean values for all subjects (n=4); All subjects partook in each session; maximal aerobic capacity testing, MPT1 and MPT2. No differences were observed in subjects' mass before, during or after the event.

*Table 5.1: Descriptive and Anthropometric Data (n=4)*

| Variable | Value |
|---|---|
| Age (*yrs*) | 42 ± 6 |
| Mass (*kg*) | 78.3 ± 3.45 |
| Height (*m*) | 1.76 ± 0.07 |
| BMI ($kg/m^2$) | 25.24 ± 1.95 |
| Body Fat (*%*) | 13.86 ± 2.72 |

Data presented as mean ± SD

### *5.3.2 Baseline Physiological Test Data*

Baseline testing was performed three weeks prior to the RAI (Table 5.2 - 5.5).

#### *5.3.2.1 Maximal Aerobic Test (Vmax)*

$VO_2$Peak was defined as the mean of the 3 highest recorded $VO_2$ values once an RQ of higher than 1.1 and 95% of age predicted heart rate maximum had been reached. Lactate Threshold (LT) was defined as the onset of blood lactate accumulation (OBLA) at a concentration of 4mmol.

*Table 5.2: Baseline Physiological Test Data (n=4)*

| Variable | S1 | S2 | S3 | S4 | Mean ± SD |
|---|---|---|---|---|---|
| Age (yrs) | 39 | 36 | 51 | 43 | 42 ± 7 |
| $VO_{2peak}$ (*ml/kg/min*) | 71.7 | 76.4 | 60.5 | 66 | 68.05 ± 7.29 |
| $VO_{2peak}$ (*L/min*) | 5.3 | 6.3 | 4.8 | 5.3 | 5.3 ± 0.69 |
| $Hr_{peak}$ (*BPM*) | 171 | 174 | 179 | 182 | 177 ± 5 |
| $PO_{peak}$ (*W*) | 400 | 425 | 375 | 375 | 394 ± 24 |
| $Lactate_{peak}$ (*mmol*) | 14.1 | 10.8 | 12.7 | 8.2 | 11.45 ± 2.55 |
| PO @ LT (*W*) | 330 | 331 | 285 | 327 | 318 ± 22 |
| HR @ LT (*BPM*) | 152 | 147 | 152 | 170 | 155.6 ± 9.8 |

Data presented as mean ± SD

### *5.3.2.2 Maximal Performance Test (MPT)*

MPT's were carried out on 3 separate occasions; 1 pre-test habituation & 2 trials. The best effort trial was used for the Ultracal analysis.

*Table 5.3: Maximal Aerobic Tests; MPT (n=4)*

| Variable | $MPT1_{mean}$ ± SD | $MPT2_{mean}$ ± SD | Percentage Difference (%) |
|---|---|---|---|
| Distance (*km*) | 10.68 ± 0.74 | 10.55 ± 0.75 | 1.22% |
| $Po_{mean}$ (*W*) | 307 ± 43.8 | 318 ± 41.9 | -3.58% |
| $Po_{mean}$ (*W/kg*) | 4.48 ± 0.5 | 4.07 ± 0.4 | 9.15% |
| $Hr_{peak}$ (BPM) | 172 ± 11 | 171 ± 4 | 0.58% |
| $Hr_{mean}$ (BPM) | 148 ± 16 | 161 ± 4 | -8.78% |

Data presented as mean ± SD

*Table 5.4: Individual Data Best Effort Maximal Performance Test (n=4)*

| Variable | S1 | S2 | S3 | S4 | Mean ± SD |
|---|---|---|---|---|---|
| Distance (*km*) | 11.2 | 11.48 | 10.08 | 10.02 | 10.68 ± 0.74 |
| $Po_{mean}$ (*W*) | 328 | 358.9 | 277.75 | 265.3 | 307.6 ± 43.8 |
| $Po_{mean}$ (*W/kg*) | 4.48 | 4.34 | 3.59 | 3.5 | 3.97 ± 0.5 |
| $Hr_{peak}$ (BPM) | 172 | 168 | 175 | 192 | 176 ± 11 |
| $Hr_{mean}$ (BPM) | 155 | 124 | 157 | 152 | 147 ± 15 |

Data presented as mean ± SD

### *5.3.3 Traditional Analysis (Actilife)*

Using the GT3X ActiGraphs proprietary software (ActiLife) the following results were generated for each variable.

*Table 5.5: Actilife Variables (n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD (n=3) |
|---|---|---|---|---|
| Cycling (*mins*) | 1,193 | 699 | 726 | 862 ± 278 |
| Rest (*mins*) | 2,926 | 3,419 | 3,392 | 3,245 ± 277 |
| Physical Activity (*kcal*) | 19,013 | 22,181 | 23,961 | 21,718 ± 2,506 |

Data presented as mean ± SD

### *5.3.4 Modified Analysis (Ultracal)*

Using the data from the GT3X actigraphs and the Ultracal assessment method the following results were calculated for each variable.

#### *5.3.4.1 Total Physical Activity (TPA)*

Table 5.6 shows the total amount of physical activity (TPA) that was recorded with the Ultracal method during the Race Around Ireland.

*Table 5.6: Ultracal Total Physical Activity (n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD (n=3) |
|---|---|---|---|---|
| Total Physical Activity (*kcal*) | 21,609 | 20,924 | 22,249 | 21,594 ± 662 |

Data presented as mean ± SD

#### *5.3.4.2 Cycle & Rest Time (CT & RT)*

Table 5.7 shows the total amount of cycle time (CT) and resting time (RT) that were recorded with the Ultracal method during the Race Around Ireland.

*Table 5.7: Ultracal Cycle and Rest Times (n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD (n=3) |
|---|---|---|---|---|
| Cycling (*mins*) | 795 | 669 | 696 | 720 ± 60 |
| Rest (*mins*) | 3140 | 3341 | 3401 | 3,294 ± 136 |

Data presented as mean ± SD

#### *5.3.4.3 Cycle Physical Activity & Rest Physical Activity (CPA & RPA)*

Table 5.8 shows the total amount of physical activity that was recorded during cycling (CPA) and resting (RPA) periods with the Ultracal method during the Race Around

Ireland. It was not possible to measure these variables with the ActiLife software package without prior knowledge of each cycle period's start and end.

*Table 5.8: Ultracal Cycle and Rest Physical Activity(n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD (n=3) |
|---|---|---|---|---|
| Cycling Activity (*kcal*) | 18,974 | 12,539 | 13,480 | 14,997 ± 3,475 |
| Rest Activity (*kcal*) | 8,635 | 8,384 | 8,769 | 8,596 ± 195 |

Data presented as mean ± SD

### *5.3.5 Actigraph vs. Ultracal Method*

This section refers to comparative analyses that were performed for variables that could be compared using data from the ActiLife proprietary software and the Ultracal method.

#### *5.3.5.1 Total Physical Activity (TPA) Comparison*

TPA was defined as the total amount of PA measured over the RAI.

*Table 5.9: Total Physical Activity (TPA) Comparison (n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD (n=3) |
|---|---|---|---|---|
| TPA ActiLife (*kcal*) | 19,013 | 22,181 | 23,961 | 21,718 ± 2,506 |
| TPA Ultracal (*kcal*) | 21,609 | 20,924 | 22,249 | 21,594 ± 662 |

Data presented as mean ± SD

#### *5.3.5.2 Cycling Time (CT) Comparison*

CT was defined as the total amount of recorded time cycling (Ultracal) or spent in vigorous or very vigorous activity (Actilife).

*Table 5.10: Cycle Time (CT) Comparison (n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD (n=3) |
|---|---|---|---|---|
| CT ActiLife (*mins*) | 1,193 | 699 | 726 | 873 ± 278 |
| CT Ultracal (*mins*) | 795 | 669 | 696 | 720 ± 66 |

Data presented as mean ± SD

#### *5.3.5.3 Rest Time (RT) Comparison*

RT was defined as the total amount of recorded time resting (Ultracal) or spent in light or moderate activity (Actilife).

*Table 5.11: Rest Time (RT) Comparison (n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD (n=3) |
|---|---|---|---|---|
| RT ActiLife (*mins*) | 2,926 | 3,419 | 3,392 | 3,246 ± 278 |
| RT Ultracal (*mins*) | 3,140 | 3,341 | 3,401 | 3,294 ± 137 |

Data presented as mean ± SD

## *5.3.6 Ultracal Method Additional Data*

The use of the Ultracal method allowed the following analysis to be made of data not available thorough the ActiLife software.

### *5.3.6.1 Weighted Intensity Per Cycle Bout*

An intensity factor scaling from 1.00 (100% of the mean power output maintained during the MPT for 20mins) to 0.00 (0% of the mean power output during the MPT for 20mins) was generated for each cycle period during the race using a velocity calculated intensity measured from the raw data of the GT3X ActiGraphs. This gave a visual representation of the intensity of each cycle bout, for each member of the team, for the duration of their data that was recorded (Illustration 5.5, full size replication in appendix 8.3).

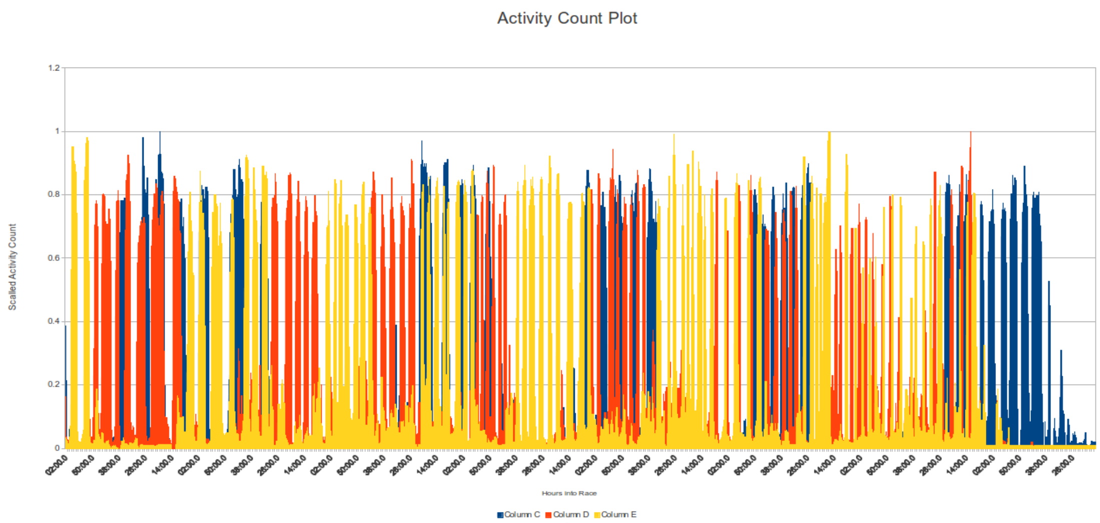



*Illustration 5.5: Normalised Activity Intensity*

### *5.3.6.2 Time Per Cycle Bout*

The duration of each cycle bout was measured from the raw data of the GT3X ActiGraphs. This gave a visual representation of the intensity of each cycle bout, for each member of the team, for the duration of their data that was recorded (Illustration 5.5, full size replication in appendix 8.3).

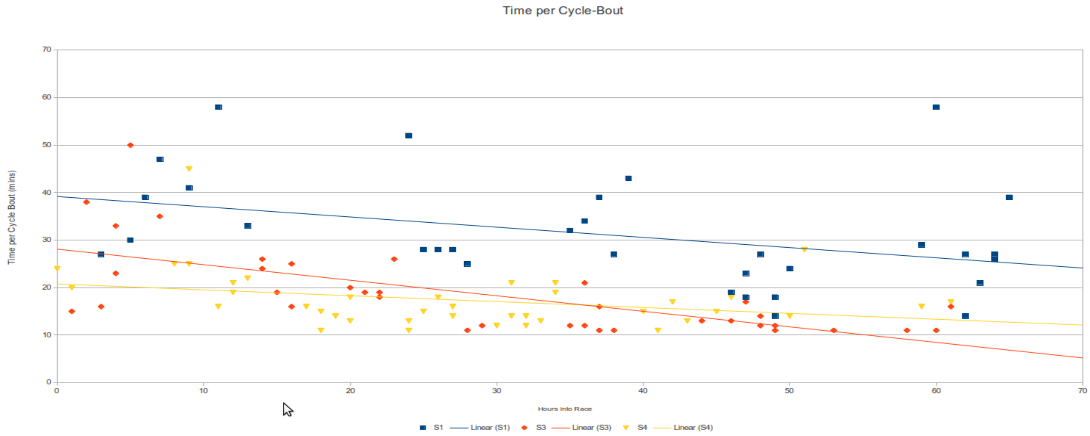



*Illustration 5.6: Performance Decay Trend-line (Cycle Bout Length)*

A linear trend-line (Illustration 5.6) was created from this data in order to investigate the rate by which the length of each cycle bout decayed over the race. This is presented in table 5.12 below.

*Table 5.12: Performance Decay Trend (n=3)*

| Variable | S1 | S3 | S4 | Mean ± SD |
|---|---|---|---|---|
| Slope<br>Decay (%) | 0.145<br>14.5 | 0.451<br>4.5 | 0.093<br>0.9 | 0.019 ± 0.017<br>7.0 ± 5.8 |

Data presented as mean ± SD

### *5.3.6.3 Estimated Power Outputs Per Cycle Bout*

A power output was estimated for each calculated cycle bout as described in section 5.2.14. Each bout was expressed as a percentage of the mean power output maintained during the best effort MPT resulting in an estimated power. This was performed for each cycle period during the race (Illustration 5.7,full size replication in appendix 8.3 ). The mean power output for each cyclist is presented in table 5.13.

*Table 5.13: Estimated Mean Power Outputs Ultracal (n=4)*

| Variable | S1 | S3 | S4 | Mean ± SD |
|---|---|---|---|---|
| Power (*W*) | 316 | 312 | 323 | 323 ± 12.83 |

Data presented as mean ± SD

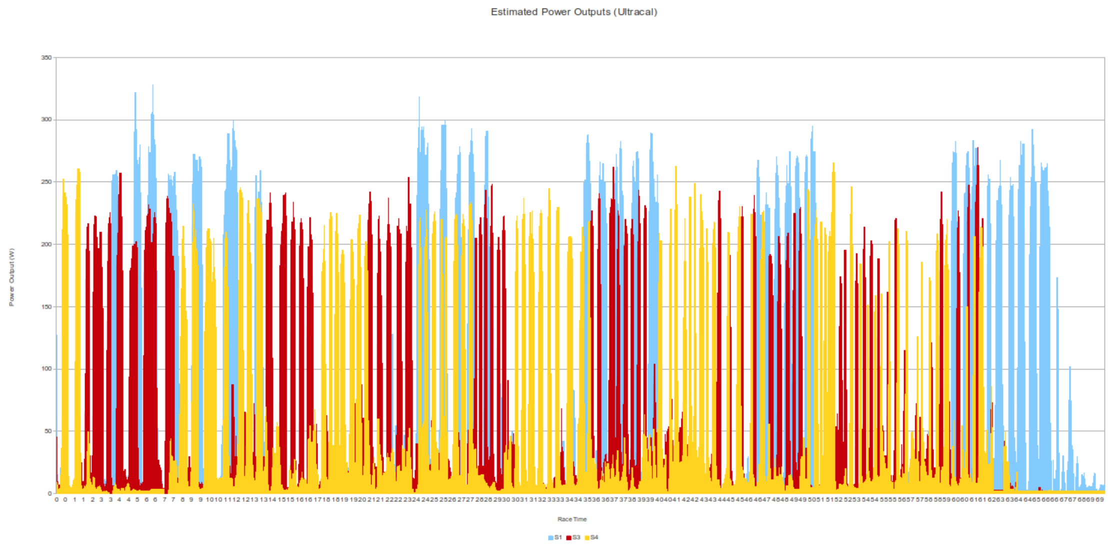



*Illustration 5.7: Estimated Power Outputs (Ultracal)*

A linear trend-line (Illustration 5.8,full size replication in appendix 8.3 ) was created from this data in order to investigate the rate by which the mean estimated power output of each cycle bout decayed over the race. This is presented in table 5.14 below.

*Table 5.14: Estimated Power Outputs Trend (n=4)*

| Variable | S1 | S3 | S4 | Mean ± SD |
|---|---|---|---|---|
| Slope | 0.024 | 0.003 | 0.004 | 0.029 ± 0.04 |
| Decay (%) | 2.4 | 0.3 | 0.4 | 2.9 ± 4 |

Data presented as mean ± SD

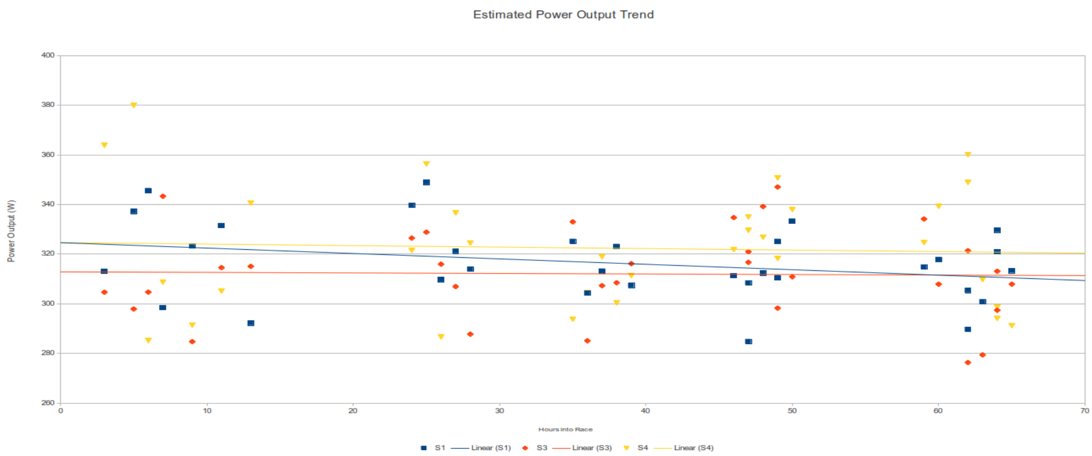



*Illustration 5.8: Performance Decay Trend-line (Estimated Power Output)*

### *5.3.6.4 Estimated Physical Activity Per Cycle-bout*

With energy expenditure estimates based on the relationship between 1W and 1kcal/min (Section 2.3.4), estimates for the energy expended during each cycle bout were calculated for each cycle bout (Illustration 5.9, full size replication in appendix 8.3).

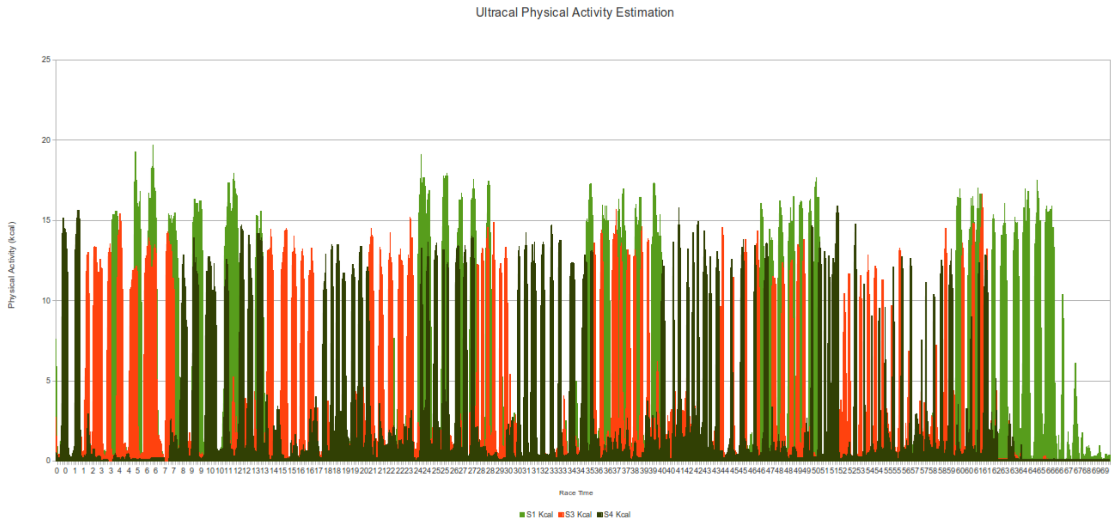



*Illustration 5.9: Physical Activity Energy Expenditure Estimation (Ultracal)*

### *5.3.7 GPS Elevation Estimate*

Data from the GPS on-board the follow vehicle recorded at 1 minute intervals for the duration of the race. From this GPS data it was possible to create a trace of the profile of the race itself from the altitude measures within the GPS data (Illustration 5.10). From this, it was hoped that PA data from the GT3X ActiGraphs could be aligned to both the GPS and video data giving contextual location data via both the GPS and video. This was only used as a test-bed for future research and no statistical analysis was performed.

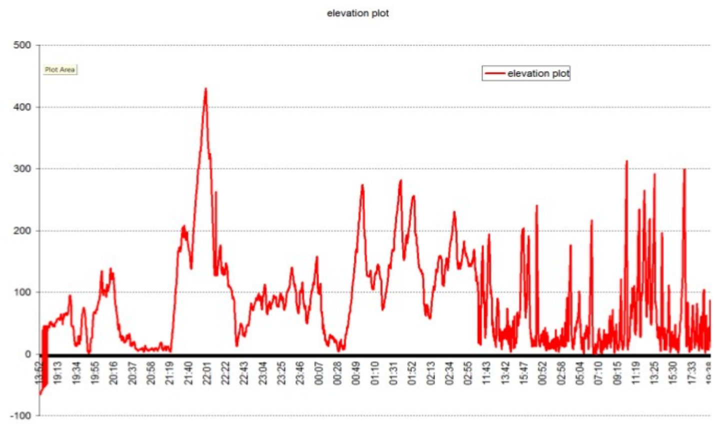



*Illustration 5.10: GPS Elevation Trace: Follow Vehicle*

### *5.3.8 GPS & Accelerometer Integration*

Following the RAI, data from the GT3X ActiGraphs and GPS were combined in an analysis performed with CLARITY researchers. This was only used as a test-bed for future research and no analysis was performed (Illustration 5.11)

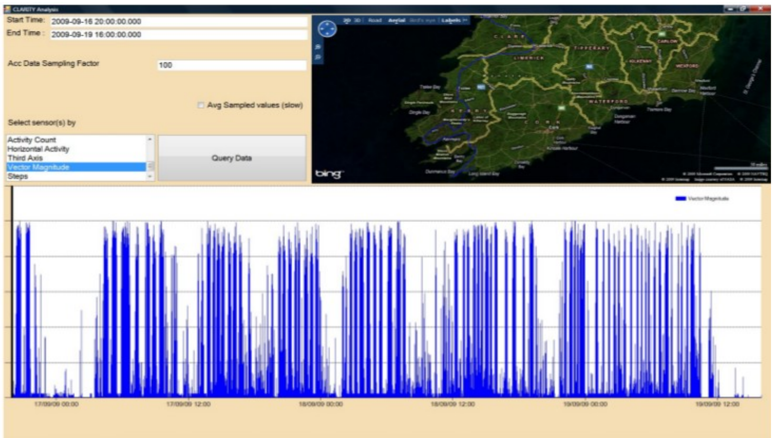



*Illustration 5.11: GPS and Acceleration Data Combined*

### *5.3.9 Synopsis*

The data presented shows the variables during the RAI for all members of the team bar where a sensor failure occurred for one subject in the later stages of the race. The implementation of a unique method of data analysis allowed the data to be examined at a finer level, despite this failure in some cases, and assess the performance of the subjects during the race. This technique allowed previously unavailable data on the duration, intensity and estimates of power for each cycle-bout during the race to be defined. By performing this analysis it was possible to investigate the decline in the duration of cycle-bouts throughout the race and the individual effects with different team members fatiguing at different rates. Furthermore, it was possible to estimate a value for both power output and energy expenditure which allowed researchers to examine the performance of the subjects themselves during resting and racing periods. This method allows for analysis to be performed in ultra-endurance cycle events incorporating both on bike and off-bike activity rates that has previously not been possible. By deploying the GT3X ActiGraph accelerometers in this ultra-endurance cycling environment, it is possible that this test-bed deployment may help with the development of future measurement methods.

## 5.4 Discussion

This study aimed to deploy an unobtrusive method of estimating physical activity during an ultra-endurance race via two different analysis techniques. This was undertaken for variables examining aspects of cycle and rest duration and physical activity using the same data examined in two separate methods. This was performed using an off the shelf accelerometer platform the GT3X ActiGraph. As the GT3X ActiGraph, or any other accelerometer based sensor platform, had not yet been used in the ultra-endurance cycling environment, this study acted as a test-bed to assess the applicability of these technologies in this environment.

### *5.4.1 Subjects*

Very few studies exist with large data sets for ultra-endurance cyclists. Therefore, no overall review exists of the anthropometric and physiological determinants related to performance in such prolonged endurance events. This is further confounded by the lack of differentiation in many papers between steady state ultra endurance events (55-65% $VO_2$max) and high intensity interval ultra-endurance events as defined by Laursen et al., (1999) as an intensity equivalent to 75% of $VO_2$max or higher. Thus it is necessary to assess data from several studies which take information from a variety of events when comparing athletes. Information that does exist categorises many ultra-endurance athletes as highly trained, but sub-elite cyclists (Laursen, 1999; Wirnitzer et al., 2008; Knechtle et al., 2005; Hulton et al., 2010).

The scientific literature reports a mean age of 24 years (range 20-33) for professional road cyclists, with the following mean anthropometric characteristics: height 1.8m (range 1.6-1.9m), body mass 69kg (range 53-80kg) (Mujika & Padilla, 2001). The subjects used in the study were recruited from a team already entered into the RAI, although older and heavier in comparison to team cyclists who had competed in RAAM (Laursen et al., 1999). This was observed as subjects recruited for this study had measured $VO_2$max values 4% lower than those in the Laursen study. However, no other values were reported for peak aerobic power output or any functional test of cycling performance in team ultra-endurance cycle racing with which to draw comparisons.

### *5.4.2 Maximal Performance Test Data*

Anecdotally, professional cyclists tend to prefer field-testing rather than laboratory testing (Faria et al., 2003). Unfortunately field testing for absolute values such as $VO_2max$ tends to be less exact than laboratory based testing. Many different systems exist to test cyclists under laboratory conditions while attempting to recreate the specific demands of cycling. When looking to investigate a specific metabolic point such as the onset of blood lactate accumulation (OBLA) for example, results may vary depending on the ergometer used to perform the test protocol (Zavorsky et al., 2005). Overall, for reliability in testing an athlete must repeat tests on the same ergometer, under the same environmental conditions, and at the same training state. For this reason all testing prior to the RAI was performed in a riding position that simulated the position that each subject planned to adopt during the race.

In order to use the data from the maximal performance tests (MPTs) to infer estimations of energy expenditure, it was necessary not only to make sure the cyclists position was similar, but also that the MPT simulated the RAI, a highly undulating course. However, to transfer data gathered on a cycle ergometer in a laboratory into an estimate of power produced outdoors is inherently flawed as indoors a cyclist does not have to deal with wind resistance, corners or changes in gradient. Ideally subjects would perform an outdoor MPT and the data gathered from an on-board cycle power meter would be used to assess their power needs. However, this in itself is not a reliable trial due to variations in wind, temperature and other environmental differences leading to trail to trial variations. For this reason the indoor MPT was chosen to represent a best 20 minute effort for each cyclist.

Although accelerometers were used in the estimation of variables in this study, it is not possible to gather laboratory data that truly represents cycling due to a lack of forward motion. Thus, data from the accelerometer platform, the GT3X ActiGraph, was not used in the assessment of the MPT. The objective data from the Velotron cycle ergometer was used in the estimation of physical activity during the race for calculations based on the Ultracal method. For calculations based on the ActiLife method, no measure of the MPT was taken into account.

### *5.4.3 Estimating Race Strategy*

During the ultra-endurance races such as the RAI, solo cyclists aim to cycle for the longest period of time possible before taking rests as any time spent not cycling is time that they are losing to a competitor. However, the four person team structure allows for different tactics to be adopted. As only one cyclist is actively cycling at any given time (UMCA 2009) teams have the ability to rotate and rest cyclists. The strategy adopted by the studied four man team was to have two pairs of cyclists rotate the cycling efforts. As two cyclists were recovering in a support van several hours away (sleep vehicle), two members were actively rotating cycling efforts. During flatter stages with fewer gradient changes certain participants were selected who could maintain a constant high power output (S2 & S4), and when the gradient increased lighter participants with higher power to weight ratios would be utilised (S1 & S3). These pre-planned rotations occurred every 20–30 minutes depending on terrain, weather, and available change-over points for the support crew to park their vehicle. This rotation time was based on members of the team who had previously managed similar teams racing in the Race Across America (RAAM). There is no scientific evidence to support this strategy, however the winners of RAAM in the two years prior to the RAI, as well as the Irish team that had placed third in RAAM in 2007, had adopted this strategy and it had proved beneficial. Therefore, it was adopted by the team management purely on the basis of other teams' past performances.

The rotational racing strategy adopted by the team during the RAI was expected to allow the active cyclist to ride at a higher intensity than they would be capable of sustaining over an extended period of time (greater than 30 minutes). This logical assumption was based on the interaction between time and sustainable power. As the length of a period of cycling increases, the mean power output that is sustainable decreases in a linear fashion for that period of time (Vautier et al., 1995; Brickley et al., 2002). As the team management were aiming for 20 minute rider rotations during the RAI a test was performed prior to the racing to assess the mean power output that each subject could sustain for the duration of the planned 20 minute cycle periods similar to 20 minute functional threshold tests performed by Coggan et al. (2011). Subjects then planned to race at a percentage of the peak intensity of this maximal performance trial (MPT) during the RAI. The intensity of each cycle-bout during the RAI could then be graphically represented at the end of the RAI as a percentage weighting of the MPT performed prior to the event (Illustration 5.5). By optimising the intensity at which the cyclists were pacing these trials, it was possible to develop an individual pacing strategy for each cyclist based on the MPT and assess the subjects' ability to adhere to it post race. Logistically it was not possible to perform repeat MPTs in an attempt to mimic the actual race strategies that were to be adopted prior to the RAI. This was primarily due to time constraints and availability of the subjects and thus did not take into account the repeat nature of the cycle bouts or the additional sleep deprivation or fatigue associated with ultra-endurance racing.

During the RAI the subjects' cycle bout length varied between 11 and 39 minutes (mean 22 $\pm$ 6mins). During the race riders both rode longer periods at an estimated lower power output, as well as shorter periods at a higher estimated power output. It is possible that by doing so the estimation made by the Ultracal method may be somewhat skewed as they are based on a percentage estimation of a fixed period cycle trial. In order to minimise the impact of the change in cycle bout duration it would be advisable to test prior to the event at multiple durations, at maximal capacity. This would allow a fatigue curve for an individual athlete based on duration and mean power output to be defined (Vautier et al., 1995; Bull et al., 2000). However, this testing protocol, similar to critical power testing, is very time consuming and therefore falling out of favour. Recently, the use of a 3-minute maximal cycle test has been investigated in the literature as a valid measure of critical power (Francis et al., 2010; Vanhatalo et al., 2008b; Vanhatalo et al., 2007; Vanhatalo et al., 2008a). By integrating a sliding power output within the Ultracal calculations, the equivalent power output from a critical power curve for a given duration, the accuracy of estimation should increase within the algorithm. Ideally, a critical power, or another analysis method, could be brought in to the Ultracal analysis in order to further refine the system that would not need to be undertaken in laboratory conditions. This would also allow for the integration of shorter higher intensity cycle periods that fall outside the endurance focused analysis that the Ultracal algorithm provides.

As it stands, the Ultracal method provides a method to gather performance test specific data on a cycle race that is separate to the generic data that is produced from the

ActiLife software. However, it is not a validated method of physical activity estimation and requires further refinement in order to be considered a useful tool.

### *5.4.4 Effect of Pre-determined Race Strategy*

After an allotted period of time (4 hours during daytime, 6 hours at night) the pairs of cyclists rotated, allowing for a period of recovery and refuelling. This in turn allowed the teams to define the orientation of the teams (S1 & S3 - S2 & S4) prior to the RAI. If, during analysis, there were periods where the pairs were not in their normal rotation it was to be assumed that the data was incorrect, or to question the video from the follow vehicle. The only stages where 2 riders from non-normal pairs would cross over were at the time when pairs of riders are rotating. During the RAI the pre-planned tactics were adopted for most of the race. However, there were times when it was not possible for subjects to switch-over at the end of the 20 minute window. Also, the data suggested that as the race progressed the cyclists were unable to sustain the planned 20 minute rotation plan and a decline was seen in the length of cycle-bouts from the start of the race to the end (Table 5.13, Illustration 5.9). For one subject, S3, the trend-line shows a decline in the length of his cycle-bouts with a 45% decrease in the length of his cycle bouts as the race progressed. As the initial cycling bouts were of extended duration, it is possible that this strategy may have resulted in a reduced performance by the end of the race. It is also possible that this subject did not pace themselves well by starting the race harder than they should have, was not capable of continuing the planned bout length, thus resulting in a sub-optimal performance. As the race was eventually decided by less than 90 minutes, it is possible that this combined with similar poor pacing choices may have resulted in the team under-performing.

Part of the reason for this large decline in performance may be due to a major change that occurred at the end of the race. The team, realising they were within 1 hour of the leaders, adopted a 4 man rotational strategy. This involved placing 3 members of the team within the leap-frog vehicle and constantly changing cyclists at a much shorter duration. The Ultracal definitions assumed that any period of activity of under 10 minutes in duration, and/or at an intensity less than 40% of that experienced during the MPTs performed prior to the RAI, were deemed a 'rest' period. This posed a problem during the final analysis as this adoption of short, cycle-bouts (<10 minutes) may have underestimated the number of cycling periods and overestimated the amount of rest for subjects. Although there was no statistical difference in the overall energy expenditure estimations (Table 5.10), cycling time (Table 5.11) or resting time (Table 5.12) estimations between Ultracal and ActiLife, it is possible that with a larger dataset this may appear to show statistical significance. However, this system and method lends itself toward this nature of race as it is also able to segment the data for more complex analysis.

### *5.4.5 RAI Performance Analysis*

With the Ultracal method it was possible to generate a data set that gave an intensity weighting for each minute of the race. Furthermore, this could be visualised as a percentage of maximal intensity for each subject compared to a previous MPT (Illustration 5.8). With the intensity and duration of each bout having been calculated, it was possible to estimate the power output for each sample in the data-set. By using the intensity and multiplying this by the mean power sustained by each subject during their MPTs, an estimation of the power for each minute was calculated. These were then applied across the detected events, summed for each minute of that event, thus a mean power output for each cycling bout was estimated (Illustration 5.10). Although this assumes a peak power was not exceeded within any minute, it allows for a more representative mean to be generated rather than applying an assumption for each 20 minute period. This gave the ability to look not only at the power output that each cyclist sustained during a given cycle bout, but also gave an indication as to the performance decay the cyclists experienced during the race (Table 5.14 and Illustration 5.11). Surprisingly, the decline in mean power output over the duration of the race was relatively small averaging 2.9% (Table 5.15).

These power estimates suggest that the subjects were working between 96% and 121% (mean 105%) of their estimated power output during the MPT performed prior to the RAI. This estimate of power outputs represents a suggested overall intensity equivalent to 82% of $VO_2max$ of the team during the RAI. This agrees with one of the few studies in the literature by Laursen et al., (1999) who estimated a team in the RAAM to be working at on mean >75% of their $VO_2max$ during the race. This team adopted a longer 30 minute rotation at stages during RAAM, but also was forced to go as low as 5 minutes due to issues associated with changes in altitude.

### *5.4.6 Ultracal Physical Activity Estimation*

After the power output was defined for each sample it was possible to estimate the physical activity for each sample, and thus for the event. This was undertaken using the power output measured during the MPTs prior to the RAI. By using a measure of the work undertaken by the cyclist, as opposed to estimates of physical activity (PA) from the accelerometers, it was hoped that error could be reduced in the calculations and a differentiation between resting and cycling PA could be generated automatically.

The algorithm was designed around the conversion that 1W = 1Joule/second. It did not make any assumption for levels of cycling efficiency that were previously reported to be around 25-29% (Moseley et al., 2004; Hopker et al., 2009). Were this to be taken into account, expected values would be lower than those presented. However, as the system that the comparison was made has no method of discerning cycling efficiency it was not deemed necessary as this would already be accounted for in the style of pedalling used during the MPT and during the race. This resulted in three separate estimates of physical activity generated with the Ultracal method; total physical activity (Table 5.6), physical activity during cycling and physical activity during non-active rest periods (Table 5.8). By estimating physical activity rates throughout the race it was possible to generate a graphical representation of the physical activity expended during entire race (Illustration 5.13).

The non-active rest periods were not differentiated based on whether they were between cycling bouts, or were a period when subjects were in the sleep vehicle. In order to further differentiate between these instances of rest, the exact periods when subjects were resting between cycling bouts and the associated intensities recorded would need to be known. The initial analysis, undertaken using ActiLife, resulted a gross estimate of total physical activity but was not capable of differentiating between cycle and rest periods without the knowledge of their start and end times. This lack of contextual data renders the data of less use for the performance analysis of subjects during the race. When the Ultracal algorithm was applied to the data it was possible to separate the cycle physical activity from the non-cycle physical activity (Table 5.12).

To further refine this non-cycling physical activity would necessitate the addition of a known energy expenditure for resting metabolic rate for each subject (Section 2.2.1). This could be calculated via a similar method to Chapter 4 where energy expenditure rates at rest can be estimated based on the anthropometrics of each subject. With this the data it could be possible to yield more accurate information on the rest periods and the energy expended during them. However, as the primary concern of the study was measuring cyclists' performance during the event, this was not investigated.

### *5.4.7 Environmental Effects*

During the RAI the subjects were exposed to a variety of weather conditions including rain, wind and temperature changes. It was not possible to combine these into any of the calculations. However, it is possible that the presented pacing strategies, when looked at in depth may be able to give an insight into the role that the main environmental aspect, sleep deprivation, played in the race.

In its current state the ActiLife software does not provide the tools for automatic segregation of sleep data and the system requires each sleep-wake cycle to be entered by the researcher post-event. However, this may be possible using a method similar to the Ultracal model. This would necessitate the extraction of the time points for each cycle bout as estimated by the Ultracal method, then the segmentation of each 64 hour file manually by the researcher, or with the help of computer scientists with specific segmentation techniques. Optionally, it may be possible to automatically extract this data from the video footage from the follow vehicle with the help of computer scientists. In order to do so in its current state necessitates the introduction of guesswork on the behalf of researchers adding inaccuracies to the data.

### *5.4.8 Sensor Applicability*

Much of the data available on accelerometers and their use in the cycling environment deal with them as methods of classifying the activity of cycling within physical activity data sets (Long et al., 2009; Brazeau et al., 2011; Crouter et al., 2006). These studies generally utilise a measurement taken at the centre of mass in order to assess gross physical activity and are undertaken at relatively low intensities. The applicability of accelerometers placed at the centre of mass for the measurement of cycling is questionable as it may not adequately capture the activity due to the lack of motion of the centre of mass during cycling (Bassett et al., 2012; Freedson et al., 2012). For this reason the GT3X ActiGraphs were located at the ankle of the subjects. It was hoped that this would not only allow for easier event detection, but allow for more accurate measures of physical activity to be made during cycling as well as rest periods. The ankle proved to be an unobtrusive place to mount the accelerometer and did not interfere with cycling or resting.

Unfortunately due to the location of the ActiGraphs, and the inclement weather experienced during the race, one sensor failure was experienced. The GT3X located on subject S2 failed with 20 hours of the race left to complete. On inspection it was found that the unit had become waterlogged and the hardware failed rendering it impossible for the researchers to recover the data. Data was eventually recovered from the unit after it had been returned to the manufacturers for inspection. However, the last 20 hours of data were never fully recovered and the assessment undertaken with ActiLife was incomplete. This waterproofing issue has been resolved since the RAI in 2009 with the introduction of the GT3X+ (as used in the study in Chapter 4).

The ability to change the rate of data recording, epoch and length was of a major benefit during the RAI. As it was not known if the team would finish within the 94 hour cut-off it was necessary to choose a recording period that would allow for a full data capture, but have a high enough granularity so as to make accurate estimates. In the case of the RAI which lasted 64.5 hours, the 1 second data capture rate provided an accurate enough granularity. However, if the system was to be applied to shorter events it would be possible to use a higher rate, or use the raw capture mode, to gather even finer data. The applicability of the Ultracal method would still stand in this recording method as the data used to calculate the intensity of each sample was performed using the raw acceleration data, albeit at a higher sample rate.

One of the major limitations to the GT3X actigraphs came not from the hardware but the software. As this is a very recent technology it has seen a large amount of development in the software since the initial data was collected (Section 2.4). This resulted in data that was captured in an older firmware and file format needing to be converted several times into a manner in which it was accessible for analysis with the modern version of ActiLife. This resulted in the loss of data from several files including the initial MPT data. The data that was used for the analysis was initially processed after the event and recorded in a separate format. Similar issues occurred when trying to work with the sheer volume of the data that was recorded during the race itself. With over 64 hours of data the proprietary software from ActiLife found it very difficult to process the information. This is more than likely due to the relatively high sample rate that was used to measure the race and the number of data points that it resulted in. This issue also occurred when trying to analyse and graph the data using Microsoft Excel. Due to a limitation in the number of rows of data this program can handle the data had to be down-sampled to 10 seconds in order to analyse it. This removed much of the granularity and thus most analysis was undertaken using LibreOffice for Linux which has no limitation in this regard and allowed all the data to be graphed.

### *5.4.9 Other Sensors*

This section details the other sensors that were deployed during the RAI but not used in the overall assessment of the race. Many of theses systems were used as ground truths when investigating the accelerometer data. Future work would ideally aim to integrate these systems into the overall analysis method.

#### *5.4.9.1 GPS & Video*

Data from the GPS located in the follow vehicle was used post-event in conjunction with other researchers from CLARITY in order to assess the path taken by the participants during the race and align it with video footage for further investigation. Ideally the GT3X actigraphs would be combined with GPS at the hardware. However, as these sensors are designed to function equally well indoors and outdoors, it is not a consideration the manufacturers are currently pursuing (communications with Actilife). This video footage acted as a ground truth to indicate which pair were cycling and which member of the pair was active. During the analysis of the data it was found that the subjects stuck to their agreed strategies throughout the race, bar a single incidence where the riders became separated from their sleep vehicle for an extra 4 hours. Initial analysis of the physical activity data for pair 1 (S2 & S4) showed an extended duration of physical activity and the video and GPS data aided in assessing what occurred post-event.

### *5.4.9.2 Combined GPS and Acceleration Data: CLARITY Analysis*

Following the RAI, data from the GT3X actigraphs and GPS were combined in an analysis performed with CLARITY researchers (May et. al., 2010; Conroy et al., 2011). This combination of GPS data and the acceleration data was used to define and classify each of the separate cycling bouts that were undertaken and where they occurred during the race (Illustration 5.13). The purpose of this system was to act as a reference tool for researchers to enable them to query the data gathered from the multiple sensors during the RAI in order to assess what occurred. It is hoped that future versions of this software may be used in order to assess other sports utilising a myriad of sensor types that can be simply "dropped" into the program. Variations of this system have been used with the RAI data (May et al., 2011) as well as the jockey data presented in chapter 3 (Conroy et al., 2011). This bridge between computer scientists and sports scientists may eventually lead to the ability to link multiple sensor data sets and query the data with minimal knowledge of the programming skills currently needed to do so.

## *5.4.10 Research Implications*

By processing the data using a context specific method it is possible to not only detect when an event occurred and segment the data based on these events, but also to easily define the data that is sought automatically. The ability to segment data from the GT3X ActiGraphs is present within the Actilife software, however it necessitates the inputting of defined periods to analyse. This requires the user to know what time events occurred and thus is not automatic. By removing this need from the user it is possible to speed up the ability to process data but also to investigate what is actually important during the event, the performance of the athletes.

By approaching the estimation of power output during the RAI using data from the MPTs as the baseline, it was possible to relate activity data to a standard measurement technique of power output. This shows promise in the ability to pro-actively predict what may occur during a race. By modulating the value for the MPT it may be possible to look at the effect of different pacing strategies and their energy demands.

Through the integration of such event specific processing methods it may be possible to pull specific events out of a dataset that are pertinent to performance within that event. Each of these events will first have to be defined using the sensor that is being used to gather the data. This definition of events would result in the ability to gather data on day-by-day activities of a subject, apply the necessary event specific methods, and gather data on each of the events.

## 5.5 Summary

Based on the findings of the present study, which acted as a deployment test-bed, the use of accelerometer based technologies in the estimation of physical activity in the cycling environment shows some promise. With the ability to measure not only the amount of physical activity undertaken, but to also define and measure specific periods of cycling and resting, they may add an additional level of context to data that has not yet been available.

The data presented suggests that in the latter stages of ultra-endurance team cycle races, switching to a shorter duration cycle bouts may allow cyclists to maintain higher power outputs. This warrants further investigation as, if this is true, the implications for team racing strategies during the RAI or RAAM are quite large. Many teams continue to adopt the 'cycle till you drop' mentality, but this data suggests that less is more when it comes to these races.

It is probable that this additional context may be of no interest in shorter traditional cycling events such as road and mountain bike racing. However, in longer ultra-endurance events such as the RAI and 24 hour mountain bike racing, it will allow the athletes and their coaches to further evaluate their performance post-event. Although this can be done using other technologies such as GPS and power meters, the integration of additional measurement taken at the user rather than the bicycle may give a better insight of what is actually occurring during these races as they involve significant amounts of time off bike for the competitors. The ability to automatically segment data, investigate physiological variables of importance and manipulate the data in order to help with future pacing strategies may help teams tailor their approach to these gruelling events.

# Chapter 6: Summary, Conclusions and Recommendations for Future Research

## *6.1 Summary*

The aim of this research was to assess the feasibility of deploying the GT3X ActiGraph accelerometer platform as a tool to measure physical activity in three distinct environments: horse-riding, search and rescue operations and ultra-endurance cycling. The GT3X actigraph was deployed in these environments in a variety of manners including: multiple units in parallel with indirect measures of energy expenditure, in conjunction with the Sensewear™ multi-sensor platform validated as an estimate of energy expenditure, and in solo deployments over prolonged durations with no other methods of estimating energy expenditure.

In each environment, limitations to the use of the GT3X ActiGraphs became apparent. Within the horse-racing environment the movement of the horse, or ergometer, overrode the sensors ability to capture applicable data. Within the search and rescue environment, the inability to deploy any form of gold standard measurement equipment for comparison gave an unclear picture as to which measurement location was best for the sensors. Within the ultra-endurance cycling environment, a lack of large numbers and equipment or any other data resulted in any gathered data being descriptive of the event rather than objectively stating what occurred during the event.

Each of the studies showed that it is feasible to deploy these sensors within each of the environments. However, without the ability to objectively state that the data is valid within each environment the data must be taken with caution until future validation studies have been performed.

In future studies with these sensors it will be necessary to deploy them within an environment and develop environmental specific measurement algorithms in order to gather data that is not only applicable to the environment itself, but to the specific sensor in a specific location.

## *6.2 Feasibility in the Horse-Riding Environment*

In the first study investigating the horse riding environment, multiple GT3X ActiGraphs located at several measurement sites were deployed on jockeys in conjunction with the the Cosmed Kb4[2], a system capable of indirect energy expenditure measurement during physical activity. Using two systems concurrently is a standard method to assess the applicability of a technology and its ability to estimate the energy expenditure during a specific physical activity within an environment.

In all but one incidence (Table 3.7) the GT3X ActiGraphs produced significantly different estimates of physical activity than the Cosmed Kb4[2]. These differences occurred indoors and outdoors across a range of riding intensities. This implies that the GT3X ActiGraph is not suitable as an estimate of physical activity during horse-riding. However, as discussed in section 2.1.4 an accelerometer generates a measurable signal that is an expression of the accelerations experienced by the unit. The ability of this signal to be correctly interpreted and transferred into a measure of physical activity is only possible under certain conditions. In the case of accelerometery measures taken during horse-riding it appears that the effect of the motion of the horse on the jockey overrides any movements created by the jockey. This results in physical activity data on the jockey being lost in the movement imparted on them by the horse itself.

The Nyquist Principal states that '*the sampling rate should be greater than or equal to twice that of the highest frequency contained within the signal*' (Chen et al., 2012). During pilot studies, raw data from a GT3X+ ActiGraph placed on the saddle of the equine simulator was analysed. It was found that the frequency of oscillation of the simulator at all but the lowest intensity (stage 2) exceeded that of the maximal sample rate of the GT3X ActiGraph (30Hz). The maximal accelerations measured via the GT3X+ ActiGraph were also seen to experience the plateau effect as noted in section 2.4.6. This resulted in a problem with using the GT3X ActiGraphs within this environment. Even in their most powerful data capture form, that of raw acceleration measurement mode, they failed to capture data that was capable of analysing the motion of the ergometer.

It is possible that the limited smaller measurement range of the GT3X ActiGraph is either failing to capture all data, or being over-ridden by the motion of the horse itself. Although this is an environment where the light weight and small size of these accelerometers is ideal, the rate at which movements occur during horse-riding and the range of acceleration simply exceed that of the capacity of the units in order to discern the rider over the mount thus, rendering them useless. Through the use of the newer GT3X+ model it may be possible to gather finer data; however it is still possible that the newer unit may also exceed its measurement range during very high intensity horse riding, e.g. galloping, which was not assessed during this study. Due to this it was necessary to analyse data in a count based mode that was down-stepped from the captured raw data. However, as it was a feasibility study to investigate the possibility of using this lightweight sensor in this environment the use of a count-based approach was not a limitation in itself as it gave an insight into what was possible with the sensors in this environment.

During testing, similarities in physical activity data existed between the ankle mounted GT3X and the saddle mounted GT3X. This further strengthens the case for the inapplicability of the GT3X in its proprietary analysis format as it appears that the action of the horse, or simulator, effectively overwrites the physical activity data of the jockey. From this it is possible to surmise that the effect of the horse on the jockey is not negligible, and may be quantifiable in this manner. This is in itself a benefit of the GT3X ActiGraphs as this may allow data to be gathered on the effect of the horse on the jockey and further the body of data that is becoming concerned with jockey training and well being (Warrington et al., 2009; Dolan et al., 2010; Dolan et al., 2011). It is also logical to assume that the action and fitness of the jockey may have an impact on the horse itself. By using technologies with higher sample ranges and rates than the GT3X it may be possible to measure this effect. However, without the limited weight penalty that the GT3X ActiGraphs bring, members of the horse-racing community may be reticent to use them.

Data is in this study was captured in a raw format, then stepped down to 1 second count-based epochs for analysis via the proprietary software. There is an opportunity for future analysis of this data in conjunction with the gathered metabolic data using the raw data gathered in this study. However, it is possible that the effect of the horse on the rider must first be investigated and taken into account before this acceleration data would be of use. This may allow for the design of horse riding specific algorithms for both indoor and outdoor riding to better estimate the amount of the energy expended during horse-riding using a simple accelerometer. The current version of the GT3X ActiGraphs do not appear to be capable of performing this task with the current physical activity analysis algorithms.

### *6.3 Feasibility in the Search and Rescue Environment*

Both the GT1M and GT3X ActiGraphs have been shown to be a valid tool in the estimation of physical activity in free living conditions (Sasaki et al., 2011). In order to further examine the feasibility of using the GT3X ActiGraph in a field environment, a deployment was made in a unique free-living environment: search and rescue operations (SAR). In many environments it is possible to deploy direct, validated measures of physical activity to better understand the activities taking place. This was not possible in the case of search and rescue operations due to the nature of the job, the operational environment and the equipment used by SAR operators. Instead, previously validated estimation tools were deployed in conjunction with GT3X+ systems in an attempt to asses the feasibility of using the GT3X+ ActiGraphs as a measure of physical activity within this environment.

Ideally, a system such as heart rate monitoring would have been used but due to electrical issues observed between these systems and the aircraft it was not possible to do so. The issue of electrical disturbance causing failures is a known limitation to heart rate monitoring systems (Chen et al., 2012) and proved to be an issue within the helicopters used for SAR operations. Thus, the deployment of an accelerometer based system that can estimate physical activity should be ideal within this environment. Due to the nature of the environment being studied, the waterproof GT3X+ ActiGraph model was used instead of the GT3X ActiGraph. Although this system captures data at a higher sample rate, the assessment of physical activity performed via the propitiatory software is undertaken at a stepped down 1 second rate so data would be comparable to other, older GT3X platforms. The GT3X+ also uses the same accelerometer sensor board that the GT3X uses so any issues associated with a change in hardware should not be negligible.

Although the results of the comparisons for physical activity and total estimated energy expenditure made between the SenseWear™ and the GT3X+ ActiGraphs were different, these differences can be attributed to the multi-sensory nature of the SenseWear™ and its ability to estimate energy expenditure via a combination of several methods (Liden et al., 2002). However, as the GT3X+ ActiGraph only measures physical activity via changes in acceleration associated with different movements it is limited to what aspects of all day activity it can record. For example, most of the energy expended whilst sleeping or sitting still would be lost as there is no associated movement. This is a primary limitation to the GT3X+ ActiGraph in this environment. As an estimate of all day energy expenditure it is not correct to assume that it is capturing all the energy expended.

During testing the ankle mounted GT3X+ ActiGraph and waist mounted GT3X+ ActiGraph did statistically differ from each other when an estimation of subjects' total daily energy expenditure was made using a calculated resting metabolic rate for each subject. In this case the ankle mounted GT3X+ ActiGraph also statistically differed from the SenseWear™. This implies that with the additional measure for the resting energy expenditure taken into account within these systems the effect of location of the sensor is still important even while the same sensor platform is being used. It is possible the waist mounted GT3X+ underestimated the amount of physical activity, but it is also possible the ankle mounted GT3X+ overestimated the physical activity due to gathering measures at a site with larger scope for movement. It may also be that one or more of these systems were reporting inaccurately, with the SenseWear™ having been previously shown to be a poor measure of high intensity exercise (Drenowatz & Eisenmann, 2011). This effect may also have been due to the multi-sensory nature of the SenseWear™ which by incorporating a thermocouple may have skewed estimates of energy expenditure due to the increased temperature experienced by SAR operators while in their immersion suits. However, without further analysis it is not possible to definitively say if this was a contributing factor.

As a physical activity monitor within the SAR environment the GT3X+ may be a feasible tool to use in order to estimate the physical activity undertaken by SAR operators. In a similar manner to the estimated energy expenditure, the physical activity estimated by the sensors differed to each other based on the location it was taken. The data also showed that there was a difference in physical activity depending on which group a SAR operator belonged to, either a habitual at home or on base sleeper. However, when subjects from the same group were studied under both environmental conditions no differences in physical activity were shown. This leans towards the the GT3X+ as a feasible measure of physical activity in this environment as there were no statistical differences shown. This also showed true for sleep variables measured with the GT3X+ platform. Although the numbers in the study are not large, they are representative of 63% of the population of the Dublin SAR base. Ideally more data would be gathered to further strengthen this argument, however this is not possible as the turn over in staff at the base is low.

The ability of the GT3X+ Actigraph to act as a multi-purpose sensor was further investigated in this study in conjunction with the SenseWear™ armband which had already been used in this capacity as a measure of sleep and physical activity (Sunseri, 2009). While the ability to gather both estimated energy expenditure data, physical activity data and sleep data is possible with multiple units, the ability to do so with one system is more desirable. Unlike the SenseWear™, the GT3X+ ActiGraph furthers this ability by being able to gather both physical activity estimations as well as sleep data using a single sensor rather than the multiple sensors that the SenseWear™ employs. This reduces the storage space needed for data and a reduction in battery consumption,resulting in longer deployment time. The ability of the GT3X+ ActiGraph to gather multiple forms of data is of massive benefit to the researcher. By deploying these systems over extended durations in a search and rescue environment it may be feasible to investigate the interaction between physical activity, sleep duration and sleep quality over prolonged periods, using a single unit. The ability to measure so many variables would also make the system useful in the evaluation of performance in any extended duration environment where repeat exposure to high amounts of physical activity or low amounts of sleep may impact performance.

However, gathering sleep data in this environment was not without its pitfalls. In order to gather sleep data from subjects it was necessary to know both the time they went to sleep and the estimated time that they woke. This must be manually segmented by the researcher during analysis and introduces another level of error to the data as these time slots are estimates provided by the user and independent of the researcher. This is in addition to the existing limitation of the current sleep algorithms which are based off a 60 second epoch and cannot account for short periods of activity during the night thus underestimating any physical activity that may occur during the 'sleep' period. Although the data from the GT3X+ ActiGraphs was consistent with regard to sleep duration or sleep efficiency, the results were, unsurprisingly, different from the SenseWear™. In all cases the GT3X+ Actigraphs overestimated sleep duration and efficiency compared to the SenseWear™. Unfortunately, until these new sensor platforms are compared against gold standard laboratory measures such as polysomonography it is not possible to say that they are accurately reporting sleep data. However, as previously outlined, this area is currently in its infancy and may not be as simple as just gathering data from subjects, and may require performing more analysis and validation studies. Despite any limitations in measurement, no significant differences were observed for sleep data between on and off-base locations. This implies that the GT3X+ ActiGraphs are feasible measurement tools no matter which sleep environment they were used in.

## *6.4 Feasibility in the Ultra-endurance Cycle Racing Environment*

In the final study the feasibility of using the GT3X ActiGraphs as both a physical activity monitor and a tool to investigate aspects of an ultra-endurance cycle race was undertaken. This deployment required a lightweight monitoring system with the capacity to perform analysis on multiple variables over the extended duration of an ultra-endurance cycle race, the Race Around Ireland (RAI). Although it is possible to take direct measures of the power output, time, and estimate the energy expended during cycle racing via systems such as the SRM power meter and Cosmed; these systems are expensive, heavy and are limited by both battery life and storage capacity.

Such systems only measure one aspect of an ultra-endurance cycle race, that of cycling, and are incapable of giving data on the larger proportion of these events that are spent off bike resting and recovering. The feasibility of deploying a relatively cheap lightweight accelerometer based technology such as the GT3X ActiGraph which is capable of gathering data from both cycle and rest periods may provide the potential to better understand the entirety of these physically demanding, prolonged events.

Previous studies have shown the limitations of accelerometer based measures of physical activity in the cycling environment due to measurements taken at the hip (Godfrey et al., 2008; Long et al., 2009). The ankle was therefore a logical deployment location in this environment in order to estimate the physical activity undertaken during the RAI. The adoption of the ankle as a point of measurement not only allowed for the measurement of the physical activity during cycling, but also for a measure to be taken of physical activity during the rest and recovery periods in the race. This called for the ability to recognise periods of cycling and rest via the accelerometer and thus segregate the data based on this. The use of the ankle as a deployment location also lead to the possibility of estimating the power outputs of each cycle bout during the race. This necessitated the development of a method of scaling the captured data to that of a laboratory standard test.

This does somewhat call into question the use of the software package designed for the GT3X ActiGraphs, ActiLife. the proprietary software from the GT3X was capable of estimating the overall physical activity during the race, it was incapable of measuring specific bouts of cycling without excessive data mining by the researchers. It was also incapable of differentiating between cycling and non cycling bouts. This limitation was not due to the feasibility of deploying the sensors within the environment, but the development of the analysis tools that are capable of dealing with the amount of data that is produced during these events. If the GT3X ActiGraphs were to be used as a performance measurement tool, they may not provide an accurate view of the physical activity during cycling periods or the impact of these bouts on the cyclist's overall performance during the race if the basic data that is taken from ActiLife is the only analysis undertaken. Due to these limitations, the development of a specific method of detecting each cycling period was undertaken in order to attempt to classify these periods.

As the GT3X ActiGraph had been shown to provide an accurate measure of the intensity of activities performed (Carr et al., 2012) an intensity weighting was defined for each cycling period during the RAI. However, as the GT3X ActiGraphs had never been deployed in this duration within the cycling domain it necessitated the development of a separate laboratory test which allowed for the intensity of each cycling period to be transformed, via a previously recorded static measure of cycling performance undertaken in a laboratory, into an estimate of the amount of power produced in each cycle period. This data was then transferred to a profile for each cycle bout for each subject throughout the race. This specific manner of analysing the data from the RAI shows how it is not necessarily the data capture device that is the limitation to the feasibility of using accelerometer driven sensors within an environment, but rather the methodology by which the data is analysed.

Although using a scaled estimate of the power produced is not ideal, this is a first attempt to utilise the data from the accelerometer in a manner that classifies an event and makes estimations based on predefined variables. In order to further develop the ability of these sensors to better represent the activities that are occurring it is necessary for a combined physiological and computer science approach to be taken in order to better assess the data these units can gather, and to move away from propitiatory software analysis.

## *6.5 Study Implications and Conclusion*

The GT3X ActiGraph and its successor the GT3X+ ActiGraph appear to provide an feasible method to estimate physical activities within certain environments. However, in cases where an activity is taking place in an environment where external motion from another body is acting on a subject, such as during horse-riding, they appear to no longer deliver relevant data. Simply put, the hardware of the sensor is not capable of differentiating between acceleration sources, nor is it capable of measuring with a range great enough to gather applicable data on these environments. This is primarily due to the accelerations being imparted onto the subjects from the source nullifying any measurements taken of the subjects themselves. This is a hardware measurement constraint which it may not be possible to overcome with current measurement techniques. Although this inability of the sensors to deliver applicable data within these environments may seem to be a contra-indication to their use in these environments, it may be possible that further analysis of the data in conjunction with computer scientists, or engineers, may allow for the captured data to be utilised through the emerging research areas of artificial neural networking or signal recognition and analysis.

This measurement constrain brings attention to the need to develop new methods of not only estimating energy expenditure based on the raw acceleration data, but also to develop methods of filtering out event specific external motions. It is possible that this may be undertaken in a crude manner by gathering data at the source itself and simply removing this signal from the subject's data. However, this is unlikely to work as the GT3X ActiGraphs are maxing out along each plane of measurement and experiencing a plateau effect, as outlined in section 2.4.6. Thus there is a need for a higher resolution version of the existing systems that can measure a greater acceleration range, thereby giving a better chance of separating the data under conditions where large external movement sources exist. Until these systems are available for use by researchers, it is not feasible to use the GT3X ActiGraph platform in environments such as horse-racing where these external accelerations occur without further investigation into the possibility of either separating the data from the mount, or developing another more applicable analysis tool.

In environments where this external motion does not appear to be a factor, the GT3X ActiGraph platform appears to have the capability to perform more than just its basic function of physical activity measurement. However, to do so still necessitated the development of specific analysis tools and methods with the aid of computer scientists in certain environments that were outside the basic 'free-living' conditions the GT3X ActiGraphs were developed for. With the application of these systems in more environments, and across a broader range of physical activities, it may be possible to build up a bank of data that can be analysed post-hoc. This may be undertaken using the developing methods of artificial neural networks and advanced computer learning techniques that are being developed by several software engineer groups.

From the presented study is not possible to objectively say that the GT3X+ ActiGraph platform can deliver accurate and reliable data in each of environments studied. However, it is feasible to gather data over prolonged periods of time, in environments where few sensors systems are capable of operating under, and with a minimal weight penalty or interference with their users during sporting events. In its current form, for the researcher who is looking to do no more than measure an event, this platform may not directly fulfil this function. However, for researchers looking to rapidly investigate a range of activities using a simple low cost tool with practically no environmental limitations it provides a valuable tool with a developing research driven community that may enable it to overcome some of its current hardware restrictions.

## *6.6 Recommendations for Future Research*

The aim of this research was to estimate physical activity in unique environments, using a simple commercially available accelerometer platform the GT3X ActiGraph. The GT3X ActiGraph provides a simple low cost method of estimating physical activity in certain environments once the environment is effectively static and not imparting any major external accelerations.

Although the GT3X ActiGraphs are capable of delivering basic contextual data on an environment, it necessitates the development of advanced methods of estimation based on the raw combined vector signals rather than based on the legacy algorithms developed for its precursors. Although a large body of research exists for these count based measures, they are not capable of measuring complex, or environment specific events that are the real components of an environment that a researcher may be interested in.

Although the studies are presented in a specific order based on number of GT3X ActiGraphs deployed, multiple units first – single units last, the studies themselves were not carried out in this order. Study 3 (Race Around Ireland) was undertaken in 2009, study 1 (Jockey Study) was undertaken in 2011 and study 2 (SAR Study) was undertaken between 2011 and 2012. During this period the GT3X actigraph was superseded once by the GT3X+ actigraph and once again by the wGT3X+ ActiGraph.

This rapid rate of development of the hardware has not been mirrored by the software methods of estimating physical activities. The algorithms embedded in the newest version of the GT3X ActiGraphs proprietary software, ActiLife, are still based on algorithms developed for the older GT1M ActiGraph, a dual axial model (Dinish et al., 2011). Due to this, many of the variables do not use all the data available to them in their calculations as they are based on single vector measures along one axis. In these cases the data used is also not the raw acceleration data, but pre-filtered data not dependant on the sample rate. When using these older assessment algorithms there are no benefits in using the more modern versions of the hardware bar increased deployment length due to storage capacity and battery life.

Advances in the analysis methods that are being used to estimate energy expenditure with the GT3X ActiGraph platform have resulted in a move away from an arbitrary count based algorithm, towards a vector acceleration based model (Sasaki et al. 2011, Freedson et al. 2012). These vector acceleration based models may lead to the possibility of activity and environment specific algorithms for energy expenditure estimation with these units as they aim to characterise activities as a three dimensional motion rather than in a single plane. However, these models still rely on a count-based data analysis rather than the pure raw data itself. With recent updates to the GT3X platform occurring on a six monthly basis, it is possible that an accelerometer board with a greater range may be in development for the platform which would allow for better use of this its raw data analysis capacity.

As the data gathered throughout this thesis was in a raw format, stepped down to count-based for analysis, it may be possible to revisit these studies at a later stage when activity specific algorithms have been developed. It may also be possible to start developing specific methods of analysing data within each of these environments with more complex versions of the Ultracal and Ergocal methods. This would not have been possible with the more traditional count based method of estimation that is commonly employed with these units. The current methods may allow for a more accurate understanding of the energy expended during specific aspects within each environment studied. However, in order to fully utilise the hardware capabilities of the GT3X ActiGraphs and its successors, software and analysis techniques will need to mirror the rate of technological development of the sensors.

## *6.7 Synopsis*

These studies aimed to asses the feasibility of deploying the GT3X ActiGraphs within each of the studied environments. Each of the studies show that the sensor platform may be physically deployed within their respective environments with minor issues, researcher input error and waterproofing being the prime concerns and cause of sensor failure.

However, the validity of these sensors within each environment must be called into question as the above studies only assess the feasibility of gathering applicable data within each of these unique environments.

It is not possible at this time to say that the data provided is one hundred percent accurate as it was not possible in most instances to deploy the sensors in conjunction with other valid measures of physical activity. But, they do provide a means by which to gather data that may be analysed in environments where it has, until now, not been possible, or feasible, to gather representative physical activity data.

With time, and utilising the data captured from the GT3X sensor platform, hopefully it may be possible, with the help of computer scientists, to further develop specific analysis techniques that may allow these sensors to provide accurate data in any of these environments.

# Chapter 7: Bibliography

Achten, Juul & Jeukendrup, A.E., 2003. Heart rate monitoring: applications and limitations. *Sports medicine (Auckland, N.Z.)*, 33(7), pp.517–38. Available at: http://www.ncbi.nlm.nih.gov/pubmed/12762827.

Argyrous, George, 2005. Statistics for research: with a guide to SPSS, 2nd ed. *SAGE Publications 2005.*

Ainsworth, B E et al., 1993. Compendium of physical activities: classification of energy costs of human physical activities. *Medicine & Science in Sports & Exercise*, 25(1), p.71. Available at: http://journals.lww.com/acsm-msse/abstract/1993/01000/compendium_of_physical_activities__classification.11.aspx.

Ainsworth, Barbara E et al., 2011. 2011 Compendium of Physical Activities. *Medicine and Science in Sports and Exercise*, 43(8), pp.1575–1581. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21681120.

Ancoli-Israel, S. et al., 2003. The role of actigraphy in the study of sleep and circadian rhythms. *Sleep*, 26(3), pp.342–92. Available at: http://www.ncbi.nlm.nih.gov/pubmed/12749557.

Atkinson, Greg et al., 2003. Science and cycling: current knowledge and future directions for research. *Journal of sports sciences*, 21(9), pp.767–87. Available at: http://www.ncbi.nlm.nih.gov/pubmed/14579871.

Balasubramanian, V., Dutt, A. & Rai, S., 2011. Analysis of muscle fatigue in helicopter pilots. *Applied ergonomics*, 42(6), pp.913–8. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21411058.

Banda, J.A. et al., 2010. Comparing physical activity measures in a diverse group of midlife and older adults. *Medicine & Science in Sports & Exercise*, 42(12), pp.2251–2257. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20421836.

Barrey, E. et al., 1993. Stride characteristics of overground versus treadmill locomotion in the saddle horse. *Acta Anatomica*, 146(2-3), pp.90–94. Available at: http://www.ncbi.nlm.nih.gov/pubmed/8470471.

Bassett, D R et al., 1996. Accuracy of five electronic pedometers for measuring distance walked. *Medicine & Science in Sports & Exercise*, 28(8), pp.1071–1077. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17461834.

Bassett, David R, Rowlands, A. & Trost, S.G., 2012. Calibration and validation of wearable monitors. *Medicine and science in sports and exercise*, 44(1 Suppl 1), pp.S32–8. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3273335&tool=pmcentrez&rendertype=abstract.

Bescós, R. & Rodríguez, F., 2012. High energy deficit in an ultraendurance athlete in a 24-hour ultracycling race. *Proceedings (Baylor …*, 25(2), pp.124–128. Available at: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3310508/.

Bessa, A. et al., 2008. High-intensity ultraendurance promotes early release of muscle injury markers. *British journal of sports medicine*, 42(11), pp.889–93. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18203867.

Bouten, C.V. et al., 1994. Assessment of energy expenditure for physical activity using a triaxial accelerometer. *Medicine & Science in Sports & Exercise*, 26(12), pp.1516–1523. Available at: http://alexandria.tue.nl/repository/freearticles/605366.pdf.

Brazeau, A. & Karelis, A., 2011. Accuracy of the SenseWear Armband™ during ergocycling. … *journal of sports* …, pp.761–764. Available at: http://www.thieme-connect.com/ejournals/abstract/sportsmed/doi/10.1055/s-0031-1279768.

Brickley, G., Doust, J. & Williams, C. a, 2002. Physiological responses during exercise to exhaustion at critical power. *European journal of applied physiology*, 88(1-2), pp.146–51. Available at: http://www.ncbi.nlm.nih.gov/pubmed/12436283.

Brooks, G. a, 2007. Lactate: link between glycolytic and oxidative metabolism. *Sports medicine (Auckland, N.Z.)*, 37(4-5), pp.341–3. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17465603.

Bull, a J. et al., 2000. Effect of mathematical modeling on the estimation of critical power. *Medicine and science in sports and exercise*, 32(2), pp.526–30. Available at: http://www.ncbi.nlm.nih.gov/pubmed/10694142.

Butte, N.F., Ekelund, U. & Westerterp, Klaas R, 2012. Assessing physical activity using wearable monitors: measures of physical activity. *Medicine and science in sports and exercise*, 44(1 Suppl 1), pp.S5–12. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22157774.

Callard, D. & Davenne, D., 2001. Nycthemeral variations in core temperature and heart rate: continuous cycling exercise versus continuous rest. … *journal of sports* …, pp.553–557. Available at: http://www.thieme-connect.com/ejournals/abstract/sportsmed/doi/10.1055/s-2001-18524.

Capani, F. et al., 1982. Measurement of energy expenditure through heart rate monitoring. *Bollettino Della Societa Italiana Di Biologia Sperimentale*, 58(3-4), pp.162–164.

Carr, L.J. & Mahar, M.T., 2012. Accuracy of intensity and inclinometer output of three activity monitors for identification of sedentary behavior and light-intensity activity. *Journal of obesity*, 2012, p.460271. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3228344&tool=pmcentrez&rendertype=abstract.

Carrier, J., 2000. Circadian rhythms of performance: new trends. *Chronobiology international*, 17(6), pp.719–732. Available at: http://informahealthcare.com/doi/abs/10.1081/CBI-100102108.

Chau, J.Y. et al., 2011. Validity of the occupational sitting and physical activity questionnaire. *Medicine & Science in Sports & Exercise*, 44(1), pp.118–25. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21659903.

Chen, K.Y. et al., 2012. Redefining the roles of sensors in objective physical activity monitoring. *Medicine and science in sports and exercise*, 44(1 Suppl 1), pp.S13–23. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3245644&tool=pmcentrez&rendertype=abstract.

Conroy, K., 2011. A Query Service for heterogeneous Sensor Devices.

Conroy, K., May, G., Roantree, M., et al., 2011. Expanding sensor networks to automate knowledge acquisition. *Advances in Databases*, pp.1–12. Available at: http://www.springerlink.com/index/G60140855357014N.pdf .

Conroy, K., May, G., Doherty, A., et al., 2011. Integration of Physical Sensors in Ultra-Endurance Cycling.

Conroy, K. et al., Knowledge Acquisition from Sensor Data in an Equine Environment.

Coyle, E F et al., 1991. Physiological and biomechanical factors associated with elite endurance cycling performance. *Medicine and science in sports and exercise*, 23(1), pp.93–107. Available at: http://www.ncbi.nlm.nih.gov/pubmed/1997818.

Coyle, Edward F, 2005. Improved muscular efficiency displayed as Tour de France champion matures. *Journal of applied physiology (Bethesda, Md. : 1985)*, 98(6), pp.2191–6. Available at: http://www.ncbi.nlm.nih.gov/pubmed/15774697.

Crespo, C. & Aboy, M., 2012. Automatic identification of activity – rest periods based on actigraphy. *Medical and Biological*, pp.329–340. Available at: http://www.springerlink.com/index/27K7777471226351.pdf.

Croft, J.L., Pittman, D.J. & Scialfa, C. (Chip) T., 2007. Gaze behavior of spotters during an air-to-ground search. *HUMAN FACTORS*, 49(4), pp.671–678.

Crouter, S.E. et al., 2006. A novel method for using accelerometer data to predict energy expenditure. *Journal of applied physiology (Bethesda, Md. : 1985)*, 100(4), pp.1324–31. Available at: http://www.ncbi.nlm.nih.gov/pubmed/16322367.

Crouter, S.E. et al., 2003. *Validity of 10 electronic pedometers for measuring steps, distance, and energy cost.*, Available at: http://www.ncbi.nlm.nih.gov/pubmed/12900704.

Devienne, M.F. & Guezennec, C.Y., 2000. Energy expenditure of horse riding. *European journal of applied physiology*, 82(5-6), pp.499–503. Available at: http://www.ncbi.nlm.nih.gov/pubmed/10985607.

Dinesh, J. & Freedson, P., 2012. ActiGraph and Actical physical activity monitors: a peek under the hood. *Medicine and science in sports and exercise*, 44(1 Suppl 1), pp.S86–9. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3248573&tool=pmcentrez&rendertype=abstract

Dolan, E., McGoldrick, A., et al., 2012. An altered hormonal profile and elevated rate of bone loss are associated with low bone mass in professional horse-racing jockeys. *Journal of bone and mineral metabolism*. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22491874.

Dolan, E. et al., 2011. Nutritional, lifestyle, and weight control practices of professional jockeys. *Journal of sports sciences*, 29(8), pp.791–9. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21506039.

Dolan, E., 2010. The Impact of Acute and Chronic Weight Restriction and Weight Regulation practices on Physiological, Osteogenic, Metabolic and Cognitive Function in Elite Jockeys. , (September). Available at: http://doras.dcu.ie/15720/.

Dolan, E., Crabtree, N., et al., 2012. Weight regulation and bone mass: a comparison between professional jockeys, elite amateur boxers, and age, gender and BMI matched controls. *Journal of bone and mineral metabolism*, 30(2), pp.164–70. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21773703.

Drenowatz, C. & Eisenmann, Joey C, 2011. Validation of the SenseWear Armband at high intensity exercise. *European journal of applied physiology*, 111(5), pp.883–7. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20972880.

Drust, B. et al., 2005. Review circadian rhythms in sports performance— an update. , 22(1), pp.21–44.

Duc, S. & Villerius, V., 2007. Validity and Reproducibility of the Ergomo® Pro Power Meter Compared With the SRM and Powertap Power Meters. *International Journal of …*, pp.270–281. Available at: http://www.fredericgrappe.com/CV/bibliographie/D23.pdf.

Eaton, M.D. et al., 1995. Maximal accumulated oxygen deficit in thoroughbred horses. *Journal of Applied Physiology*, 78(4), pp.1564–1568. Available at: http://www.ncbi.nlm.nih.gov/pubmed/7615470.

Enqvist, J.K. et al., 2010. Energy turnover during 24 hours and 6 days of adventure racing. *Journal of sports sciences*, 28(9), pp.947–55. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20544486.

Falleti, M.G. et al., 2003. Qualitative similarities in cognitive impairment associated with 24 h of sustained wakefulness and a blood alcohol concentration of 0.05%. *Journal of sleep research*, 12(4), pp.265–74. Available at: http://www.ncbi.nlm.nih.gov/pubmed/14633237.

Fallon, K.E. et al., 1999. Changes in haematological parameters and iron metabolism associated with a 1600 kilometre ultramarathon. *British Journal of Sports Medicine*, 33(1), pp.27–31. Available at: http://bjsm.bmj.com/cgi/doi/10.1136/bjsm.33.1.27.

Faria, E.W., Parker, D.L. & Faria, I.E., 2005a. The Science of Cycling Physiology and Training – Part 1. *Training*, 35(4), pp.285–312.

Faria, E.W., Parker, D.L. & Faria, I.E., 2005b. The science of cycling: factors affecting performance - part 2. *Sports medicine (Auckland, N.Z.)*, 35(4), pp.285–312. Available at: http://www.ncbi.nlm.nih.gov/pubmed/15831059.

Francis, J.T. et al., 2010. Defining intensity domains from the end power of a 3-min all-out cycling test. *Medicine and science in sports and exercise*, 42(9), pp.1769–75. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20142776.

Frankenfield, D.C., Muth, E.R. & Rowe, W.A., 1998. The Harris-Benedict studies of human basal metabolism: history and limitations. *Journal of the American Dietetic Association*, 98(4), pp.439–445. Available at: http://www.ncbi.nlm.nih.gov/pubmed/9550168.

Freedson, P. et al., 2012. Assessment of physical activity using wearable monitors: recommendations for monitor calibration and use in the field. *Medicine and science in sports and exercise*, 44(1 Suppl 1), pp.S1–4. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3245520&tool=pmcentrez&rendertype=abstract.

Fruin, M.L. & Rankin, J.W., 2004. Validity of a Multi-Sensor Armband in Estimating Rest and Exercise Energy Expenditure. *Medicine & Science in Sports & Exercise*, 36(6), pp.1063–1069. Available at: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00005768-200406000-00021.

Gastin, P., Netto, K. & Williams, K, 2008. Determination of stride frequency using an accelerometer during equine locomotion.

Gauvreau, G.M. et al., 1995. Comparison of aerobic capacity between racing standardbred horses. *Journal of Applied Physiology*, 78(4), pp.1447–1451.

Gianetti, G., Burton, L. & Donovan, R., 2008. Physiologic and Psychological Responses of an Athlete Cycling 100+ Miles Daily for 50 Consecutive Days.

*Current sports …*, 1110, pp.343–347. Available at: http://journals.lww.com/acsm-csmr/Abstract/2008/11000/Physiologic_and_Psychological_Responses_of_an.11.aspx.

Gnehm, P. et al., 1997. *Influence of different racing positions on metabolic cost in elite cyclists.*, Available at: http://www.ncbi.nlm.nih.gov/pubmed/9219211.

Godfrey, a et al., 2008. Direct measurement of human movement by accelerometry. *Medical engineering & physics*, 30(10), pp.1364–86. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18996729.

Green, K. et al., 2007. A Real-Time Position, Velocity, and Physiological Monitoring and Tracking Device for Equestrian Training. *adamjhill.com*, (September), pp.25–28. Available at: http://adamjhill.com/Green + Hill - ION GNSS 2007.pdf.

Grissom, C., Thomas, F. & James, B., 2006. Medical helicopters in wilderness search and rescue operations. *Air medical journal*. Available at: http://www.sciencedirect.com/science/article/pii/S1067991X05001847.

Hansen, T.A.S. et al., 2012. Arterial Oxygen Pressure Following Whole-Body Vibration at Altitude. *Aviation, Space, and Environmental Medicine*, 83(4), pp.431–435. Available at: http://www.ingentaconnect.com/content/asma/asem/2012/00000083/00000004/art00009.

Hettinga, F.J. et al., 2007. The effect of ambient temperature on gross-efficiency in cycling. *European journal of applied physiology*, 101(4), pp.465–71. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2039810&tool=pmcentrez&rendertype=abstract.

Hitchens, P. et al., 2011. Predictors of race-day jockey falls in jumps racing in Australia. *Accident; analysis and prevention*, 43(3), pp.840–7. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21376874.

Hitchens, P.L. et al., 2010. Predictors of race-day jockey falls in flat racing in Australia. *Occupational and environmental medicine*, 67(10), pp.693–8. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20573845.

Howe, C.A., Staudenmayer, J.W. & Freedson, Patty S, 2009. Accelerometer prediction of energy expenditure: vector magnitude versus vertical axis. *Medicine & Science in Sports & Exercise*, 41(12), pp.2199–206. Available at: http://www.ncbi.nlm.nih.gov/pubmed/19915498.

Hulton, A. et al., 2010. Energy expenditure in the Race Across America (RAAM). *Int J Sports*, pp.463–467. Available at: http://www.thieme-connect.com/ejournals/abstract/sportsmed/doi/10.1055/s-0030-1251992.

Jakicic, J.M. et al., 2004. Evaluation of the SenseWear Pro Armband to Assess Energy Expenditure during Exercise. *Medicine & Science in Sports & Exercise*, (14), pp.897–904. Available at: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00005768-200405000-00024.

Jenkins, J.L. et al., 2006. Strategies to improve sleep during extended search and rescue operations. *Prehospital emergency care : official journal of the National Association of EMS Physicians and the National Association of State EMS Directors*, 11(2), pp.230–3. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17454814.

Jeukendrup, A.E., 2005. Measurement of substrate oxidation during exercise by means of gas exchange measurements. *International journal of sports medicine*, 26 Suppl 1, pp.S28–37. Available at: http://www.ncbi.nlm.nih.gov/pubmed/15702454

Jobson, S. & Hopker, J., 2009. Effect of the Rotor crank system on cycling performance. *Journal of Sports …*, (May), pp.463–467. Available at: http://wlv.openrepository.com/wlv/handle/2436/82895.

John, D et al., 2011. Calibrating a novel multi-sensor physical activity measurement system. *Physiological measurement*, 32(9), pp.1473–89. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3248574&tool=pmcentrez&rendertype=abstract.

John, Dinesh et al., 2012. Biomechanical examination of the "plateau phenomenon" in ActiGraph vertical activity counts. *Physiological measurement*, 33(2), pp.219–30. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22260902.

John, Dinesh, Tyo, B. & Bassett, David R, 2010. Comparison of four ActiGraph accelerometers during walking and running. *Medicine & Science in Sports & Exercise*, 42(2), pp.368–374. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2809132&tool=pmcentrez&rendertype=abstract.

King, G. a. et al., 2004. Comparison of Activity Monitors to Estimate Energy Cost of Treadmill Exercise. *Medicine & Science in Sports & Exercise*, 36(7), pp.1244–1251. Available at: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00005768-200407000-00024.

Kingston, J.K. et al., 2006. Use of a global positioning and heart rate monitoring system to assess training load in a group of Thoroughbred racehorses. , 36, pp.106–109.

Klesges, R.C. et al., 1990. The accuracy of self-reports of physical activity. *Medicine & Science in Sports & Exercise*, 22(5), pp.690–697. Available at: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00005768-199010000-00022.

Knechtle, B., Enggist, A. & Jehle, T., 2005. Energy turnover at the Race Across AMerica (RAAM)-a case report. *International journal of*, pp.499–503. Available at: http://www.thieme-connect.com/ejournals/abstract/sportsmed/doi/10.1055/s-2004-821136.

Koehler, K. et al., 2011. Assessing energy expenditure in male endurance athletes: validity of the SenseWear Armband. *Medicine and science in sports and exercise*, 43(7), pp.1328–33. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21131865.

Kozey, S.L. et al., 2010. Accelerometer output and MET values of common physical activities. *Medicine & Science in Sports & Exercise*, 42(9), pp.1776–1784. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20142781.

Kozey-Keadle, S. et al., 2011. Validation of wearable monitors for assessing sedentary behavior. *Medicine and science in sports and exercise*, 43(8), pp.1561–7. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21233777.

Kripke, D.F. et al., 2010. Actigraphy Wrist actigraphic scoring for sleep laboratory patients : algorithm development. , pp.612–619.

Kusunose, R. & Takahashi, Toshiyuki, 2003. Reliability of EquiPILOT ® for Measuring Aerobic Fitness in. , pp.4–8.

Lanzola, E., Tagliabue, A. & Cena, H., 1990. Skin temperature and energy expenditure. *Annals of nutrition metabolism*, 34(5), pp.311–316.

Latif, S.N. et al., 2010. Saddle pressure patterns of three different training saddles (normal tree, flexible tree, treeless) in Thoroughbred racehorses at trot and gallop. *Equine veterinary journal*, 42 Suppl 3, pp.630–6. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21059072.

Laursen, P., 1999. Physiological analysis of a high intensity ultraendurance event. *Strength & Conditioning Journal*, 21(1), pp.26–38. Available at: http://journals.lww.com/nsca-scj/Abstract/1999/02000/Physiological_Analysis_of_a_High_Intensity.6.aspx.

Laursen, P.B. et al., 2005. Relationship between laboratory-measured variables and heart rate during an ultra-endurance triathlon. , 23(October), pp.1111–1120.

Levine, J. a, 2007. Measurement of energy expenditure. *Public Health Nutrition*, 8(7a), pp.1123–1132. Available at: http://www.journals.cambridge.org/abstract_S1368980005001382.

Liden, C.B. et al., 2002. Characterization and Implications of the Sensors Incorporated into the SenseWear $^{TM}$ Armband for Energy Expenditure and Activity Detection. , pp.1–7.

Long, X., Yin, B. & Aarts, R.M., 2009. Single-accelerometer-based daily physical activity classification. *Conference Proceedings of the International Conference of IEEE Engineering in Medicine and Biology Society*, 2009, pp.6107–6110. Available at: http://www.ncbi.nlm.nih.gov/pubmed/19965261.

Lovett, T., Hodson-Tole, E. & Nankervis, K., 2004. A Preliminary investigation of rider position during walk, trot & canter. *Equine and Comparative Exercise Physiology*, 2(2), pp.71–76.

Machado-Rodrigues, a M. et al., 2012. Concurrent validation of estimated activity energy expenditure using a 3-day diary and accelerometry in adolescents. *Scandinavian journal of medicine & science in sports*, 22(2), pp.259–264. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20561269.

Malavolti, M. et al., 2007. A new device for measuring resting energy expenditure (REE) in healthy subjects. *Nutrition, metabolism, and cardiovascular diseases : NMCD*, 17(5), pp.338–43. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17562571.

Martin, J.L. & Hakim, A.D., 2011. Wrist actigraphy. *Chest*, 139(6), pp.1514–27. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3109647&tool=pmcentrez&rendertype=abstract.

Martin, J.S. et al., 2012. Relationship of Chronotype to Sleep, Light Exposure, and Work-Related Fatigue in Student Workers. *Chronobiology International*, 29(3), pp.295–304. Available at: http://informahealthcare.com/doi/abs/10.3109/07420528.2011.653656.

Martínez-Gómez, D. et al., 2009. *Comparison of the ActiGraph accelerometer and Bouchard diary to estimate energy expenditure in Spanish adolescents.*, Available at: http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&list_uids=20049374.

May, G.C. et al., 2011. Assessment of Physical Activity in Search and Rescue Operations Using Accelerometer Based Technologies. *Amerecian College of Sports Medicine*.

May, G.C. et al., 2010. Correlating multimodal physical sensor information with biological analysis in ultra endurance cycling. *Sensors (Basel, Switzerland)*, 10(8), pp.7216–35. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3231179&tool=pmcentrez&rendertype=abstract.

Miwa, H., 2009. Development of Mental Health Monitor.

Montgomery-Downs, H.E., Insana, S.P. & Bond, J. a, 2011. Movement toward a novel activity monitoring device. *Sleep & breathing = Schlaf & Atmung*. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21971963.

Moseley, L. et al., 2004. No differences in cycling efficiency between world-class and recreational cyclists. *International journal of sports medicine*, 25(5), pp.374–9. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21345628.

Mougin, F., Bourdin, H. & Simon-Rigaud, M., 2001. Hormonal responses to exercise after partial sleep deprivation and after a hypnotic drug-induced sleep. *Journal of sports*, pp.89–97. Available at: http://www.tandfonline.com/doi/abs/10.1080/026404101300036253.

Mujika, I. & Padilla, S., 2001. Physiological and performance characteristics of male professional road cyclists. *Sports medicine (Auckland, N.Z.)*, 31(7), pp.479–87. Available at: http://www.ncbi.nlm.nih.gov/pubmed/11428685.

Mukai, K. et al., 2006. Effect of detraining on cardiorespiratory variables in young thoroughbred horses. *Equine Veterinary Journal Supplement*, (36), pp.210–213. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17402420.

Noakes, T.D., 2006. The limits of endurance exercise. *Basic research in cardiology*, 101(5), pp.408–17. Available at: http://www.ncbi.nlm.nih.gov/pubmed/16915533.

de Oliveira, C.G. & Nadal, J., 2005. Transmissibility spines of pilots of helicopter vibration in the in flight. *AVIATION SPACE AND ENVIRONMENTAL MEDICINE*, 76(6), pp.576–580.

Orzeł-Gryglewska, J., 2010. Consequences of sleep deprivation. *International journal of occupational medicine and environmental health*, 23(1), pp.95–114. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20442067.

Padilla, S. et al., 2001. Exercise intensity and load during mass-start stage races in professional road cycling. *Medicine and science in sports and exercise*, 33(5), pp.796–802. Available at: http://www.ncbi.nlm.nih.gov/pubmed/11323551.

Patterson, M. et al., 2010. Quantifying show jumping horse rider expertise using IMUs. *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, 2010, pp.684–7. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21095894.

Pfau, T., Witte, T.H. & Wilson, A.M., 2006. Centre of mass movement and mechanical energy fluctuation during gallop locomotion in the Thoroughbred racehorse. *The Journal of experimental biology*, 209(Pt 19), pp.3742–57. Available at: http://www.ncbi.nlm.nih.gov/pubmed/16985191.

Powers, P. & Harrison, A., 2002. Effects of the rider on the linear kinematics of jumping horses. *Sports biomechanics International Society of Biomechanics in Sports*, 1(2), pp.135–146. Available at: http://www.embase.com/search/results?subaction=viewrecord&from=export&id=L137608393.

Randle, H., Edwards, H. & Button, L., 2010. The effect of rider position on the stride and step length of the horse at canter. *Journal of Veterinary Behavior*, 5(4), p.220. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1558787809002093.

Ravi, N. et al., 2005. Activity Recognition from Accelerometer Data N. Jacobstein & B. Porter, eds. *Neural Networks*, 20(3), pp.1541–1546. Available at: http://www.aaai.org/Papers/AAAI/2005/IAAI05-013.pdf.

Reilly, Thomas & Brooks, G.A., 1990. selective persistence of circadian rhythms in physiological responses to exercise. , 7(I), pp.59–67.

Reilly, Thomas & Edwards, Ben, 2007. Altered sleep – wake cycles and physical performance in athletes. , 90, pp.274–284.

Rush, E.C., Valencia, M.E. & Plank, L.D., 2008. Validation of a 7-day physical activity diary against doubly-labelled water. *Annals of Human Biology*, 35(4), pp.416–421. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18608111.

Santos-Lozano, A. et al., 2012. Technical variability of the GT3X accelerometer. *Medical engineering & physics*, pp.8–11. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22417978.

Sasaki, Jeffer E, John, Dinesh & Freedson, Patty S, 2011. Validation and comparison of ActiGraph activity monitors. *Journal of science and medicine in sport / Sports Medicine Australia*, 14(5), pp.411–6. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21616714.

Sazonova, N., Browning, R.C. & Sazonov, E., 2011. Accurate prediction of energy expenditure using a shoe-based activity monitor. *Medicine and science in sports and exercise*, 43(7), pp.1312–21. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21131868 [Accessed May 2, 2012].

Schils, S.J. et al., 1993. Kinematic analysis of the equestrian-Walk, posting trot and sitting trot. *Human Movement Science*, 12(6).

Scott, J., 2004. Sleep deprivation, energy expenditure and cardiorespiratory function. *International journal of sports*. Available at: http://www.thieme-connect.com/ejournals/abstract/sportsmed/doi/10.1055/s-2004-815845.

Scott, J. & McNaughton, L., 2006. Effects of sleep deprivation and exercise on cognitive, motor performance and mood. *Physiology & behavior*, 87, pp.396–408. Available at: http://www.sciencedirect.com/science/article/pii/S0031938405005196.

Shambroom, J.R., Fábregas, S.E. & Johnstone, J., 2011. Validation of an automated wireless system to monitor sleep in healthy adults. *Journal of sleep research*. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21859438.

Song, Y. et al., 2007. Speed Estimation From a Tri-axial Accelerometer Using Neural Networks. In *International Conference of the IEEE Engineering in Medicine and Biology Society*. pp. 3224–3227.

Staudenmayer, John, Zhu, W. & Catellier, D.J., 2012. Statistical considerations in the analysis of accelerometry-based activity monitor data. *Medicine and science in sports and exercise*, 44(1 Suppl 1), pp.S61–7. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22157776.

Sunseri, M. et al., 2002. The SenseWear ™ Armband as a Sleep Detection Device. , pp.1–9.

Symes, D. & Ellis, R., 2009. A preliminary study into rider asymmetry within equitation. *Veterinary journal London England 1997*, 181(1), pp.34–37. Available at: http://www.ncbi.nlm.nih.gov/pubmed/19375366.

Troiano, R.P., 2006. Translating accelerometer counts into energy expenditure: advancing the quest. *Journal of Applied Physiology*, 100(4), pp.1107–1108. Available at: http://www.ncbi.nlm.nih.gov/pubmed/16540708.

Trowbridge, E.A., Cotterill, J.V. & Crofts, C.E., 1995. *The physical demands of riding in National Hunt races.*, Available at: http://www.ncbi.nlm.nih.gov/pubmed/7729441.

Tuck, K., 2007. Power Cycling Algorithm using the MMA73x0L 3-Axis Linear Accelerometer. *Sensors Peterborough NH*, pp.1–5.

Vanhatalo, A., Doust, J.H. & Burnley, M., 2008a. A 3-min all-out cycling test is sensitive to a change in critical power. *Medicine and science in sports and exercise*, 40(9), pp.1693–9. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18685519.

Vanhatalo, A., Doust, J.H. & Burnley, M., 2007. Determination of critical power using a 3-min all-out cycling test. *Medicine and science in sports and exercise*, 39(3), pp.548–55. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17473782.

Vanhatalo, A., Doust, J.H. & Burnley, M., 2008b. Robustness of a 3 min all-out cycling test to manipulations of power profile and cadence in humans. *Experimental physiology*, 93(3), pp.383–90. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17951327.

Vanhelst, J. et al., 2012. Comparison of two ActiGraph accelerometer generations in the assessment of physical activity in free living conditions. *BMC research notes*, 5(1), p.187. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22534207.

Vautier, J.F. et al., 1995. Critical power as an endurance index. *Applied ergonomics*, 26(2), pp.117–21. Available at: http://www.ncbi.nlm.nih.gov/pubmed/15677008.

Vermeulen, a D. & Evans, D.L., 2006. Measurements of fitness in thoroughbred racehorses using field studies of heart rate and velocity with a global positioning system. *Equine veterinary journal. Supplement*, 36(36), pp.113–7. Available at: http://www.ncbi.nlm.nih.gov/pubmed/17402404.

De Vries, S.I., Engels, M. & Garre, F.G., 2011. Identification of Children's Activity Type with Accelerometer-Based Neural Networks. *Medicine & Science in Sports & Exercise*, 43(10), p.1994. Available at: http://www.ncbi.nlm.nih.gov/pubmed/21448085.

Walter, P.L., 2007. The History of the Accelerometer: 1920s-1996 - Prologue and Epilogue, 2006. *Sound And Vibration*, 41(1), p.84.

Walters, P., 2002. Sleep, the athlete, and performance. *Strength & Conditioning Journal*, 24(2), pp.17–24. Available at: http://journals.lww.com/nsca-scj/Abstract/2002/04000/Sleep,_the_Athlete,_and_Performance.5.aspx.

Warrington, G. et al., 2009. Chronic weight control impacts on physiological function and bone health in elite jockeys. *Journal of sports sciences*, 27(6), pp.543–50. Available at: http://www.ncbi.nlm.nih.gov/pubmed/19337879.

Welk, Gregory J, McClain, J. & Ainsworth, Barbara E, 2012. Protocols for evaluating equivalency of accelerometry-based activity monitors. *Medicine and science in sports and exercise*, 44(1 Suppl 1), pp.S39–49. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22157773.

Westerling, D., 1983. A study of physical demands in riding. *European Journal Of Applied Physiology And Occupational Physiology*, 50(3), pp.373–382.

Wirnitzer, K.C. et al., 2008. Exercise intensity during an 8-day mountain bike marathon race. *European journal of applied physiology*, 104(6), pp.999–1005. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18777040.

van Wouwe, N.C., Valk, P.J.L. & Veenstra, B.J., 2011. Sleep monitoring: a comparison between three wearable instruments. *Military medicine*, 176(7), pp.811–6. Available at: http://www.ncbi.nlm.nih.gov/pubmed/22128724.

Zaryski, C. & Smith, D.J., 2005. Training Principles and Issues for Ultra-endurance Athletes.

Zavorsky, G.S. et al., 2007. Laboratory 20-km Cycle Time Trial Reproducibility. , (1), pp.743–748.

# Chapter 8: Appendix

## *8.1 Study 1: Ergocal Analysis*

Post data collection, a GT3X+ ActiGraph accelerometer was placed on the saddle of the equine ergometer in order to attempt to assess the relative velocity during each stage. A high speed camera was placed perpendicular to the equine ergometer. A measuring tape was placed on a board behind the ergometer to measure the horizontal displacement. The GT3X+ ActiGraph was set to record raw data and acted as the marker for video measurements. The ergometer was allowed to perform multiple 4 minute runs at each setting while being filmed. The horizontal displacement of the marker was then calculated for each of the 5 stages. This was undertaken with no jockey on the ergometer but using the mean of the subject group for the anthropometric data that was necessary to initialise the GT3X+.

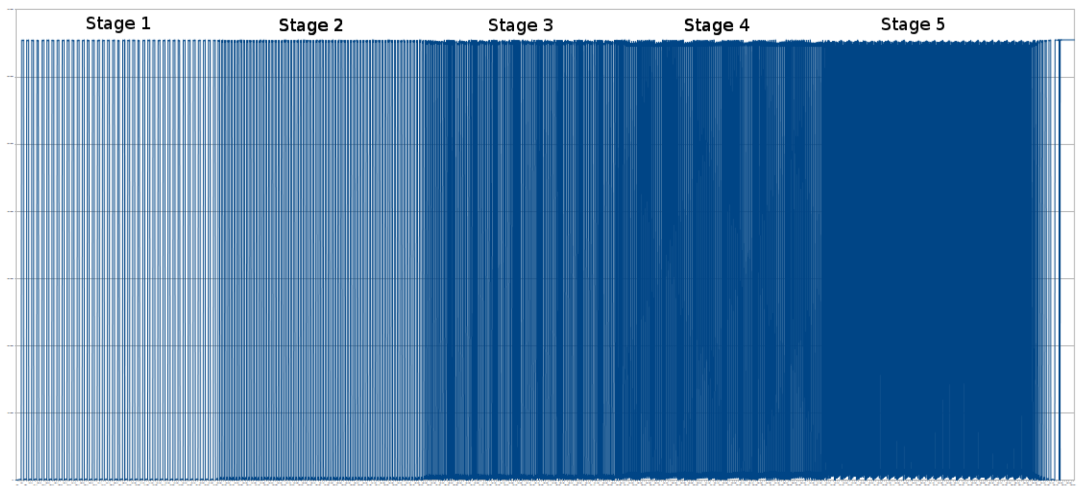



*Illustration 8.12: Changes in Frequency of Equine ergometer Raw Signal*

The raw acceleration signal increased in frequency as the stages progressed (Illustration 8.1). However, the magnitude of the signal does not change due to the limited range of the GT3X+ ActiGraph (Sasaki et al., 2011; John et al., 2012). Using this data it was possible to calculate the frequency at which the ergometer moved each minute for each stage (Table 8.1).With a known displacement for each period the distance that the 'horse' would cover per minute if it were moving over real ground was estimated.

*Table 8.15: Simulator Movement Period (Ergocal)*

| Stage | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Period/min | 38 | 65 | 90 | 104 | 128 |

Data presented as mean

As equine stride length differs with each gait, due the ambulatory differences of bipedal versus quadrupedal animals, the assumption of a single stride length was made for the simulated horse (Barrey et al., 1993). From this a rough estimation for the relative speed was calculated (Table 8.2).

### *8.1.2 Gait Detection*

The addition of a GT3X ActiGraph to the pommel of the saddle during outdoor testing was introduced to facilitate the possible differentiation of each of the equine gaits. It was hoped that due to the highly individual patterns of each of the gaits that a simple low cost accelerometer would be capable of delivering not only physical activity data, but contextual data on the environment. This data was not investigated as part of this thesis and formed part of another research project. Velocity was estimated for the indoor condition using the Ergocal method (section 3.3.10 and 3.5.6). The following velocities were estimated for each of the speed settings on the ergometer (Table 8.2) and the GPS (Table 8.3).

*Table 8.16: Velocity Estimations Indoor (Ergocal)*

| Stage | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Velocity (*kph*) | 8.89 | 15.24 | 21.17 | 24.41 | 29.98 |

Data presented as mean

*Table 8.17: Velocity Estimations Outdoor (GPS)*

| Stage | Walk | Trot | Canter |
|---|---|---|---|
| Velocity (*kph*) | 5.58 $\pm$ 0.79 | 12.58 $\pm$ 1.51 | 28.08 $\pm$ 2.19 |

Data presented as mean $\pm$ SD

**Note:** Stage 1 (S1) was not used as part of the testing protocol as the subjects never use this setting during their own training.

### *8.1.3 Indoor and Outdoor Comparisons Based on Velocity Assumptions*

A comparison was made using the velocity based calculations from section. Data were compared based on the closest approximating velocity indoors to that of the velocity experienced during an outdoor gait. Estimated energy expenditure and physical activity data were then compared for each couple.

#### *8.1.3.1 Stage 2 vs. Trot:*

A moderate correlation (R=0.63) and significant differences were observed for estimated energy expenditure measured with the Cosmed ($p<0.01$). Significant differences in physical activity were observed for each GT3X actigraphs at each site: Ankle $p<0.01$, waist $p<0.01$, chest $p<0.01$, wrist $p<0.01$ and saddle $p<0.01$ Strong correlations in physical activity were seen between each condition at the chest R=0.85 and moderate correlations at the ankle R=0.69.

#### *8.1.3.2 Stage 5 vs. Canter*

A moderate correlation (R=0.63) and significant differences were observed for estimated energy expenditure measured with the Cosmed ($p<0.01$). Significant differences in physical activity were observed for each GT3X actigraphs at each site: Ankle $p<0.05$, waist $p<0.05$, wrist $p<0.05$ and saddle $p<0.05$ Strong correlations in physical activity were seen between each condition at the saddle R=0.97 and wrist R=0.71.

### *8.1.4 Velocity Comparison*

In order to make energy expenditure and physical activity comparisons, based on velocity gathered from the GPS, it was necessary to attempt to classify the velocity of each ergometer stage. As there is no forward movement of the ergometer relative to its initial position, it is impossible to calculate the actual speed the ergometer is travelling at overground. At best, the presented data for the ergometer provide no more than an estimate of velocity. However, with no information available from the manufacturers an attempt at classifying each stage was undertaken in order to make this estimation. When matched by the energy expenditure measured on the Cosmed, the estimations for the ergometers velocity did not match those of outdoor riding. This implies that either the method of estimating the velocity of the ergometer was inaccurate or, as noted in the previous section, the disparity of outdoor energy expenditure rates to indoor stages is also similar for velocity based assumptions of energy expenditure.

Assuming that the velocities calculated using the Ergocal method are correct it would be possible to train at a selection of different velocities which result in a known energy expenditure for a given set of anthropometric variables of jockey and horse. However, as the results show very little agreement between physical activity rates, and no similarities in the stages and gaits matched via energy expenditure rates, it is quite probable that the estimation of physical activity expenditure rates based on velocity alone is not applicable in horse-riding. This method is however used by GPS technology companies such as Garmin for cycling and running. Although no studies have been undertaken comparing GPS based estimates of physical activity rates and other methods, Garmin claim that the estimation algorithms they use are comparable to within 5% or their heart rate based methods (ref). The necessity of this method of estimating energy expenditure is not clear as the addition of extra sensors such as heart rate measurement or activity measurement via accelerometery can lead to more accurate results. However, as a back-up or extra layer of data within an energy expenditure estimation algorithm the use of velocity based calculations may help to further refine the data.

### *8.1.5 Application of Ergocal*

Currently this method is restricted to its use within equine ergometry. Although this may be a method that would allow for outdoor analysis, it needs further refinement in order to do so. This would include the inclusion of other factors such as; the individual stride length of the horse, the surface they are running on and whether they are adopting a traditional running gait or a modified motion, i.e. piaffe movement during dressage. In the case of a horse performing a piaffe, the signal may look like that of a normal trot, however there would be no associated forward motion. Ideally these individual gaits and their differences would be modelled using a multi axial motion that could take account of the accelerations in several planes in order to differentiate between such gait abnormalities. Although the GT3X ActiGraph can measure in three axis, the sample rate is possibly not enough to allow for accurate data to be captured. With the newer GT3X+ models it may be possible to further refine this method and apply it to outdoor horse-riding as they have a far higher sample rate.

*Table 8.18: Velocity Estimations Indoor (Ergocal)*

| Stage | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Velocity (*kph*) | 8.89 | 15.24 | 21.17 | 24.41 | 29.98 |

Data presented as mean

Currently this method is restricted to its use within equine ergometry. Although this may be a method that would allow for outdoor analysis, it needs further refinement in order to do so. This would include the inclusion of other factors such as; the individual stride length of the horse, the surface they are running on and whether they are adopting a traditional running gait or a modified motion, i.e. piaffe movement during dressage. In

the case of a horse performing a piaffe, the signal may look like that of a normal trot, however there would be no associated forward motion. Ideally these individual gaits and their differences would be modelled using a multi axial motion that could take account of the accelerations in several planes in order to differentiate between such gait abnormalities. Although the GT3X ActiGraph can measure in three axis, the sample rate is possibly not enough to allow for accurate data to be captured. With the newer GT3X+ models it may be possible to further refine this method and apply it to outdoor horse-riding as they have a far higher sample rate.

## *8.2 Study 2: Temperature Changes*

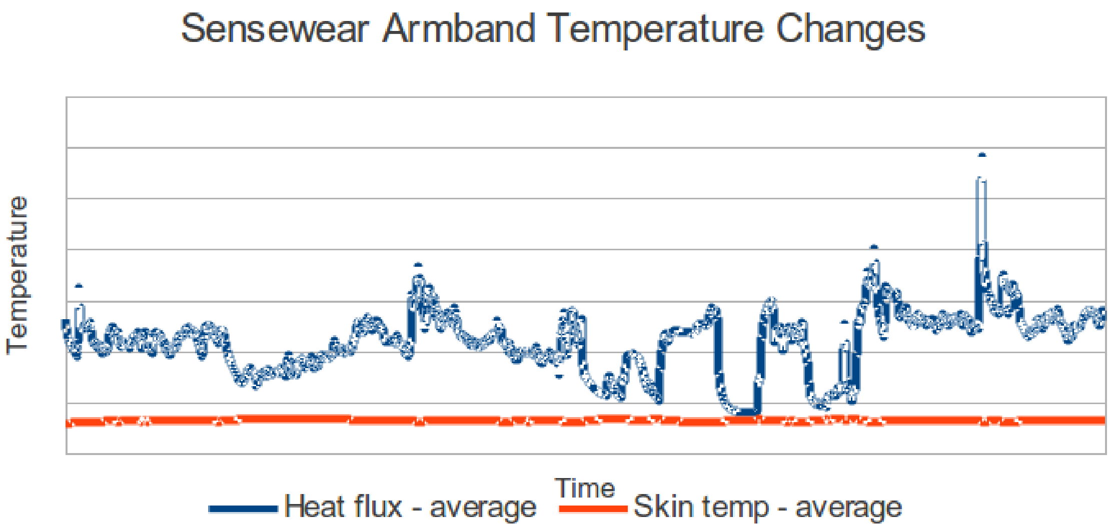
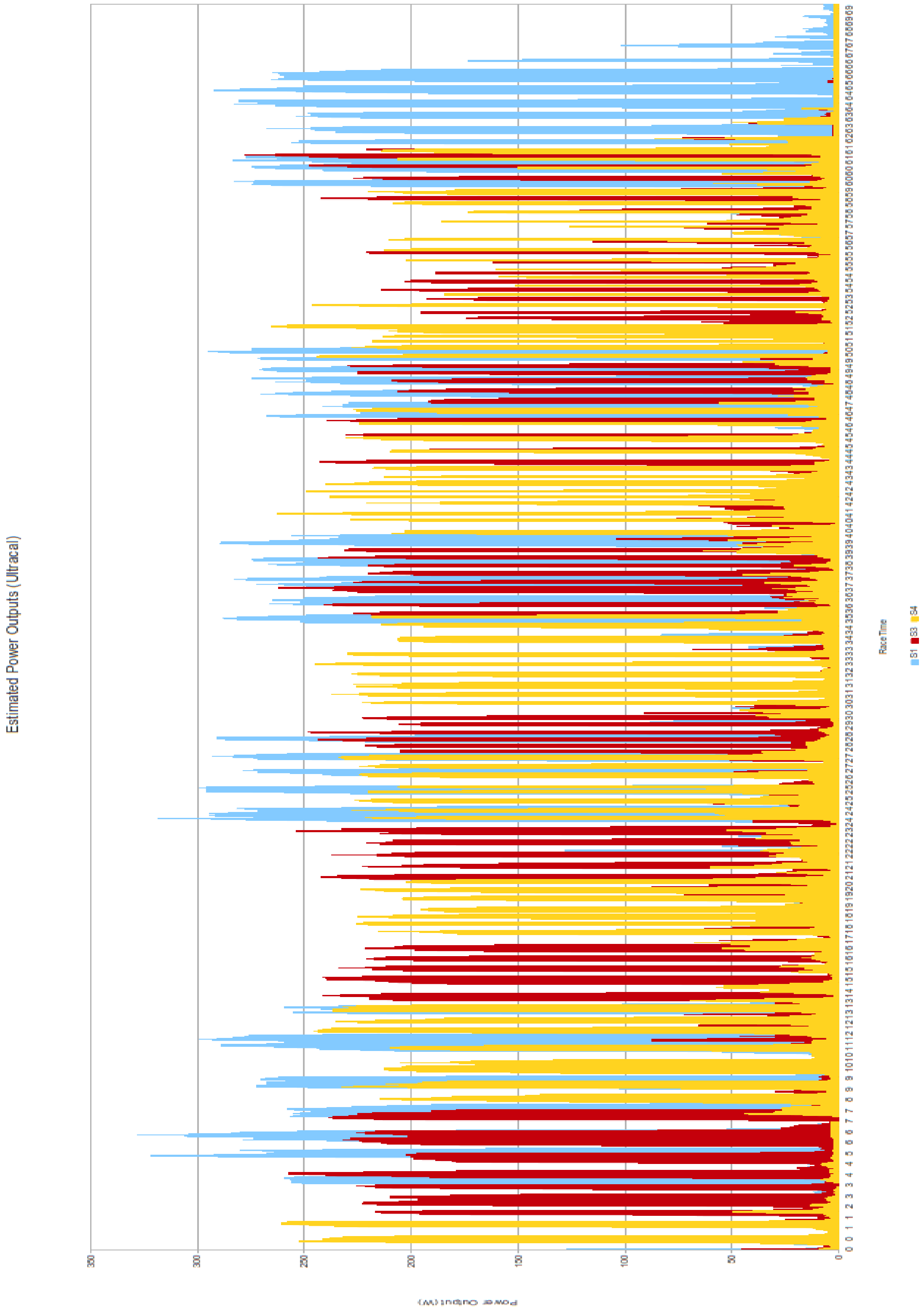



*Illustration 8.13: Sensewear Armband Temperature Variations*

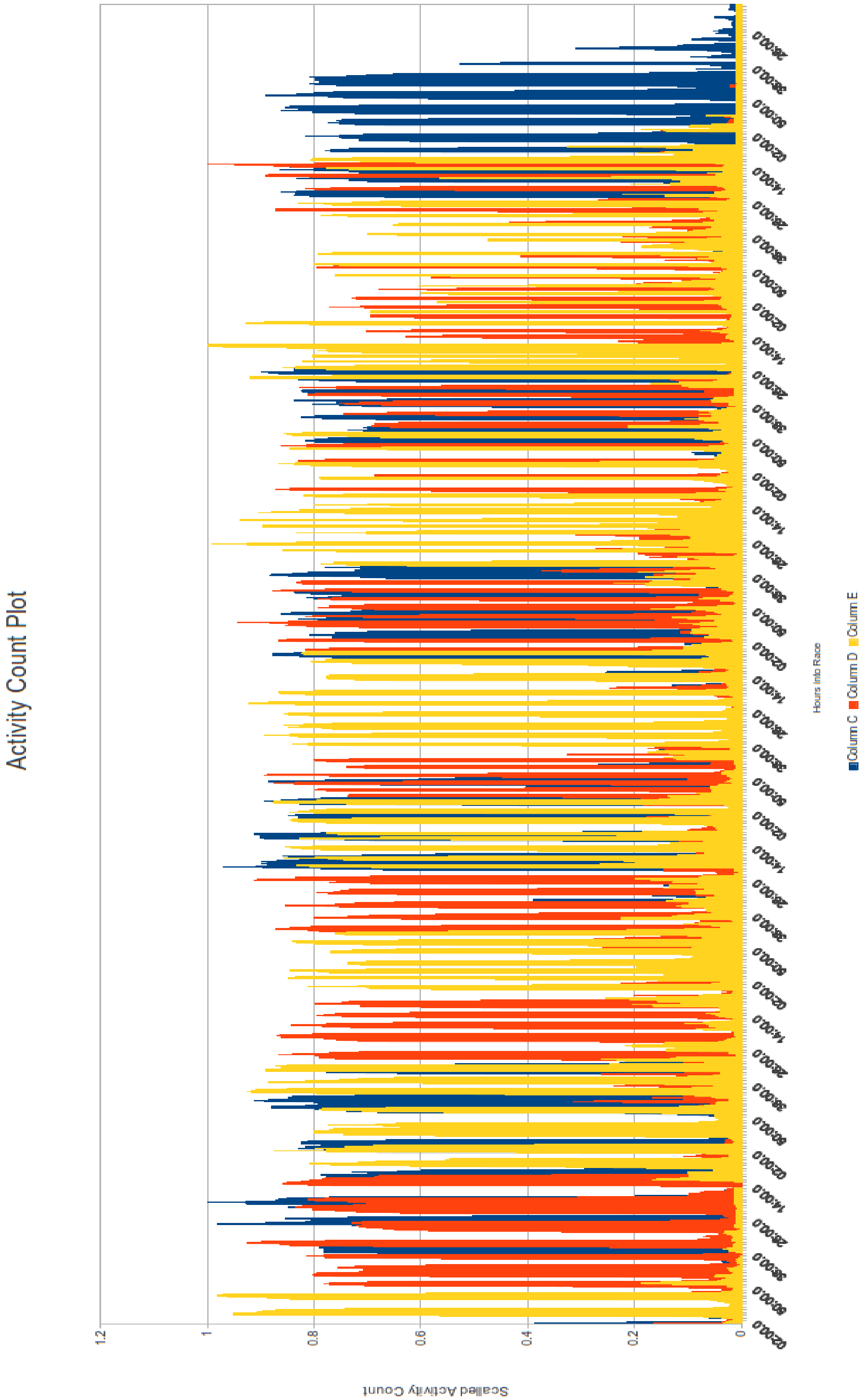
## 8.3 Study 3: Expanded illustrations from RAI Study

### 8.3.1 Estimated Power Outputs Per Cycle Bout

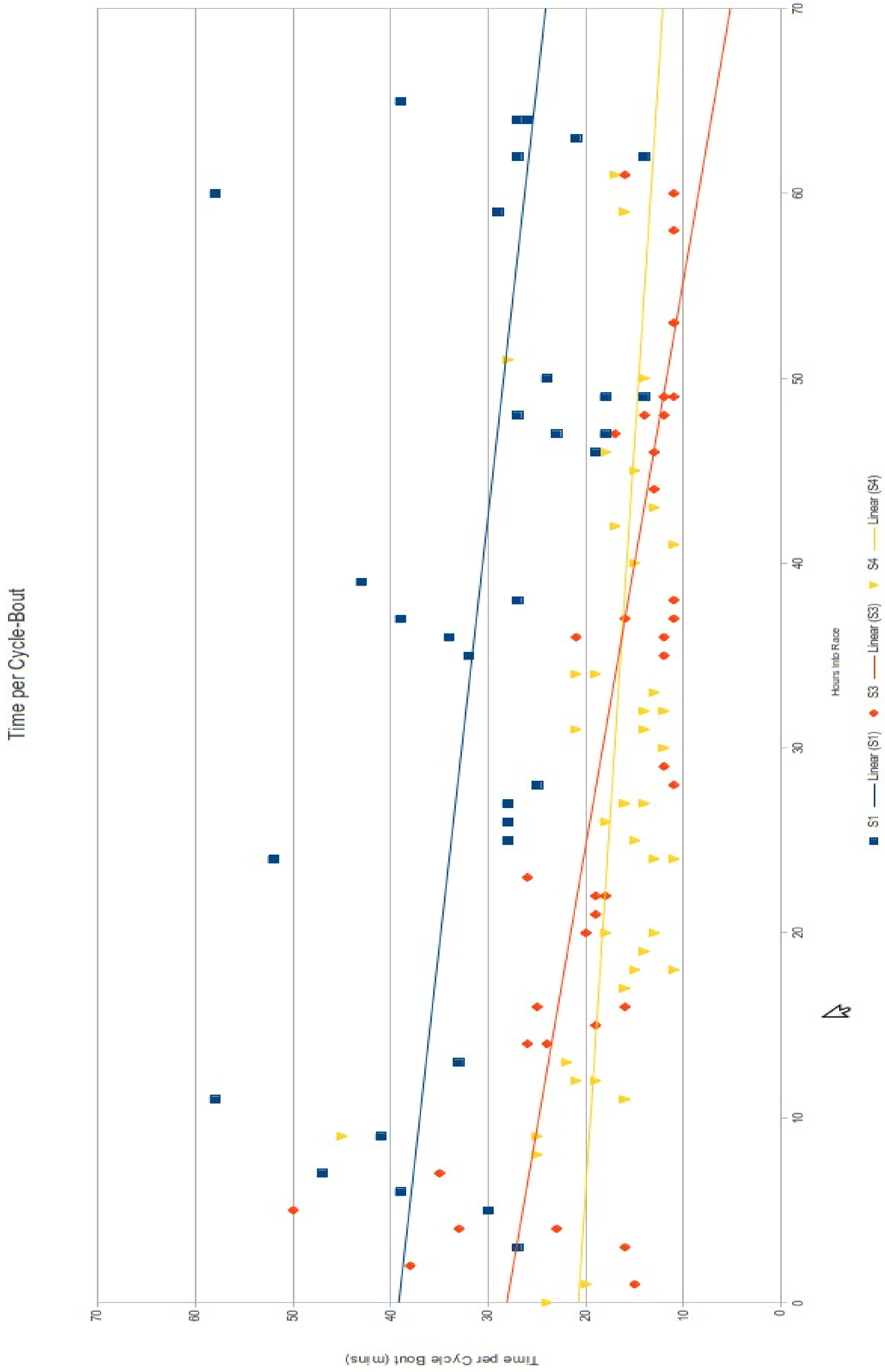


### *8.3.2 Performance Decay Trend-line (Estimated Power Output)*

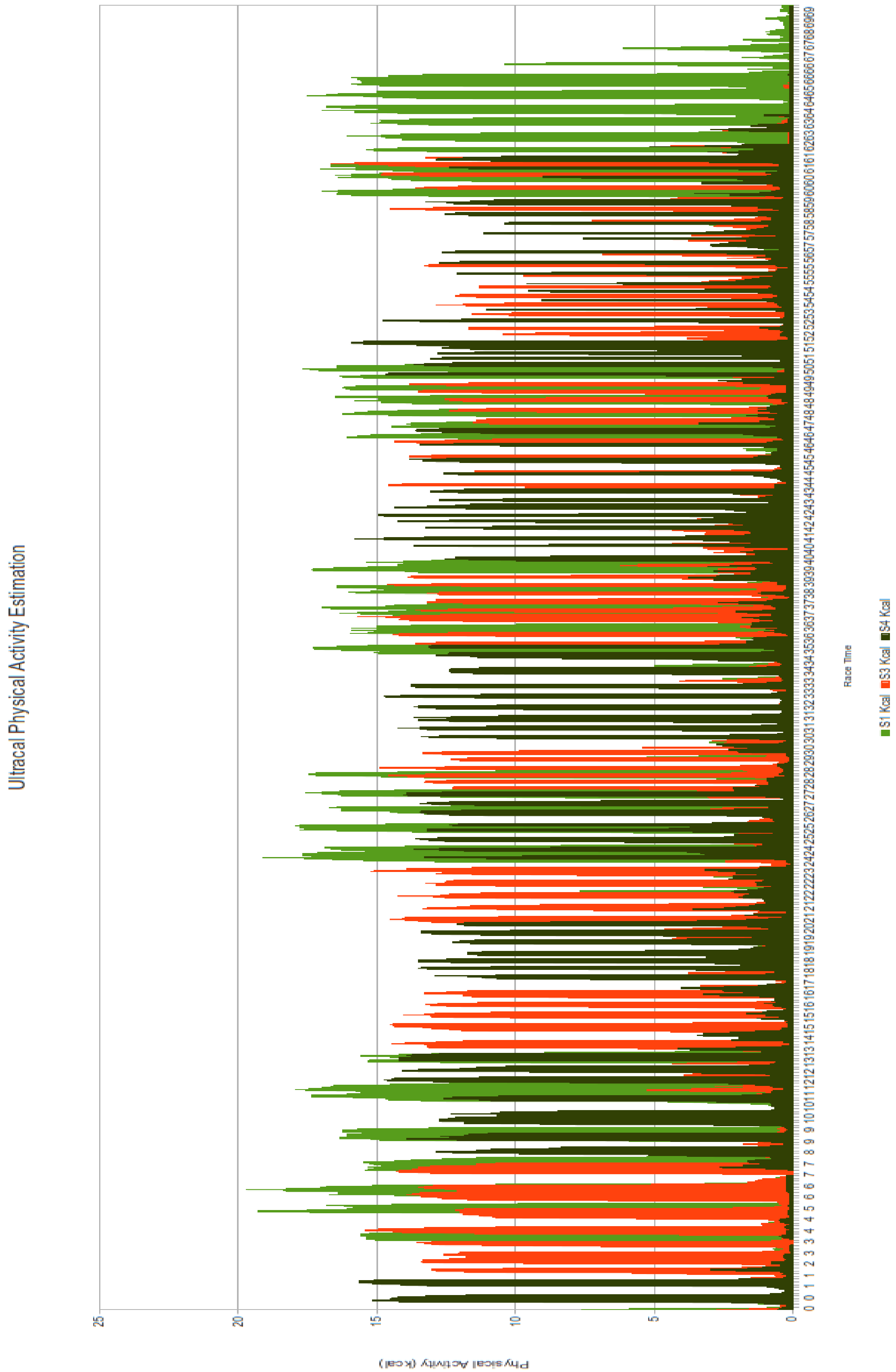
### *8.3.3 Weighted Intensity Per Cycle Bout*



### *8.3.4 Time Per Cycle-bout*



### *8.3.5 Estimated Physical Activity Per Cycle-bout*



## *8.4 Documentation*

### *8.4.1 General Health Questionnaire*

# School Of Health and Human Performance

**Dublin City University**

**General Health Questionnaire**

Name:……………………………….. Occupation:……………………………

Address:………………………………………………………………………….

Telephone: (Home)………………….. (Work):………………………………..

---

| | | |
|---|---|---|
| Do you have, or have you ever suffered from: | -Diabetes? | Yes / No |
| | -Asthma? | Yes / No |
| | -Epilepsy? | Yes / No |
| Have you ever had pains in your chest or heart? | | Yes / No |
| Do you ever feel faint or have spells of dizziness? | | Yes / No |
| Do you have or have you ever had high blood pressure? | | Yes / No |
| Do you have a muscle, back or joint problem that could be aggravated by physical activity or made worse with exercise? | | Yes / No |
| Do you have any current injuries? | | Yes / No |
| In the past week, have you suffered from any illness which required you to be in bed or off work for one day or more? | | Yes / No |
| Do you smoke? | If yes, how many per day? | Yes / No |
| Do you drink? | If yes, how many units per week? | Yes / No |
| Is there a good physical reason not mentioned here why you should not carry out laboratory testing? | | Yes / No |

Please provide any further information concerning any condition/complaints which you suffer from and any medication which you may be taking by prescription or otherwise:

…………………………………………………………………………………………………

…………………………………………………………………………………………………

…………………………………………………………………………………………………

…………………………………………………………………………………………………

Date: Signature:

Authorising Signature:

*8.4.2 Activity Diary (SAR)*

# 3 Day Physical Activity Recall Diary

**Name**
**ID**

| HRS | Shift 1 | Shift 2 | Shift 3 |
|---|---|---|---|
| 1-2pm | | | |
| 2-3pm | | | |
| 3-4pm | | | |
| 4-5pm | | | |
| 5-6pm | | | |
| 6-7pm | | | |
| 7-8pm | | | |
| 8-9pm | | | |
| 9-10pm | | | |
| 10-11pm | | | |
| 11pm-12am | | | |
| 12am-7am | | | |
| 7-8am | | | |
| 8-9am | | | |
| 9-10am | | | |
| 10-11am | | | |
| 11-12pm | | | |
| 12-1pm | | | |