On-animal motion sensing using accelerometers as a tool for monitoring sheep behaviour and health status

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Declaration

I certify that the substance of this thesis has not already been submitted for any degree and is not currently being submitted for any other degree or qualification.

I certify that any help received in preparing this thesis, and all sources used, have been acknowledged in this thesis.

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Jamie DJ Barwick

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Summary

An opportunity exists to infer the physiological and physical state of an animal from changes in their behaviour. As resting, eating, walking and ruminating are the predominant daily activities of ruminant animals, monitoring these behaviours could provide valuable information for monitoring individual animal health and welfare status. Conventional animal monitoring methods have relied on visual observations of animals by human labour. This can only provide information on an animal's behaviour for the period in which they are being observed. Historically, observations could be made for long periods where shepherds were employed to observe their flocks nearly constantly. This is obviously no-longer feasible in the current livestock industry.

Recently, with the advent of small, low power accelerometer technology, the ability to remotely monitor animal movement continuously has arisen. This is achieved through the application of on-animal inertia monitoring unit (IMU) sensors. This movement data might potentially lead to continuous behavioural monitoring of livestock. These devices have been developed for higher value livestock such as dairy cattle but little research or development has been directed towards their use in sheep. Previous work has evaluated collar and leg deployments however the sheep industry demands these devices be in an eartag form factor to align with current industry practices. Therefore, this thesis aims to evaluate the potential for using ear-borne accelerometer devices to detect and categorise key behaviours expressed by sheep. Deviation from normal patterns of behaviour may be used as an indicator of changes in individual health status. If behaviour can be categorised using the data collected by these body worn devices and radio telemetry incorporated, animal health could be monitored in near real time allowing early treatment intervention when necessary, ultimately improving on-farm productivity.

Scoping work in this thesis identified the difference in acceleration signals between the basic sheep behaviours: grazing, walking and resting, giving potential for discrimination between behaviours with classification algorithms. Subsequently a successful behaviour classification algorithm was developed based on accelerometer

data obtained from the ear deployment, yielding activity predictions similar to those obtained through visual observation. To apply this technology to a commercial application, a simulated lameness experiment was designed, where lame walking behaviour was discriminated from sound walking events successfully using the ear and leg modes of deployment. The final experiment investigated the application of ear deployed accelerometer devices to detect behavioural changes associated with increased infection by internal parasites, a disease of extreme economic importance within Australia. Animals with a higher faecal worm egg count were shown to have a lower probability of engaging in longer periods of activity, however this experiment was limited by a very mild level of infection.

Overall this thesis demonstrates that sheep behaviour can be classified using an ear-mounted tri-axial accelerometer sensor, the first of its kind to date. It also explored the suitability of using time-series behavioural classification data as an early indicator of health and welfare issues. This work aims to link a previous "research only" technology in sheep, to a commercial application, a stepping stone towards bridging the gap between research and industry adoption.

Table of contents

List of acronyms

- 24-hour-a-day, 7-days-a-week (24/7)
- Animal Ethics Committee (AEC)
- Artificial neural networks (ANN)
- Automatic livestock monitoring systems (ALMS)
- Average Intensity (AI)
- Average X-axis (Ax)
- Average Y-axis (Ay)
- Average Z-axis (Az)
- Body condition score (BCS)
- Bovine respiratory disease (BRD)
- Classification and regression trees (CART)
- Clinical illness scores (CIS)
- Contagious ovine digital dermatitis (CODD)
- Decision tree (DT)
- Dry matter (DM)
- Eggs per gram (EPG)
- Faecal condition score (FCS)
- Faecal egg count (FEC)
- False negative (FN)
- False positive (FP)
- Fast Fourier transformation (FFT)
- Footrot (FR)
- Gastro-Intestinal Nematodiasis (GIN)
- Generalised additive mixed model (GAMM).
- Global Navigation Satellite Systems (GNSS)
- Global Positioning Systems (GPS)
- Haematocrit (hct)
- Hectares (Ha)
- Hertz (Hz)

- Hidden markov model (HMM)
- Inertia monitoring unit (IMU)
- Integrated pest management (IPM)
- Interdigital Dermatitis (ID)
- k nearest neighbour (kNN)
- Kaplan-Meier (KM)
- Larvae 3 (L3)
- Left front (LF)
- Left hind (LH)
- Linear discriminant analysis (LDA)
- Linear mixed model (lmm)
- Logistical regression (LR)
- Maximum X (MaxX)
- Maximum Y (MaxY)
- Maximum Z (MaxZ)
- Micro-electromechanical systems (MEMS)
- Minimum X (MinX)
- Minimum Y (MinY)
- Minimum Z (MinZ)
- Movement intensity (MI)
- Movement Variation (MV)
- Naive Bayes (NB)
- Ovine Johnes Disease (OJD)
- Packed cell volumes (PCV)
- Precision Agriculture (PA)
- Precision livestock (PL)
- Principal component analysis (PCA)
- Quadratic discriminant analysis (QDA)
- Random forest (RF)
- Rapid eye movement (REM)
- Right front (RF)
- Right hind (RH)

- Sensitivity (Se)
- Sequential forward selection (SFS)
- Signal Magnitude Area (SMA)
- Single feature classification (SFC)
- Slow wave sleep (SWS)
- Specificity (Sp)
- Standard deviation (SD)
- Standard error (SE)
- Store on board (SOB)
- Support vector machine (SVM)
- True negative (TN)
- True positive (TP)

Chapter 1

General introduction

Imagine this: a sheep grazier is sitting at the breakfast table with his cup of tea. Before heading off into the paddock to do the daily activities he checks his iPad. On the screen he can see the location of all his flocks and a health status icon hovers over each providing an indication of any problems. A small sensor has been monitoring the behaviour and activity of each animal 24 hours a day providing an early warning of any behavioural changes. Algorithms are applied to the data from the sensor to predict sub-clinical disease states enabling the producer to prioritise their routine inspections and potentially implement treatments well before they would have traditionally noticed a problem. Our farmer gulps the last of his tea and heads out to the back paddock, there's three sheep showing the signs of flystrike that need to be attended to. While it might sound fanciful at the moment, this technology is really only just around the corner and is already being rolled out in other livestock industries.

The Australian wool and lamb industries have an estimated value of $1.8 billion and $1.75 billion respectively (Rowe, 2010). Trends over the past 20 years have seen an overall decrease in the Australian sheep flock to an estimated low of 68.1 million (Australian Bureau of Statistics, 2011). As the push for greater production from a smaller resource base continues, Australian graziers are being forced to look for ways to sustainably increase outputs. With world population predicted to plateau at 9 billion around 2050, a 70% increase in food production within plant and animal systems will be required to feed this number of people (Capper & Bauman, 2013). In addition, the changing demographics associated with rising incomes in developing countries anticipated past trends in meat production to 470 million tonnes annually by 2015 (Beddington, 2010). United Nations projections show an increase in meat consumption of 73% and dairy consumption of 53% by 2050 (FAO, 2011). This demand will have to be met by improved management that enables increased production per unit land area, without putting further strain on the resource base. There are numerous constraints to animal production: land, water and nutrient resources along with the animal's genetic and phenotypic characteristics however there are also a number of opportunities to increase efficiencies within the grazing system.

As well as the need to increase production, graziers are faced with another key challenge. One of the biggest hurdles facing livestock production not just in Australia but globally, is that of animal welfare. At a basic level, consumers are increasingly demanding that food meets high standards of quality and animal welfare, all at an affordable price. Even more challenging is the rise of an anti-animal production movement which has seen some groups actively targeting livestock industries with an intent to cause significant social concern. This presents a challenge to the sheep industry as satisfying the labour demand to monitor animals more closely (to address welfare concerns) may not always be available and in many cases is likely to be uneconomical (Petherick & Edge, 2010). In Australia, the labour resources available for extensive farming enterprises are on the decline because of an aging population and competing industries offering higher wages (AWI, 2010). If these trends remain, many smaller farms may sell or merge with large enterprises resulting in large scale enterprises operating with limited labour and infrastructure (Morris, Cronin, & Bush, 2012; Petherick, 2006). As sheep are often farmed under conditions where human monitoring is an infrequent occurrence (Umstätter, Waterhouse, & Holland, 2008), animals can go uninspected for extended lengths of time adding further difficulty. It has previously been suggested that the facilitation of regular monitoring and inspection of livestock is one of the major problems faced by farm personnel (Petherick & Edge, 2010). Therefore the Australian sheep industry faces a challenge to increase production efficiency leading to the preservation of future food security whilst also ensuring adequate animal welfare standards are maintained in the face of reduced labour resources. Within these challenges lie opportunities for embracing new technologies in the food supply chain which is requiring a safe, secure and sustainable food production system.

One of the largest constraints to improving production efficiency and one of the key challenges to animal welfare is disease. A report by Sackett, Holmes, Abbott, Jephcott, and Barber (2006) indicated diseases present significant costs to Australian sheep enterprises through increased treatment costs and reduced income. Not only can diseases significantly reduce productivity, they can potentially result in adverse animal welfare at the individual and/or flock level (Roger, 2008). Sheep disease is one of the most obvious candidates for the application of technologies that might enable remote monitoring, detection and subsequent early intervention.

Behaviour is commonly used as an indicator of animal disease and welfare (Haley, De Passillé, & Rushen, 2001; Krohn & Munksgaard, 1993; Martiskainen et al., 2009; Mattachini, Riva, Pompe, Bisaglia, & Provolo, 2011) and can provide a clear indication of the animals' physical and physiological state (Frost et al., 1997). Traditionally, the identification of health problems is dependent on farm personnel using subjective measures based on accumulated experience (González, Tolkamp, Coffey, Ferret, & Kyriazakis, 2008; Weary, Huzzey, & Von Keyserlingk, 2009). This approach relies on detecting signs of disease where the effect on the animal becomes apparent (Morris et al., 2012), however, González et al. (2008) indicated the early identification of infected animals is often difficult and certainly sub-clinical disease can escape detection.

A remote sensor based 24/7 monitoring system that can detect animal behaviour has the potential to reduce the need for visual inspection of animals therefore decreasing labour requirements, identify individual animals with possible health concerns earlier, allowing treatment to be initiated sooner, leading to reduced productivity losses and associated lost income. Whilst much literature has alluded to the possibility of utilising various forms of technology for health monitoring (McLennan et al., 2015; Morris et al., 2012) a systematic approach as to how these technologies can be implemented on farm and in particular for the sheep industry is still lacking. The research reported in this thesis focuses on the quantitative analysis of animal behaviour measured using animal-borne sensor devices.

Chapter 2

Review of literature & objectives of thesis

The aim of this literature review is to first examine the current knowledge around sheep behaviour and discuss ways in which behaviour has traditionally been monitored. Activity based disease symptoms can be detected autonomously. It is critical therefore, to understand normal sheep behaviour. Furthermore, the way in which behaviour has previously been used to monitor disease status in livestock will be reviewed. This component will be extended into a review of some sheep diseases which present significant economic and welfare concerns. Secondly, available technologies which can be used to monitor animal behaviour will be examined and the applications of these technologies to the sheep industry will be outlined.

In brief this review is broken down into three components, 1; aspects of sheep behaviour, 2; sheep diseases and their effect on activity and 3; technology available to monitor animal behaviour with a focus on accelerometers.

2.1 Sheep behaviour

Behaviour can be defined as “anything that an organism does involving action and response to stimulation” or “the way in which something functions or operates” (Webster, 1996). Whilst these definitions seem broad, it is well recognised that animal behaviour differs greatly between domesticated livestock species (Goetsch, Gipson, Askar, & Puchala, 2010). Due to the complexity of the thesis topic, a review of sheep behaviour has been condensed to key points that are fundamental to monitoring animal health and welfare status, which also have the potential to be monitored autonomously. Interested readers should consult the references listed throughout for further explanation.

An animal's behaviour is a central part of its biology, with behaviour being a culmination of the animal's response to its environment and its physiological condition (Shepard et al., 2008). The behaviour of sheep can be divided into 5 categories: rest, grazing, rumination, locomotion and reproductive behaviour. Reproductive behaviour is beyond the scope of this review. The daily patterns of these behaviours vary with season, sheep breed, geographical distribution of resources and the nutritional qualities of the grazing pasture *(as cited in review by* Fraser, 1974). Much of the research in this space is quite dated and has not been repeated as it has quite clearly shown what the main behaviours of sheep are. A thorough understanding of the main sheep behaviours and the motivation to perform such behaviours is necessary as there are many factors which can affect behaviour of which disease is just one possibility.

2.1.1 Flock structure

Almost all activities of sheep behaviour are highly coordinated and carried out as an entire flock with animals showing strong social behaviour (*as cited in review by* Ratner & Hafez, 1975). The level of such grouping behaviour varies according to breed, flock size, terrain, time of day and the particular behaviour performed. Hediger (1950) referred to the level of dispersion within a flock as "individual distance" and the individual distance is dependent on the type of activity being performed by the group. Contact between individuals is maintained largely through vision. As the flock grazes, each individual throws up its head and presumably responds to the position of other members (*as cited in review by* Ratner & Hafez, 1975). At night and during periods of inactivity, sheep form close aggregations. During the day they may adopt a number of different organisations for feeding: group feeding, sub-group feeding and solitary feeding (Squires, 1975). In large flocks, sheep tend to split into sub-groups during grazing, occupying different areas of the paddock (*as cited in reviews by* Ratner & Hafez, 1975; Squires, 1975). Arnold and Pahl (1967) found Merinos form sub-groups of varying size and of no fixed composition while British breeds form smaller sub-groups at a given age. Sub-grouping behaviour may be exacerbated under poor forage conditions with groups of 2-3 sheep up to 3km apart being observed (Dudzinski & Arnold, 1967; Lynch, 1974). As sheep cease grazing, small flocks begin to amalgamate, aggregating around camping grounds or watering points (Squires, 1975).

2.1.2 Grazing

Foraging is defined as "the behaviour of animals when they are moving around in such a way that they are likely to encounter and acquire food for themselves or their offspring" (*as cited in review by* Broom, 1981). Grazing is the term commonly used to describe such behaviour in ruminants. Animals must take a series of steps in order to find, ingest and digest food and this relies on an animal's mental, motor and digestive abilities (Broom, 1981; Broom & Fraser, 2007). For ruminants, the individual must assess the herbage and decide whether to lower their head and bite, how large of a bite to take, the rate at which to bite and when to stop biting, when to chew, whether to swing their head, whether to take a small step or whether to raise their head and conduct another behaviour. Following this it must decide whether to continue grazing or perform another activity (*as cited in review by* Broom & Fraser, 2007).

Ingestion

There are a number of factors operating before and during the onset of grazing behaviour. The hunger system is comprised of (i) perceptual mechanisms to recognise food; (ii) a central hunger mechanism for integrating causal factors for eating and coordinating movements; and (iii) motor mechanism for locating and ingesting food (Bolhuis & Giraldeau, 2005). The rate of ingestion limits intake and this will depend on (i) oral mechanics; (ii) the physical and chemical properties of the food; (iii) the availability of water; and (iv) the nutrient quality of the food (Broom & Fraser, 2007). Sheep graze in cycles which are interrupted by periods of rumination, rest and idling (*as cited in review by* Ratner & Hafez, 1975). Figure 2-1 below shows the grazing periodicity of sheep over a 24-hour period.

Free ranging ruminants can have between three and five grazing events within a 24 hour period, with the major grazing bouts occurring in early morning and late afternoon/dusk (Broom & Fraser, 2007; Gregorini, 2012; Ratner & Hafez, 1975). The interval from mid- morning to mid-afternoon is the period of least activity. The total grazing time usually amounts to approximately 10 hours, however individual grazing times can vary markedly from the flock average (*as cited in review by* Ratner & Hafez, 1975). Gregorini (2012) has published a comprehensive review on the diurnal grazing patterns of livestock. Please refer to this review paper for a greater depth of information than is presented here.

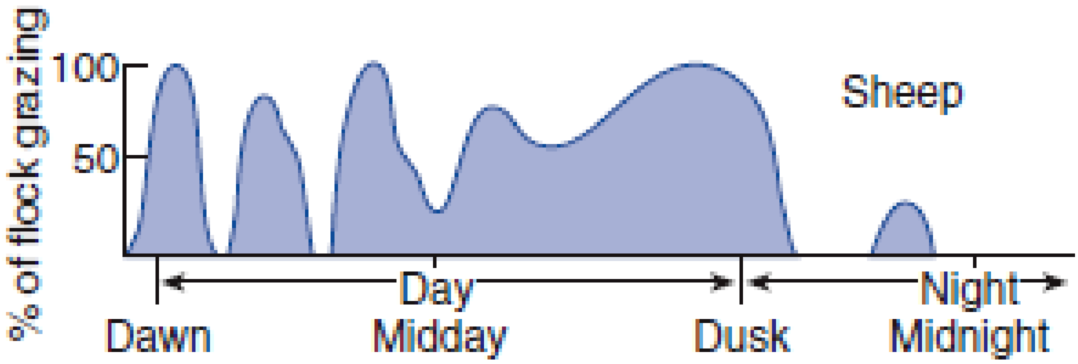


Figure 2-1. Typical diurnal distribution patterns of grazing sheep during spring, summer and autumn (Broom & Fraser, 2007)

The onset of sheep grazing is closely correlated with sunrise (Broom & Fraser, 2007; Fraser, 1974). Since the longest and most intensive rumination events happen during the night, rumen fill is lowest at dawn. Hunger motivation is high at dawn, leading to ruminants grazing when herbage offers the lowest feeding value. The circadian release of neuropeptides and hormones simulated by the the diurnal fluctuations in light intensity, provides the cue to start this dawn grazing event (Gregorini, 2012). The late afternoon grazing dominates nutrient intake, occupying 45% of total daily grazing time (Orr, Penning, Harvey & Champion, 1997; Gibb, Huckall & Nuthall, 1998; Taweel, Tas, Dijkstra & Tamminga, 2004). As indicated in the review of Gregorini (2012), this grazing event is likely to be an adaptive feeding strategy which aids to maximise daily energy acquisition resulting in a steady release of nutrients overnight. Herbage breakdown from this grazing event is additionally facilitated during ingestion by the dry matter (DM), sugars and essential fatty acids, resulting from photosynthesis and transpiration throughout the day, that dilute fibre and protein contents which assists particle breakdown (Gregorini, 2012). Penning, Rook, and Orr (1991) found that set stocked sheep spent 25–48% of total daily grazing time during the 4 h before sunset which is associated with the highest daily values for bite rate and mass (DM basis).

The point at which grazing ceases depends on the individual animal's gut size and input to the brain from sensory receptors (*as cited in review by* Broom & Fraser, 2007). A study by Squires (1971) found the cessation of grazing events occurred after sunset. Hart (1964) proposed it is not sunset itself which is the environmental cue but rather a certain threshold of light intensity. The phenomenon of ruminants filling their rumens to capacity at this time of day offers support for the hypothesis that animals seek a stable release of nutrients throughout the ensuing period of non-grazing where there is an increase need for vigilance due to the higher risk of predation (Gregorini, 2012). As grazing diminishes alertness (Charnov, Gordon & Hyatt, 1976), this may explain why animals' have a diurnal pattern of preference for grass over legumes during the late afternoon grazing event, because grass would maintain rumen fill during the night longer than legumes and supply a steady release of nutrients (Rutter, 2006). Shorter and less intense grazing events occur at night. In cattle, these represent a small percentage of daily grazing time (~10–15%) and contribute minimally (<10%) to daily herbage intake (Krysl & Hess, 1993; Stobbs, 1970).

What can affect grazing activity?

Grazing decisions depend on grazing environments, the current state of the animal, and on the past and anticipated states of the animal (*as cited from review by* Gregorini, 2012). The frequency, distribution and characteristic ingestive behaviour of different grazing events throughout the day for ruminants has been related to diurnal fluctuation in herbage chemical composition (Gibb, 1996; Gregorini, Gunter, & Beck, 2008; Gregorini et al., 2011; Gregorini, Tamminga, & Gunter, 2006; Orr, Penning, Harvey, & Champion, 1997), rumen function and fill (Taweel, Tas, Dijkstra, & Tamminga, 2004; Thomson, Cruickshank, Poppi, & Sykes, 1985), photoperiod (Gregorini et al., 2011; Linnane, Brereton, & Giller, 2001), predator avoidance strategies (Gregorini et al., 2006; Newman, Parsons, Thornley, Penning, & Krebs, 1995) and climatic conditions. During hot weather in summer, night grazing is increased as animals seek shade during the heat of the day while cold and wet weather in winter can reduce night grazing (Broom & Fraser, 2007; Johnson, 1987). Animals adapt their feed intake to the environmental temperature, as if appetite is a thermoregulatory mechanism (Ratner & Hafez, 1975). As the ambient temperature drops, sheep's intake levels rise however very cold temperatures can inhibit the sheep's appetite (*as cited in review by* Fraser, 1974). Environmental influences such as low temperature can accelerate the onset of subsequent grazing events (Broom & Fraser, 2007). Heavy rain or wind conditions can reduce grazing behaviour as normal feeding movements are difficult in such conditions.

Feed intake

Sheep consume approximately 2-5%/day of their bodyweight in food (*as cited in reviews by* Broom & Fraser, 2007; Fraser, 1974). The mechanical difficulties of breaking plant material, finding suitable herbage and the act of swallowing set limits on the rate at which animals can eat (Broom & Fraser, 2007). Consumption levels are also influenced by individual energy requirements, feed availability and environmental conditions.

2.1.3 Rumination

Sheep ruminate on average eight times during a 24 hour period at irregular intervals throughout the day and night (*as cited in review by* Ratner & Hafez, 1975) however, this may increase to 15 times during a 24 hour period (Fraser, 1974). Chewing the bolus during rumination is characterised by regular intervals or short pauses for swallowing and regurgitation. The total rumination time is approximately 8-10 hours with 91 chews per minute (*as cited in review by* Ratner & Hafez, 1975). The length of each period may differ vastly, from one minute to anything up to 2 hours (Fraser, 1974). Rumination requires both time and consciousness, and the thorax must be maintained in an upright position for the proper functioning of the reticulorumen (*as cited in review by* Ratner & Hafez, 1975). Therefore rumination only occurs during standing or resting in an upright position.

2.1.4 Drinking

The amount of water sheep drink varies with breed, climatic conditions, pasture quality, season and reproductive phase (Fraser, 1974; Ratner & Hafez, 1975). Adult water intake on dry pasture ranged from 3 to 6 litres while animals on a hay and concentrate diet drank 0.15 to 3 litres of water daily (Ratner & Hafez, 1975). Daws and Squires (1974) reported Border Leicesters responded to elevated temperatures by drinking earlier in the mornings as night time temperatures rose, while such a response was not seen in Merinos.

2.1.5 Locomotion

Locomotion is defined as "the process by which animals transport themselves from one location to another, commonly through walking and running" (Pandy, Kumar, Berme, & Waldron, 1988). This movement is essential to sustain life in the search of food and the avoidance of danger (Broom & Fraser, 2007). During locomotion the limbs act synchronously in one of a variety of patterns termed a "gait". Gaits can either be symmetrical where the movements of limbs on one side of the body repeat those of the other side, or asymmetrical where the gaits on either side do not repeat those of the other (Broom & Fraser, 2007). The walk and trot are symmetrical gaits where the pair of feet move approximately half a cycle out of phase with each other (Jayes & Alexander, 1978). A stride refers to the full cycle of leg movements (Alexander, 1984; Broom & Fraser, 2007), with a stride deemed to commence when a particular foot is set down (Jayes & Alexander, 1978). Stride length is the distance covered between successive imprints of the same foot (Alexander, 1984; Broom & Fraser, 2007). Within a stride each limb acts in a support and a non-support or swing phase. During the walking gait, the support phase has a longer duration than the swing phase. As walking speed increases, the duration of the support phase decreases while the swing phase increases (Broom & Fraser, 2007). The step length and stride length also increase as speed increases (Jayes & Alexander, 1978). In cattle, Telezhenko (2009) found significant correlations (R^2 of 0.51–0.66) between the stride and step length, step angle and width with the cow height and length. Age and reproductive status may also have an effect as Van Nuffel (2014) reported a decrease in step length and speed with age and gestation stage.

It is worth noting that much of the research on ruminant gait movement has been performed on dairy cattle and many of the following descriptions on gait patterns have been inferred to be similar for sheep.

Gait mechanics

Symmetrical gaits include the walk and trot. Asymmetrical gaits include the canter and gallop. A detailed description of asymmetrical gaits can be found in Broom and Fraser (2007). Walking is defined as a slow, regular symmetrical gait where the left legs perform the same movements as the right, half a stride later. Either two, three or four legs support the body at any one time (Broom & Fraser, 2007). The sequence of leg movements in quadruped walking is left front (LF), right hind (RH), right front (RF), left hind (LH) or beginning with the right front (Broom & Fraser, 2007; Clive Phillips, 2008). The forelegs support approximately 60% of the static animal weight due to their closer proximity to the centre of gravity, whilst the hind legs are important for propulsive movement (Van Nuffel et al., 2015). The work of Pandy et al. (1988) on one Nubian goat supports the findings of Manter (1938) in cats, with forces exerted by the forelimbs being consistently higher than the hindlimbs for all gaits.

Trotting is a medium speed gait where the animal is supported by alternating diagonal pairs of limbs. The front limbs are off the ground longer than the hind limbs to allow the front feet to clear the ground prior to the placement of the hindlimbs. The sequence of leg movements in quadruped trotting is LF and RH then RF and LH (Broom & Fraser, 2007).

Distance travelled

The distance travelled while grazing is affected by both genetic differences between breeds and the immediate environment surrounding the flock (Fraser, 1974; Ratner & Hafez, 1975; Squires, 1975) with the location of food and water being a significant determinant (Broom & Fraser, 2007). Where water and quality food are located in close proximity, the distance travelled by animals is short and predominantly occurs while grazing (Broom & Fraser, 2007). The total distance travelled by grazing sheep is reported to vary from 8 to 16 km per day (Cresswell, 1960; Fraser, 1974; Louw, Havenga, & Hamersma, 1948) with a large variation in reported distances. Squires, Wilson, and Daws (1972) reported sheep travelled 9-14 km per day in range conditions. England (1954) and Tribe (1949) reported sheep travelled 3.2 – 4.8 km per day while Cory (1927) reported range sheep travelled 6 km per day attributing the increase in distance travelled to an increase in total grazing time. Sheep grazing quality pasture areas may travel as little as 1 km per day (Broom & Fraser, 2007). Tribe (1949) also reported that in temperate climates sheep walk more at night during summer than in winter. Sheep travelled further in the morning graze compared to the afternoon graze yet grazed longer in the afternoon (Bowns, 1971). Variation between breeds has also been reported. Merino sheep walked 10 km per day on semi-arid pasture in Australia (Lynch, 1974; Squires, 1971). Cresswell (1960) indicated Cheviot breeds travelled further than the Romney Marsh breed in hill country however only slightly more when grazing flat areas. When food and water were 4 km apart, daily distances were 14 km for Border Leicesters, 13.7 km for Merinos and 9 km for Dorset Horns (Squires et al., 1972). Reported walking speeds were 2.2-2.7 km/h for Border Leicesters and Merinos, but only 0.8 km/h for Dorset Horns. These variations in walking distances highlight the significant effect environmental conditions and genetics can have on the movement behaviour of sheep.

2.1.6 Inactivity

Sheep usually spend about half of their time in a relative inactive state (*as cited in review by* Ratner & Hafez, 1975). Periods of inactivity can be segregated into standing, lying, drowsing, resting and sleeping behaviours. A biological clocking system exists in the body which adapts the rhythms of organs and cells to environmental cues such as photoperiodic stimuli which signal to the animal it is time to rest (Fraser, 1974). During rest, animals adopt a recumbent posture (standing or lying) which reduces energy utilisation. Wakefulness is apparent during resting which permits activities such as rumination. Occasional limb and body shifting may be observed. Drowsing is a state of wakefulness with head movement and eye closure alternating between light sleep. Sleep is defined by brain changes and the loss of behavioural responses to stimuli. Two forms of sleep are evident in sheep; slow wave sleep (SWS) and rapid eye movement (REM) (Broom & Fraser, 2007).

Ruminants do not enter the state of sleep experienced by other domestic animals. Sheep have periods of "inactivity" scattered throughout the entire day however a large proportion of this occurs at night (Ratner & Hafez, 1975; Ruckebusch, 1972). Sheep are awake for approximately 16 hours per day (Broom & Fraser, 2007), 10 hours during daytime and 6 hours at night (Fraser, 1974). They drowse for a total of 4.3 hours, 2.7 at night and 1.6 during the day (Fraser, 1974). Slow wave sleep (SWS) occupies 3.5 hours per day and REM sleep occurs in 7 periods for a total of 43 minutes (Broom & Fraser, 2007; Fraser, 1974). Ruckebusch, Bell, Barbey, Guillemot, and Sertherlon (1970) reported REM sleep occurred only during the night time. Examining the duration of sleep states during the circadian cycle of farm animals, Ruckebusch (1972) reported sheep spent 70% of their time standing and 30% in a recumbent state. Munro (1955) reported 18 month old sheep slept for periods up to 38 minutes in duration. Balch (1955) postulated sleep in ruminants is directly linked to the digestive needs of the animal. The movement behaviours associated with standing and lying activity are shown in Figure 2-2. Note that although Figure 2-2 uses a cow for the illustration, similar movements can be inferred for sheep.

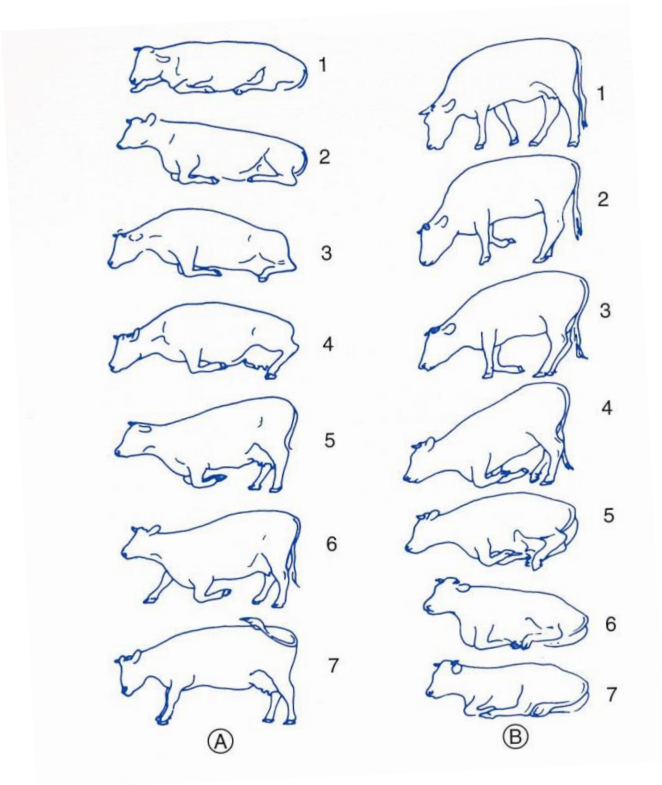


Figure 2-2. Typical movement patterns of a ruminant when standing up (a) and lying down (b). In (a), a recumbent animal stands up by lifting its body on its hind limbs first; in (b), the animal investigates the ground first and then lets its weight fall onto its flexed forelimbs (Broom & Fraser, 2007).

Resting behaviour is influenced by the environment, social facilitation and individual sheep genetics. Certain breeds of sheep develop definite camping behaviour i.e. Merinos have more definite camping areas compared to Dorset Horns (Ratner & Hafez, 1975). During cold weather sheep camp on high ground, whilst during hot weather camping near water and/or under shade is common. Camping sites also vary with the topography of the pasture. In hilly areas, high ground is preferred whereas trees are preferred on plains. Paddock and flock size may also influence camping sites. Small numbers of sheep in small (less than 4 ha) adjacent paddocks usually camp either along a common boundary or in contiguous corners (*as cited in review by* Ratner & Hafez, 1975). Abnormalities from normal camping and resting patterns may have symptomatic significance (Fraser, 1974) for the inference of individual health status.

2.2 Using behaviour to predict disease

An animal's behaviour is commonly analysed to provide an indication of their wellbeing (Gonyou, 1994). Behaviour is an important adaption to dealing with disease for individuals (Broom & Fraser, 2007). Traditionally, evaluations of animal health have been based on subjective assessments of debilitative signs, i.e. animals which appear depressed or show reduced appetite are classed as "ill" (Weary, Huzzey, & Von Keyserlingk, 2009). To date, there is limited research that specifically addresses the value of behaviour as a disease indicator (Weary et al., 2009). There are however a number of general behavioural changes which occur when animals appear ill.

2.2.1 Why does behaviour change?

It has been argued that a number of the behaviours displayed by ill animals are part of a coordinated response to fight disease (Dantzer, 2004; Hart, 1988). An explanation of why activity changes in sick animals from a physiological perspective at the molecular level has been reported by Smith, Vanzant, Carter, and Jackson (2015).

2.2.2 Behavioural changes

Altered behaviour is usually the first indication of illness (Broom & Fraser, 2007). The commonly recognized behavioural changes manifested with disease and illness are lethargy, depression, anorexia, lack of responsiveness and reduced grooming (Ahmed, Mun, Islam, Yoe, & Yang, 2016; Broom & Fraser, 2007; Hart, 1988). Physical injuries or disease can result in a loss of normal functioning regardless of whether the animal feels ill (Weary et al., 2009). A valid question when considering behaviour as an indicator of illness, is which behaviours respond as a result of sickness and why? A reduction in feed intake and reproductive activities coupled with increased resting behaviour displayed by sick animals is a likely means of conserving energy for the febrile response and mounting an immune response (Hart, 1988). Weary et al. (2009) suggest that behaviours which offer longer-term fitness will most likely decline with illness as animals divert resources to those functions of critical short term value. Environmental sampling and play behaviour are two activities which are promising cases to consider when assessing animals' response to illness as both of these candidates are of longer term value. It is also important to understand the causal links; does the behaviour increase the risks of illness or does illness cause changes in behaviour (Weary et al., 2009)?

Research on using behaviour as a predictor of illness has primarily focused on feeding behaviour because of the clear links between feed intake and production (Weary et al., 2009). The majority of this work has been performed on cattle. The physical behaviour of cows has been reported to be an early detector of diseases such as lameness (Olechnowicz & Jaskowski, 2011) an indicator of pain (Gonzalez et al., 2010), heat stress (Allen, Anderson, Collier, & Smith, 2013) and social interaction within a herd (Ketelaar-de Lauwere, Devir, & Metz, 1996). Research has shown healthy feedlot steers spent 30% more time feeding than morbid steers and were also reported to visit the feed bunk more often immediately after feed delivery (Sowell, Bowman, Branine, & Hubbert, 1998). Quimby et al. (2001) used the same electronic monitoring system as Sowell et al. (1998) and detected animal morbidity 4.1 days earlier than traditional clinical evaluations in commercial feedlots. Electronically monitored feeding behaviour of 101 cows for 5 weeks over the calving period was studied by Huzzey, Veira, Weary, and Von Keyserlingk (2007). Cows prone to metritis had decreased feeding time and intake relative to healthy cows and these differences in feed intake were evident 2 weeks prior to calving and before any clinical signs of infection were observed. Changes in short term feeding behaviour of dairy cows subject to ketosis, acute locomotory problems and chronic lameness was studied using computerised feeders. Ketosis was characterised by a rapid decrease in feed intake, feeding time and feeding rate at an average of 3.6 days prior to diagnosis by farm staff. Acute locomotion disorders showed smaller daily decreases in feed intake, feeding time and a daily increase in feeding rate during an average of 7.7 days prior to diagnosis (González et al., 2008). It has further been proposed that the abnormal feeding and drinking behaviour and reduced activity is often considered to be associated with a general malaise (Baumgartner et al., 1999).

Most farm animals are prey species which suggests they should normally be stoic and where possible, sick animals should mask any signs of vulnerability particularly if the illness makes them an easier target for predation (Weary et al., 2009). Measures of behaviour need to be sufficiently sensitive enough to detect very subtle changes in behaviour which the animals are unable to hide. This challenge is foreseen to be especially important for early stage infection as animals may be less capable of masking their state (Weary et al., 2009). The ability to monitor small incremental changes in behaviour may be useful for detecting subtle changes associated with sub-clinical disease (Morris et al., 2012). Weary et al. (2009) suggested that automated measures of behaviour monitoring may hold particular importance in this respect as they allow for increased use of objective measures opposed to traditional, subjective measures based on the accumulated experience of livestock handlers. As eating, ruminating and resting are the main daily activities of ruminant livestock (Hancock, 1954), monitoring these and similar behaviours may provide a valid indicator of animal well-being.

2.2.3 Behaviour and welfare

The Brambell Committee (Brambell, 1965) defined welfare as "a wide term that embraces both the physical and mental well-being of the animal". Therefore, "any attempt to evaluate welfare must therefore take into account the scientific evidence available concerning the feelings of animals that can be derived from their structure and functions and also form their behaviour". The requirement of monitoring sheep to maintain adequate welfare standards has been well documented and Wemelsfelder and Farish (2004) have reviewed behavioural observations to categorise sheep welfare. If behaviour could be monitored continuously it would provide one objective measure of animal welfare. Animal welfare is often considered in terms of the 'five freedoms' which define ideal states for acceptable welfare. The 'five freedoms' are freedom from hunger and thirst; from discomfort; from pain, injury and disease; to express normal behaviour and; from fear and distress. However, the concept of "Five Freedoms" is an ethical statement related to animal welfare and does not provide an objective measure for assessing an animal's welfare. From a scientific perspective, scientists have used two main frameworks to understand animal welfare; affective state and biological functioning (Hemsworth, Mellor, Cronin, & Tilbrook, 2015). Affective state refers to "the welfare of an animal derives from its capacity for affective experiences" (Duncan & Fraser, 1997). Biological functioning considers the extent of biological activity underlying the animal's ability to cope with its environment, including; body repair systems, immunological defences, physiological stress responses and behavioural responses (Hemsworth et al., 2015). This is important when considering behaviour as a measure of welfare since the ability of an animal to cope with the challenges it faces will be reflected in the normality of its biological functioning and fitness (Hemsworth & Coleman, 2010). The way in which we objectively measure animal welfare in extensive grazing systems remains a question. Please refer to Gonyou (1994), Dwyer (2009) and Kilgour (2012) for a more in depth description of behaviour and welfare.

2.3 Sheep diseases

2.3.1 Overview of disease in Australia

In the early days of the Australian sheep industry scab, footrot and anthrax were common diseases in flocks (Bull, 1951). This differs to the present day disease challenges facing the sheep industry with intestinal nematodes, lice and flies representing the main diseases of economic significance (Sackett et al., 2006). Before the 1900's there was little knowledge around the causes of sheep diseases. Sheep were run under extensive grazing systems, used almost exclusively for wool production, had a low monetary value and losses associated with disease were viewed as inevitable. Woolgrowers were not interested in the study of diseases in Australia, however in areas where stocking rates were higher and graziers inspected sheep more regularly, there was a growing awareness of the annual sheep losses (Bull, 1951).

Fast-forward to the present day scenario, individual sheep have a higher monetary value and many on farm management decisions are made in an effort to reduce the impact of disease. Sackett et al. (2006) reported the main diseases of sheep in Australia and provided an estimate of the costs associated with each disease. The main diseases in Australia are listed in Table 2-1. There are also a number of diseases of lower economic importance or specific to particular regions of Australia (e.g. mastitis) that have not been included.

Table 2-1. Major diseases and disease related outcomes of sheep in Australia (Sackett et al., 2006).

High economic impact	***Medium economic impact***	***Low economic impact***
Abortion & still birth	Caseous lymphadenitis	Clostridia
Arthritis	Fluke	Dermatophilosis
Blowfly	Foot abscess	Grain poisoning
Lice	Redgut	Hypercalcaemia
Ovine Johnes Disease (OJD)	Scabby mouth	Mycoplasma ovis
Peri-natal mortality	Yersinia	Nitrate poisoning
Post-weaning mortality	Trace element deficiency	Ovine brucellosis
Scouring		Pneumonia
Worms		Pregnancy toxaemia

Figure 2-3 illustrates the national cost of the top 11 economically significant sheep diseases in Australia as reported by Sackett et al. (2006). In Australia the leading sheep diseases in terms of national cost are internal parasites, flystrike and lice, respectively. Whilst the diseases listed in Figure 2-3 result in large financial costs to the sheep industry, they can also present a significant animal welfare concern.

There are a number of common diseases that often occur annually that affect weight and/or mobility at an individual and flock level. Diseases associated with weight loss include internal and external parasites (e.g. worms, fluke, coccidia, blowfly and lice) as well as some bacterial and viral infections (e.g. OJD, scabby mouth and cheesy gland) along with mineral deficiencies/toxicities. Those diseases associated with reduced mobility include severe cases of the conditions mentioned above as well as metabolic disease (e.g. pregnancy toxaemia, hypocalcaemia and grass tetany), mastitis, hypothermia, pneumonia and foot related conditions such as foot rot and foot abscess.

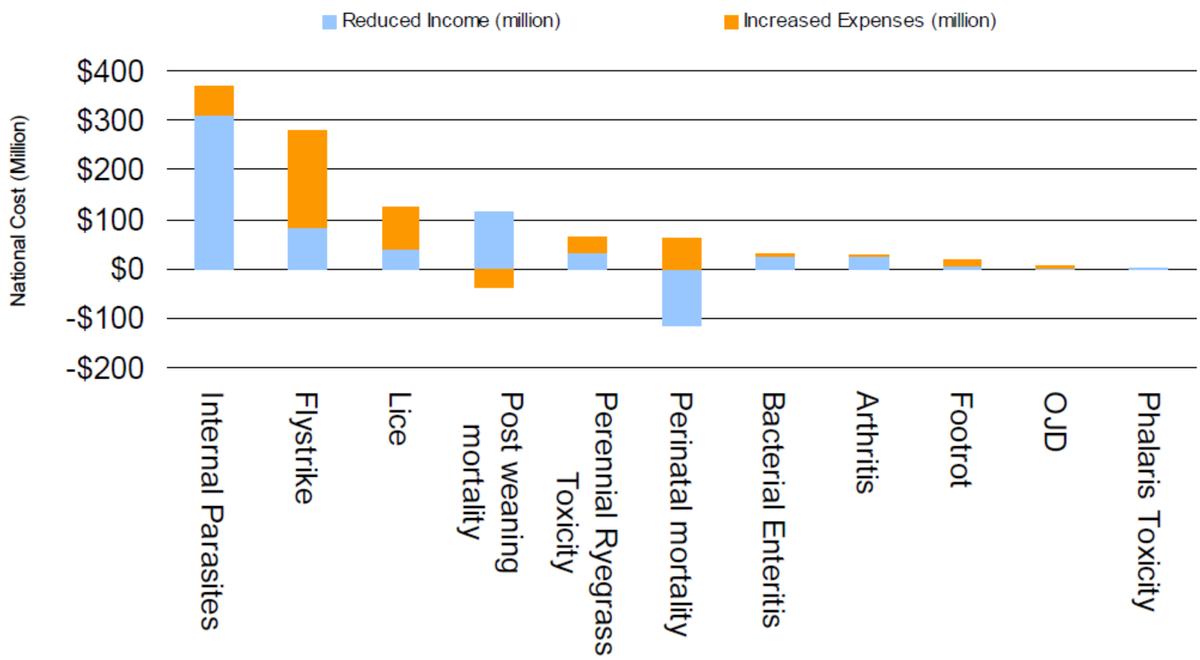


Figure 2-3. National cost of disease to the sheep industry (Sackett et al., 2006).

This thesis examines two specific diseases, lameness and internal parasites. The following section will provide a general overview of these diseases, their importance and impact. A more detailed review of the specific symptoms and how they might be detected using sensors is provided in Chapter 7 and Chapter 8, respectively.

2.3.2 Internal parasites

Economic impact

Gastro-Intestinal Nematodiasis (GIN) is the most significant disease of sheep and goats in both temperate (McLeod, 1995) and tropical (Walkden-Brown & Banks, 1987) areas around the world. Intestinal parasites presents the highest disease associated cost to Australian sheep producers with an estimated annual cost of $369 million of which $310 million is attributed to reduced income and $59 million accounting for increased expenses (Sackett et al., 2006). A comprehensive breakdown of GIN associated costs is provided by McLeod (1995) and Sackett et al. (2006).

Nematode species

The most economically important species of nematodes affecting domestic ruminants belong to the family Trichstrongyloidea with the major genera involved being *Haemonchus*, *Trichostrongylus* and *Ostertagia* (Walkden-Brown & Kahn, 2002). Summer rainfall regions are dominated by three major species of the Trichostrongylidae family, *Haemonchus contortus*, *Teladorsagia circumcincta* and *Trichostrongylus colubriformis* (Kelly, 2011). As adults these nematodes inhabit the abomasum or anterior small intestine. All of them are ingested off pasture as infective 3rd stage larvae (L3) and proceed through moults to L4 and then adult (Walkden-Brown & Kahn, 2002).

Pathogenesis and impact on the host

While there are many common features in the pathogenesis and host immune response to these nematodes, each represents a unique disease and the effects on the host and the host response, vary with both nematode species and the stage of the life cycle involved (Walkden-Brown & Kahn, 2002). *Haemonchus contortus* is the most pathogenic nematode which dominates in summer rainfall regions (Donald, Southcott, & Dineen, 1978). High burdens can lead to host blood losses greater than 400 ml per day as a characteristic of the central pathogenesis of *H. contortus* being haemorrhagic anaemia (Kelly, 2011). During favourable weather conditions, L3 larvae can quickly contaminate pastures given the high reproductive rate of *H. contortus*, rapidly increasing worm burden with such outbreaks often being associated with mortality (Gordon, 1967; Kelly, 2011).

Key distinguishing features of the pathogenesis of GIN include marked reductions in voluntary feed intake, disturbances in the metabolism of protein, energy and some minerals due predominantly to the mounting of a gut based immune response (Walkden-Brown & Kahn, 2002). These and other pathological changes can lead to clinical disease distinguished by hyperproteinemia, oedema, anaemia, diarrhoea, osteoporosis, weight loss and reduced fertility depending on the species of nematode involved (Falzon, Schneider, Trotter, & Lamb, 2013; Walkden-Brown & Kahn, 2002). It must be noted there are a number of practical difficulties associated with measuring the impact of GIN (Kelly, 2011).

The level of feed intake reduction is dependent on host age, stage of immunity and the burden and species of nematode involved (Kelly, 2011). A reduction in feed intake can account for up to 40-90% of lost production (Van Houtert & Sykes, 1996). This depression in feed intake can vary in its magnitude from anorexia to mild inappetance (Walkden-Brown & Kahn, 2002). Coop, Sykes, and Angus (1976, 1977) indicated a reduced feed intake due to challenge with *T. colubriformis* and *T. circumcincta* can occur without the presence of clinical signs. Animals infected with only *H. contortus* typically do not show a reduced feed intake (Knox & Steel, 1999; Wallace et al., 1998) while mixed infections of *H. contortus* and *T. colubriformis* have been shown to have a higher level of feed intake reduction than infection with *T. colubriformis* alone (Knox & Steel, 1999).

Mortality is the most severe manifestation of GIN infection. While many production systems aim to limit mortality through anthelmintic treatment, mortality may still be significant (Barger, 1982). Mortality rates of 68% and 31% have been reported in uncontrolled infections of young and mature sheep respectively (Cohen, Eastoe, Hotson, & Smeal, 1972). Mortality is higher in sheep under 2 years of age in areas dominated by *H. contortus* with the amount of blood loss, resulting in anaemia and death, being determined by the worm number, mass and egg production (Le Jambre, 1995).

In cattle, Szyszka and Kyriazakis (2013) found higher faecal egg counts (FECs) corresponded to greater mean distances per time step (breaking the distance down to a standard interval of time to calculate speed). Falzon et al. (2013) reported similar findings in sheep concluding that a possible biological explanation for this increase in distance per time step associated with a higher FEC is that animals with a higher FEC had to either graze for longer periods or travel to water more frequently (Falzon et al., 2013). The findings of Falzon et al. (2013) indicated that even low FEC levels have an impact on productivity with those animals with higher FEC levels likely to have a greater energy expenditure resulting from the increased average distance per time step.

Treatment and control

Traditional intestinal nematode control has relied heavily on anthelmintic treatment of the host. Whilst this method can successfully prevent clinical signs of the disease and reduce production losses (Johnstone et al., 1979), treatment is often implemented with limited knowledge of infection status (Walkden-Brown et al., 2006). This leads to increased number of treatments and the acceleration of anthelmintic resistance in the worm population (Besier & Love, 2004). To alleviate such issues an integrated pest management (IPM) approach is often proposed.

Whilst the control and management of GIN infection has received a significant level of research over the past 40 years, the impact of GIN remains a significant economic burden to the Australian sheep industry and GIN still represents the most significant sheep health cost. The extent to which such costs can be alleviated by management change remains an important question (Kelly, 2011).

2.3.3 Lameness

What is lameness?

Lameness can be defined as "the clinical manifestation of painful disorders, mainly related to the locomotor system, resulting in impaired movement or deviation from normal gait or posture" (Van Nuffel et al., 2015). The severity of this abnormal locomotion can vary from stiffness or decreased symmetry of limb movement to an inability to bear weight on a limb, or even total recumbancy. To understand abnormal locomotion and the associated changes in animal gait and posture, an insight into normal gait is necessary. Much of this research has focused on the behaviour of dairy cattle given the high prevalence of lameness in dairy herds. However, similar principles can be applied to quadrupedal movement in other species such as sheep.

Effects of lameness in sheep

Lameness is a clinical symptom associated with a number of sheep diseases. It is one of the most common and persistent health problems in sheep flocks around the world

(Abbott & Lewis, 2005) which has resulted in lameness becoming a common cause of economic and welfare concern in many sheep producing countries (Winter, 2008). Lameness has adverse effects on both the economic and physical performance of a flock (Hodgkinson, 2010). Without alliance to a specific lameness related disease, the biological effects of general lameness on the animal include reduced weight gain, poor body condition leading to decreased fertility in rams and predisposition to metabolic disease in pregnant ewes, lower birth weight in lambs, poor colostrum production and increased lamb mortality due to mismothering (Hodgkinson, 2010; Agnes Winter, 2004). Lameness during late pregnancy can lead to recumbancy, precipitating pregnancy toxaemia due to poor feed intake and reduced mobility (Eze, 2002; Harwood, Cattell, Lewis, & Naylor, 1997). Detrimental effects of chronic lameness on bodyweight, lamb growth rates and wool growth have also been demonstrated (Marshall, Walker, Cullis, & Luff, 1991; Stewart, Clark, & Jarrett, 1984).

Causes

The causes of lameness are widespread. Lameness may be the result of hard environmental terrain, hoof problems, wetness, trauma, fractures, and inflammation of anatomical structures and glands (Caroprese, Casamassima, Rassu, Napolitano, & Sevi, 2009; Mohammed, Badau, & Kene, 1996). It is important to understand that lameness is also a symptom of diseases unrelated to the hoof and legs such as mastitis. Some common examples of diseases resulting in lameness include tetanus, white muscle disease, foot and mouth disease, bluetongue, mastitis, arthritis, epididymitis, interdigital dermatitis, footrot and foot abscess (Kahn & Kahn, 2005; Kaler, 2008; Agnes Winter, 2004). These diseases not only cause production losses, they also present animal welfare concerns particularly if left undiagnosed and untreated. As lameness is a symptom associated with a number of diseases a detailed review of each disease will not be provided here.

Is lameness a welfare issue?

As stated by Hodgkinson (2010) "lameness is still the biggest welfare issue present on sheep farms". Since sheep are stoical prey animals they usually exhibit few obvious signs of pain or distress. Animals which are demonstrably lame, therefore indicates that they are experiencing significant pain (Winter, 2008) raising potential welfare concerns.

Hence the need arises to identify these lame animals as early as possible to ensure adequate welfare and reduce productivity losses in the short and long term. This is especially important in the case of contagious infections such as footrot and contagious ovine digital dermatitis (CODD) where early identification is necessary to reduce transmission and also assist in decreasing susceptibility to secondary diseases such as pregnancy toxaemia and flystrike.

Lameness associated behaviours

There is limited literature on the behavioural symptoms associated with lameness in sheep. Lame animals obviously show a reduced amount of weight bearing on single or multiple limbs depending on the cause and disease severity. Animals experiencing pain often deviate from their normal behaviour by altering activity (either through an increase or decrease), posture, gait, appetite and appearance (Anil, Anil, & Deen, 2002). In cattle, lameness has been associated with longer lying and standing times, and decreased feeding behaviour (Blackie, Amory, Bleach, & Scaife, 2011; González et al., 2008; Singh, Ward, Lautenbach, Hughes, & Murray, 1993). Similarly, a lame sheep spends more time lying down which also predisposes it to an increased risk of flystrike (Hodgkinson, 2010). This decreased feeding behaviour may also be a result of the predisposing condition, such as mastitis, causing a depressed animal state. Furthermore gangrenous mastitis affected ewes characteristically drag one hind leg behind the other while walking (Broom & Fraser, 2007).

The change in gait is one of the most visual signs of lameness. Flower, Sanderson, and Weary (2006) found that lame cows walked slower, had longer stride durations, shorter strides and a more uneven weight distribution over the limbs than non-lame cows. The change in weight distribution is one of the first signs detected by farmers in sheep affected with conditions of the foot such as footrot, with severely affected sheep easily spotted due to the hobbling or kneeling action (Ford & Brian, 2016). Whilst the literature related to sheep did not mention a relationship between head movements and lameness, a lameness characteristic in cattle is that of the head “bobs” (i.e., nodding, vertical movements of the head as the lame limb makes contact with the ground) (Distl & Mair, 1993; Flower et al., 2006; Nordlund, Cook, & Oetzel, 2004). A similar lameness characteristic can be inferred for sheep. Excessive flicking of the head has also been linked with lameness (Kaler, 2008) which is most likely associated with agitation and discomfort. These behavioural changes are a manifestation of discomfort or pain and occur as an adaption in an effort to minimise the level of experienced pain. Van Nuffel et al. (2015) provides a more detailed description on how lameness affects the quadrupedal gait patterns.

2.4 Conventional animal behaviour monitoring

Determining animal wellness status is frequently based on visual appraisal or performance parameters (Theurer, Amrine, & White, 2013). Conventional methods to evaluate animal's health, welfare and productivity rely upon stockman's auditory, olfactory and visual senses to obtain an overall productivity status of their animals (Wathes, Kristensen, Aerts, & Berckmans, 2008). As identification of health problems relies on farm personnel, early identification is difficult and sub clinical disease may escape detection (González et al., 2008). Veterinary treatments are normally more effective the earlier they are initiated after infection. Therefore the earlier infected animals are identified, the quicker treatment can be administered, ultimately improving the effectiveness of treatment and reducing costs (González et al., 2008). In terms of improving welfare it is not the diagnosis of disease that improves welfare but the consequent treatment (Broom & Fraser, 2007).

It is well established that health challenges such as stimulation of the immune response and/or infection with a pathogen can lead to changes in animal behaviour (Weary et al., 2009). Behavioural changes can precede any clinical signs of the disease and these may have diagnostic value (González et al., 2008). The behavioural changes displayed by diseased animals may be related to a specific disease (e.g. anaemia in the case of *Haemonchus contortus* infection) or more commonly may be related to a number of different diseases (e.g. lameness).

Monitoring of animal behaviour has both practical applications at the farm level and also in animal behavioural studies. Quantifying animal behaviour has previously relied upon direct observation or video monitoring, both of which require significant labour and time (Müller & Schrader, 2003). Furthermore, these traditional observation methods are often restricted to daylight hours. In a commercial context the observation of animals for welfare assessment needs to be conducted in a short period of time and as infrequently as possible to ensure operational efficiency (Edwards, 2007). Additionally, direct observation is limited in that it only provides a behavioural assessment over the period in which the animals are actually observed. The consequence of this is that the behavioural states being relied upon for welfare assessment (for example grazing activity or travelling) may not be actually observed during the short inspection. Direct observation is undoubtedly the "gold standard" for behavioural studies however this method carries a number of limitations (Dobos, 2013; Theurer et al., 2013).

In animal behaviour studies, a common approach to determine animal pain and wellness is having a trained observer to monitor animals for clinical signs of pain or disease. Scoring systems which assign a value based on level of illness are common and used frequently in disease research (Coetzee et al., 2012; Hanzlicek, White, Mosier, Renter, & Anderson, 2010; Perino & Apley, 1998; White, Anderson, & Renter, 2012). The trained observer can assign individual clinical illness scores (CIS) which represents the current state of the animals (Theurer et al., 2013). The CIS correlates with the need for an intervention or the probability of a specific outcome (Hayes, Mathews, Kruth, Doig, & Dewey, 2010). Accurately recording rapid behaviours, such as ear flicks, as they occur is challenging and this can be further complicated when recording these behaviours on more than one animal simultaneously (Altmann, 1974; Theurer et al., 2013). Dobos (2013) further indicated that maintaining a suitable team of observers for studies over extended time periods and the ability of teams to only monitor a limited number of animals simultaneously are disadvantages of direct observation.

From a behavioural research perspective, there are two levels of decision which must be made in relation to the recording method. The first relates to identifying which subjects to watch (sampling rules), while the second refers to how the behaviour is to be recorded (recording rules) (Martin & Bateson, 2007). Sampling rules encapsulates ad-libitum, focal, scan and behaviour sampling. The recording rules covers continuous and time sampling (Martin & Bateson, 2007). These approaches to measuring animal behaviour rely on either visual observation using an observer or, video recordings which can be analysed after the event. This section will highlight some of the previously used approaches to monitor animal behaviour and distinguish between the various methods available.

Recording animal behaviour uses two main approaches: visual observation with a human observer or, video recordings. Studies on cattle have shown the presence of a human observer may alter animal behaviour (Grignard, Boissy, Boivin, Garel, & Le Neindre, 2000; Ishiwata, Kilgour, Uetake, Eguchi, & Tanaka, 2007). There is also potential for observer bias when assigning a behavioural state to an animal (Dobos, 2013). This can be described as both intra (within a single observer) and inter-observer (between multiple observers) reliability. Kristensen et al. (2006) found that a small amount of training increased the overall agreement between veterinarian observers when assigning body condition scores to cows indicating that training of observers may alleviate this issue to some degree. Observing behaviour frequencies is also difficult in low ambient light and artificial lights have been shown to alter dairy cow lying time (Phillips & Schofield, 1989). Furthermore it is difficult to monitor animal behaviour 24 hours a day without altering behavioural patterns and therefore behaviour is commonly monitored through video analysis (Theurer et al., 2013).

Video technology gives an exact visual record of the behaviour and allows observers to post analyse recordings (Martin & Bateson, 2007). The quality of video recording is determined by the specific behaviour(s) monitored, environmental conditions and the number of animals observed (Theurer et al., 2013). Video recordings are useful for studying behaviours which occur too fast to analyse in real time and offer the advantage of being able to repeatedly analyse observations in different ways. One of the major upsides for video recordings is the capacity to allocate multiple behaviours with a specific time code (Martin & Bateson, 2007).

Video recording has been used extensively in both wildlife and livestock studies. Trotter, Falzon, Dobos, Lamb & Schneider (2011) and Dobos (2013) highlighted issues associated with remote video technology with the study area being constrained within the field of view of the camera being identified as a significant limitation. A drawback to this approach of behaviour recording is time (Martin & Bateson, 2007). Analysing video recordings can be extremely time consuming with only a small time-period of behaviour commonly taking hours to code correctly. Depth perception is decreased compared to live observation and therefore it may be difficult to determine if animals are eating/drinking or just standing near the water/feeder (Theurer et al., 2013).

To alleviate some of the issues highlighted above, sampling and recording methods such as scan sampling, time sampling and focal sampling have been developed which minimise the labour needed to classify video segments whilst still accurately determining animal behaviour (Theurer et al., 2013). Continuous sampling/recording "aims to provide an exact and faithful record of the behaviour, measuring true frequencies and durations and the times at which behaviour patterns stopped and started" (Martin & Bateson, 2007). Continuous video surveillance is a non-invasive method of behaviour monitoring however logging the movement of animals over long periods of time can be cost prohibitive and labour intensive (Robert, White, Renter, & Larson, 2009).

Scan sampling is where "the whole group of animals is rapidly scanned at regular intervals and the behaviour of each individual is recorded at that instant" (Martin & Bateson, 2007). The frequency of activity during the observation period is representative of behavioural activity over the entire period of data collection (Colgan, 1978). This method restricts the observer to measuring only a few behaviour categories, limiting the information obtained (Martin & Bateson, 2007). This method has been used to accurately evaluate frequency of cattle behaviours compared to continuous sampling; however when the scan interval was 30 minutes or greater, the correlation decreased (Mitlöhner, Morrow-Tesch, Wilson, Dailey, & McGlone, 2001). A disadvantage of this method is the results may be biased towards particular individuals and/or behaviours (Martin & Bateson, 2007) and the resolution of information obtained is much coarser compared to continuous recording.

Time sampling involves "sampling behaviour periodically" (Martin & Bateson, 2007). For example, identifying behaviour for a period of 10 minutes at the start of each hour and then multiplying the frequency of activity for the entire hour (Arnold-Meeks & McGlone, 1986). Mitlöhner et al. (2001) found time sampling had a low correlation compared to continuous sampling for identifying standing, feeding, lying, drinking and walking activity. Please refer to the book of Martin & Bateson (2007) for further information on time sampling.

Focal sampling is observing a portion of animals from a population to determine the activity of the entire group (Theurer et al., 2013). This is considered the most satisfactory approach to studying group behaviour and allows a number of behaviour categories to be recorded (Martin & Bateson, 2007). Mitlöhner et al. (2001) found this method to accurately determine standing, lying, feeding and walking behaviour in cattle when only 1 out of 10 animals was monitored, however drinking behaviour required 4 animals to be monitored. The accuracy of this sampling method may be influenced by individual animal variation in the behaviour of interest (Theurer et al., 2013). Furthermore, the focal individual can move out of the field of view or be obscured by other animals which can be problematic in field conditions (Martin & Bateson, 2007).

In summary, the occurrence of behaviour patterns is often erratic over time and activity recording requires long periods of observation. Due to practicality and labour resources, on-farm assessments need to be conducted in a short period of time and these factors are likely to increase as farm sizes expand. Hence, interest in developing automated measures of animal behaviour has emerged (Rushen, Chapinal, & De Passille, 2012). The availability of equipment which can measure the behaviour of animals automatically may help resolve some of these problems (Blokhuis, Veissier, Miele, & Jones, 2010). Additionally, the use of on-animal sensors may offer some respite from the labour and cost issues associated with grazing behavioural research of ruminants (Dobos, 2013) and may also provide information on animal health status. However, further research is required to validate the use of on-animal sensors to monitor sheep behaviour.

2.5 Remote animal behaviour monitoring

Grazing-based livestock industries, primarily the red-meat and wool production systems, have yet to fully explore the potential of "Precision Agriculture" (PA) technologies. Recently, the need for more efficient animal productivity is driving many producers to evaluate PA technologies that could be applied in their grazing systems (Trotter, 2013). Development of technology has led to new openings for animal behaviour monitoring (De Passille, Jensen, Chapinal, & Rushen, 2010). Historically, animal-borne sensors were bulky, heavy and had limited data storage and battery life. Over recent decades however, there have been considerable advances in device miniaturisation and reduction in power consumption of electronic devices (Greenwood, Valencia, Overs, Paull, & Purvis, 2014), allowing on-animal attachment for considerably longer deployments. One of the main challenges is developing a device small enough to be deployed as an ear tag yet robust enough to survive the harsh conditions it will face in the field (Trotter, 2013).

One technology gaining interest amongst graziers is the development of automatic livestock monitoring systems (ALMS) (Trotter, 2013). Commercially, automated sensor-based behaviour classification systems have already been developed and are being used in the dairy industry (Umstätter et al., 2008) to detect oestrus enabling increased conception rates (Valenza et al., 2012) and monitor lameness (Kokin, Praks, Veermäe, Poikalainen, & Vallas, 2014). The red-meat and wool industries are increasingly interested in the potential of this class of technology to provide a 24-hour-a-day, 7-days-a-week (24/7) monitoring to generate information on the location and behaviour of their animals (Trotter, 2013). The constant 24/7 surveillance provided by ALMS can directly and significantly increase labour use efficiency for graziers through the reduced need for visual stock inspection. Inspecting sheep is labour intensive and in many countries skilled labour shortages are widely reported (Umstätter et al., 2008). Furthermore, the provision of remote alerts for health status is possible (Falzon et al., 2013; Wathes et al., 2008). This would enable producers to undertake strategic actions to validate the symptoms (e.g. targeted faecal sampling) and/or implement more timely control actions (Trotter, 2013). In addition to the quantifiable savings in terms of reducing labour, ALMS are likely to provide producers with more qualitative benefits, particularly "peace-of-mind" regarding the location and state of livestock, which could have significant benefits in terms of producer health and mental wellbeing (Trotter, 2013).

The development of a monitoring system is needed for assessing the welfare status of small ruminants at the farm level. The assessment of welfare could be used to quantify the impact of different husbandry conditions on animals. Furthermore it could also be used for legislative requirements, as a certification system and as an advisory and management tool by farmers (Main, Leeb, Whay, Hovi, & Webster, 2004). In addition, consumers demanding high quality food also expect animal products to be obtained and processed with greater respect for the welfare of the animals (Caroprese et al., 2009). Such a system may be one component which has the potential to quantitatively validate welfare on farm.

As outlined previously, on-farm measures of animal welfare using behavioural indicators has historically been challenging. However the increased availability of low cost technology opens the possibility of feasible, automated animal monitoring systems (Rushen et al., 2012). Some of the original technology used to document livestock activity include devices that measure the electrical resistance of jaw opening (Matsui & Okubo, 1991; Penning, 1983; Rutter, 2000), pendulum pedometers (Phillips & Denne, 1988; Umemura, Wanaka, & Ueno, 2009) and mercury tilt switches (Champion, Rutter, & Penning, 1997; O'Driscoll, Boyle, & Hanlon, 2008). Some of the more recently evaluated activity meters include IGER behaviour recorders, Global Positioning Systems (GPS), SCR collars and accelerometers. The IceTag accelerometer by IceRobotics is one of the most commonly used accelerometer based activity monitors used in livestock research. A more detailed description of these devices is provided in the following sections.

Laca and WallisDeVries (2000) used video recordings and a wireless microphone to distinguish biting and chewing sounds in order to estimate forage intake. The microphone was taped to the forehead of four steers, with a transmitter attached to the halter, and managed to accurately classify 954 biting and chewing registrations with 94% accuracy. O'Driscoll et al. (2008) attached a data logger with a mercury tilt switch to a cow's hind leg, and was able to sense if the cow was in a lying or standing position. The logger was a good alternative to manual observations, obtaining concordance values of 96.9% and 93.7% for standing and lying respectively. Similar results have also been reported by Champion et al. (1997).

2.5.1 Global Positioning Systems (GPS)

Recent developments in Global Navigation Satellite Systems (GNSS) technologies has resulted in an increased availability and reduced cost of portable GNSS devices which has dramatically elevated their application in livestock movement research (Trotter, Lamb, Hinch, & Guppy, 2010). Research has gone beyond using this technology just for a simple geographical location with researchers now examining a variety of animal behaviour and animal resource interactions (Guo et al., 2009; Putfarken, Dengler, Lehmann, & Härdtle, 2008; Swain, Wark, & Bishop-Hurley, 2008; Taylor et al., 2011; Tomkins, O'Reagain, Swain, Bishop-Hurley, & Charmley, 2009; Trotter, Lamb, & Hinch, 2009). For a more comprehensive review on the history of GPS animal tracking see Swain, Friend, Bishop-Hurley, Handcock, and Wark (2011), Matthews et al. (2013) and Tomkiewicz, Fuller, Kie, and Bates (2010).

How a GPS works

A GPS works by receiving signals from satellites orbiting the earth. Each GPS satellite transmits data that indicate the current time and its location. Signals moving at the speed of light arrive at a GPS receiver (on the animal) at slightly different times because some satellites are further away than others. Both the GPS receiver and the satellites contain clocks, and based on the time it takes the signal to reach the receiver, the distance is calculated between the satellites and receiver (Hamadani & Khan, 2015; Swain et al., 2011). In order to calculate the receiver’s position (in terms of latitude, longitude and elevation), distance measures from several satellites is required, and the more satellites supplying signals, the higher the accuracy of the receiver’s position. For a more detailed description of GPS technology, see Rempel and Rodgers (1997), Turner, Udal, Larson, and Shearer (2000) and Swain et al. (2011).

Monitoring animal behaviour from GPS

Whilst GPS technology enables the tracking of animal movement, this information is enhanced if the location data have a corresponding activity assigned (Bailey, VanWagoner, Weinmeister, & Jensen, 2008; Guo et al., 2009; Ungar et al., 2005). Harry Stobbs was one of the first researchers to attempt to measure grazing behaviour using automated recording devices (Stobbs, 1970; Stobbs & Cowper, 1972) while Schlecht, Hülsebusch, Mahler, and Becker (2004) were the earliest authors to suggest using GPS data to characterise cattle foraging behaviour. More recently, GPS devices have been used to determine activity states of cattle (Anderson et al., 2012; Augustine & Derner, 2013; Guo et al., 2009; Handcock et al., 2009; Homburger, Schneider, Hilfiker, & Lüscher, 2014; Putfarken et al., 2008; Schleppe, Lachapelle, Booker, & Pittman, 2010; Schwager, Anderson, Butler, & Rus, 2007; Trotter et al., 2010; Ungar et al., 2005) and sheep (Dobos et al., 2015; Falzon et al., 2013; Manning et al., 2014; Putfarken et al., 2008). A commonality across many GPS livestock studies is the deployment of collar mounted GPS devices because the size of the devices often prevents alternative deployment modes.

Homburger et al. (2014) tracked grazing cows in Switzerland at 20 second intervals. Using distance and turn angle metrics, random forest analysis achieved an accuracy of 36%, 95% and 58% for walking, grazing and resting respectively. Putfarken et al. (2008) recorded the positons of sheep and cattle every 5 minutes using GPS. Grazing activity was assumed if the position of the animal had changed more than 6 m but less than 100 m within 5 minutes. Using a similar approach Augustine and Derner (2013) partitioned activity on the basis of the distance moved in a 5 minute interval and the proportion of time the animal was in a head down position using a classification tree. This study incorporated a dual axis activity sensor that recorded up/down and side/side head movements. Beef cows tracked at time intervals of 1 second had threshold values of mean movement rate calculated for one minute periods to discern between walking, grazing, and resting (Anderson et al., 2012). A model that used thresholds to classify activities was better than a discriminant model that utilised only observational data.

Differing to the studies above, Schleppe et al. (2010) developed an eartag based GPS to record the velocity and position of feedlot cattle with the vision of modelling the behaviour of sick and healthy animals to improve survival rates through earlier disease detection. Whilst general movement patterns were evident, velocity data were noisy and detection of daily velocity patterns was difficult. Deployment time was short with the best run time being 3.7 days because of the limited power source. While the majority of these studies demonstrated location and movement data are valuable for determining animal behaviour, there remains an underlying question of the value of using GPS data alone to determine behaviour as additional sensor data are often required to refine the classification (Swain et al., 2011).

GPS technology presents a number of challenges hindering commercial adoption. These limitations include power efficiency, data storage, cost, size, accuracy and the ability to have real time updates. Poor battery life leads to high maintenance costs, prohibiting commercial uptake and limiting the deployment time and data completeness in a research domain (Mason & Sneddon, 2013). Linked with power efficiency is data storage capacity which remains a balance between energy consumption, deployment period and battery size. This also constrains the sample interval ultimately affecting the positional accuracy of GPS fixes (Swain et al., 2011). A low sampling interval using a sleep/burst mode may not provide the level of data resolution necessary to classify specific behaviours (Theurer et al., 2013). Tomkiewicz et al. (2010) previously stated that the major challenge with positional sampling frequencies approaching continuous observations is the current requirement for battery power. This level of energy requirement often means long term deployment requires a collar or body attachment hence limiting their potential to be deployed in an ear tag form factor.

The low spatial resolution of "free to air" GPS tracking collars has often been viewed as being insufficient for certain studies. Some research shows a discrepancy between visual and tag position of an average standard deviation of 9 m ± 7 m (Schleppe et al., 2010). Other work illustrates that 99.9% of positional fixes fell within 20 m and 97.3% within 10 m of a known point (Trotter et al., 2010). Based on these accuracies, the GPS can give approximate location of individuals, but these values may not be discrete enough to classify finer scale behaviours (Theurer et al., 2013).

The surrounding landscape i.e. hills and canopy cover, can reduce the chances of obtaining good satellite signals and hence an accurate GPS fix. James III, Krausman, Jansen, and Morgart (2005) stated the topography, vegetation and animal behaviour can influence the performance of GPS collars, affecting fix success rate leading to location error. Furthermore, satellite connection loss in the areas of the field covered by trees has been frequently reported (Oudshoorn, Kristensen, & Nadimi, 2008). This makes GPS less practical in terms of long term studies and less reliable for animal monitoring in some environments (Nadimi, Søgaard, & Bak, 2008).

Overall the accuracy of GPS based behavioural classification depends on several factors: GPS positional accuracy, behavioural variation between individuals, the time interval between consecutive GPS fixes and the statistical approach used for classification (Homburger et al., 2014). The trade-offs of battery life and positional update frequency limit the potential uses of GPS systems in situations where the behaviour needs to be continually monitored for longer periods of time (Theurer et al., 2013). These limitations hinder the commercial adoption of GPS technology in the present market.

2.5.2 IGER behaviour recorders

The IGER grazing behaviour recorders (IBR) (Ultra Sound Advice, London, UK; Rutter et al., 1997) is an automatic microcomputer-based system for the digital recording of jaw movements in cattle and sheep (Rutter, Champion, & Penning, 1997). A data logger records the amplitude of the animal's jaw movements as 8 bit integers at 20 Hz onto an MS-DOS formatted CompactFlash card. The data file on the CF card is subsequently read into a PC, where it is processed using the GRAZE jaw movement analysis software (Ultra-Sound-Advice, 2015). The recorded data can be processed to determine periods of eating and ruminating, and count the number of mastications and prehensions (Rutter et al., 1997). Classification of foraging activity assumes rhythmic jaw activity is indicative of grazing or ruminating, and the absence of jaw movement is indicative of resting or travelling. Differentiating between grazing and ruminating behaviour is achieved through distinguishing between biting and chewing jaw movements (Eugene David Ungar & Rutter, 2006).

The IBR system was validated by Rutter et al. (1997) in grazing sheep to identify three behavioural states: eating, ruminating and other. The behaviour of eight sheep was recorded simultaneously by both the IBR system and through manual observation. The overall index of concordance between the manual observers and the automatic system was 91.0% with the disagreements between the two methods attributed to inaccuracies in manual observations. Ungar and Rutter (2006) compared the IBR with an acoustic monitoring device to measure cattle jaw movements and found discrepancies between the two systems for the proportions of bites and chews. O'Driscoll, O'Brien, Gleeson, and Boyle (2010) used the IBR system to record grazing and ruminating times (min/day), number of bouts, bout duration, bites/min, number of boluses and mastication number and rates in dairy cows however no calibration with visual observations was reported.

Limitations of the IBR system include its capacity to only measure grazing and rumination behaviours. This restrains the technology to providing information on ingestion rather than an overall activity profile. The system also requires considerable animal instrumentation and commercially this is not viable in terms of labour efficiency and deployment longevity. Hence, this technology has only been used in the research domain. Finally the IGER behaviour recorder is no longer manufactured (Ultra-Sound-Advice, 2015).

2.5.3 SCR Collars

A technology available to the dairy industry is the SCR monitoring system (SCR Engineers Ltd., Netanya, Israel). The currently available collar mounted system contains a motion sensor, microprocessor, memory and a specially tuned microphone (SCR by Allflex, 2013). The logger is positioned on the left side of the neck. Recorded data are calculated and summarized in 2 hour intervals and stored in the memory of the logger for up to 22 hours. Data can be downloaded using radio frequency via readers positioned at locations within the barn or by a handheld reader (Schirmann, von Keyserlingk, Weary, Veira, & Heuwieser, 2009). Body movements and rumination times are then used for heat detection and health monitoring (SCR by Allflex, 2013).

Rumination is considered one of the leading signs of cow health and decreased rumination is interpreted as an indicator of stress (Herskin, Munksgaard, & Ladewig, 2004), anxiety (Bristow & Holmes, 2007), or disease (Welch, 1982). Re-gurgitation and rumination produce distinctive sounds that are recorded via a microphone, processed, and digitally stored on the collar until downloaded. Based largely on rumination pattern analysis through specific software (Data Flow software, SCR Engineers Ltd.), an SCR health report is generated which shows rumination times of individual animals allowing animals with a sudden drop in rumination activity to be identified (SCR by Allflex, 2013).

Schirmann et al. (2009) validated this technology for measuring rumination time in dairy cows. Rumination times from the electronic system were highly correlated with those from direct observation ($r = 0.93$, $r^2 = 0.87$, $n = 51$). Goldhawk, Schwartzkopf-Genswein, and Beauchemin (2013) reported a much lower correlation ($r= 0.41$) between sensor values and visual observations in beef cattle. The physical and dietary differences between beef and dairy animals were offered as possible explanations for the reported differences. Bar and Solomon (2010) equipped 75 Holstein cows with SCR neck collars and monitored rumination times for 150 days and alluded to the benefits of this information for tracking potential individual/herd health problems and nutritional changes. This technology is specifically designed for dairy cattle and a review of the literature indicates the application of this device to sheep has not been tested.

2.6 Accelerometer based activity monitoring

2.6.1 How an accelerometer works

Accelerometers are sensors which measure the linear acceleration of an object in motion along a reference plane in relation to the accelerometer and the earth's gravitational field vector (Pedley, 2013; Yang & Hsu, 2010). Acceleration is defined as the rate of change of velocity with respect to time (Miedema, 2009; Semiconductor, 2007) and is commonly measured in gravitational units (g) with 1 g = 9.8 m/s^2 (Brown, Kays, Wikelski, Wilson, & Klimley, 2013; Chen & Bassett, 2005; Shepard et al., 2008). As acceleration is proportional to the net external force involved, this is more reflective of the energy costs involved in a given activity and hence acceleration is the preferred measurement rather than speed (Chen & Bassett, 2005). Acceleration also provides a more information rich signal from which speed and distance values can be calculated (Webster, 1998).

When an accelerometer is moving, the sensor outputs are a result of both static and dynamic acceleration (Laich, Wilson, Quintana, & Shepard, 2008; Sato, Mitani, Cameron, Siniff, & Naito, 2003). Static acceleration is a measure of the accelerometer inclination with respect to the earth's gravitational field whereas dynamic acceleration represents the change in velocity due to body motion (Shepard et al., 2008). When the dynamic acceleration measured is zero, this means the sensor is no longer changing speed however it may still be moving at a constant speed (Chen & Bassett, 2005). Static acceleration ranges from +1 to -1 g in each axis with +1 g being recorded when facing directly upwards away from the earth's gravitational field (Shepard et al., 2008).

The movement component of acceleration (dynamic acceleration) is produced from several different accelerations which are generated by the rotational and transitional body movements (Farkas & Doran, 2011). The dynamic acceleration is derived simply by subtracting the static acceleration values over the same time period (Wilson et al., 2006). Therefore at points of zero dynamic acceleration, the total acceleration recorded will be equal to the static acceleration. Whilst static acceleration is able to characterise some behaviours, animals often have 1 to 2 predominant behaviours during which a diverse range of behaviours are performed (Shepard et al., 2008). Hence analysis of the dynamic acceleration component is required to classify these behaviour patterns.

2.6.2 Types of accelerometers

An accelerometer's operating principle is based on a mechanical sensing element consisting of a proof mass (or seismic mass) attached to a mechanical suspension system (Yang & Hsu, 2010). According to Newton's Second Law, an initial force due to acceleration or gravity will cause the proof mass to deflect and the acceleration may be measured with the physical changes in displacement of the proof mass with respect to the reference frame (Yang & Hsu, 2010). The types of accelerometers include piezoresistive, piezoelectric, differential capacitance accelerometers and micro-electromechanical systems (MEMS) (Godfrey, Conway, Meagher, & OLaighin, 2008; Pedley, 2013).

Piezoresistive accelerometers

Piezoresistive accelerometers respond to acceleration through a change in resistance of silicon resistors (Plasqui & Westerterp, 2007). This motion of the proof mass (caused by acceleration) is detected by piezoresistors in the cantilever beam and proof mass (Yang & Hsu, 2010). The piezoresistors are arranged as a Wheatstone bridge (Yang & Hsu, 2010) and produce a voltage proportional to the amplitude and frequency of the measured acceleration (Plasqui & Westerterp, 2007; Yang & Hsu, 2010). Piezoresistive accelerometers are simple and inexpensive (Yang & Hsu, 2010) and respond to constant acceleration such as gravity, however they require an external power source (Bouten, Koekkoek, Verduin, Kodde, & Janssen, 1997), exhibit temperature sensitive drift and have a lower level of output signals (Yang & Hsu, 2010).

Piezoelectric accelerometers

Piezoelectric accelerometers generate an electric charge in response to a mechanical force (Bouten et al., 1997). The sensor contains a piezoelectric element and a seismic mass (Figure 2-4). When the sensor experiences acceleration, the seismic mass causes the piezoelectric element to be deformed through bending, direct tension or compression. These conformational changes cause a displaced charge to build up on one side of the sensor. This charge generates a wave-like voltage signal which is proportional to the applied acceleration (Brown et al., 2013; Chen & Bassett, 2005; Yang & Hsu, 2010).

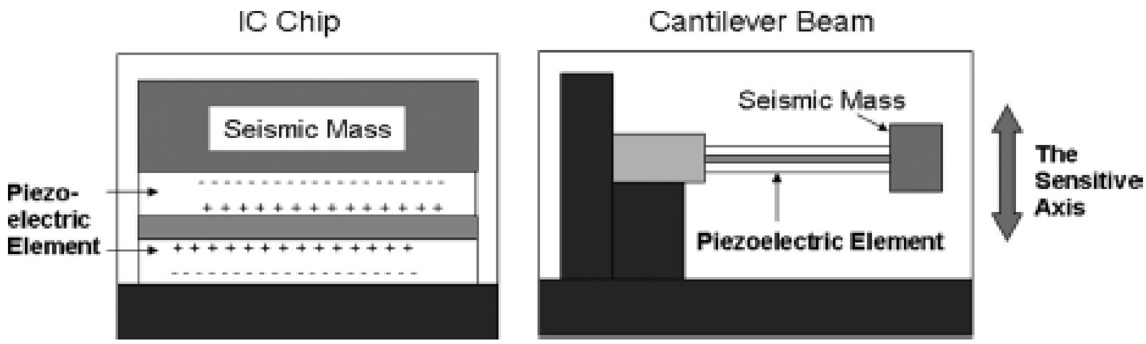


Figure 2-4. Schematic of two piezoelectric accelerometer configurations (Chen & Bassett, 2005).

The piezoelectric element in the beam configuration is most sensitive in the bending direction and due to this it is often referred to as uniaxial, however deformations in other planes can also result in acceleration signals. To measure accelerations in multiple directions, numerous unidirectional accelerometer units must be mounted orthogonally to each other (Chen & Bassett, 2005).

A limitation of piezoelectric accelerometers is the phenomenon of 'leakage', which occurs when the initial change in charge in the piezoelectric element dissipates in time, even when the static loading which caused the initial change is still present (Chen & Bassett, 2005). The rate of leakage depends on the time constant (Togowa, 1998). The inability of piezoelectric accelerometers to detect static acceleration (Plasqui & Westerterp, 2007; Yang & Hsu, 2010) means they are not well suited to measuring angles with respect to gravity and therefore cannot detect postural changes such as sitting and walking (Chen & Bassett, 2005). They do have the advantage of not requiring an external power source except for data storage which results in a significant reduction in sensor size and weight (Plasqui & Westerterp, 2007).

Micro-electromechanical system (MEMS) accelerometers

MEMS accelerometers were first produced in 1979 (Andrejašic, 2008; Yang & Hsu, 2010). A MEMS accelerometer is a type of differential capacitive accelerometer. In a capacitive accelerometer the seismic mass is enclosed between two electrodes (Figure 2-5). The differential capacitance is proportional to the deflection of the seismic mass between the two electrodes (Yang & Hsu, 2010).

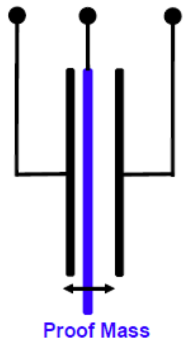


Figure 2-5. Simplified transducer model of a MEMS accelerometer (Pedley, 2013).

In a MEMS accelerometer an upper proof mass is suspended by restoring springs to a reference frame (Andrejašic, 2008; Pedley, 2013). A gravitational field to the left and a linear acceleration of the sensor to the right will deflect the proof mass towards the left. This deflection of the proof mass is measured by the change in capacitance between the sensing plates and fingers of the proof mass (Figure 2-6). Internal circuitry converts the small capacitance to a voltage signal. In digital accelerometers this voltage signal is digitized and output as a digital word over a serial bus (Pedley, 2013).

The three primary sources of noise for a MEMS accelerometer are: the mechanical vibration of the springs, signal conditioning circuitry and from the measurement system directly (Andrejašic, 2008). The advantage of capacitive accelerometers is their low power consumption, fast response to motions, large output level and better sensitivity due to the low noise level (Yang & Hsu, 2010).

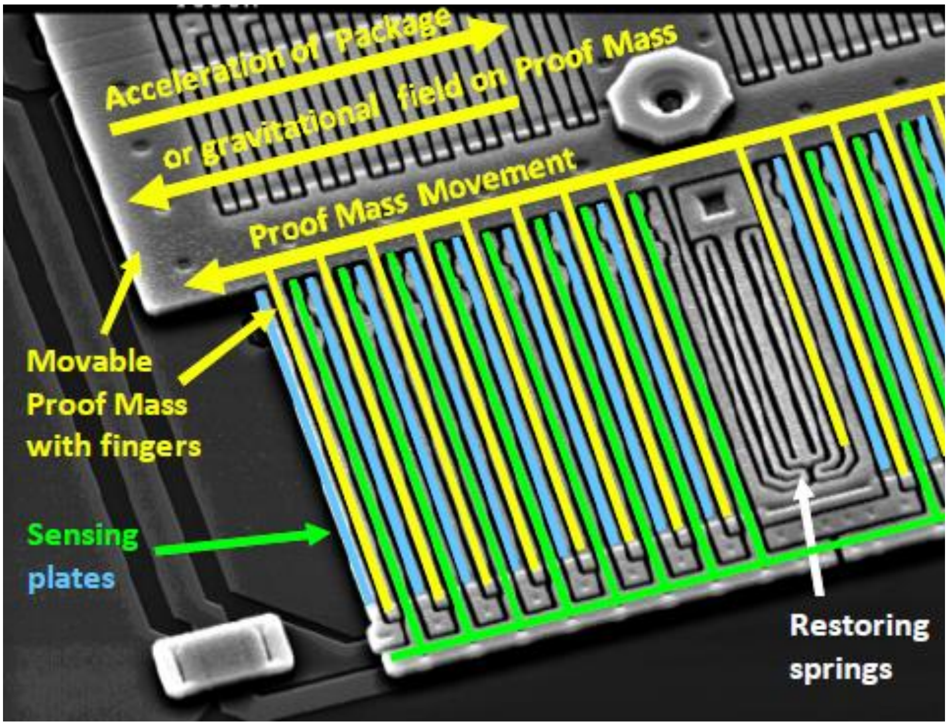


Figure 2-6. Electron microscope image of a MEMS accelerometer proof mass and sensing plates (Pedley, 2013).

2.6.3 Axis orientation

Uniaxial accelerometers measure accelerations in a single direction whereas tri-axial accelerometers measure acceleration in three directions (Plasqui & Westerterp, 2007). The direction of the X, Y and Z acceleration varies depending on the placement of the accelerometer on an animal. Terms such as heave, surge and sway are commonly used to describe the dorso-ventral, anterior-posterior and lateral axes orientations (see Figure 2-7) (Brown et al., 2013; Shepard et al., 2008; Soltis et al., 2012).

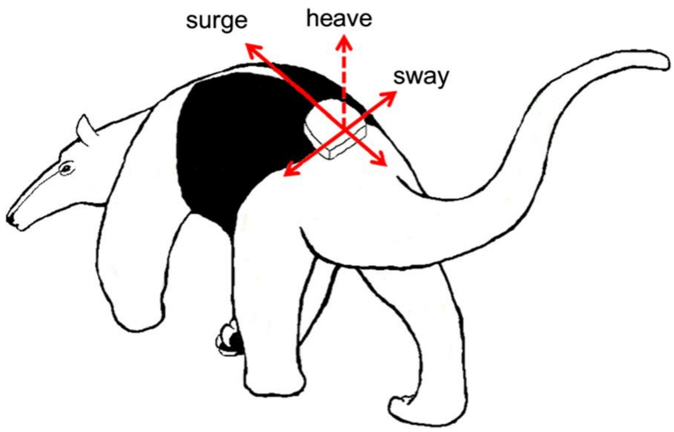


Figure 2-7. Graphical representation of the surge, heave and sway directions (Brown et al., 2013).

Changes in orientation around the *X, Y* and *Z* axis may also be described by rotations in roll, pitch and yaw respectively (Pedley, 2013). Pitch (ρ) is defined as the angle of the X-axis relative to ground and roll (ϕ) is defined as the angle of the Y-axis relative to the ground and theta (θ) is defined as the angle of the Z-axis relative to gravity (Tuck, 2007). These terms are commonly used in tilt sensing. Tilt sensing uses the gravity vector and its projection on the axes of the accelerometer to determine the tilt angle of the device (Fisher, 2010; Yang & Hsu, 2010). An underlying assumption in tilt sensing is that only static acceleration is recorded (Fisher, 2010). Assuming this, the acceleration measurements should be in the range of -1 g to +1 g throughout 360^{o} of tilt (Tuck, 2007). Upright and lying postures may be distinguished according to acceleration measurements using tilt sensing (Karantonis, Narayanan, Mathie, Lovell, & Celler, 2006) as the static acceleration recorded will be dominant in a particular axis of each posture. A disadvantage of tilt sensing is its difficulty in distinguishing behaviours which display similar postures i.e. standing and sitting in humans as both are upright postures (Yang & Hsu, 2010).

2.6.4 Summary of studies using accelerometers

Table 2-2 and Table 2-3 below summarise previous research which has attempted to classify animal behaviour based on acceleration signals. This highlights the variation in recording frequency, attachment location, behaviours classified and classification methods previously used.

Table 2-2. Review of papers using accelerometers for animal (non-livestock) behaviour classification.

Species	***Accelerometer***	***Axes***	***Frequency (Hz)***	***Attachment Location***	***Behaviours Identified***	***Classification Method***	***Source***
Multiple species		3				kNN	Bidder et al. (2014)
Birds	E-Obs GmbH; Munich, Germany	3	3.3	Back	Standing / running / eating / passive flight / active flight	SVM/CART/RF/ANN/ LDA	Nathan et al. (2012)
	NR	3	8 and 9	Lower back	Standing / sitting / floating on water / flying / walking / diving	Visual	Laich et al. (2008)
Seals	ADXL210, Analog Devices, Inc., Norwood, USA	2	1/16	Back	Swimming speed and angle	Filtering	Sato et al. (2003)
Elephants	X9-2mini; GCDC	3	320	Collar	Feeding/bathing/walking/ swaying	PCA/DFA	Soltis et al. (2012)
Dogs	G6A CEFAS Technology Ltd, Lowestoft, UK	3	1	Neck	Running/standing/walking/ sitting	SVM	Campbell, Gao, Bidder, Hunter, & Franklin (2013)
		3	100		Lay/sit/stand/walk/trot/ gallop/canter	SVM	Gerencsér, Vásárhelyi, Nagy, Vicsek, & Miklósi (2013)
	Locometrix 3D transducer	3	100	Back	Gait patterns	PCA/ANOVA	Barthélémy et al. (2009)
Badgers	X8M-3; GCDC	3	25	Collar	Walking/trotting/snuffling/ resting	Spectral analysis/PCA/ kNN/ DT	McClune et al. (2014)
Elk	Actiwatch™	3	NR	Collar	Resting/feeding/travelling	DFA	Naylor & Kie (2004)
Horses		3	10	Leg	Lameness	Frequency distribution	Scheibe & Gromann (2006)
		1	50	Halter	Lameness	Paired *t* test	Keegan, Yonezawa, Pai, & Wilson (2001)
				Hoof	Gait classification	LDA	Robilliard, Pfau, & Wilson (2007)

Table 2-3. Review of papers using accelerometers for livestock behaviour classification.

Species	***Accelerometer***	***Axes***	***Frequency (Hz)***	***Attachment Location***	***Behaviours Identified***	***Classification Method***	***Epoch used***	***Summary features used***	***Source***
Goats	HOBO	3		Chest belt/collar/ dog harness	Resting/eating/walking	Threshold values		Moving averages	Moreau, Siebert, Buerkert, & Schlecht (2009)
Pigs	HOBO	3	1	Leg/back	Standing/lying/stepping	Threshold values	5	No	Ringgenberg, Bergeron, & Devillers, (2010)
		3		Back	Activity/movement/disease	Duncan's multiple range tests	7200	Axis Sum	Ahmed et al. (2016)
Beef cattle		3	100	Hind leg	Lying/standing/walking	Classification trees	3/5/10	MeanX,Y,Z/vector magnitude average/ vector magnitude max /SMA/SVM	Robert et al. (2009)
	CSIRO collars	3	10	Collar	Foraging/ruminating/resting/ travelling	DT	10	Mean/SD	González, Bishop-Hurley, Handcock, & Crossman (2015)
	Monnit	3	0.1	Ear	Health status	Threshold			Nagely (2012)
	CowManager SensOor	3		Ear	Feeding/ruminating/active/ resting	Proprietary algorithms	N/A	N/A	Wolfger et al. (2015)
	CowManager SensOor	3		Ear	Feeding/ruminating/active/ resting	Proprietary algorithms	N/A	N/A	Bikker et al. (2014)
		3	10	Collar/leg	Lameness/standing/walking/ grazing/ ruminating	Frequency distribution	5/10		Scheibe & Gromann (2006)
		3	98	Halter/ear	Pasture intake				Greenwood et al. (2014)
		3		Ear	Health	Activity count thresholds	300	Hourly activity counts	Smith et al. (2015)
		1	0.25	Collar	Foraging	LR/LDA	60	Sum	Yoshitoshi et al. (2013)
		3	100	Leg	Standing/lying/walking	Generalised mixed models	5	MeanX,Y,Z/vector magnitude average/vector magnitude max	Theurer (2013)
	GCDC X16	3	10	Collar	Standing/grazing/walking/runnin g	naive Bayes/ kNN/QDA/ LDA	5	Energy/entropy	Trotter, Falzon, Dobos, Lamb, & Schneider (2012)
Dairy calves	HOBO	3	33/11/1	Hind leg	Standing/walking/jumping/ running			Summed acceleration/peaks/mean	Luu, Johnsen, Passillé, & Rushen (2013)
	HOBO	7	33	Hind leg	Walk/trot/gallop	Threshold values		Vector sum/interpeak intervals	De Passille, Jensen, Chapinal, & Rushen (2010)

		2	10	Hind leg	Standing / walking / eating / getting up / lying awake / lying asleep	DT/ANN/LR	1	Mean/median/SD/SMA	White et al. (2008)
		3	25	Collar	Sleep	SVM	20	Mean/variance/ wavelet variance	Hokkanen, Hänninen, Tiusanen, & Pastell (2011)
	IceTag3D™	3	8	Hind leg	Lying/standing/moving	IceTagAnalyser®	N/A	N/A	Trénel, Jensen, Decker, & Skjøth (2009)
Dairy cows		3	10	Collar	Grazing/searching/resting/ walking/ruminating	DT	5/6		Hämäläinen et al. (2010)
		3	10	Collar	Grazing/searching/resting/ walking/ruminating	PCA/LDA/DT/kNN			Bishop-Hurley et al. (2014)
		2/3	1	Neck	Grazing	Threshold values			Oudshoorn et al. (2013)
		3	0.0312	Halter	Eating/resting/ruminating	QDA	60	Mean/variance/ inverse coefficient of variance/	Watanabe, Sakanoue, Kawamura, & Kozakai (2008)
		3	10	Collar	Standing/lying/ruminating/ feeding/walking/lame walking	SVM	10	Mean/SD/kurtosis/max/ min/energy	Martiskainen et al. (2009)
		2	1	Halter	Activity/inactivity	Classification tree		Pitch/ velocity	Nadimi et al. (2008)
		3		Collar	Movement	HMM			Guo et al. (2009)
		3	25	Leg	Lameness	Maximal overlap wavelet transform	20	Variance/wavelet variance/total acceleration	Pastell, Tiusanen, Hakojärvi, & Hänninen (2009)
	Bluesky Telemetry	3	50/10/5/1	Collar	Standing/lying/eating	Threshold values	10	Median	Miedema (2009)
	Honeywell HMC6343	3	10	Collar	Grazing/walking/ruminating/ resting/other	PCA/Fuzzy C means/Self Organising Map network/Ensemble classification/Binary Tree/LDA/Naïve Bayes classifier/kNN/ Adaptive Neuro Fuzzy Inference	5	Negentropy/ energy/auto-regressive/mean/ area under curve/SD/kurtosis/skewness	Dutta et al. (2015)
	iPhone	3	100	Halter	Grazing/rumination				Andriamandroso, Lebeau, & Bindelle (2014)
		3	10	Collars	Grazing/walking/resting/ ruminating/other	SVM/NB/kNN/LR/RF		X/Y/Z/pith/roll/absolute magnitude/skew/entropy /kurtosis/frequency	Smith et al. (2016)

	HOBO	2	0.2	Halter	Grazing/non-grazing	LDA	No	No	Blomberg (2011)
	IceTag3D™	3	16	Hind leg	Grazing/non-grazing	IceTagAnalyser®	N/A	N/A	Blomberg (2011)
	HOBO	3	0.0167	Leg	Standing/lying	Tilt thresholds	No	Tilt	
	IceTag2D™	2	8	Leg	Lying/standing/moving	IceTagAnalyser®			Mattachini, Riva, Pompe, Bisaglia, & Provolo (2011)
	IceTag®				Standing/lying/activity/oestrus	IceTagAnalyser®	N/A	N/A	McGowan, Burke, & Jago (2007)
	IceTag3D™	3	16	Leg	lameness	IceTagAnalyser®	N/A	N/A	Kokin, Praks, Veermäe, Poikalainen, & Vallas (2014)
	IceTag3D™	3		Hindleg	Lameness	IceTagAnalyser®	N/A	N/A	Higginson, Millman, Leslie, & Kelton (2010)
	IceTag3D™	3	16	Hindleg	Lying/standing/walking	IceTagAnalyser®	N/A	N/A	Endres & Barberg (2007)
	IceTag3D™	10	16	Hind leg	Walking/standing	Moving window threshold values	3/5	Step count / motion index	Nielsen, Pedersen, Herskin, & Munksgaard (2010)
	IceTag3D™	3	16	Leg	Feeding/lying/standing/walking	IceTagAnalyser®			MacKay, Deag, & Haskell (2012)
	IceTag3D™	3	16	Leg	Lying/standing/walking/lameness	IceTagAnalyser®	N/A	N/A	Chapinal, De Passillé, Rushen, & Wagner (2010)
	IceTag3D™	3	16	Hind leg	Lying/standing/walking	IceTagAnalyser®	N/A	N/A	Munksgaard, van Reenen, & Boyce (2007)
Sheep		3	5/10/25	Halter	Grazing/lying/standing/walking /running	RF/DT	3/5/10	SMA/SVM/ MV/energy/ entropy/pitch/roll/ inclination	Alvarenga et al. (2016)
	Actiwatch Mini®	1/25		Collar	Low, medium and high activity	ANOVA			McLennan et al. (2015)
		3	100	Collar	Walking/grazing/running/lying/ standing	LDA/QDA	5.12	Mean/SD/Variance/Skewness/kurtosis/max/min/energy/SVM/correlation/ Frequency entropy	Marais, Le Roux, Wolhuter, & Niesler (2014)
	BlueSky Telemetry	3	0.033	Collar	Active / inactive	LDA/DT	No	Max pitch/min pitch/max roll/ min roll	Umstätter et al. (2008)
		3	0.5	Halter	Standing/grazing/foraging/laying	PCA/DFA	No	No	Mason & Sneddon (2013)

RF = random forest, DT = decision tree, HMM = hidden markov model, LR = logistical regression, kNN = k nearest neighbour, LDA = linear discriminant analysis, QDA = quadratic discriminant analysis. SVM = support vector machine, NB = Naive Bayes. *Grey cells represent where data were not available.

2.6.5 Sampling frequency

Sampling frequency refers to the number of readings recorded by the accelerometer per second. The accelerometer sampling frequency should satisfy the Nyquist criterion (Oppenheim, Willsky, & Nawab, 1983) which stipulates that the sampling frequency should be at least twice the frequency of the most rapid movement (Nathan et al., 2012; Yost, Cooper, & Bremner, 1983). If the Nyquist criterion is not satisfied, high frequency motion measurements will be distorted (Chen & Bassett, 2005). Most accelerometers can be programmed to sample at frequencies in the range of 0.5 to 10,000 Hz depending on the accelerometer's capacity (Brown et al., 2013). Sampling frequencies used in livestock studies range from 0.0167 through to 100 Hz however few livestock studies have compared sampling rates. The sampling frequency should ultimately be dictated by the research question and the desired spatio-temporal resolution as unnecessarily high sampling frequencies can waste digital storage space (Brown et al., 2013; Halsey, Green, Wilson, & Frappell, 2009). Therefore, as with other forms of monitoring technology i.e. GPS, there is inevitably a trade-off between sampling rate and the length of time that the devices can be used (De Passille et al., 2010).

2.6.6 Epoch setting

The time period over which accelerometer counts are grouped and summary features are calculated is termed an "epoch" or "burst" (Cain, Sallis, Conway, Van Dyck, & Calhoon, 2013; Chen & Bassett, 2005; Dow, Michel, Love, & Brown, 2009; Robert et al., 2009; Yang & Hsu, 2010). These activity counts are representative of the estimated intensity of measured activities during the set time period (Yang & Hsu, 2010). Selecting a short epoch may be suitable if activity is accumulated in a number of short bouts. A longer epoch has the advantage of a normal data-smoothing through time averaging. The main disadvantage of longer epochs is they may contain a mixture of two or more activities of varying intensity and the average data may reflect an intermediate intensity. Also if the activity bout is shorter than the epoch, the average value for that burst will differ from the actual activity intensity leading to misclassification. Therefore there is a trade-off which must be accounted for when selecting the epoch length (Chen & Bassett, 2005).

Epoch lengths used vary substantially throughout the literature (see Table 2-2 and Table 2-3). Trotter et al., (2011) used a 5 second epoch and found this to be sufficient time to capture the key features for each behavioural state in beef cattle from a collar mounted accelerometer. In a similar experiment Martiskainen et al. (2009) used a 10 second window to classify dairy cow behaviour while Soltis et al. (2012) used a 20 second window to identify behavioural states in elephants. Robert et al. (2009) compared the accuracy of a 3, 5 and 10 second epoch to classify behaviour patterns in cattle and found greater agreement between video and accelerometer measurements for the 3 (98.1%) and 5 second epochs (97.7%) compared to the 10 second epoch (85.4%). The reduced classification accuracy for the 10 second interval was attributed to a higher variability in accelerometer readings. In contrast, González et al. (2015) reported correct classification of 90.5% of data points from a collar mounted motion sensor on cattle aggregated over a 10 second epoch. Epochs in the range of 1-10 seconds appear to be the most common size used for livestock studies.

2.6.7 Sensor deployment

Sensor deployment refers to the locations where the sensors are placed and the method used to attach the sensors to those locations (Yang & Hsu, 2010). It is commonly acknowledged that devices attached to animals may have adverse effects on their behaviour, fitness and performance and the level of impact is dependent on the sensor characteristics and the species involved (Hawkins, 2004; Ropert-Coudert & Wilson, 2004). Additionally, animals may require a period of time to adapt to instrumentation. There appears to be a lack of consistent guidance on the period from device deployment until data should be used (MacKay, Deag, & Haskell, 2012). Some studies have used data from accelerometers within a few hours (Aharoni et al., 2009; N Blackie, Scaife, & Bleach, 2006), however others have waited for 24 h after deployment (Bewley et al., 2010) or a 14 h habituation period (Gibbons, Medrano-Galarza, de Passillé, & Rushen, 2012). Most scientists appear to assume a habituation period needs to take place, but the extent and duration of this has not been consistently reported (MacKay et al., 2012). IceTag3D™ accelerometers were attached to the hind limb of 28 dairy cows and found an increase in standing time between tagged and untagged cows which became non-significant by day 3 and suggested a habituation period of two days (MacKay et al., 2012). A reduction in sensor size and weight along with selecting a suitable mode of attachment may alleviate some of the animal discomfort concerns.

In addition to the standard concerns of attachment longevity, device retrieval and effect on animal behaviour (Ropert-Coudert & Wilson, 2004), attachment method of accelerometers is particularly sensitive as a shift in the sensor position could impact the interpretation of the 3 axis signal (Brown et al., 2013). It is important to ensure equipped animals can perform the same behaviour as non-equipped animals, their physical and physiological fitness does not deteriorate due to logger attachment and their breeding cycle is not modified (Ropert-Coudert & Wilson, 2004). Ensuring a similar sensor position between individuals, especially those of different body sizes, reduces the signal to noise ratio of the accelerometer, minimising errors in data interpretation (Brown et al., 2013; Shepard et al., 2008). As stated by Mathie, Coster, Lovell, and Celler (2004) sensor deployment should consider the following: the wearable instrument must be easy to use, comfortable and as unobtrusive as possible. Researchers should also strive to minimise stress resulting from an animal's manipulation (Le Maho et al., 1992) of which sensor placement and attachment are critical.

Sensor design

The main considerations for sensor design include mass, shape, functionality and colour. Adding extra mass to an animals' body can have a significant physiological impact causing discomfort and distress (Baumans et al., 2001). Cuthill (1991) suggested that the weight of sensors should be less than 5% of the animal's body weight. Hulbert, Wyllie, Waterhouse, French, and McNulty (1998) found that a collar carrying a lightweight GPS weighing only 2.2% of body weight had no influence on the behaviour of 16 Scottish Blackface ewes. In contrast, Blanc and Brelurut (1997) reported that a satellite-tracking collar weighing 3.5% of body weight significantly decreased the grazing activity of red deer and disturbed other behavioural activities. Clearly, sensors should weigh as little as possible and not restrict the animal's freedom of movement (Yoshitoshi et al., 2013).

Sensor attachment

Common methods of sensor attachment in livestock species include include halters attached to the head, collars around the neck, or bracelets attached to the (extremity of the) leg. Recently, some studies have started to evaluate an eartag form factor (Bikker et al., 2014; Nagely, 2012; Wolfger et al., 2015). A collar attachment has commonly been used due to the historically large size of sensors. The placement of an accelerometer around a cow's neck has been shown to recognise rumination and eating behaviours, however sudden, and sometimes very violent, head movements can potentially disturb the recognition of other behaviour patterns (Hämäläinen et al., 2010). An issue identified by Trotter et al. (2011) and Hämäläinen et al. (2010) with the placement of sensors on the neck is the positional movement of the collar. Collars can move freely, and the position of the accelerometer is not necessarily always the same although the posture of an animal would be exactly the same. Unsecured sensors cause displacement and vibration which is liable to produce extraneous signal artefacts degrading sensing accuracy (Yang & Hsu, 2010). A rigid attachment ensures the movement being measured does not change over the deployment period and the acceleration of the sensor independent of animal movement is kept to a minimum (Brown et al., 2013). When collars or bracelets must be used, a completely rigid attachment may not be possible unless the sensor can be prevented from turning around the neck/leg (Watanabe, Izawa, Kato, Ropert-Coudert, & Naito, 2005) which may present a welfare concern (Brown et al., 2013).

Using a collar deployment, Martiskainen et al. (2009) found periods of activity and inactivity could be clearly distinguished from raw acceleration profiles, but certain behaviour patterns had nearly identical profiles, i.e. standing, lying, and ruminating; normal and lame walking; and lying down and standing up. Furthermore, due to the head movements, the accelerometer registers much more weak-amplitude movements when fixed on the animal's neck than on its body (Moreau et al., 2009). These concerns limit the behaviours which can be discriminated using a collar mounted accelerometer.

An eartag form factor is the most suitable mode of deployment for industry. There are a number of reasons to choose an eartag, the first being acceptance by industry. Secondly, personnel are familiar with eartag application with effective tools and procedures already in place. This also alleviates some concerns around collars becoming caught in fences, feeders etc. The third factor being cost as it is felt that ultimately an eartag could be produced at prices lower than a collar. Some obstacles preventing long term deployment include the following: the tag must remain light to prevent the animals' ear from tearing and/or drooping. This limits the battery size and any auxiliary power sources such as solar panels. This also limits sensor size. As tags are prone to tear out, advances in tag design must also be a consideration (Schleppe et al., 2010).

Trotter et al. (2011) further highlighted some sources of signal variation arise from differences in physical structure of individual animals and it would be unrealistic to expect sensors could be placed in exactly the same position and orientation for all animals. Ultimately the method of attachment must strive to shorten the handling time during instrumentation (Ropert-Coudert & Wilson, 2004), have a limited effect on animal behaviour and provide high classification accuracy.

2.6.8 Methods of data analysis for accelerometers

Accelerometer sensors produce raw wave-like voltage signals which before analysis must be converted into acceleration using calibration equations (Brown et al., 2013). To describe the acceleration waveforms, summary features are often calculated using each burst's population values or a subsample of the continuous measurements (Brown et al., 2013; Nathan et al., 2012). The two main techniques that are used to identify the important features and reduce dimensionality in pattern recognition are feature transformation and feature selection (Zhang & Sawchuk, 2011). Feature transformation is creating new features based on transformations or combinations of the original extracted feature set. Feature selection is selecting the best subset of the extracted features (Jain, Duin, & Mao, 2000; Zhang & Sawchuk, 2011). High quality features are essential to provide a high classification accuracy of any pattern recognition system (Zhang & Sawchuk, 2011). Zhang and Sawchuk (2011), Brown et al. (2013) and Martiskainen et al. (2009) summarise a number of the metrics used in accelerometer based activity research. Table 2-4 identifies some of the summary features previously reported in the literature. These metrics will be described in detail in subsequent chapters.

To systematically assess the usefulness and identify which features/summary statistics are the most important for discriminating different activities, feature selection techniques are used (Zhang & Sawchuk, 2011). Such techniques can be grouped into three categories: wrapper methods, filter methods and embedded methods (Saeys, Inza, & Larrañaga, 2007). Saeys et al. (2007) and Zhang and Sawchuk (2011) summarised a number of these feature selection methods including Relief-F, Sequential forward selection (SFS) and Single feature classification (SFC). In addition to these methods Nathan et al. (2012) indicated summary statistic selection may be done before training and testing of the model however it may also be conducted in an iterative manner by examining model results. Dimensionality reduction techniques such as Principal component analysis (PCA) which create a secondary, smaller set of features from the original summary metrics have also been used (Bishop-Hurley et al., 2014; Dutta et al., 2015; Mason & Sneddon, 2013).

Table 2-4. Previously used summary metrics for accelerometer data.

Summary Metric	**Source(s)**
Signal magnitude area	Campbell et al. (2013) Zhang & Sawchuk (2011) Gao, Campbell, Bidder, & Hunter (2013) Robert et al., (2009) Karantonis et al. (2006) Khan, Lee, Lee, & Kim (2010) Alvarenga et al. (2016)
Energy	Trotter et al. (2012) Marais et al. (2014) Farkas & Doran (2011) Zhang & Sawchuk (2011) Martiskainen et al. (2009) Alvarenga et al. (2016)
Entropy	Trotter et al. (2012) Alvarenga et al. (2016) Smith et al. (2016)
Standard deviation	Marais et al. (2014) Campbell et al. (2013) Farkas & Doran (2011) Martiskainen et al. (2009)
Waveform length	Campbell et al. (2013) Alvarenga et al. (2016)
Maximum, minimum	Marais et al. (2014) Martiskainen et al. (2009) Watanabe, Sato, & Ponganis (2012)
Mean	Marais et al. (2014) Martiskainen et al. (2009) Shepard et al. (2008) Laich et al. (2008) Hokkanen et al. (2011)
Skewness	Marais et al. (2014) Martiskainen et al. (2009)
Correlation	Farkas & Doran (2011)
Root mean square	Farkas & Doran (2011)
Variance	Farkas & Doran (2011) Marais et al. (2014) Watanabe, Sakanoue, Kawamura, & Kozakai (2008) Laich et al. (2008) Davis et al. (1999) Hokkanen et al. (2011)
Mean	Watanabe et al. (2008) Alvarenga et al. (2016)
Movement intensity	Zhang & Sawchuk (2011)
Signal vector magnitude	Robert et al. (2009) Alvarenga et al. (2016)

Feature selection is an important step in the data analysis procedure as to achieve the best classification performance, the dimensionality of the feature vector should be as small as possible using the most salient and complementary features. The most important objectives of feature selection are to avoid overfitting data and improve model performance, to provide faster and more cost-effective models and to gain a deeper insight into the underlying processes that generated the data (Saeys et al., 2007). Some of the summary metrics may be redundant or irrelevant and provide no information to improve the classification accuracy and may possibly confuse the classifier (Zhang & Sawchuk, 2011). Marais et al. (2014) found improvement of a QDA algorithm to classify sheep behaviour when the number of input features was reduced from an original analysis where 10 metrics were used. Due to the "curse of dimensionality", the performance of the classifier may degrade significantly if additional features are added and there is insufficient training data to reliably learn the parameters of each behaviour category (Bishop, 2006). However, the advantages of feature selection techniques come at a certain price, as the search for a subset of relevant features introduces an additional layer of complexity (Saeys et al., 2007).

There are a number of approaches to analysing time series data including fast fourier transformation (FFT) where the individual frequencies that are present in the raw acceleration waveform are identified (K. M. Scheibe & Gromann, 2006), and continuous wavelet transformation which identifies the frequencies present and when they are present in the signal (Brown et al., 2013; Sakamoto et al., 2009). Shepard et al. (2008) and Laich et al. (2008) suggest that such complex analyses are not essential and simpler statistics are both practically and intuitively more suitable. However it was acknowledged when behaviours are transitory and/or highly variable, the more complicated statistical techniques may be beneficial to identify different behaviours. Alternative statistical methods include various forms of discriminant analysis and machine learning algorithms.

There have been a number of statistical methods used in the literature to classify animal behaviour from accelerometer data. Some researchers have suggested the use of various machine learning approaches as a means to classify acceleration data automatically. The uptake of this approach may have been inhibited for two reasons: 1, most machine learning algorithms require selection of summary statistics which alter the decision mechanisms by which classifications are arrived (as described above) and; 2, they are difficult to implement without appreciable computational skill. One criticism that is often levelled at machine learning algorithms is that they are 'black box' methods that are difficult for biologists to implement or appreciate how classifications are derived (Bidder et al., 2014).

Statistical algorithms to cluster accelerometer waveforms with similar characteristics to a particular behaviour group (Watanabe et al., 2012) or using known behaviours to train an algorithm that will assign the remaining data to specific behaviour categories are two commonly used approaches for automatic waveform classification (Brown et al., 2013). The former method has the potential to detect previously unknown or unobserved behaviour states while the latter has the advantage of linking behaviour to direct observations (Brown et al., 2013). Statistical methods used to assign accelerometer waveforms to behaviour categories can be grouped into unsupervised algorithms such as cluster analysis and supervised algorithms such as regression trees, random forests, LDA and QDA, logistic regression, support vector machines and artificial neural networks. Table 2-5 summarises some of the commonly used algorithms represented in the literature. For further information please refer to Brown et al. (2013) and Nathan et al. (2012).

Table 2-5. Statistical algorithms used to classify behaviour states using accelerometer data.

Analysis method	**Source(s)**
Support vector machines (SVM)	(Martiskainen et al., 2009) (Nathan et al., 2012) (Campbell et al., 2013)
Linear discriminant analysis (LDA)	(Nathan et al., 2012) (Marais et al., 2014) (Bishop-Hurley et al., 2014) (M Trotter et al., 2012) (Umstätter et al., 2008) (A. M. Khan et al., 2010)
Quadratic discriminant analysis (QDA)	(Marais et al., 2014) (Pober, Staudenmayer, Raphael, & Freedson, 2006)
Classification and regression trees (CART)	(Nathan et al., 2012)
Artificial neural networks (ANN)	(Nathan et al., 2012)
Principal component analysis (PCA)	(Bishop-Hurley et al., 2014) (Soltis et al., 2012)
Decision trees (DT)	(Bishop-Hurley et al., 2014) (Robert et al., 2009)
Hidden semi Markov model	(M Trotter et al., 2012)
Random forests (RF)	(Nathan et al., 2012)
k-Nearest neighbour (kNN)	(Bishop-Hurley et al., 2014) (Bidder et al., 2014)

Nathan et al. (2012) reviewed and compared linear discriminant analysis (LDA), support vector machines (SVM), classification and regression trees (CART), random forests (RF) and artificial neural networks (ANN). Comparison between SVM, naïve bayes (NB), k nearest neighbour (kNN), logistic regression (LR) and RF models to classify behaviours in cattle has previously been reported (Smith et al., 2016). A more detailed description of RF, QDA, LDA and PCA is provided in Chapter 3. Regardless of the method used, many of the algorithms are custom developed to deal with a particular domain of activities and they may not be easily adapted or suitable for acceleration data across different environments or over a different range of movements (Mathie, Celler, Lovell, & Coster, 2004). In summary, the optimum metric for evaluation of classification algorithms is dependent on the questions being asked as the importance of the various parameters are highly study specific (Bidder et al., 2014).

2.6.9 The initial use of accelerometers for basic movement observations

The use of accelerometers for studying organism movement originated in the 1950's to assess changes in human physical activity in relation to health status (Chen & Bassett, 2005; Plasqui & Westerterp, 2007; Yang & Hsu, 2010). Due to technological advances such as the introduction of airbag technology in vehicles, relatively inexpensive accelerometers which consumed little power were developed (Sellers & Crompton, 2004). Such technological improvements led to human motion being studied through accelerometry in more detail during the 1970's (Morris, 1973).

Animal studies using portable acceleration sensors did not appear until the late 1990's (Scheibe et al., 1998) with the initial studies being confined to captive and domesticated species and aquatic organisms (Davis et al., 1999; Kooyman, 2004; Yoda et al., 1999). However, the past decade has witnessed an exponential rise in the amount of research on remote monitoring of animal behaviour through accelerometry, see reviews by Brown et al. (2013) and Shepard et al. (2008), due to advances in battery size, computer microprocessors, weight and longevity (Brown et al., 2013). MacKay et al. (2012) stated that "accelerometers open up the possibility of monitoring large numbers of animals over long periods of time with minimum human intervention".

2.6.10 Using accelerometers to monitor livestock movement

The specific use of accelerometers in livestock behaviour monitoring, especially dairy, has increased significantly over the past decade and their use for activity monitoring has been well documented for a number of livestock species. Their application in ruminant behaviour research has historically been confined to the dairy and beef sectors. Hämäläinen et al. (2010) placed accelerometers recording at 10 Hz around the neck of 21 dairy cows and found that with video observations, decision trees correctly classified 98% of lying or standing with only minor head movements, 38% of lying or standing with marked head movements, 85% of walking, 53% of lying down, 70% standing, 71% of rumination and 81% of eating behaviours. Similarly Yoshitoshi et al. (2013) deployed a single axis collar mounted accelerometer recording at 32 Hz on four beef cows to distinguish foraging behaviours while on a steeply sloping pasture. With visual observations recorded at 1 minute intervals, logistic regression (LR) and LDA correctly discriminated foraging and other behaviours 92.4% and 85.6% respectively, based on pooled accelerometer recordings from all four animals. A similar experiment was conducted by Trotter et al. (2012) attaching GCDC X16 accelerometers sampling at 10 Hz to neck collars on beef steers. Using LDA with entropy and energy metrics, both the training data and leave-one-out cross validation yielded highly accurate (95%) classifications based on annotations from video observations. Robert et al. (2009) attached tri-axial accelerometers to the lateral aspect of the offside rear leg proximal to the hind-leg fetlock of fifteen crossbred calves at a sampling frequency of 100 Hz. Using classification trees to predict behaviour, lying and standing activities yielded an accuracy of 99.2% and 98% respectively whilst walking was significantly lower with an accuracy of 67.8%. The poor classification of walking was also seen by Moreau et al. (2009) who attached accelerometers to goats using either a chest belt, dog harness or neck collar. Accuracies for the true recognition of activities were in the range of 87% to 93% for eating, 68% to 90% for resting and 20% to 92% for walking. The large variation in accuracies for resting and walking was attributed to the type of mounting system used for logger fixation and the number of observations for resting and eating. Results from these and similar studies show that whilst accelerometers are capable of remotely measuring behaviour, the classification is affected by the specific behaviour to be measured, sensor location and the data analysis method used.

The sheep industry is yet to fully explore the potential accelerometers have for behaviour modelling with only a few studies reported to date (Alvarenga et al., 2016; Cronin et al., 2016; Fisher et al., 2010; Marais et al., 2014; Mason & Sneddon, 2013; McLennan et al., 2015; Umstätter et al., 2008). McLennan et al. (2015)

deployed collar mounted accelerometers onto nine Texel ewes and segregated six different behaviours into three activity categories: low activity (lying ruminating, lying), medium activity (standing, standing ruminating, and grazing) and high activity behaviours (walking). Limited information was provided on the methods used to classify behaviour. Higher levels of accuracy in distinguishing between activity levels were achieved when combining high and medium activity level behaviours. In a similar study, Marais et al. (2014) attached collar mounted accelerometers to five sheep and using LDA and QDA classifiers achieved an overall behaviour classification accuracy of 87.1% and 89.7%, respectively. Using a halter attachment, Alvarenga et al. (2016) successfully classified five sheep behaviours using a decision tree algorithm. A review of the literature did not find any research using ear attached accelerometers to classify sheep behaviour. These studies have demonstrated accelerometers can be used to successfully classify sheep activity using collar and halter deployments however, an eartag form factor is still yet to be evaluated for sheep, the mode of attachment required for by industry.

2.6.11 Limitations of using accelerometers to identify behaviour

The use of accelerometers for behaviour monitoring has some inherent limitations. These include; cost, data processing and technological constraints, classification error, power supply, sensor size and storage capacity. Transforming the accelerometer data into useable behavioural measurements can be achieved with validated algorithms; however the data processing technique is time consuming (Theurer et al., 2013). There is also an associated intrinsic misclassification error between activities that produce similar total acceleration (Pober et al., 2006). Additionally the standard on-animal sensor concerns of sufficient battery life, on board memory storage (or ability to wirelessly transmit data), and being small enough to be easily affixed to the animal (Theurer et al., 2013) remain constraints to the long term commercial deployment of this technology.

2.7 Commercially available accelerometers for cattle

Many of the accelerometer devices used in the animal studies listed above have not been specifically designed for such uses or have been developed for research only applications. There are specially designed motion sensors developed for particular commercial applications in the livestock industries which include the IceTag3D™ and CowManager SensOor devices (see Table 2-3 above). Applying these devices to other livestock species may be troublesome as they rely on specific classification algorithms.

2.7.1 IceTag3D™

The IceTag3D™ device is a commercially available accelerometer device designed for use on dairy cattle (Figure 2-8). Using accelerometer technology, the sensor is programmed to record the *g-force* in three dimensions (Kokin et al., 2014) and determines the proportion of time an animal spends standing, lying or being active (McGowan, Burke, & Jago, 2007). These small (95 x 85 x 32 mm) and lightweight (170 grams) devices (Goetsch et al., 2010) record acceleration at 16 Hz (Nielsen, Pedersen, Herskin, & Munksgaard, 2010) and are housed in a rigid plastic case designed to withstand the farm environment (Mattachini et al., 2011). They are attached to the lateral side of the cows hind leg above the metatarsophalangeal joint and are capable of storing measurements for up to 60 days (Kokin et al., 2014). The IceTag3D has been surpassed by the IceQube, which is a near real time monitoring device for commercial dairy cattle.

The IceTagAnalyser calculates 1) the time cows spend lying and standing as determined by the sensor passing a specific threshold between the horizontal/vertical position, 2) number of lying bouts determined by the start and end time of each lying bout, 3) step count determined by the number of times the cow lifts the instrumented limb and 4) the motion index which reflects the average magnitude of acceleration on each of the 3 axes (IceRobotics, 2015; Kokin et al., 2014; Nielsen et al., 2010).

Figure 2-8. Example of an IceTag™ sensor (IceRobotics, 2015).

The IceTag3D™ sensor has been used to detect lameness (Kokin et al., 2014), activity (Endres & Barberg, 2007; Mattachini et al., 2011; McGowan et al., 2007; Trénel, Jensen, Decker, & Skjøth, 2009) and ovulation (McGowan et al., 2007) in dairy cattle. It has been used to determine the proportion of time lying, standing, active and the step count for 15 non-lactating dairy cows (McGowan et al., 2007). The sensor has accurately recorded 100% of lying bouts within ±1 minute of visually recorded data. Behavioural patterns of 107 lactating dairy cows using the IceTag2D yielded high sensitivity (Se ≥ 0.961) and specificity (Sp ≥ 0.951) values for lying and standing. In contrast, moving behavioural patterns displayed low levels of sensitivity and greater among-cow variability. This resulted in a probability of the IceTag2D recording true moving behaviour of between 25-30% (Mattachini et al., 2011). Trénel et al. (2009) found similar results when using the IceTag3D™ sensor on dairy calves. Twelve hour video surveillance showed the device to accurately measure lying and standing behaviours (sensitivity + specificity >1.90), yet a poor ability to measure moving behaviour (sensitivity + specificity = 1.39). Therefore the ability of the IceTag3D™ activity monitor to detect locomotion in dairy cattle is questionable. Kokin et al. (2014) evaluated the possibility of using the IceTag3D™ for the early detection of lameness in dairy cows. Sensors were attached to the lateral side of the cows (14 lame and 19 sound cows) hind leg above the metatarsophalangeal joint over a 15 day period. It was concluded that further research was required to synchronise video observations with sensor values to identify threshold values. Chapinal, De Passillé, Rushen, and Wagner (2010) reported similar findings using IceTag3D™ accelerometers recording at 16 Hz attached to the cows right hind leg above the fetlock. Results showed lame cows shifted weight between contralateral legs more often, had greater asymmetry in the weight applied to the rear legs, had longer lying bouts and walked slower than sound cows.

A disadvantage of the IceTag3D™ sensor is the inability to measure feeding behaviour, different aspects of standing (idle or perching) or location (Mattachini et al., 2011). Endres and Barberg (2007) reported active and lying classification at the same time in 10.4% of the data. This could be a reflection of the transition phase between lying and standing and could result in an underestimation of lying time. Nielsen et al. (2010) validated the IceTag3D™ sensor based on registrations from ten cows, all equipped with a sensor on both hind legs. In comparison with video observations, they concluded that the IceTag3D™ can estimate the number of steps taken, and the frequency and duration of standing and walking with a fairly high accuracy. They reported concerns about the ability of the IceTag3D™ to detect walking periods when only one leg carries the device as there may be seconds when no steps are recorded during walking periods as the animal is moving the legs which are not equipped with a sensor.

2.7.2 CowManager SensOor

The CowManager SensOor is a commercially available system designed to monitor cow welfare 24 hours-a-day, 7 days-a-week (CowManager, 2015). The on-animal sensor is a moulded microchip which fits into adapted ear identification tags (Supertag; Dalton ID Ltd., Oxfordshire, UK)
Figure 2-9). Data are collected continuously and classified into four behaviour categories for each minute (ruminating, resting, eating and active). These behaviours are expressed as a percentage of behaviour per hour or per day. Data are transferred through a wireless connection to a computer via a router and a coordinator (connects to the computer and receives data from the sensor and/or

router) (CowManager, 2015). The data can then be accessed through a web based CowManager software program. The sensor has a store on board (SOB) memory capable of storing up to 48 hours of data (Bikker et al., 2014). The CowManager SensOor has a built in 3 dimensional accelerometer. Based on the principle that behaviour can be identified by ear movements (Bikker et al., 2014) this technology can potentially be used for oestrus detection, health and rumination monitoring

(CowManager, 2015).

Figure 2-9. Example of the CowManager SensOor deployed in a cow's ear (CowManager, 2015) .

The CowManager system was evaluated by Bikker et al. (2014) who monitored the behaviour of 15 cows both visually and with the sensor. The time animals spent ruminating, eating, resting, and active as recorded by the sensor were 42.6, 15.9, 31.6, and 9.9% respectively, and 42.1, 13.0, 30.0, and 14.9% respectively as recorded through visual observation. Kappa agreement values for the comparison between the sensor and visual observations were 0.85, 0.77, 0.86, and 0.47 for ruminating, eating, resting, and active, respectively. Using mixed logistical regression to analyse accelerometer signals of feedlot cattle activity, Wolfger et al. (2015) reported sensitivity and specificity values of 95% and 76% for feeding and 49% and 96% for rumination respectively using direct observation to validate accelerometer values. Bikker et al. (2014) stated the CowManager SensOor system can be used to monitor ruminating and resting behaviour of freestall-housed dairy cattle, however more research is required to determine the technology's suitability to monitor activity in dairy cattle. These results show promise for the use of ear deployed accelerometers to monitor animal behaviour.

2.8 Scope of thesis

Much of the research and commercial application of precision livestock (PL) technologies described thus far has been applied in the intensive livestock industries, particularly dairy. Because their availability is now widespread, understanding how these technologies can be used within the extensive livestock production systems is required.

This review has highlighted that there is scope for more research using PL technologies, particularly accelerometers to monitor livestock behaviour and therefore help producers make more informed decisions on the health, welfare and behaviour of their livestock.

The aim of this thesis is therefore to investigate the use of accelerometers in predicting sheep behaviour and use the quantified behavioural measurements to identify individual animals that are unhealthy. The following objectives were established:

- *To determine if grazing, standing and walking behaviour of sheep can be detected using a single accelerometer deployed on the sheep's ear, front leg or attached to a neck collar (Chapter 5).*
- *To develop a statistical algorithm capable of classifying sheep behaviour from a continuous stream of accelerometer data (Chapter 6).*

- *To investigate the possibilities of using ear mounted accelerometers to detect changes in behaviour related to intestinal nematode infections in a 'real life' grazing flock (Chapter 7).*
- *To investigate the capabilities of an ear, front leg and collar mounted accelerometer to detect lameness movement in sheep (Chapter 8).*

Chapter 3

Methodology for using tri-axial accelerometers for behaviour monitoring

3.1 Introduction

This chapter is somewhat unconventional as it introduces the technologies and main analytical procedures used throughout this thesis. A more detailed description of experiment specific procedures is provided later within the relevant chapters devoted to each specific trial. Chapter 3 will outline the types of accelerometers used and their specifications, the three deployment modes evaluated, methods used to annotate the accelerometer data and the statistical analysis procedures employed to classify basic movement behaviours.

3.2 Accelerometer specifications

Two types of accelerometer were used for animal monitoring; GCDC X16-mini and the Axivity AX3. Both accelerometers record acceleration along 3 orthogonal axes, have an internal power supply (battery) and contain store on board (SOB) memory. Both types are three dimensional sensors and were preferred over single axis devices due to their ability to measure animal movement in all spatial dimensions therefore generating a more precise estimate of orientation and activity (Gao et al., 2013). A detailed description of the X16 and AX3 is provided below.

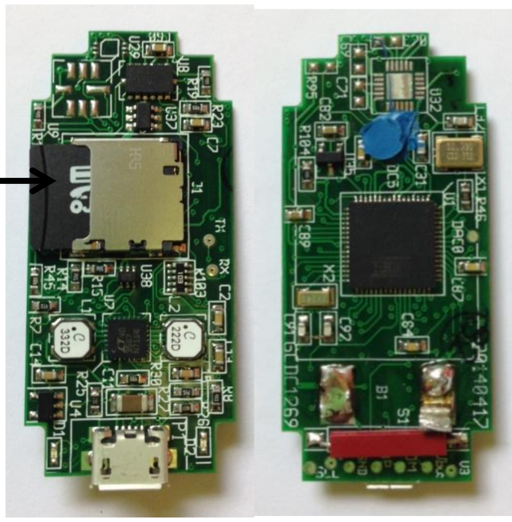
3.2.1 GCDC X16-mini

The X16-mini is a tri-axial, 16-bit resolution MEMS accelerometer capable of recording data up to 800 Hz. The accelerometer is powered by an internal 250 mAh lithium polymer rechargeable battery and records data to a removable 8 GB micro SD card.

Figure 3-1 shows the X16-mini plastic housing and the relevant orientation of each orthogonal axis.

Figure 3-1. GCDC X16-mini accelerometer axis orientation and plastic housing (GCDC, 2014).

8GB
microSD-card



(a) (b)

Figure 3-2. Top (a) and bottom (b) view of the X16-mini circuit board.

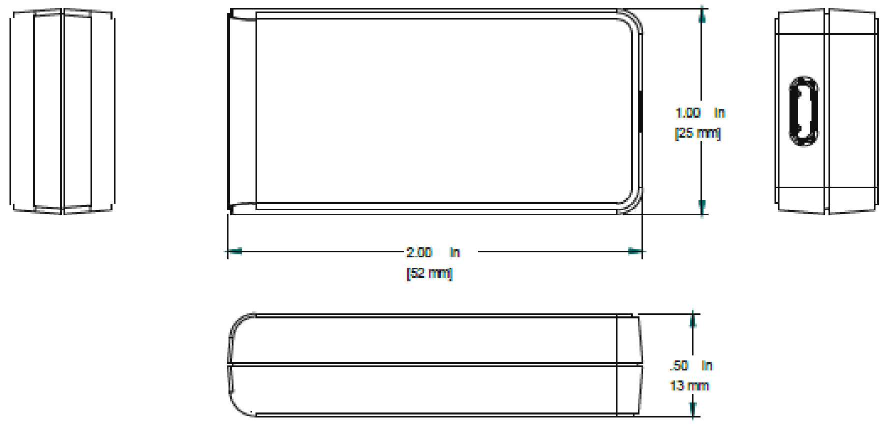


Figure 3-3. X16-mini plastic housing dimensions (GCDC, 2014).

The X16-mini is housed in a plastic enclosure which provides some basic impact protection however does not shield the sensor from environmental conditions such as rain and water submersion. The battery is recharged when the sensor is attached to a USB port or a USB 5 V power adapter. Accelerometer settings are user defined and configured in a .txt file stored on the internal flash memory. Using XLR8.jar software (Gulf Coast Data Concepts), configuration files are written to a .CSV format with the header containing the relevant start time and sampling frequency. Each reading is time stamped in the format "seconds relative to the start" using the on board real time clock (GCDC, 2014). X16-mini specifications are listed in Table 3-1.

Table 3-1. GCDC X16-mini sensor specifications (GCDC, 2014).

Sample Rates	12, 25, 50, 100, 200, 400, 800 Hz
Axes	3
Power Supply	250 mAh Internal Li-Poly battery
Memory	8 GB internal flash memory
Operating Life	8 days
Sampling Range	+/- 16 g
Weight	17 grams
Time	Real Time Clock (RTC)
Sensor Class	MEMS
Temperature Range	-20°C to 55°C
Charging Time	90 minutes
Moisture Ingress	Not specified
Dust Ingress	Not specified

3.2.2 Axivity AX3

The AX3 is a combination logging sensor containing a 3 axis accelerometer, light and temperature sensor. The sensor is housed in a polycarbonate casing which is hermetically sealed to an IP68 waterproofing allowing the device to be used in a variety of environments (Ladha, Hammerla, Hughes, Olivier, & Plötz, 2013). Data are continuously logged at a user defined sampling interval to the internal NAND flash memory and can be exported in .CSV format through a microUSB port.

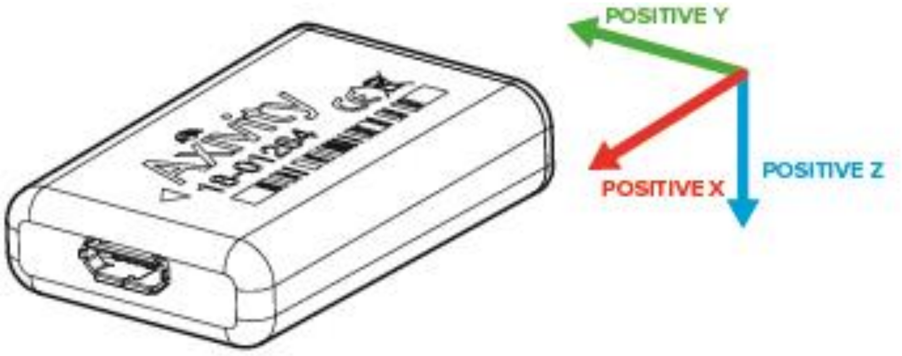


Figure 3-4. Axivity AX3 accelerometer sensor axis orientation (Axivity).

Figure 3-5. AX3 accelerometer sensor platform without the polycarbonate casing (Axivity).

Table 3-2. AX3 sensor specifications (Axivity, 2015).

Sample Rates	12.5 - 3200 Hz
Axes	3
Power Supply	150 mAh Internal Li-Poly battery
Memory	512 MB NAND flash memory
Operating Life	21 days @ 100 Hz
Sampling Range	+/- 16 g
Weight	9 grams
Time	Real Time Clock (RTC)
Sensor Class	MEMS
Temperature Range	0°C to 65°C
Charging Time	120 minutes
Moisture Ingress	IPx8
Dust Ingress	IP6X

The accelerometer used throughout this thesis was changed for 3 reasons 1) the GCDC X1-6mini was discontinued, limiting the total number of available devices to 5, 2) the X16-mini is liable to water and dust ingress while the AX3 has a moisture ingress rating of IP68 and 3) the operating life of the AX3 is considerably longer compared to the X16-mini making it more suitable to the study presented in Chapter 7.

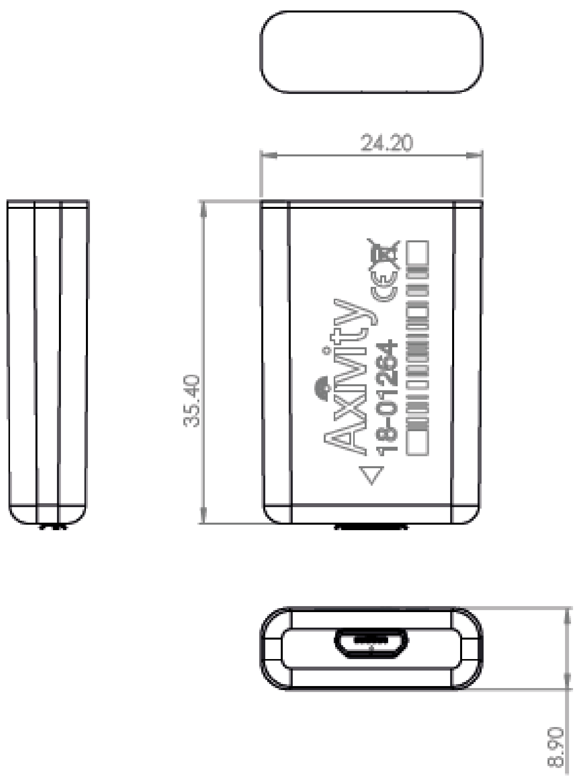


Figure 3-6. AX3 polycarbonate housing dimensions (units in millimetres).

3.3 Accelerometer attachment on experimental sheep

As outlined in the Chapter 2, a key focus of this project was to evaluate the different deployment modes of accelerometer sensors with a focus on the potential for ear tag deployment. Three deployment locations on sheep were evaluated: front leg, collar and ear. This section provides a description of the methods used for attachment of the X16-mini and AX3 devices to each deployment location and the sensor axis orientation. All deployment locations had the same axis orientations and this orientation was standard across all experiments. Whilst the direction of each axis is irrelevant to the sensor readings, it is critical the axis orientations are known for data interpretation. Orientations of the *X*, *Y* and *Z* axis were dorso-ventral, lateral and anterior-posterior respectively (Figure 3-7).

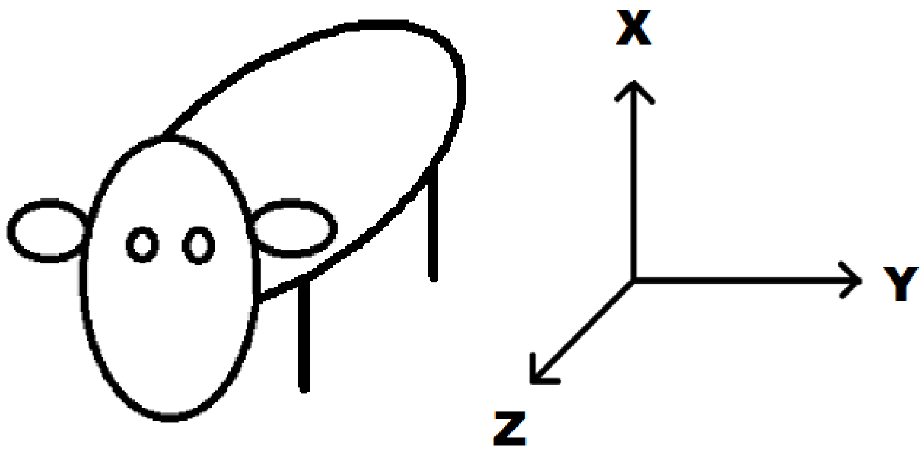


Figure 3-7. Sensor axis orientations.

3.3.1 GCDC X16-mini

The X16-mini sensor was deployed on the front side of a UNE Tracker GPS collar polycarbonate housing, the anterior side of the nearside front shin and the ventral side of the offside ear. Collar deployed accelerometers were attached to the GPS polycarbonate case using electrical tape and collars were placed around the sheep's neck (Figure 3-8).

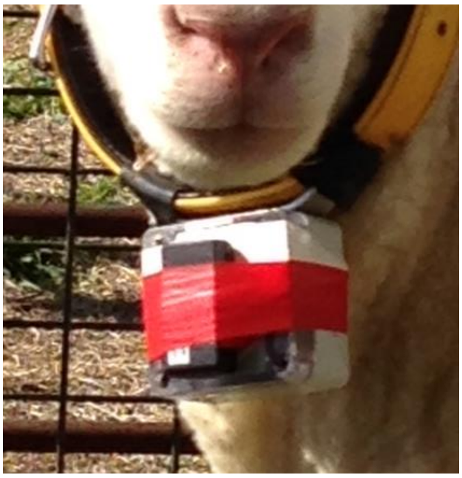


Figure 3-8. Collar mounted X16-mini sensor showing collar placement around the animal’s neck.

Front leg mounted sensors were attached to the foreleg shin using Vetflex adhesive bandage (Figure 3-9). Whilst this method did not provide a completely rigid attachment and some movement of the sensor was observed, given the short deployment time this method of attachment was selected due to the minimal human interference necessary and the limited animal discomfort associated with Vetflex bandage. This method has previously been used by Luu, Johnsen, Passillé, and Rushen (2013) to attach accelerometers to the legs of dairy cows.

Figure 3-9. Front leg deployed X16-mini using Vetflex adhesive bandage to attach the sensor to the anterior side of the nearside front shin.

Ear deployed sensors were attached to a trimmed Allflex management tag using electrical tape. Eartag sensors were placed in the central lower half of the animals' offside ear (Figure 3-10) to simulate "real life" management practices. This location is suitable to achieving a similar placement in all animals for synchronicity.

Figure 3-10. Ear deployed X16-mini accelerometer.

(a) (b)

Figure 3-11. Front (a) and side (b) view of the X16-mini eartag sensor prototype.

Figure 3-12. Experimental animal displaying the three X16-mini accelerometer locations evaluated.

3.3.2 Axivity AX3

The AX3 sensor was only deployed as an eartag form factor (Chapter 7). The sensor was attached to a trimmed Allflex management tag using Selleys Plasticfix adhesive. Clear heat shrink was placed over the tag and sensor to further ensure the sensor would not separate from the tag over the deployment period (see Figure 3-13). Similar to the X13-mini ear deployment location, the AX3 sensors were placed in the central lower half of the ear (see Figure 3-14).

(a) (b) (c)

Figure 3-13. Side (a), back (b) and front (c) view of the AX3 eartag sensor prototype.

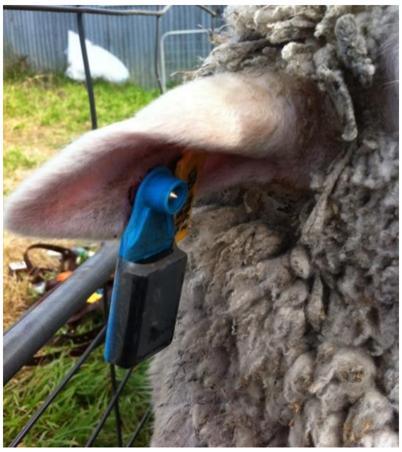


Figure 3-14. An example AX3 eartag sensor deployed in a sheep's offside ear showing correct placement allowing the sensor to move freely without dragging in the surrounding wool.

Some studies have indicated a habituation period is required prior to data collection (Bewley et al., 2010; Gibbons et al., 2012). No adverse effects on animal behaviour were observed in the present study due to sensor attachment. The work conducted throughout this thesis was predominantly focused on investigating the acceleration signals related to basic movement behaviours. The amount of time animals spent within each activity was not investigated until Chapter 7, where a habituation period was applied, in line with the findings of previous studies which have reported changes in activity proportions with instrumentation (MacKay et al., 2012).

The sheep used in these studies were regularly handled and as such were familiar with having a range of sensor based experimental protocols running on them. It may be that other studies reporting a requirement for habituation used more naïve animals.

3.4 Accelerometer sample rate

The accelerometers report acceleration measurements at a predetermined rate (the sampling rate). The AX3 and X16-mini accelerometers were configured to 6 Hz and 12.5 Hz respectively. This was the lowest sampling rate available on each of these devices. This sampling rate is on the lower spectrum of those reported for animal behaviour classification ranging from Mason and Sneddon (2013) at 0.5 Hz to Soltis et al. (2012) at 300 Hz. A low sample rate was specifically chosen in line with the overall thesis objective. This was to develop a computationally efficient classification algorithm, and as such, the lowest possible sampling rate was selected to reduce the amount of data recorded and required for processing.

3.5 Behaviour classification

Animal behaviour was classified according to the following description adapted from Robert et al. (2009) and Marais et al. (2014).

Table 3-3. Descriptions of the four behaviour states monitored.

Behaviour	Classification Description
Grazing	Grazing with head down or chewing with head up either standing still or moving. Rumination was classed as standing or lying.
Walking	Minimum of 2 progressive steps either forward/ back or sideways.
Standing	Static standing with minor limb and head movements. Animal is in a standing posture whilst idle or inactive. Head may be up or down.
Lying	Animal is in a lying posture whilst idle or inactive assuming a recumbent position with minor head movements.

3.6 Accelerometer signal annotation

To evaluate the ability of the accelerometer sensor to predict basic movement behaviour, the acceleration signals had to be calibrated with their corresponding visual behaviour observations.

Annotation is the process of matching the accelerometer signals with their corresponding behaviours. Correct time synchronisation between accelerometer devices and the manual behaviour recording device is necessary to ensure the accelerometer data points are annotated with the correct behaviour. There is little information in the literature on how this is achieved. Ultimately, model development is reliant on the success with which accelerometer signals are correctly annotated with their associated behaviours. A minor time deviation can have a large effect on the interpretation of the data (Blomberg, 2011).

Two methods of annotating accelerometer signals were used; in trial recording of behaviour states using the WhatISee app (Heuser, 2014) and post-trial annotation from video recordings. The latter method used custom built MATLAB® software to synchronise observations with their corresponding accelerometer signals.

3.6.1 Mobile application based behaviour state recording

WhatISee (Heuser, 2014) is an application able to be installed on any mobile device (i.e. iPhone or iPad) which enables you to make behavioural observations of subjects in the field. This application has previously been utilised for behaviour recording of cattle (Dutta et al., 2015; González et al., 2015; Trotter et al., 2011). Each observation can record: the subject, the action or state of the subject, time, date and location in terms of latitude, longitude and altitude (Heuser, 2014). The layout configuration is user defined allowing the behaviours and number of animals recorded to be altered for specific tasks. The 4 behaviour states: grazing, walking, standing and lying along with the date and time were configured for the present study (see Figure 3-15). It is important to only have the parameters which are to be observed on the app interface to avoid errors when recording behaviours in the field. This process of annotation was used for Chapters 4 and 5.

Figure 3-15. Configuration of the WhatISee application used.

WhatISee uses the time of the device as the time stamp for each observation. Therefore it is necessary to ensure the device (iPad or iPhone) and the accelerometers are synchronised within 1 second of each other to ensure the time stamp of the observations correspond to the correct accelerometer signals.

The accelerometers and iPad were time synchronised to AEST time using a Dell Precision M4700 laptop.

As the animals are being observed in the field, the area on the screen corresponding to the performed behaviour is tapped, creating a time stamp with that behaviour observation. As animals change behaviours the new behaviour field is tapped. It is important the tapping of the corresponding behaviour is completed as soon as the behaviour is commenced to minimise the chance of incorrect annotation of the accelerometer file. Human delay was accounted for by removing the first and last 2 seconds of data for each behavioural event post classification.

Once a recording/observation session has been completed, the data can be stored on the device or emailed as a .CSV file. The disadvantage of using this method is behaviours must be recorded manually in the field and therefore it is liable to be affected by the issues outlined in Section 2.4

3.6.2 Behaviour classification interface for video recordings

A purpose built MATLAB® annotation interface was developed to code accelerometer signals captured by video behaviour observations. This method of annotation was used for Chapters 5, 6 and 8. Alternate programs for accelerometer data annotation are available including Logger *Pro* (Vernier, 2016) and SAAR (Gao et al., 2013) however these are expensive and the simplicity of an annotation program specifically designed for this project's requirements was preferred.

Accelerometers and observations must be synchronised to ensure each behaviour observation is related to the correct accelerometer signal. There is limited information in the literature on how this is achieved, therefore a new a systematic workflow was developed and applied (Figure 3-16).

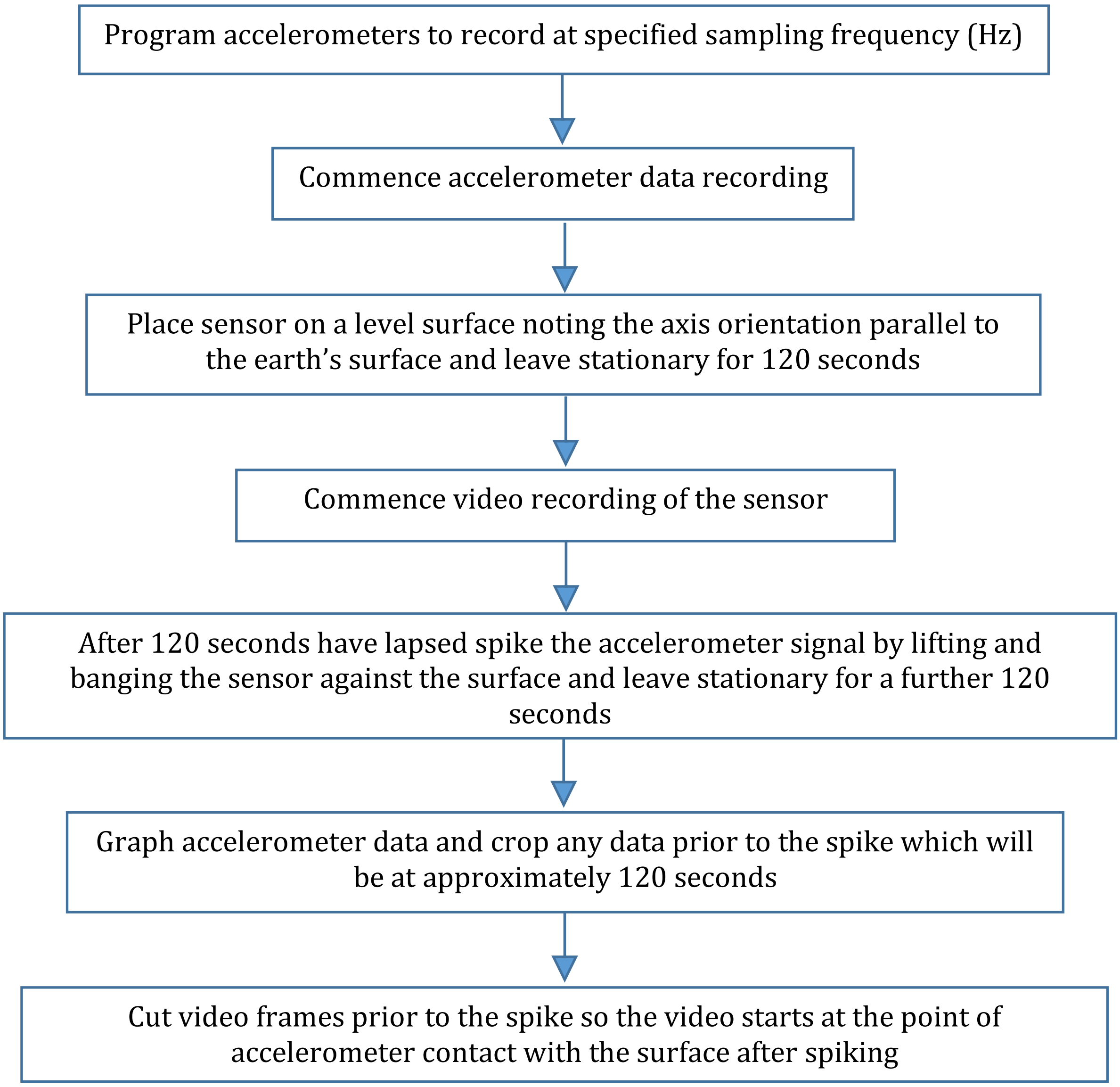


Figure 3-16. Description of the time synchronisation between accelerometers and video.

The "signal spiking" process was not used in Chapter 7. Rather, a digital iPhone clock placed in front of the camera prior to recording events provided a point of accelerometer and video synchronisation. This was done due to accelerometers already being attached to the animal.

A behaviour classification interface allowing video observations to be time stamped with the corresponding behaviours was developed. The interface (Figure 3-17) has three primary sections; 1) the video screen 2) behaviour buttons (walking, standing, grazing, lying and unknown) selected by the observer and 3) a list of the recorded behaviours with their corresponding times. Errors in behaviour selection can be deleted by typing the serial number of the event in delete events window and selecting the 'clear events' tab.

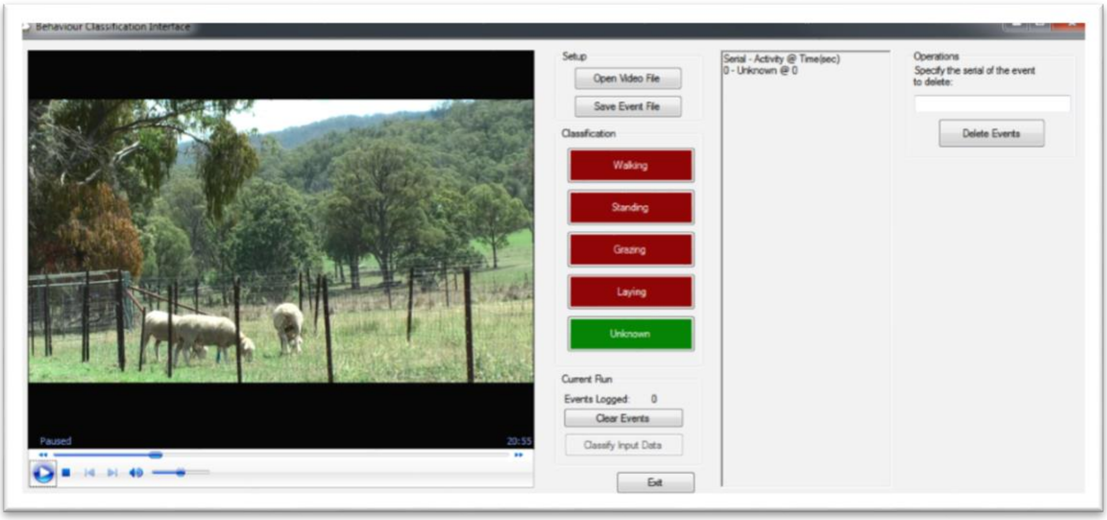


Figure 3-17. MATLAB® Annotation software interface.

Basic instructions for the program are as follows:

1. Open the interface software.
2. Select the video to be time stamped
3. Play the video and select the behaviour which the animal is performing by clicking on the corresponding button. The button which is highlighted in green is the selected behaviour.
4. Once the observation period has ended, save the event file as a .txt file.

Linking accelerometer and event files

Accelerometer files were trimmed by graphing the 3 axes in MATLAB® and removing data prior to the spike in the signal which appeared between records 600 and 1100. This ensures the accelerometer signals and video files have the same starting point. The accelerometer signal and event file were combined in MATLAB®. This created a .txt file where each accelerometer record was annotated with its corresponding behaviour with each behaviour category allocated a numerical value (walking =1, grazing = 2, standing = 3, lying = 4 and unknown = 5). The annotated .txt file was used for all future data processing. The procedure was repeated for each observed animal's dataset.

3.7 Data processing and analysis

Most approaches to activity classification involve a multi-stage process. Firstly acceleration signals are divided into windows or epochs of which one or more features are derived. This is often referred to as feature extraction. A subset of these features is then selected (feature selection) which are then used as inputs to a classification algorithm that associates each epoch with a particular activity.

In short, data processing can be broken down into four sections: feature extraction, feature selection, classification analysis and validation.

3.7.1 Feature extraction

Epoch length

The first step in feature extraction is to select an appropriate epoch length. Epoch lengths of 5 and 10 seconds were used in the current work. The values were selected based on previous findings in earlier work, for example Robert et al. (2009). Further discussion on epoch size was provided in Section 2.6. Each epoch is classed as a single event which was categorised into one behaviour category.

Calculating the metrics

The following features were calculated using either a 5 or 10 second epoch length.

- ***Average X-axis (Ax)***: The average value of the X axis acceleration over the epoch.

$$A_x = \frac{1}{T}\sum_{t=1}^{T} x\,(t)$$

(Equation 1)

Where T is the total number of counts in the epoch.

- ***Average Y-axis (Ay)***: The average value of the Y axis acceleration over the epoch.

$$A_y = \frac{1}{T}\sum_{t=1}^{T} y\,(t)$$

(Equation 2)

Where T is the total number of counts in the epoch.

- ***Average Z-axis (Az)***: The average value of the Z axis acceleration over the epoch.

$$A_z = \frac{1}{T}\sum_{t=1}^{T} z\,(t)$$

(Equation 3)

Where T is the total number of counts in the epoch/burst.

The mean values provide information about the orientation of the movement (Hokkanen et al., 2011).

- ***Movement Variation (MV):*** Also referred to as waveform length, MV is the total amount of variance within the signal epoch through the cumulative measure of amplitude, frequency and duration of the acceleration (Campbell et al., 2013). Simply, MV measures the total amount of variance of signal vibration through 3 dimensions (Gao et al., 2013). Variance provides information about the total amount of movement.

$$MV = \frac{1}{N}\left(\sum_{i=1}^{N-1}|x_{i+1} - x_i| + \sum_{i=1}^{N-1}|y_{i+1} - y_i| + \sum_{i=1}^{N-1}|z_{i+1} - z_i|\right)$$

(Equation 4)

Where N is the total number of records in the epoch.

Source (Campbell et al., 2013) and (Gao et al., 2013).

- ***Signal Magnitude Area (SMA)***: The acceleration magnitude summed over three axes within each epoch normalised by the epoch length (Zhang & Sawchuk, 2011). Simply, it is a measure of movement intensity within all three axes (Khan, Lee, & Lee, 2010). Khan, Lee, and Kim (2008) found the SMA to be a suitable measurement of movement intensity and is capable of distinguishing between active and inactive behaviours from tri-axial accelerometer data.

$$SMA = \frac{1}{T}\left(\sum_{t=1}^{\boldsymbol{T}}|\boldsymbol{a_x(t)}| + \sum_{t=1}^{\boldsymbol{T}}|\boldsymbol{a_y(t)}| + \sum_{t=1}^{\boldsymbol{T}}|\boldsymbol{a_z(t)}|\right)$$

(Equation 5)

Where a_x, a_y and a_z are the absolute values from the acceleration signals of the *X, Y* and *Z* axes and *T* is the number of values for each replicate.

- ***Movement intensity (MI)***: A measure of the acceleration reading for each record across the epoch burst. Movement Intensity is independent of the orientation of the sensing device, and measures the instantaneous intensity of movements at index *t* (Zhang & Sawchuk, 2011). Movement Intensity is not used directly. Rather, *AI* is calculated over the epoch.

$$MI(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2}$$

(Equation 6)

Where a_x, a_y and a_z are the absolute values from the acceleration signals of the *X, Y* and *Z* axes and *T* is the number of values for each replicate.
Source (Zhang & Sawchuk, 2011).

- ***Average Intensity (AI)***: The average of MI across the epoch.

$$AI = \frac{1}{T}\left(\sum_{t=1}^{T} MI(t)\right)$$

(Equation 7)

Where T is the total number of counts in the epoch.
Source (Zhang & Sawchuk, 2011).

- ***Entropy:*** Measure the predictability of the information content of a random variable. Time windows that encapsulate smooth motion are more predictable than windows capturing random motion and therefore possess a lower entropy (Smith et al., 2016). A simple explanation of entropy is a measure of “disorder’ or freedom of motion.

$$S = \frac{1}{n}\sum(1 + Ts_i)\ln(1 + Ts_i)$$

(Equation 8)

Where *n* is the number of records in the burst and *Ts = A*z + *A*y + *A*z
Source (Alvarenga et al., 2016; M. Trotter et al., 2011).

- ***Energy:*** Calculated as the sum of the squared signal components from each axis, normalized by the epoch length (Zhang & Sawchuk, 2011).

$$E = \frac{1}{n}\sum\left(TSS_i^2\right)$$

(Equation 9)

Where n is the number of records in the burst and $TSS = A_z^2 + A_y^2 + A_z^2$
Source (Alvarenga et al., 2016; Trotter et al., 2011).

- ***Maximum X (MaxX):*** The maximum *X-axis* acceleration value within the epoch – (Equation 10)
- ***Maximum Y (MaxY):*** The maximum *Y-axis* acceleration value within the epoch – (Equation 11)
- ***Maximum Z (MaxZ):*** The maximum *Z-axis* acceleration value within the epoch – (Equation 12)
- ***Minimum X (MinX):*** The minimum *X-axis* acceleration value within the epoch – (Equation 13)
- ***Minimum Y (MinY):*** The minimum *Y-axis* acceleration value within the epoch – (Equation 14)
- ***Minimum Z (MinZ):*** The minimum *Z-axis* acceleration value within the epoch – (Equation 15)

The maximum/minimum values provide an indication of the intensity of sensor movement in each direction.

3.7.2 Feature selection

From the derived features, it is necessary to identify those which have a high discriminative ability (Kiani, Snijders, & Gelsema, 1997). This feature set should vary considerably between different activities yet show little variation between repetitions of the same movements (Preece et al., 2009). Any redundancy between features should be minimised as this can be an unnecessary computational cost

(Preece et al., 2009). Contrasting with dimensionality reduction techniques such as PCA, feature selection techniques do not alter the original representation of the variables. Rather they merely select a subset of them, hence preserving the original connotations of the variables allowing interpretation and comparison between the feature properties and behaviour (Saeys et al., 2007). To systematically assess the usefulness and identify the most important features for discriminating different activities, random forest ranking of importance was performed.

Random Forest (RF) analysis as a metric selection tool

Random forest (RF) is an embedded classification algorithm that uses an ensemble of classification trees (Díaz-Uriarte & De Andres, 2006; Saeys et al., 2007). Each classification tree is built using a bootstrap sample of the data with a subset of explanatory variables chosen randomly at each node (Díaz-Uriarte & De Andres, 2006; Genuer, Poggi, & Tuleau-Malot, 2010). First, at each node, a given number (denoted by mtry) of input variables are randomly chosen and the best split is calculated only within this subset. Second, no pruning step is performed so all the trees of the forest are maximal trees (Genuer et al., 2010). The predictions from all these trees are then combined (Cutler et al., 2007). The advantages of using RF include its very high classification accuracy compared to other statistical approaches and its ability to be a novel method for determining variable importance (Cutler et al., 2007). Refer to Cutler et al. (2007) and Breiman (2001) for a more comprehensive description of the processes involved in RF classification.

The use of RF as a variable selection tool has been previously documented (Genuer et al., 2010; Nathan et al., 2012; Sandri & Zuccolotto, 2006). Variables of importance were selected based on their Gini index which is used to measure the error across the random forest ensemble of trees. Variables with the highest Gini index were selected. Random forest allows for the reduction of predictors, thereby reducing multicollinearity of predictor variables. Variables are retained based on their importance, which is calculated during the building of the random forest (Homburger et al., 2014).

When using RF the choice of *mtry* and *ntree* are important for the variable importance computation (Genuer et al., 2010). Defined as the number of variables tried at each split, Díaz-Uriarte and De Andres (2006) proposed using an *mtry* value equal to the square root of the total number of variables. The present study used the default *mtry* value of 4 which Andy Liaw and Matthew Wiener (2002) indicated as an acceptable option. An *ntree* value 500 was used throughout the present work.

Visual selection

Visually analysing the distribution of a given feature for different activities has previously been proposed by Pärkkä et al. (2006). This method involves selecting features which change substantially between activities yet show little overlap between different activities (Preece et al., 2009). Metrics calculated in Chapter 5 Part A were plotted to visually identify the features which differed in value between behaviours. Metrics were examined visually to ensure there was some level of delineation between behaviours within the selected features.

Principal component analysis (PCA)

Principal component analysis (PCA) is a dimensionality reduction technique (Saeys et al., 2007) used to extract features from time series data variables (Bishop-Hurley et al., 2014). In data sets with many variables there are often groups of variables which move together with more than one variable measuring the same driving principle governing the behaviour of the system. Principal component analysis can take advantage of this redundancy of information by replacing a group of variables into a new set of variables called principal components. Each of the principal components is a linear combination of the original variables (MathWorks®, 2016). Each principal component is an orthogonal vector which accounts for a certain amount of variance in the data with a decreasing degree of importance (Bishop-Hurley et al., 2014). The reason for doing this is that some features may be irrelevant or redundant providing little information to improve the classification accuracy of the model. Certain features may even confuse the classifier rather than help discriminate various activities. In short, PCA combines the original set of features to define a new set of variables (Preece et al., 2009), which in the present work were used as the input metrics to the LDA and QDA classifier in an attempt to develop a superior classification accuracy.

A disadvantage of using PCA is that if PCA is applied prior to the data being processed through the classification algorithm then the output is no longer directly interpretable as the decision rules are based on the principal components rather than the original summary statistics (Nathan et al., 2012). However the advantage of using a PCA prior to classification algorithm evaluation is similarities and differences in summary statistics can be highlighted and the dimension of the feature space may be reduced without much loss of information (Long, Yin, & Aarts, 2009).

3.7.3 Classification analysis

When selecting the statistical methods to be used throughout this study, emphasis was placed on selecting algorithms which would: 1) provide a valid, accurate and reliable discrimination between behaviours, 2) be simplistic in their discrimination approach and 3) be as efficient as possible in terms of computing power and speed. Four data analysis techniques have been used: PCA, LDA, QDA and RF all of which are classed as supervised machine learning algorithms.

Discriminant analysis

Discriminant analysis is a classification method that assumes different classes generate data from different Gaussian distributions (Dutta et al., 2015; MathWorks®, 2016) which has previously been used to classify animal behaviour based on accelerometer data (Marais et al., 2014; Nathan et al., 2012; Trotter et al., 2011; Umstätter et al., 2008). Discriminant analysis can assign an input vector x (features) to one of K classes using a decision boundary (Marais et al., 2014) and determines which feature or feature set is able to discriminate between 2 or more classes (Scholkopft & Mullert, 1999). The classification process using discriminant analysis (both LDA and QDA) involves training (creating) the classifier where the fitting function estimates the parameters of a Gaussian distribution for each class. The classifier is then used to predict the classes of new data by finding the class with the smallest misclassification cost (MathWorks®, 2016).

With LDA, an underlying assumption is that all classes share the same covariance matrix. The decision boundary can be changed from linear to quadratic if a covariance matrix for each class is employed (Marais et al., 2014; Scholkopft & Mullert, 1999). Quadratic discriminant analysis (QDA), models the likelihood of each class as a Gaussian distribution, then uses the posterior distributions to estimate the class for a given test point (Friedman, Hastie, & Tibshirani, 2001). Both LDA and QDA were used as the classification algorithms throughout this thesis.

3.7.4 Validation

Following development of the classification model which provided a general idea on the prediction accuracy for each behaviour, data were validated using a leave-one-out cross validation to ensure stability of the model. Leave-one-out cross validation has previously been used for the evaluation of accelerometer based classification (Pärkkä et al., 2006; Preece et al., 2009; Soltis et al., 2012). This commonly used procedure consists of consecutively training the model on all but one of the records, testing it on the one dropped from the training set, and averaging the resulting scores (Pober et al., 2006). As the predictive ability of the classification method is tested on data that were not used to train or create the model, the resulting estimates of classification accuracy are valid estimates of those that would be obtained from a true external validation (Stone, 1974).

Leave-one-out cross validation has the advantage of all observations being used for both training and validation, and each observation is used for validation only once. This method provides more reliable estimates of the classifier performance as compared to a simple split of the data into training and testing subsets (Hokkanen et al., 2011).

3.7.5 Evaluating the performance of the classifier

Evaluation of the classification algorithms was performed using accuracy, precision, specificity, sensitivity and total accuracy calculations for each model.

Table 3-4. Description of the performance calculations used (Alvarenga et al., 2016; Campbell et al., 2013; Gao et al., 2013).

Sensitivity	The proportion of actual behaviour events that were predicted as positive.
Specificity	The proportion of true negatives that are correctly identified.
Precision	The proportion of positive predictions that are actual behaviours.
Accuracy	The overall percentage of behaviour events predicted correctly.
Total accuracy	The total accuracy provides an easily comparable value for overall performance of the behaviour classification.

$$sensitivity = \frac{true\ positives}{(true\ positives + false\ negatives)}$$

(Equation 16)

$$specificity = \frac{true\ negatives}{(true\ negatives + false\ negatives)}$$

(Equation 17)

$$accuracy = \frac{(true\ positives + true\ negatives)}{(true\ positives + true\ negatives + false\ positives + false\ negatives)}$$

(Equation 18)

$$precision = \frac{true\ positives}{(true\ positives + false\ positives)}$$

(Equation 19)

Where true positive (TP) is the number of instances where the behavioural state of interest was correctly classified. False negative (FN) is the number of instances where the behavioural state of interest was visually observed but was incorrectly classified as some other behaviour. False positive (FP) is the number of instances where the behavioural state of interest was incorrectly classified in the behaviour of interest and true negative (TN) is the number of instances where the behavioural state of interest was correctly classified as not being observed (Alvarenga et al., 2016).

Chapter 4

Interpreting tri-axial acceleration signals

In terms of time budgeting, sheep behaviour is mainly comprised of three basic movement related behaviours: grazing, walking and resting (either in a standing or lying posture). Tri-axial accelerometers measure acceleration forces in three directions referred to as the *X*, *Y* and *Z* plane. The measured acceleration in each plane is a result of both static and dynamic acceleration forces experienced by the sensor (Laich, Wilson, Quintana, & Shepard, 2008; Sato, Mitani, Cameron, Siniff, & Naito, 2003). Each axis has a positive and negative direction and the directional movement produces either a positive or negative acceleration value based on the sensor orientation. This "orientation variation" effectively shows the posture change during an activity (Long et al., 2009). Understanding how each part of the body moves during activity and the orientation of each axis during the key behaviours allows the relationship between the animal's behaviour and the corresponding acceleration signal to be interpreted. A simple explanation relating acceleration to basic sheep movement patterns is lacking in the current literature.

4.1 Research objectives

The aim of this chapter is to introduce how accelerometer data relate to sheep movement and activity. In this chapter we will introduce each of the key behaviours: walking, grazing and resting. At the same time acceleration signals obtained from a collar, leg and ear deployed accelerometer have been analysed for the three behaviours. In a departure from the standard sequence of introduction, materials and methods, results and discussion, a discussion of each movement state will be accompanied by samples of the accelerometer signals from each deployment with key features discussed.

4.2 Materials and methods

The study was conducted at the University of New England, Armidale, NSW Australia. All animal experimental procedures were approved under the University of New England Animal Ethics Committee, AEC13-170.

A single Merino ewe was equipped with a GCDC X16-mini accelerometer sampling at 12 Hz deployed in three locations: neck, leg and ear. The orientation of accelerometer axes and methods of accelerometer attachment are provided in Section 3.3.1. In the present study, the *X* axis measured up/down movement, *Y* axis measured left/right movement and the *Z* axis measured forward/back movement (refer to Figure 3-7).

Animals were monitored to obtain a short period of grazing, walking and resting activity. Behavioural states were classified as listed in Section 3.5 and observations recorded using the WhatISee application (Section 3.6.1). The accelerometer signals were annotated with the corresponding behaviour from the observation data file and a 5 second snapshot of the raw acceleration signals for each behaviour in each deployment were graphed for interpretation.

4.3 Resting

4.3.1 Leg deployment

Resting activity involves a recumbent posture, either lying or standing (Broom & Fraser, 2007). Lying posture was not observed in the present study, however Robert et al. (2009) provide a description of how lying and standing behaviours can be discriminated from a leg mounted accelerometer signal based on the static acceleration signals. If an activity has been detected as static (i.e. little dynamic body movement), the type of static activity can be identified from the orientation of the body segments (Veltink, Bussmann, De Vries, Martens, & Van Lummel, 1996).

For a leg attached accelerometer, discrimination between lying and standing is related to the specific orientation of the leg in respect to the gravitational field (Robert et al., 2009). In the present study, when an animal is standing, the full force of gravity is recorded on the *X* axis while the *Y* and *Z* axes are at right angles to the gravitational field which is reflected in Figure 4-1. However, in the lying posture, these readings are reversed as the *X* axis is flipped from a vertical to a horizontal position (refer to Figure 4-2 below). This changes the recorded acceleration in the *X* axis from ~1 g to ~0 g.

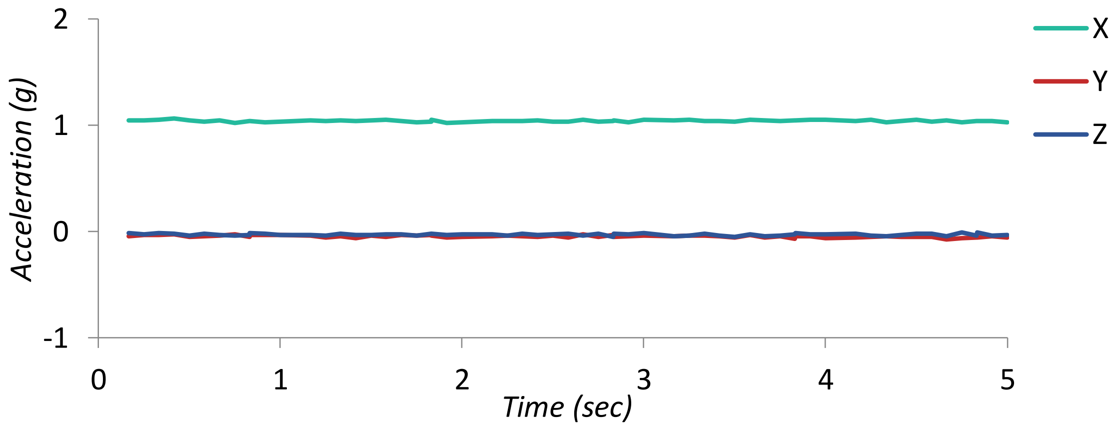


Figure 4-1. Five second acceleration signal of standing behaviour recorded by a front leg attached accelerometer. The signal amplitude remains largely unchanged, the *Y* and *Z* axis show a 0 g reading whilst the *X* axis, which is orientated vertically with the *X* axis downward, is recording 1 g as expected due to the earth's gravitational force.

(a) (b)

Figure 4-2. Standing (a) and lying (b) postures and the corresponding *X* axis orientation of the leg accelerometer.

Resting is a restorative process which allows metabolic recoveries and where energy is conserved (Fraser, 1974), hence body movements are minimised. From Figure 4-1 it is evident resting behaviour is characterised by little dynamic acceleration in all three axes. The recorded acceleration in the *X* axis is static gravitational acceleration. Limb and head movements were observed during standing behaviour however they were not detected by the leg accelerometer in the 5 second window shown.

4.3.2 Collar deployment

The standing acceleration signal recorded by the collar attached accelerometer is shown in Figure 4-3. Again the gravitational acceleration is acting on the *X* axis.

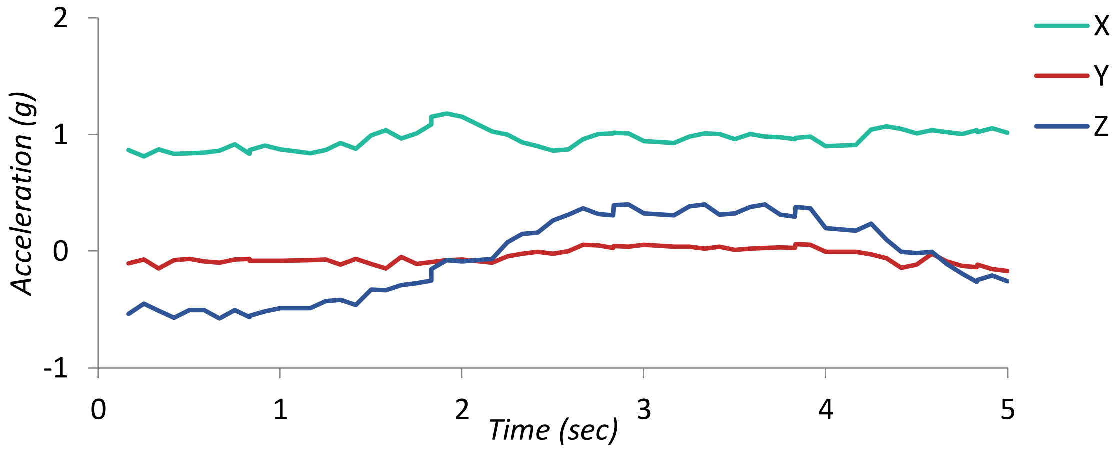


Figure 4-3. Five second acceleration signal from the collar attached accelerometer during standing behaviour.

Movement of the animals between head up/down and left/right creates little movement of the neck collar, hence the acceleration recorded in the *X* and *Y* axes remained relatively stable. Due to the loose attachment of the collar some movement in the left/right plane is to be expected and this is shown by the small fluctuations in the *Y* axis. Head turning is unlikely to be recorded from the collar accelerometer as this movement creates minimal movement of the brisket area where the sensor is placed. Movement of the *X* axis around 1 g may be associated with the raising and lowering of the head creating small up/down movements of the sensor, however it may also be associated with the movement of the *Z* axis with respiration.

Sheep have a respiration rate of 12-20 breaths/minute (Sheep101.info, 2015). It is proposed that the movement of the *Z* axis (forward/back) results from the rising and falling of the animal's chest cavity during each breath. A period of 5 seconds (Figure 4-3) corresponds to 12 breaths/minute. As air is inhaled, the chest cavity expands causing the sensor to move forward creating a positive acceleration. As air is exhaled the chest cavity deflates causing the sensor to move back resulting in a negative acceleration. These data demonstrates the feasibility of measuring the resting respiration of sheep using a collar or breast mounted accelerometer.

4.3.3 Ear deployment

The standing ear acceleration signal is distinct from those produced by the leg and collar accelerometers. Again the primary direction of gravity is acting on the *X* axis. However, Figure 4-4 indicates the *Y* and *Z* axes may also be recording this static acceleration.

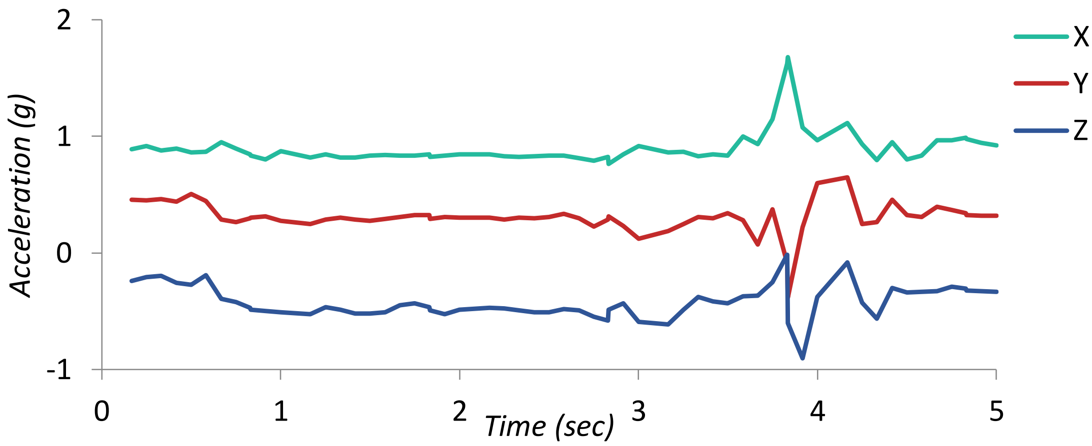


Figure 4-4. Five second acceleration signal from the ear attached accelerometer during standing posture.

Examining the way the sensor lies in relation to the vertical and horizontal planes helps explain the reasons for this. As shown in Figure 4-5, the *X* axis does not lie directly vertical. The *Z* and *Y* axes similarly do not lie parallel with the earth's surface (i.e. normal to the field). This highlights the particular susceptibility of accelerometers of the dimension used in this work, when mounted at a single pinpoint (i.e. an eartag pin) to produce distorted values.

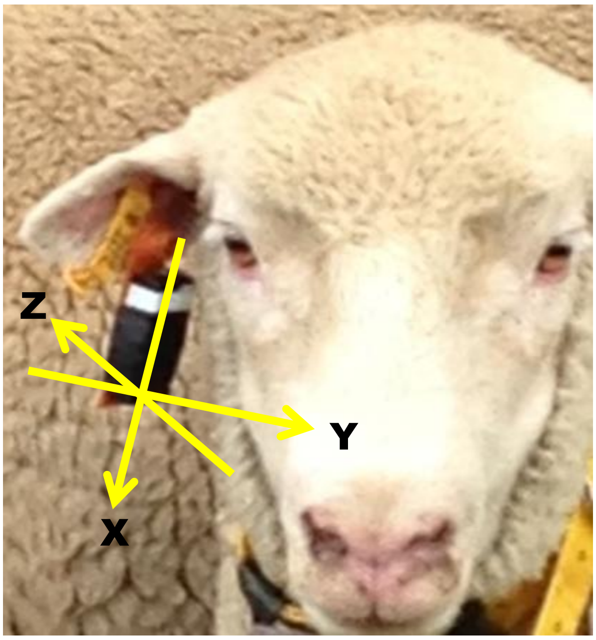


Figure 4-5. Axis orientations of the ear accelerometer during standing/lying posture.

As is indicated in Figure 4-4, neither the *Z* axis nor *Y* axis are recording a null acceleration, and the *X* axis acceleration value is less than 1 g. The peak in the signal around the 4 second point indicates a head turn as this would produce a *Y* axis acceleration. The sensor is susceptible to rotating left/right given the eartag design. As the head is turned, the sensor will swing in the opposite direction to the movement leading to acceleration being recorded by the *X* axis as this axis is now orientated in the direction of the movement. Such a head turn is indicated by the peak in recorded acceleration by the *X* axis.

As the ear does not provide a rigid attachment location and the sensor is susceptible to movement in all 3 directions, any movement involving the head will result in some level of recorded acceleration. Broom and Fraser (2007) indicated activities such as rumination are evident during resting activity and the fluctuations in the axes of the collar and ear accelerometers may reflect this. Furthermore, sheep can remain vigilant whilst resting or performing other behaviours such as grazing or walking. A component of vigilance behaviour in sheep is ear movement. Sheep can rotate the ear towards the direction of sound, hence variance (error) could be involved in the ear-based accelerometer data.

4.4 Walking

Walking is defined as "strides where each leg is lifted by shortening of the limb through flexion of the joints using especially the hip, knee, hock and digital flexor muscles" (Van Nuffel et al., 2015). As quadrupeds walk, each limb is lifted off the ground by shortening the leg through flexion of the joints. The limb then enters the swing phase and is placed on the ground through slow extension of the joint. Once on the ground, the limb then supports the load by tensing all the extensor muscles. The sole of the foot is then pushed against the ground by contracting the digital flexors, allowing the pushing phase to begin which is followed by the hanging and swing phases (Phillips, 2008). The motion of the fore and hind limbs during walking is shown in Figure 4-6 with the right most leg in each diagram being the first movement of the stride. Labels 1 and 2 show legs in the hanging or swinging phases, while labels 3 and 4 show legs in the supporting phases.

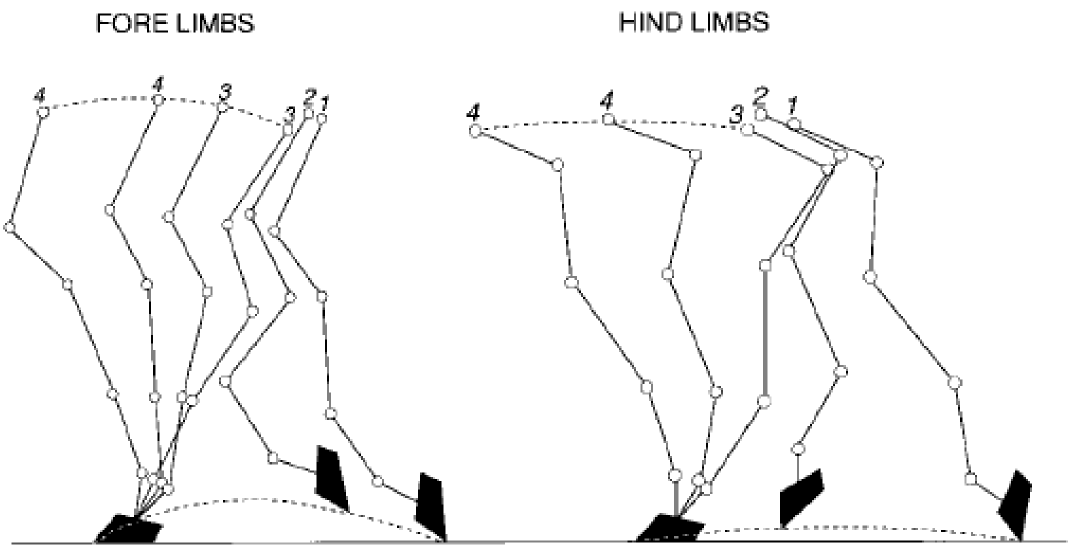


Figure 4-6. Movements of the fore and hind limbs during walking; 1 lifting; 2 swinging, 3 supporting and; 4 thrusting (Phillips, 2008).

The sequence of leg movements in quadruped walking is left front, right hind, right front, left hind or the inverse beginning with the right front as shown in Figure 4-7 (Broom & Fraser, 2007; Phillips, 2008). To allow the hind limb to overlap the front limb imprint, the front leg is usually lifted just before the hind limb is placed. During a normal walk, the duration of support exceeds that of swing, and different limbs show less than 50% overlap in the swing phase of two successive steps (Van Nuffel et al., 2015). Studies in sheep have shown the proportion of time spent within each phase was 59% support phase and 41% swing phase for the forelimbs versus 62% support phase and 39% swing phase for the hind limbs (Agostinho et al., 2012).

During forward motion, the centre of gravity is moved towards the front limb by the propulsive efforts of the hind limb, and the front limb is raised and repositioned to maintain the animal's balance (Phillips, 2008). This action leads to greater forces exerted on the forelimbs than the hindlimbs during walking (Pandy et al., 1988) due to their closer proximity to the animal's centre of gravity (Broom & Fraser, 2007). Agostinho et al. (2012) indicated the body weight distribution between the limbs of healthy sheep during walking is approximately 30% on each forelimb and 20% on each hind limb.

4.4.1 Leg Deployment

A leg attached accelerometer shows a cyclical pattern (refer to Figure 4-8) which is indicative of the cyclical nature of limb movement (Phillips, 2008). All limb movements contain an accelerative and decelerative force (Phillips, 2008) and as the animal walks these forces can be detected as acceleration.

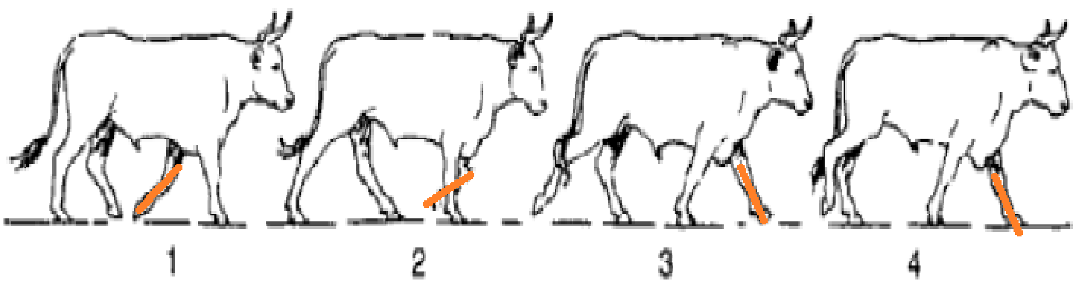


Figure 4-7. Quadruped walking patterns (Nickel, Schummer, & Seiferle, 1986).

All three axes show cyclical patterns of dynamic and static acceleration. The dynamic acceleration is recorded when the limb is moving during the swinging and hanging phases while the acceleration values during the supportive phases are mostly related to gravitational force.

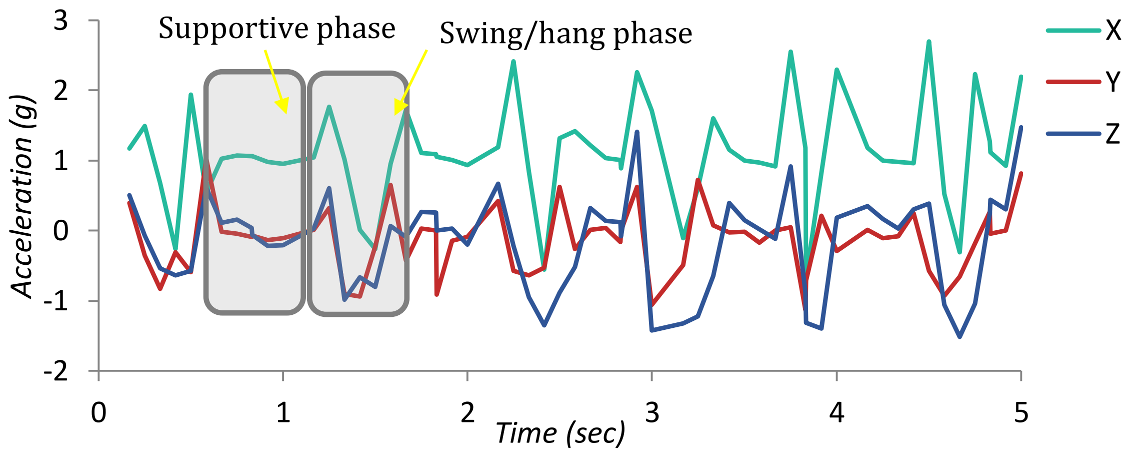


Figure 4-8. Five second acceleration signal from the leg attached accelerometer during walking behaviour.

Figure 4-8 highlights various phases of limb movement from the leg accelerometer signal. The periods where the *X* axis is recording ~1 g represent the times when the foreleg is in the supportive phases. The accelerative, decelerative signals reflect the thrusting, lifting and swinging phases. These movements are represented by a small positive acceleration as the animal lifts its leg, rapid negative acceleration as the leg is pushed backward followed by a positive acceleration as the limb is in the swinging phase (see the highlighted limb in Figure 4-7 for the movement patterns of the instrumented limb). Similar acceleration graphs have been presented by De Passille et al. (2010) showing leg movements in dairy calves and by Tanida et al. (2008) describing the gait patterns in dairy cows.

Examining the illustrations in Figure 4-7, it is seen in diagram 2, when the left front leg is lifted the shin is at an approximate angle of 45^{o} to the ground. This causes some of the gravitational force to be placed on the *Z* axis causing a negative acceleration value (as positive *Z* axis acceleration is recorded through backwards movement of the sensor). This part of the signal also contains dynamic acceleration due to the forward propulsion of the animal. The *Z* axis records the positive and negative acceleration during the lifting and swing phases respectively. As the leg is lifted backwards this creates a positive acceleration and the swinging of the leg forward (swing phase) causes a negative acceleration value. Due to the very clear cyclical pattern obtained from the leg deployment, many early studies selected this mode of attachment as it provides a clear differentiation between upright, lying and movement behaviours.

The measured acceleration in the *Y* axis may be associated with the accelerometer placement not being aligned on the posterior of the shin. As the shin is round and the accelerometer casing is square the sensor is susceptible to moving around the leg. This would result in some of the forces exerted during the lift and swing phases (as explained above for the *Z* axis) being recorded by the *Y* axis. Also, as sheep walk their front legs do not rise, swing and fall in a common plane. Rather the front legs follow a slight outward semi-circle motion, therefore creating some left/right movement. Positioning of the limb to stabilise the body may also create small left/right and forward/back movement as indicated by the *Y* and *Z* axis recordings during the support phases of Figure 4-8.

4.4.2 Collar deployment

As quadrupeds walk, their bodies rise and fall because the forces their feet exert on the ground are not constant; the displacement and force are half a cycle out of phase with each other (Jayes & Alexander, 1978). This rising and falling action as the sheep walk causes up/down movement of the collar accelerometer as shown in Figure 4-9. This is further highlighted by the cyclical pattern of the *X* axis acceleration signal shown in Figure 4-10.

Figure 4-9. Collar accelerometer sensor movement as the animal walks.

As the collar does not provide a rigid attachment (i.e. the collar can swing left/right and forward/back), any form of animal locomotion is expected to cause some displacement of the sensor in the forward/back and/or left/right directions. The *Y* axis and *Z* axis acceleration signals shown in Figure 4-10 reflect this. As the shoulders are a central point of movement during forward propulsion, each step pushes the collar forward and slightly away from the swinging limb creating an irregular acceleration pattern in these two directions.

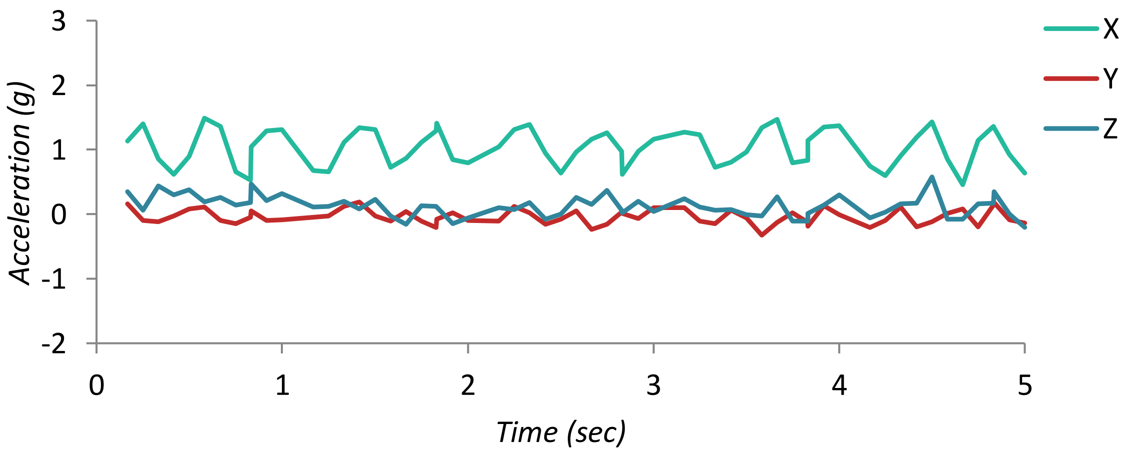


Figure 4-10. Five second acceleration signal from the collar attached accelerometer during walking behaviour.

4.4.3 Ear deployment

There is little information in the literature on head movements during locomotion. As indicated earlier the heads of quadrupeds rise and fall when walking. During locomotion it was observed the sheep's head moved up and down and swayed left to right. When walking the sheep's ears frequently moved forward and backwards and this was further exacerbated on the instrumented ear. As the point of attachment to the animal acts similar to a fulcrum, this creates a semicircle motion as the animal walks which is shown in Figure 4-11. This also changes the gravitational force between the *X* and *Z* axes.

Figure 4-11. Motion of the ear accelerometer during walking.

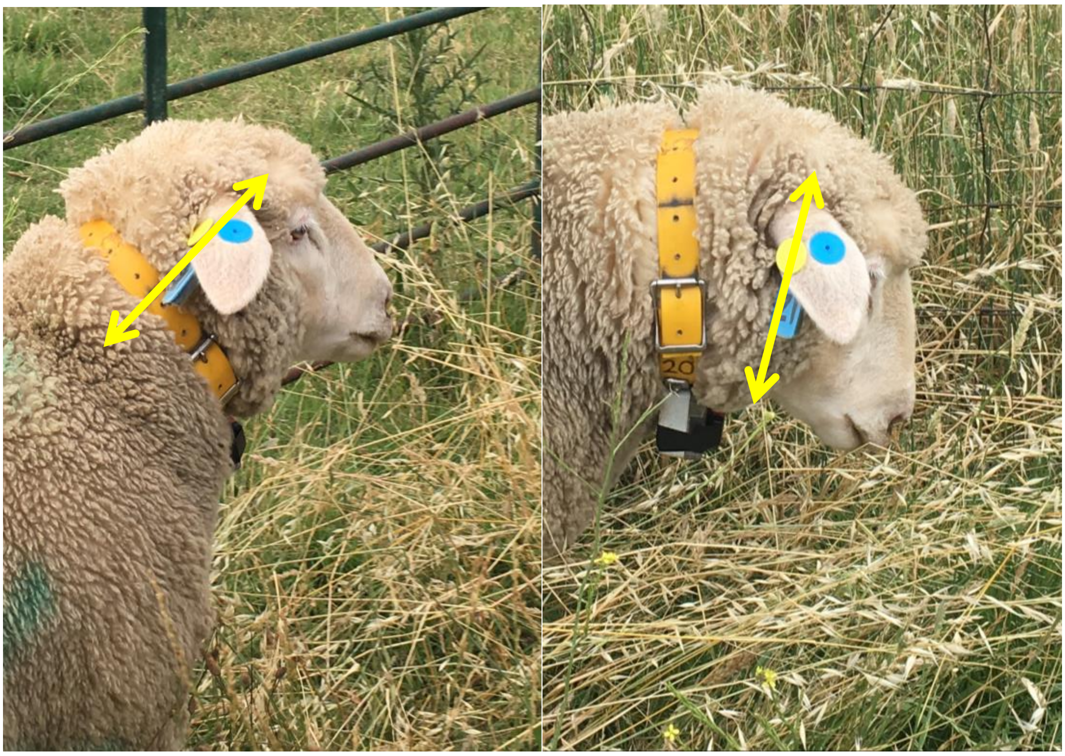


Figure 4-12. Changes in the *X* axis orientation when attached to the ear during walking behaviour.

Figure 4-12 illustrates the changes in the *X* axis orientation during walking. The dominant direction of movement is forward/back, which creates positive and negative acceleration in the *Z* axis as the sensor swings. This is also demonstrated by the acceleration signal shown in Figure 4-13. The changes in *X* axis signal is directly linked to the changes in gravitational field as the sensor swings from a vertical to a horizontal position as the animal walks. The *Y* axis signal may again be explained by the eartag design. As the eartag uses a circular male pin to connect with the female part of the tag, a small hole is left in the animal's ear allowing the tag to swing freely left to right. As the animal walks it is observed that the forward/back swinging of the tag also creates a left/right swinging movement which is recorded along the *Y* axis.

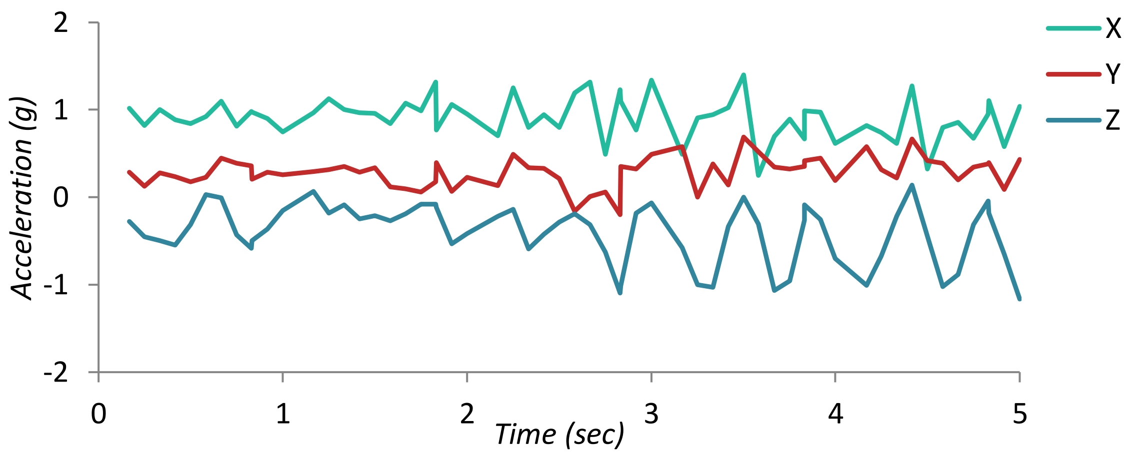


Figure 4-13. Five second acceleration signal from the ear attached accelerometer during walking behaviour.

4.5 Grazing

Sheep have a cleft upper lip which permits very close grazing with the lower incisor teeth and the dental pad being used as the principal prehensile structures (Ratner & Hafez, 1975). As sheep graze, pasture is pressed against the dental pad and severed by the lower incisors as the head is jerked slightly forwards and upwards (Lynch, Hinch, & Adams, 1992; Ratner & Hafez, 1975) with this process being repeated several times a minute in ruminants (Phillips, 2008). The animal's head is moved posteriorly with a sudden jerking movement and may also swing from side to side searching for fresh pasture. In cattle, there can be a great number of pauses within a bout and the grass is ripped off the sward by jaw movements and by shaking the head upwards (Blomberg, 2011). The fore and hind limbs take steps forward as the animal moves to new areas of pasture (Lynch et al., 1992). Therefore during grazing there are two primary movements: jaw and head movements to break and ingest food and the locomotive movements involved in searching for food. Analysis of the raw accelerometer signals from the three deployment locations demonstrates these associated movements.

4.5.1 Leg deployment

Figure 4-14 shows the acceleration signal produced during grazing behaviour from the leg accelerometer. As the leg is not subject to the head movements described above, the leg accelerometer only detects the locomotive movements associated with grazing behaviour; the small steps to reach new areas of pasture. A comparison of Figure 4-8 and Figure 4-14 reveals similar cyclical patterns of movement between walking and grazing events; however the support phases are extended during grazing (4 supportive phases during grazing compared to 5 during walking within the 5 second periods presented here) indicating fewer steps are taken in the same time period. This is consistent with Shipley, Spalinger, Gross, Hobbs, and Wunder (1996) who indicated as herbivores feed they are constantly slowing and stopping to capture food, therefore the animals velocity is constantly increasing and decreasing.

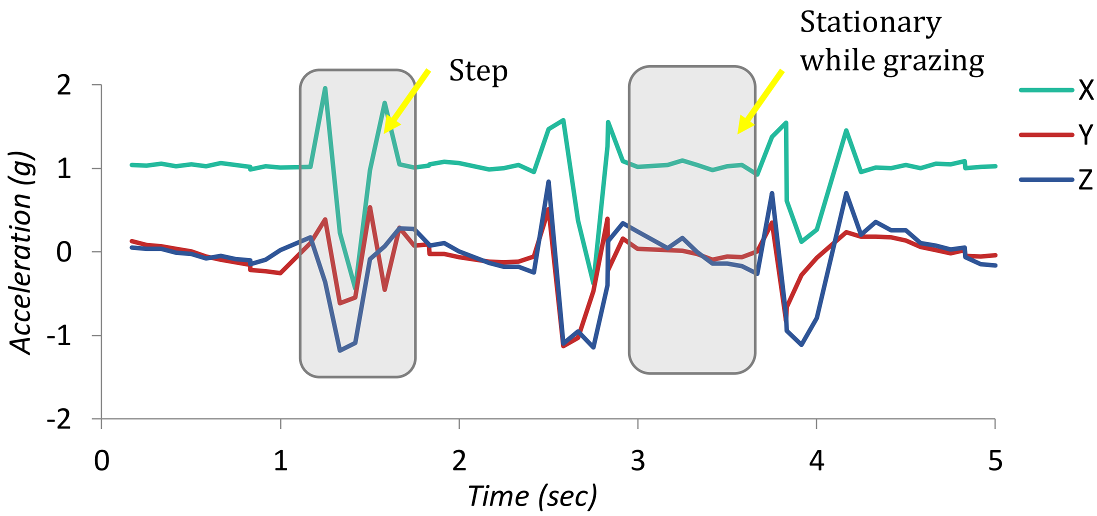


Figure 4-14. Five second acceleration signal from the leg attached accelerometer during grazing behaviour.

4.5.2 Collar deployment

As animals graze the head is lowered to the ground which tilted the collar forward (Figure 4-15) causing a negative forward acceleration value in the *Z* axis.

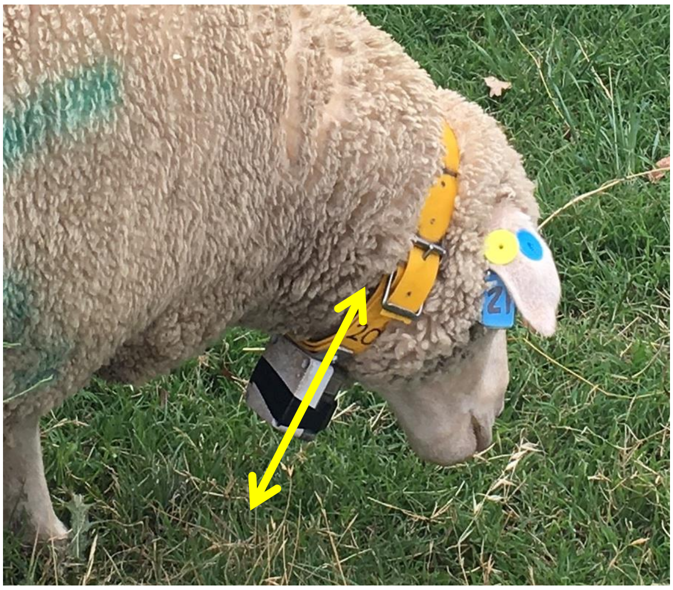


Figure 4-15. Orientation of the of the collar accelerometer during grazing activity. Note the forward tilt of the sensor.

Jerking of the head forwards and upwards to sever pasture creates small acceleration values in the X and Z axes while the sideways swinging of the head is measured by the Y axis. Figure 4-16 illustrates the low amplitude of these movements, indicating feeding behaviour does not result in large movement of the neck. Again, due to the loose attachment of the collar, the associated grazing head movements can cause sensor displacement in a number of directions which is shown by the irregular signal pattern and limited evidence of periodicity in Figure 4-16. This is similar to the collar accelerometer signals reported by Trotter et al. (2012) for grazing cattle.

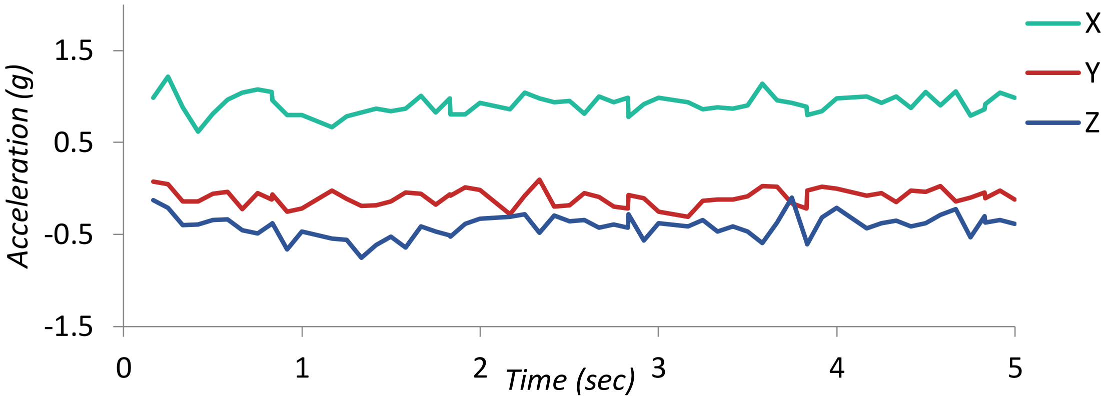


Figure 4-16. Five second acceleration signal from the collar attached accelerometer during grazing behaviour.

4.5.3 Ear deployment

Similar to the collar data, head movements to sever pasture are recorded by all three axes from the eartag accelerometer (see Figure 4-17), which is indicative of the eartag design allowing a high degree of movement. The head jerking reaction used to break off pasture causes small vertical movements of the animal's head causing displacement of the ear sensor similar to that described for Figure 4-11.

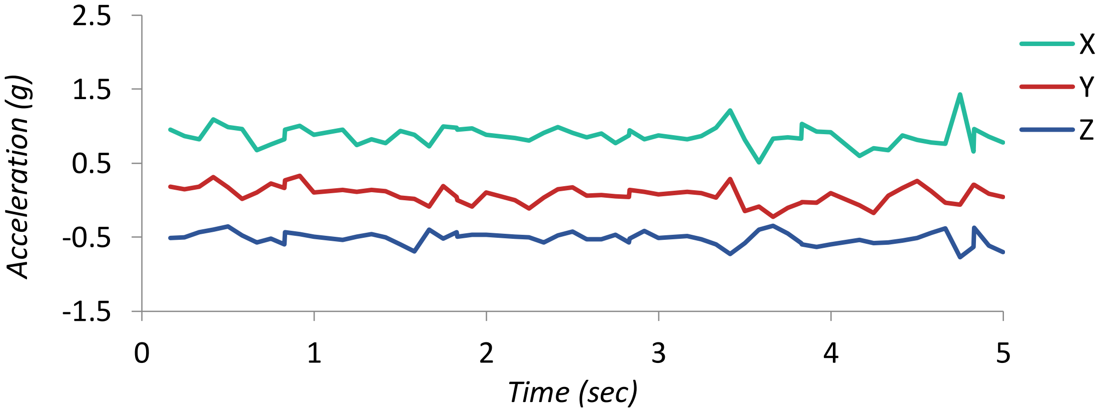


Figure 4-17. Five second acceleration signal from the ear attached accelerometer during grazing behaviour.

As the animal's head is lowered to the ground to feed, the sensor's freedom to 'hang' sees it maintain a similar orientation to that shown during standing.

Using an ear mounted accelerometer to detect ear drooping in cattle, Nagely (2012) highlighted the similar orientation of the tag between an erect and drooping ear due to the 'dangling' nature of the tag and the susceptibility of the tag to rotation in the ear due to the method of fixation.

Research on the ear movements during ruminant feeding is limited and as such results for the ear accelerometer have not been compared to other studies. Wolfger et al. (2015) and Bikker et al. (2014) measured ear movement of feeding steers and dairy cows respectively, using SensOor accelerometers however, raw acceleration signals were not reported nor explained.

Due to high degree of movement in a number of directions shown by the ear, there is no evidence of a cyclical pattern during both walking and grazing behaviour. This represents a need to develop analysis techniques which focus on capturing the variation in movement between behaviours rather than looking for pattern recognition of individual behaviours.

4.6 Conclusion

This chapter has provided an overview of how accelerometer signatures can be related to sheep movement and the influence deployment location can have on the signal obtained. In summary, leg deployed accelerometers are 'stable' and provide a clear indication of the walking component of grazing and, of course locomotion. Neck accelerometers are susceptible to both head and chest movements which tend to have acceleration signals associated with resting, grazing and walking. They are susceptible to swing during walking but this may provide added sensitivity of delineation for that particular state. Eartag accelerometers are the most prone to movement for all states. The freedom of the eartag to 'swing' about the pin which acts as a low resistance fulcrum makes it particularly sensitive. On one hand this bodes well for detection of the various states although on the other hand this may make delineation between activity states more difficult. This information will be the basis for interpreting behaviours in the ensuing chapters.

Chapter 5

Post-event classification of basic sheep movement from a tri-axial accelerometer

5.1 Introduction

As described in Section 2.2, observing and interpreting animal behaviour, especially normal compared to non-normal behaviour, can help inform the observer of the physical and welfare state of livestock.

5.2 Research objectives

The aim of this chapter is to determine the ability of a tri-axial accelerometer mounted on a collar, attached to the front leg and deployed on an ear tag to classify basic sheep movement, namely standing, grazing and walking. To achieve this the following objectives were investigated:

Part A:

1. Determine the most suitable classification algorithm (QDA or LDA) for discriminating between the movement behaviours from accelerometer data obtained from three deployment locations; collar, leg and ear;
2. Determine the three extractable metrics of most importance within each deployment location (collar, leg and ear) for discriminating between the three movement behaviours evaluated (grazing, standing and walking);
3. Calculate the performance statistics (accuracy, precision, sensitivity, specificity and total accuracy) of the classification model which yielded the highest prediction accuracy within each deployment.

Part B

4. Apply the selected metrics identified in Research Objective 2 above, to classify accelerometer signals derived from multiple individual sheep into mutually exclusive behaviours. This will evaluate the transferability of metrics across different animals and determine whether it is necessary to select a new subset of metrics when the classification algorithm developed for a single sheep is applied to a group of animals.

Part A – Proof of concept

Part A involved testing the ability of a QDA and LDA algorithm to classify accelerometer signals derived from a single animal into 1 of 3 mutually exclusive behaviours: grazing, standing or walking.

5.3 Materials and methods

The study was conducted at the University of New England, Armidale, NSW Australia. All animal experimental procedures were approved under the University of New England Animal Ethics Committee, AEC13-170.

5.3.1 Animals

Two Merino sheep (1 ewe and 1 wether), three years of age and weighing approximately 65 kg were contained in a 1 ha paddock. Both animals were accustomed to daily human interaction. The ewe was the only instrumented animal in this experiment and the wether was used as a companion animal.

5.3.2 Instrumentation

The GCDC X16-mini accelerometer sampling at 12 Hz was used in this study. Detailed specifications of the GCDC X 16-mini are provided in Section 3.2.1. Given the quiet nature of both sheep, yards were not required for restraint. The ewe was captured in a paddock corner and restrained whilst accelerometers were attached. The orientation of accelerometer axes and methods of accelerometer attachment are provided in Section 3.3.1. The collar accelerometer was deployed first followed by the ear and leg deployments. Both animals were released to carry out normal daily behaviours in the 1 ha paddock.

5.3.3 Observations & annotation

Upon release after instrumentation, animals were visually monitored for a total of 3 hours, to achieve a minimum of 10 minutes in each behavioural state; walking, grazing and standing within each deployment; collar, leg and ear. Behavioural states were classified as listed in Table 3-3 and observations recorded using the WhatISee application (Section 3.6.1). The animals showed little inclination to walk and so both animals were encouraged to move around the paddock for short periods at a time. The recorded walking behaviour was stimulated by an external force, namely humans entering the animal's flight zone following De Passille et al. (2010).

Upon completion of approximately 10 minutes monitoring of each behaviour, the ewe was restrained, accelerometer removed and attached to the next deployment location. To ensure there was no confusion between accelerometer signals from each deployment location, the accelerometer was restarted in order to create a new data file for each deployment.

Accelerometer data were downloaded using XLR8.jar software (Gulf Coast Data Concepts) and exported as a comma separated value (CSV) file. Each accelerometer sample was annotated with the corresponding behaviour (Table 3-3) from the observation data file downloaded through iTunes from the WhatISee application (Section 3.6.1). Data were split into 5 second epochs of a single behaviour with any behavioural bouts of less than 5 seconds being excluded from the analysis i.e. a continuous 30 second bout of walking activity is separated into 6 x 5 second epochs. Transitional activities (where animals change between behaviour states) were not included in this analysis. Transitional states will be investigated later in Chapter 6. The following metrics were calculated for each epoch in the three annotated accelerometer data files (collar, leg and ear); *Ax, Ay, Az, MV, SMA, AI, Entropy* and *Energy* using equations 1 to 9 in Section 3.7.1.

5.3.4 Behaviour classification

Four statistical algorithms were employed; principal component analysis (PCA), linear discriminant analysis (LDA) (Venables & Ripley, 2002), quadratic discriminant analysis (QDA) (Venables and Ripley, 2002) and random forest (RF) (Liaw & Wiener, 2002). A detailed description of these analysis procedures is provided in Section 3.7. Principal component analysis (PCA) was used to reduce the dimensionality of the dataset from 8 variables into 3 factors; PC1, PC2 and PC3. The scores of these three factors were used as discriminating metrics in the LDA and QDA classification algorithms.

A random forest variable importance (Diaz-Uriate, 2014) analysis was used to select a subset of three metrics. The three most important features based on the Gini Index (Section 3.7.2) were selected and used as discriminating metrics in the LDA and QDA models. Leave-one-out cross validation was performed on the highest performing model for each deployment as determined from the prediction accuracy values. Accuracy, sensitivity, specificity, precision and total accuracy were calculated for the cross validated confusion matrix results using equations 16 to 19 in Section 3.7.5.

5.3.5 Developing the behavioural classification model

A summary of the workflow procedures for building the classification model is shown in Figure 5-1 with references to earlier descriptions of methodology. These procedures were repeated on the datasets for each deployment mode: collar, leg and ear.

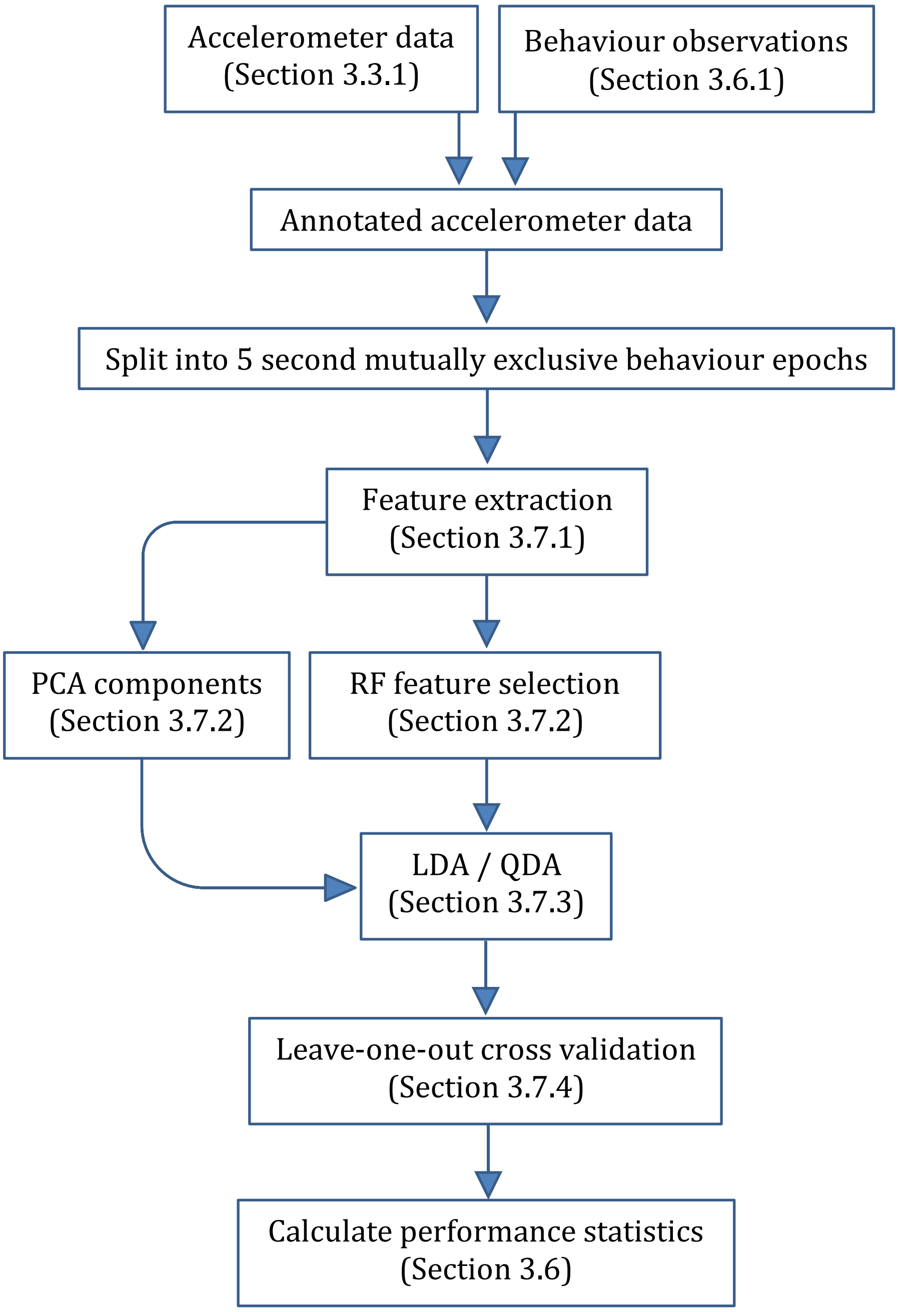


Figure 5-1. Workflow of the steps employed to classify sheep behaviour from a tri-axial accelerometer.

5.4 Results & discussion

5.4.1 Observations

The duration of the observational period for each individual deployment (collar, leg and ear) varied as this was dependant on the animal's behaviour. Whilst the aim was to obtain approximately 10 minutes of recorded data for each behaviour, observation times for the three deployments were approximately 45 minutes, 55 minutes and 35 minutes for the ear, leg and collar, respectively. Ideally an accelerometer would have been attached to each location simultaneously, eliminating the need to repeat three observational sessions, however technology constraints prevented this in the current experiment. No apparent adverse effects on animal behaviour were observed in the present study due to sensor attachment.

As shown in Table 5-1, there was an uneven distribution of behaviour epochs across the three deployments with amount of data for walking behaviour being substantially lower during the collar deployment. Due to the 'start stop' walking activity observed, the number of walking bursts from each deployment included in the analysis was reduced compared to the total amount of observed walking behaviour.

Table 5-1**.** Total number of mutually exclusive 5 second epochs for each behaviour obtained from the three deployment locations.

	Accelerometer attachment location		
	Leg	Ear	Collar
Standing	32	12	24
Walking	14	27	6
Grazing	23	13	19

5.4.2 Collar deployment

The RF variable selection processes yielded the following order of importance of metrics as determined from the mean decrease in Gini value; *MV, Energy, AI, SMA, Ax, Entropy, Ay* and *Az.* These data are depicted in Figure 5-2.

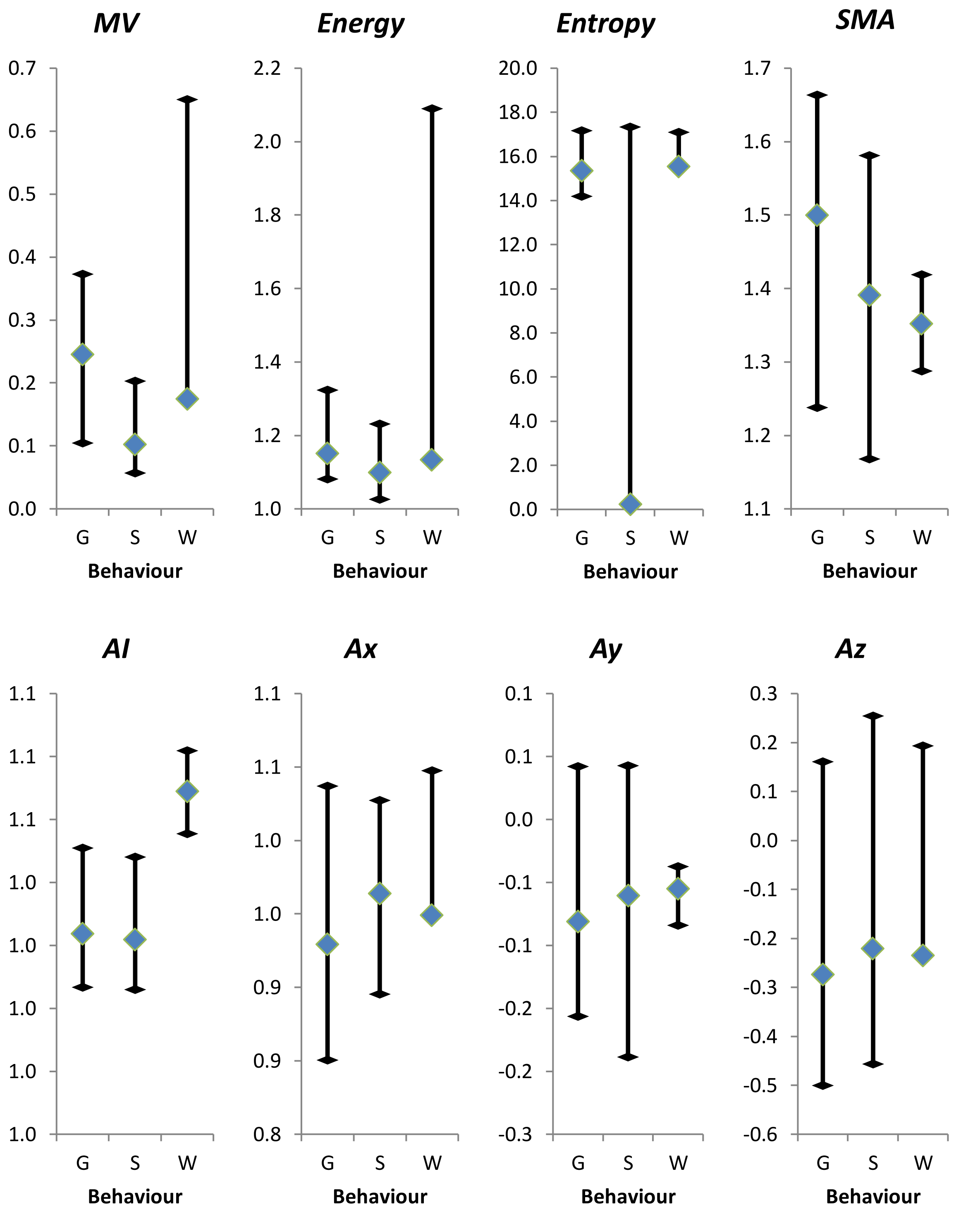


Figure 5-2. Visual representation of the average (blue diamond) and range (max/min) for each feature calculated from the collar deployment where G=grazing, S=standing inactive and W=walking. This visual representation of the collar data shows suitability of the *AI* metric for discrimination based on the least overlap of behaviour ranges.

Visual examination of the data in Figure 5-2 suggests walking behaviour can be differentiated from grazing and standing behaviour by metric *AI*. With *AI* calculating the intensity of movement by combining signals from all axes, the higher acceleration involved in walking (especially in the *Z axis* plane, see Figure 4-10) is recorded allowing delineation from the other two behaviours. All other metrics show overlap between the maximum and minimum values across activity states, hence exhibited little discrimination power (Preece et al., 2009). In earlier work, Marais et al. (2014) deployed collar mounted accelerometers on sheep and indicated the most important feature for classifying behaviour was the "MaxMin" metric which is the maximum and minimum value for each axis. The present findings show no clear difference between the maximum and minimum values for each behavioural state (data not shown). The inclusion of different metrics, in particular *MV* in the present study which measures the total variance within the epoch through accounting for differences between consecutive points, offers some reasoning for the discrepancy in feature importance between the two studies. Campbell et al. (2013) and Alvarenga et al. (2016) reported classification success using the *MV* metric which the RF analysis selected as being the most important feature. However, visual examination in this work shows no clear differentiation between the three activity states for the *MV* metric. In contrast to Marais et al. (2014) and Trotter et al. (2011), *Entropy* provided little discrimination value in the present work. As *Entropy* is a measure of disorder, behaviours which show little dynamic movement should yield lower entropy which is shown by the reduced mean value for standing compared to grazing and walking. Given the similarities in sensor orientation across the three behaviours when deployed on the collar, the mean values for individual behaviours are similar within the *Az*, *Ax* and *Ay* metrics.

From the calculated metrics, clear discrimination between all three behaviours is not provided by any individual metric, therefore a combination of metrics may be the only option for behaviour discrimination using the LDA and QDA classifiers. Earlier work using a QDA classifier to categorise basic sheep behaviour using neck mounted accelerometers indicated three metrics was a suitable number for classification (Marais et al., 2014). However, it is unclear which three features were used. This work achieved a classification accuracy of 88.7% using only the first three features from a "greedy feature selection", while a small increase in accuracy to 89.7% was achieved when all ten features were used. Therefore, by retaining only the first three features, only a 1% in classification accuracy is sacrificed.

The three principal components derived from the original 8 metrics cumulatively explained 94.6% of the variance in the data. Table 5-2 presents the behavioural prediction accuracies for the LDA and QDA algorithms (confusion matrix) using the three most important metrics identified from the RF analysis (*MV, AI* and *Energy*) along with the three derived principal components for their ability to discriminate behaviour states.

Table 5-2. LDA and QDA confusion matrices for the collar evaluation data set using three principal components and the metrics *MV*, *Energy* and *AI*. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)					
	Grazing	Standing	Walking	Grazing	Standing	Walking
Evaluation data set	LDA			QDA		
Principal components 1, 2, 3						
Grazing	**14**	2	0	**15**	3	0
Standing	5	**22**	0	4	**21**	0
Walking	0	0	**6**	0	0	**6**
Prediction accuracy	*74%*	*92%*	*100%*	*79%*	*88%*	*100%*
MV, Energy, AI						
Grazing	**15**	1	0	**15**	1	0
Standing	4	**23**	0	4	**23**	0
Walking	0	0	**6**	0	0	**6**
Prediction accuracy	*79%*	*96%*	*100%*	*79%*	*96%*	*100%*

Based on the prediction accuracies there was no difference between the LDA and QDA confusion matrix results using metrics *MV, Energy* and *AI* for discrimination. Using the principal components as discriminating metrics yielded a lower prediction accuracy for standing in both the LDA and QDA algorithms. It is worth noting that this difference is due to a misclassification of 2 out of 24 events in the LDA and 3 out of 24 events in the QDA. One should be careful in reading too much into this result. However, it is safe to say that PCA introduces complexity into the analysis and given there is no notable improvement in prediction accuracy with PC analysis the ensuing analysis focuses on the metric combinations only.

A leave-one-out cross validation was conducted on the QDA model using *MV, Energy* and *AI* metrics (Table 5-3) yielding no difference between the evaluation and validation analysis.

Table 5-3. Leave-one-out cross validation matrix for the QDA model using *MV, Energy* and *AI* metrics extracted from the collar accelerometer data. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events) Grazing	Standing	Walking
Cross validation		QDA	
MV, Energy, AI			
Grazing	**15**	1	0
Standing	4	**23**	0
Walking	0	0	**6**
Prediction accuracy	*79%*	*96%*	*100%*

Similar to previous work by Marais et al. (2014), grazing behaviour was misclassified as standing and vice versa. Ambiguity between lying and grazing behaviours was also reported by Marais et al. (2014) with grazing being misclassified as lying in 33.5% of cases. This most likely occurred due to the similar traits in sensor movement resting and grazing behaviours share, with the signals being dominated by static acceleration (refer to Figure 4-3 and Figure 4-16). This is a limitation associated with the collar mode of deployment. The short pasture may provide some reasoning for this as the ewe kept her head low to the ground when grazing, hence minimal dynamic acceleration was recorded. Martiskainen et al. (2009) found periods of activity and inactivity could be clearly distinguished from raw acceleration profiles, but certain behaviour patterns had nearly identical profiles, i.e. standing, lying, and ruminating. No grazing events were misclassified as walking in the current study and walking behaviour was well classified (100% prediction accuracy) reflecting the high discriminative ability of the *AI* metric to differentiate walking from other activities. In contrast to current findings, Umstätter et al. (2008) found it difficult to differentiate between walking and grazing as sheep often show these two behaviour types in combination. Caution should be taken when interpreting the present finding given the very low number of observations of this behaviour.

Results of the present study suggest that walking and standing behaviours were more readily distinguished than grazing behaviour from the collar accelerometer. In contrast González et al. (2015) found the population of foraging data points to be well separated from other activities in steers, with the mean X axis (measuring vertical acceleration) being highlighted as suitable to separate this behaviour from others. It was noted however the position of the head while foraging may change depending on the height and type of the vegetation being grazed. As available forage is depleted over time the threshold value separating head up and head down could change. The mean of the X axis acceleration in the present study showed substantial overlap between behaviours and was not identified as an important feature for discrimination.

The performance statistics of the leave-one-out QDA classification matrix for the collar deployment is presented in Table 5-4.

Table 5-4. Performance values of the QDA leave-one-out cross validation model using metrics *MV*, *AI* and *Energy*. Lower values are highlighted in bold.

	Grazing	Standing	Walking
MV, Energy, AI			
Sensitivity	**79%**	96%	100%
Specificity	97%	**84%**	100%
Accuracy	90%	90%	100%
Precision	94%	**85%**	100%
Total accuracy		*93%*	

Sensitivity. Sensitivity for grazing was low (79%) while standing and walking values were higher indicating the model is better at predicting the latter two behaviours. Similar results for grazing were reported by Martiskainen et al. (2009) in cattle (75%) using SVM. This differs to other results reported in cattle where foraging activity was predicted with high sensitivity (98.4%) (González et al., 2015). Similarly, Diosdado et al. (2015) reported 98.78% sensitivity for feeding prediction in dairy cows based on a decision tree algorithm. The lower sensitivity value in the present study arises due to 4 grazing events being misclassified as standing which is a reflection of the similarities in the acceleration signatures between these two behaviours. Please refer back to Figure 4-3 and Figure 4-16 which highlight the acceleration recordings these behaviours share, namely the dominant measurement of static acceleration due to the low level of dynamic movement of the collar during standing and grazing activity. In contrast to the work of Martiskainen et al. (2009) who predicted walking with only 79% sensitivity, walking behaviour in the present study was predicted with 100% sensitivity. As sensitivity values were generally high, this means few negative behavioural events were falsely classified as positive.

Specificity. Grazing and walking behaviours were predicted with high specificity while standing was slightly lower (84%). Similar specificity values for grazing were reported for steers using decision trees models (99.4%) based on collar derived acceleration signals (González et al., 2015). The high specificity value of walking indicates all true negatives (where walking was correctly classified as not being observed) of this behaviour category were correctly identified.

Accuracy. The QDA algorithm classified grazing, standing and walking activity with high accuracy. Similar accuracy results in earlier work on cattle have been reported (Martiskainen et al., 2009), with grazing (96%) and standing (87%) behaviours having slightly lower accuracies than walking (99%).

Precision. Grazing and walking behaviours were predicted with high precision (94% and 100% respectively). This shows that the majority of behavioural events predicted in these two categories are correct with only 1 standing event being incorrectly predicted as grazing. Standing behaviour had a slightly lower prediction value (85%) as 4 grazing events were incorrectly predicted as standing. Similarly, Martiskainen et al. (2009) and Diosdado et al. (2015) also reported low precision values for standing behaviour in cattle using collar deployed accelerometers.

Total accuracy. The collar deployment had a total behaviour classification accuracy of 93%. This total accuracy of the QDA model is similar to that reported by Marais et al. (2014) who yielded overall accuracies of 87% (LDA) and 89% (QDA) using 10 metrics with grazing being misclassified in both algorithms. Classifying behaviour as either “active” or “inactive”, Umstätter et al. (2008) reported classification accuracies of greater than 90% for LDA and decision tree classification methods.

These results confirm the assertions of Miedema (2009) in so far as there are a number of challenges associated with a collar deployment which may limit the behaviours that can be recorded. An issue identified by Trotter et al. (2011) and Hämäläinen et al. (2010) with the placement of sensors on the neck is the positional movement of the collar relative to the animal. Collars can move freely, and the position of the accelerometer is not necessarily always the same although the posture of an animal could be exactly the same. Trotter et al. (2011) further highlighted some sources of signal variation arise from differences in physical structure of individual animals and it would be unrealistic to expect sensors could be placed in exactly the same position and orientation for all animals.

5.4.3 Leg deployment

The RF variable selection processes yielded the following order of importance of metrics as determined from the mean decrease in Gini value; *MV, SMA, Energy, AI, Entropy, Ax, Az* and *Ay.* These data are depicted in Figure 5-3.

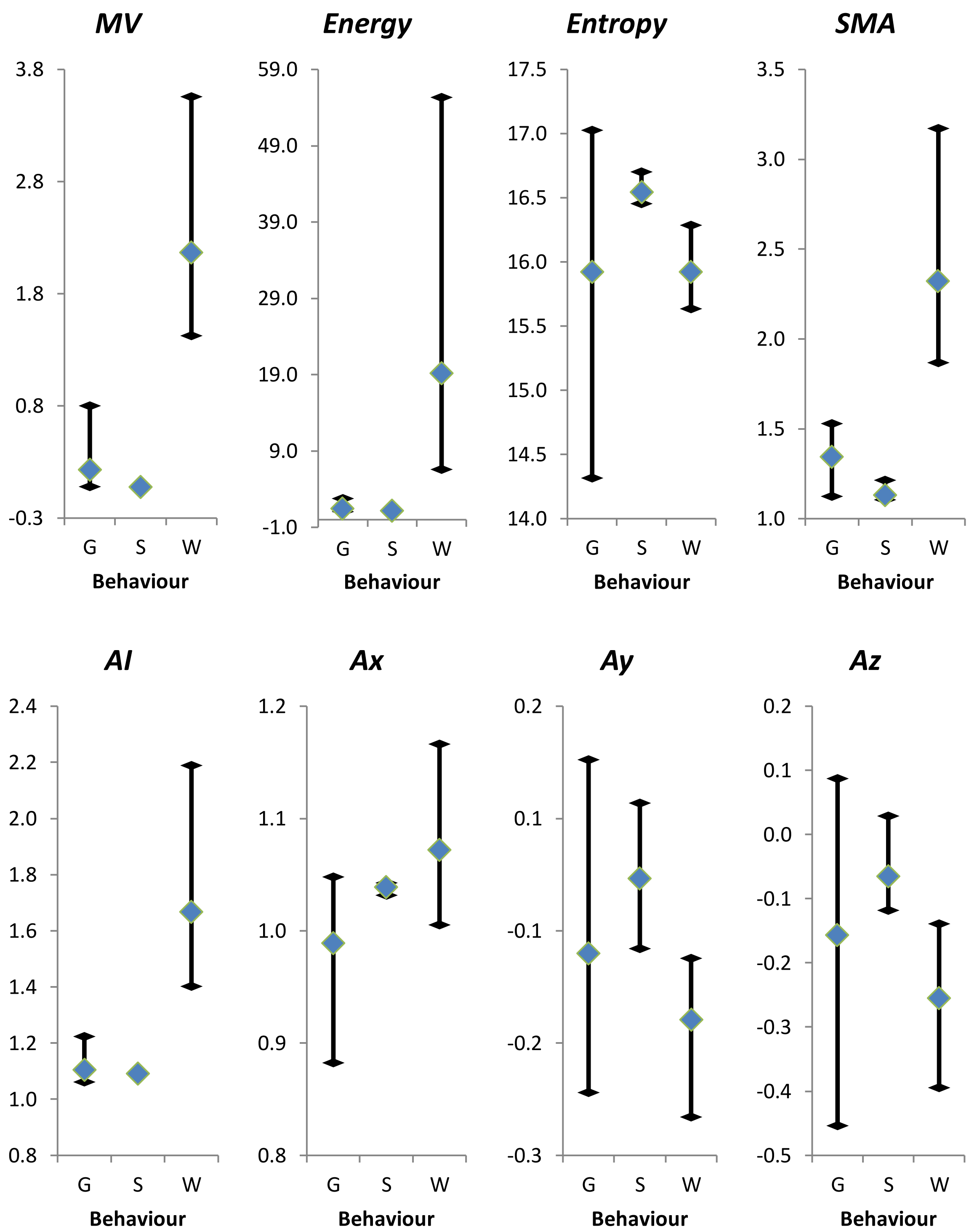


Figure 5-3. Visual representation of the average (blue diamond) and range (max/min) for each feature calculated from the leg deployment where G=grazing, S=standing inactive and W=walking. This visual representation of the leg data shows suitability of *MV, AI, Energy* and *SMA* for discrimination, agreeing with the RF analysis of variable importance.

Visual examination of the data in Figure 5-3 suggests walking can be differentiated from standing and grazing behaviour using the *MV, AI, Energy* and *SMA* metrics (as denoted by there being no crossover between the maximum and minimum values across activity states). As depicted in Figure 4-1, when the animal is stationary the *X* axis records static gravitational acceleration. This is further shown by the *Ax* metric which highlights the stability of the leg when the animal is standing as little signal vibration is recorded. Metrics *AI* and *SMA* also depict the stability of all axes when the animal is standing. As animals walk the signal vibration recorded through the leg accelerometer is much greater than when the leg is stationary. This higher amount of variance within the signal resulting from the sinusoidal walking pattern is reflected in the substantially higher *MV* value for walking compared to grazing and standing. Similar explanations can be applied to the *AI* and *SMA* metrics.

For the leg accelerometer, grazing behaviour is characterised by infrequent steps followed by periods of minimal leg movement. Therefore the metrics which measure the various components of movement intensity, namely *MV*, *AI* and *SMA* identify the higher range of sensor movement in grazing behaviour compared to standing. In other work, Robert et al. (2009) found *SMA* and signal vector magnitude (SVM), which is similar to *AI* in the present study, useful in differentiating standing and walking activity. Similarly, (Karantonis et al., 2006) used SVM (or *AI*) to differentiate between intensities of dynamic activities. Signal magnitude area *(SMA)* has previously been shown to discriminate periods of dynamic activity from periods of rest (Bouten et al., 1997; Karantonis et al., 2006; Mathie et al., 2004) while overlap between the maximum and minimum range between grazing and standing is evident across all 8 metrics, showing support for the use of multiple metrics in the LDA and QDA classification algorithms.

White et al. (2008) successfully used the *SMA* feature using only 2 axes to differentiate standing and lying behaviour in beef calves after castration. Lying behaviour was not observed in the present study. Had it been, the *X* axis (which measured up/down acceleration) may have had greater importance given the change in orientation of this axis between lying and upright postures. Previous work of Robert et al. (2009) indicated the primary discrimination between these two activities is related to the specific orientation of the leg in respect to the gravitational field, which in the present study, the *X* axis moves from a perpendicular to a parallel orientation when the animal adopts a lying position.

The three principal components derived from the original 8 metrics cumulatively explained 96.9% of the variance in the data. Table 5-5 presents the behavioural prediction accuracies for the LDA and QDA algorithms (confusion matrix) using the most important metrics identified from the RF analysis (*MV*, *SMA* and *Energy*) along with the three derived principal components for their ability to discriminate behaviour states.

Table 5-5. LDA and QDA confusion matrices for the leg evaluation data set using three principal components and the metrics *MV, SMA* and *Energy*. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)					
	Grazing	Standing	Walking	Grazing	Standing	Walking
Evaluation data set	LDA			QDA		
Principal components 1, 2, 3						
Grazing	**15**	0	0	**23**	0	0
Standing	8	**32**	0	0	**32**	0
Walking	0	0	**14**	0	0	**14**
Prediction accuracy	*65%*	*100%*	*100%*	*100%*	*100%*	*100%*
MV, SMA, Energy						
Grazing	**16**	0	0	**23**	0	0
Standing	7	**32**	0	0	**32**	0
Walking	0	0	**14**	0	0	**14**
Prediction accuracy	*70%*	*100%*	*100%*	*100%*	*100%*	*100%*

As with the earlier collar deployment results, PCA does not offer any improvement on the prediction accuracy over the 3 metrics (again misclassifying one extra event in the LDA) and likewise the ensuing analysis focuses on the 3 metrics.

Behaviour classification for standing and walking events were similar across the QDA and LDA algorithms with both models achieving 100% accuracy. This differs to Robert et al. (2009) who reported accuracies of 99% and 98% for lying and standing respectively while walking was only predicted with 68% accuracy. Luu et al. (2013) reported similar results using the Icetag3D™ sensor with lying and standing having a combined sensitivity and specificity value of 1.90 whilst moving behaviour was only 1.39.

Differences between animals of the same species and between ovine and bovine walking patterns may explain some of the variation in classification accuracy between studies. In reference to the Icetag3D™, Nielsen et al. (2010) suggested a better estimate of leg movement could be achieved if the accelerometer was placed in a fixed position on the leg as was the case in the present study. Grazing was misclassified as standing in both LDA models indicating the data are separated better with a quadratic boundary provided by the QDA model.

Table 5-6. Leave-one-out cross validation matrices for the QDA model using *MV*, *SMA* and *Energy* extracted from the leg accelerometer data. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events) Grazing	Standing	Walking
Cross validation		QDA	
MV, SMA, Energy			
Grazing	**22**	1	0
Standing	0	**31**	0
Walking	1	0	**14**
Prediction accuracy	*96%*	*97%*	*100%*

The leave-one-out cross validation prediction accuracies are similar to those seen from the evaluation data set. Slight reductions in grazing and standing prediction arise due to a single event being misclassified in both behaviour categories.

The performance values of the leave-one-out QDA classification model for the leg deployment is presented in Table 5-7.

Table 5-7. Performance of the leave-one-out cross validation matrix for the QDA model using *MV*, *SMA* and *Energy*. Lower values are highlighted in bold.

	Grazing	Standing	Walking
MV, SMA, Energy			
Sensitivity	96%	97%	100%
Specificity	98%	100%	98%
Accuracy	97%	99%	99%
Precision	96%	100%	**93%**
Total accuracy		*98%*	

Sensitivity. As sensitivity values were generally high, this means few negative behavioural events were falsely classified as positive. Similar standing sensitivity values have been reported previously using the Icetag™ device attached to the hind leg of cattle (Mattachini et al., 2011; Trénel et al., 2009). The high sensitivity value for walking behaviour differs to previous findings of Trénel et al. (2009) and Mattachini et al. (2011) who both reported very low sensitivity values for movement behaviour in cattle. Comparison between classification processes used in these studies is difficult due to the proprietary classification algorithms used with the Icetag™ system. Similar results were also reported by Robert et al. (2009) showing lower agreement between video and accelerometer recordings for walking classification (67.8%). The placement of the accelerometer may explain the differences in classification success between studies. Robert et al. (2009) placed accelerometers onto the animal's hind leg whereas the current study attached accelerometers to the sheep's forelimb. As shown in Figure 4-6, the forelimbs experience a greater range of movement compared to the hind limbs as quadrupeds walk, thereby creating higher levels of dynamic acceleration leading to a more distinct acceleration profile which can be differentiated from grazing and standing activity.

Specificity. The high specificity values for all grazing, standing and walking indicates the majority of true negatives for each behaviour category were correctly identified. Similar findings were reported by Mattachini et al. (2011) in dairy cows with specificity values of 0.95 and 0.98 for standing and moving behaviours respectively. The 98% value for grazing and walking results from just a single standing and grazing event being misclassified in each of these behaviour categories.

Accuracy. The QDA algorithm classified grazing, standing and walking behaviours with high accuracy. Compared to the collar deployment, grazing and standing behaviours were predicted with greater accuracy from the leg accelerometer resulting from the difference in leg motion between these two behaviours.

Precision. All three behaviours were predicted by the QDA model with high precision. This shows that the majority of behavioural events predicted within each category is correct with the exception of only 1 grazing event being predicted as walking and 1 standing event being predicted as grazing. The slightly lower walking precision value (93%) is a reflection of the small number of behavioural epochs in the category.

Total accuracy. The total accuracy of the QDA model across the three behaviours was high (98%) and is slightly better than the collar deployment (93%). Similar overall accuracies have been reported in earlier work on cattle with a 3 and 5 second epoch achieving 98.1% and 97.7% respectively (Robert et al., 2009).

5.4.4 Ear deployment

The RF variable selection processes yielded the following order of importance of metrics as determined from the mean decrease in Gini value; *MV, Energy, AI, Ay, Entropy, SMA, Az* and *Ax*. These data are depicted in Figure 5-4. Similar to the leg deployment, visual examination of the data in Figure 5-4 suggests walking behaviour can be differentiated from grazing and standing behaviour by *MV* and *AI.* Grazing and standing activity can be separated by the *Ay* metric. The side to side head movement when grazing creates left/right movement of the sensor (see Section 4.3) and this is recorded by the *Y* axis. Such movement is not evident in standing and walking as animals rise and fall when walking which is shown by the large range for walking in the *Ax* metric. Additionally the motion of walking makes the sensor swing forward and back (see Figure 4-11) shown here by the *Az* metric having a much larger max/min range for walking compared to the other behaviours. Similar to the leg deployment, the metrics which measure the various components of movement intensity, namely *MV*, *AI* and *SMA* identify the higher signal variance associated with walking activity. Due to the ear not providing a rigid fixation point, the ear deployed accelerometer is susceptible to record acceleration independent of the animal's body which can create similarities in the acceleration signal between different behaviours. Each of the calculated metrics has overlap between the maximum and minimum range between at least 2 of the recorded behaviours.

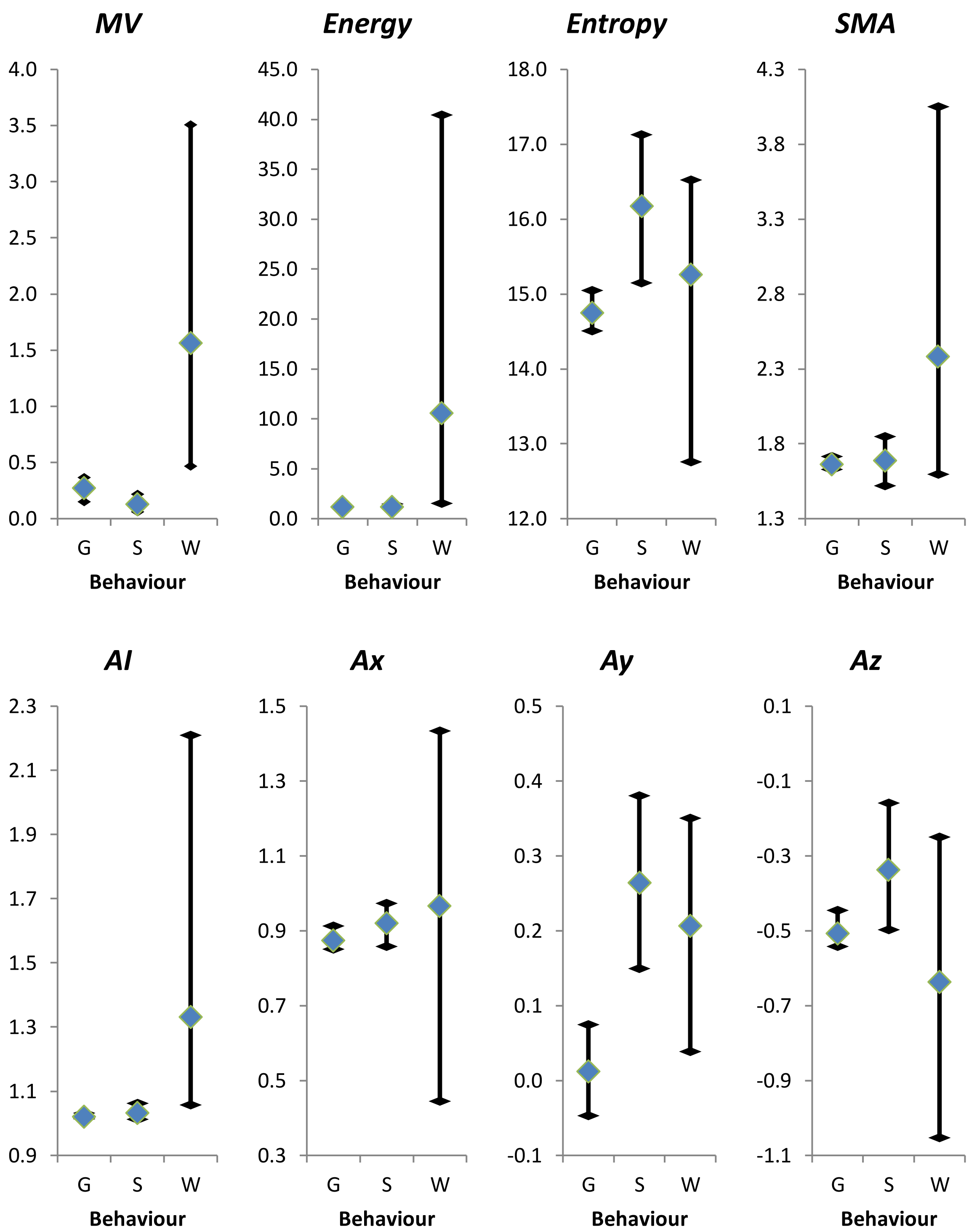


Figure 5-4. Visual representation of the average (blue diamond) and range (max/min) for each feature calculated from the ear deployment where G=grazing, S=standing inactive and W=walking. This visual representation of the ear data shows suitability of *MV, AI*, and *Ay* metrics for discrimination.

The three principal components derived from the original 8 metrics cumulatively explained 94.1% of the variance in the data. Table 5-8 presents the behavioural prediction accuracies for the LDA and QDA algorithms (confusion matrix) using the 3 most important metrics identified from the RF analysis (*MV, Energy* and *AI*) along with the three derived principal components for their ability to discriminate behaviour states.

Table 5-8. LDA and QDA confusion matrices for the ear evaluation data set using three principal components and the metrics *MV, Energy* and *AI*. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)					
	Grazing	Standing	Walking	Grazing	Standing	Walking
Evaluation data set	LDA			QDA		
Principal components 1, 2, 3						
Grazing	**13**	1	1	**13**	0	0
Standing	0	**11**	3	0	**12**	0
Walking	0	0	**23**	0	0	**27**
Prediction accuracy	*100%*	*92%*	*85%*	*100%*	*100%*	*100%*
MV, Energy, AI						
Grazing	**13**	0	2	**13**	0	0
Standing	0	**12**	0	0	**12**	0
Walking	0	0	**25**	0	0	**27**
Prediction accuracy	*100%*	*100%*	*93%*	*100%*	*100%*	*100%*

The QDA outperformed the LDA in both models tested with each QDA model yielding 100% prediction accuracies for each behaviour. This suggests the more flexible boundary provided by the QDA is better suited to discriminating behaviour states using the ear acceleration data. No difference was observed for the QDA models between using the three principal components or the combination of *MV, AI* and *Energy* metrics for discrimination. Similarly, using the CowManager SensOor devices, Bikker et al. (2014) reported strong agreement between sensor and visual observations for resting behaviour in cattle (*k value* of 0.86). However, in contrast to the present study, comparisons between visual and sensor recordings were much lower for eating (0.77) and active (0.47) behaviours. As a sheep's ear is much smaller than cattle, it has lower inertia. Hence, when a sheep walks the velocity created by the sensor movement is likely to be higher in comparison. This means the range of movement experienced by the sensor between grazing and walking is likely to be much more distinguished in sheep than in cattle.

The leave-one-out cross validation prediction accuracies (Table 5-9) are similar to those seen in the evaluation data set. All grazing and walking events are correctly predicted from the ear accelerometer while 2 standing events were misclassified as walking. Given the low number of grazing epochs used in this analysis, this result should be interpreted with caution.

Table 5-9. Leave-one-out cross validation matrix for the QDA model using *MV, Energy* and *AI* metrics extracted from the ear accelerometer. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events) Grazing	Standing	Walking
Cross validation	QDA		
MV, Energy, AI			
Grazing	**13**	0	0
Standing	0	**10**	0
Walking	0	2	**27**
Prediction accuracy	*100%*	*83%*	*100%*

Results of the present study suggest grazing and walking events were more readily distinguished than standing behaviour from the ear accelerometer. The misclassification of 2 standing events as walking is unusual given the difference in raw acceleration signatures between these two behaviours. This highlights the need for further analysis using larger data sets.

The intensity of sensor movement whilst grazing, standing and walking is well captured by the *MV* feature, with the forward/back swinging motion producing a large range in acceleration values, especially during walking. Previous work may have avoided the ear as an attachment location as unsecured sensors cause displacement and vibration which is liable to produce erroneous signal artefacts degrading sensing accuracy (Yang & Hsu, 2010). However, the present study demonstrates with adequate discriminating features this erroneous movement can actually play a valuable role in the classification process. As the different positions of the head occur during grazing, it is valid to argue for a head attachment (Blomberg, 2011) and this is supported by findings in the present study.

The performance values of the leave-one-out cross validation for the QDA classification model for the ear deployment are presented in Table 5-10.

Table 5-10. Performance values of the QDA leave-one-out cross validation model using metrics *MV*, *Energy* and *AI*. Standout values are highlighted in bold.

	Grazing	Standing	Walking
MV, Energy, AI			
Sensitivity	100%	**83%**	100%
Specificity	100%	100%	**92%**
Accuracy	100%	96%	96%
Precision	100%	100%	**93%**
Total accuracy		*97%*	

Sensitivity. The sensitivity for standing behaviour classified from the ear accelerometer is reduced (83%) compared to grazing and walking activity. This results from 2 standing events being classified as walking. This is similar to the findings of Wolfger et al. (2015) in cattle, where feeding behaviour had a sensitivity of 95%. The high sensitivity of grazing and walking behaviour indicate all of these behaviour events were correctly predicted. Given the clear distinction of walking behaviour depicted in Figure 5-4 this is to be expected.

Specificity. Grazing, standing and walking events were predicted with high specificity, indicating the true negatives of each behaviour category were often correctly identified. In cattle, Wolfger et al. (2015) reported a specificity value of 76% for feeding, differing to current findings. The walking specificity value is slightly lower than that previously reported for the leg and collar accelerometers, possibly highlighting the clearer distinction in walking acceleration signals produced by the collar and leg accelerometers.

Accuracy. The QDA algorithm classified grazing, standing and walking activity with high accuracy. Using a different approach Bikker et al. (2014) reported kappa values for agreement between sensor and visual observations of 0.85, 0.77, 0.86 and 0.47 for ruminating, feeding, resting and active indicting a poor ability to predict active behaviour, differing to our findings.

Precision. Grazing and standing behaviours were predicted with 100% precision from the ear accelerometer data. This differs to the findings of Wolfger et al. (2015) who reported a positive predictive value (the same as precision) of 54% for feeding behaviour in cattle using the ear attached SensOor device. The lower precision value for walking results from 2 standing events being misclassified as walking and indicates some variability in acceleration signals between walking events.

Total accuracy. The ear deployment had a total behaviour classification accuracy of 97%. This is similar to the total accuracy yielded by the leg accelerometer (98%) yet slightly higher than the collar (93%). Using a different approach, Bikker et al. (2014) reported a less accurate classification of behaviours with an overall kappa value of 0.78 for the comparison between sensor and visual observations in cattle where resting, active, eating and ruminating observations were recorded.

An issue with the ear deployment is the observed variation in ear physiology and movement between animals. The ear is subject to between animal signal variations. Only one animal was tested in the present study and as such this between animal variation was not captured. Future studies should endeavour to investigate the variation in ear movement between individual animals across a range of behaviours.

Similar to the collar deployment, it is anticipated that lying and standing acceleration signals would be similar. Therefore discrimination between these two behaviours based on ear acceleration signals would be difficult as Umstätter et al. (2008) observed sheep spend most of their time in sternal recumbence, compared to other recumbent postures. Future work may combine lying and standing recumbent postures as an “inactive” behaviour class. A similar approach could be adopted for “active” behaviours, combining grazing and walking activity.

Part B – Testing the transferability of metrics to classify behaviour across multiple animals

Part B firstly applies the classification metrics selected for each mode of deployment in Section 5.3, to classify the behavioural states of 5 different sheep. Secondly a new model is developed with RF analysis of feature importance selecting a subset of discriminating metrics based on the grouped accelerometer data which takes into account the between sheep variation in acceleration signals. Similar to Part A, both models were developed and validated using only mutually exclusive behaviour in 5-second epochs.

5.5 Materials and methods

This study was conducted at the University of New England, Armidale, NSW, Australia. All animal experimental procedures were approved under the University of New England Animal Ethics Committee, AEC14-066.

5.5.1 Animals

Ten Merino x Poll Dorset ewes, approximately 11 months of age with an average weight of 62 kg were used. The study was conducted in a small paddock (80 m x 6 m) in close proximity to sheep yards which were used for animal selection and instrumentation. Five animals were selected at random for instrumentation.

5.5.2 Instrumentation

The GCDC X16-mini configured to collect signals at 12 Hz was used in this study (detailed specifications provided in Section 3.2.1). Due to the limited number of accelerometers, only one animal was instrumented at a time. A single animal was randomly selected and restrained in a small catching pen. Accelerometers were attached to the animals front leg (or foreleg), collar and ear following the protocol provided Section 3.3.1, after which three animals (one instrumented and two non-instrumented) were released into the small paddock for visual observation. This process was repeated on five different sheep.

5.5.3 Observations

Upon release after instrumentation each animal was monitored for approximately 2.5 hours and video recorded (see Section 3.6.2). The sheep were not disturbed by the experimenters during the first hour and were noted to perform mainly grazing and some resting behaviour. After the first hour, animals were walked up and down the laneway for approximately 15 minutes. This period of walking was often followed by a 15-20 minute period of standing behaviour without walking, then a mixture of standing and grazing. Given the high ambient temperatures during the trial days, the maximum duration of "forced" walking was 15 min to prevent from becoming heat stressed. Observations were classified according to the description in Section 3.5. Upon completion of the observation period, animals were returned to the yards where the instrumented animal was subject the simulated lameness treatment. Lameness behaviour will be analysed in Chapter 8. Accelerometers and video observation files were downloaded at the conclusion of each observation event.

5.5.4 Developing the behaviour classification model

Accelerometer data were downloaded using XLR8.jar software and exported as a comma separated value (CSV) file. The workflow procedures for building the classification model are shown in Figure 5-5. Files containing the accelerometer signals were annotated using the steps outlined in Section 3.6.2. The annotated files were divided into 10 second epochs with unknown and transitional behaviour epochs being excluded from the analysis at this stage. The following features were extracted for each 10 second epoch; *Ax, Ay, Az, MV, SMA, AI, MI, Entropy*, *Energy Min-X, Min-Y, Min-Z, Max-X, Max-Y* and *Max-Z,* using equations 1 to 15. Data files within each deployment were combined following metric calculations creating a single file for each deployment. Total number of epochs in each deployment is provided in Table 5-11.

Based on the behaviour models developed in Chapter 5, a QDA is the only model used as it provided the highest behaviour discrimination accuracy for the three deployments. First, the three metrics identified as having the highest importance in Chapter 5 Part A were used as the discriminating metrics in the QDA classifier. These were: collar (*MV*, *Energy* and *AI*), leg (*MV*, *SMA* and *Energy*) and ear (*MV*, *Energy* and *AI*).

Second, RF analysis was performed on each of the three deployment datasets to identify the most important features for the new dataset. The top three metrics identified by the RF analysis for each deployment mode were then used as the discriminating metrics in the QDA classifier. The prediction accuracies of both confusion matrices were compared to identify the subset of features which yielded the best classification results.

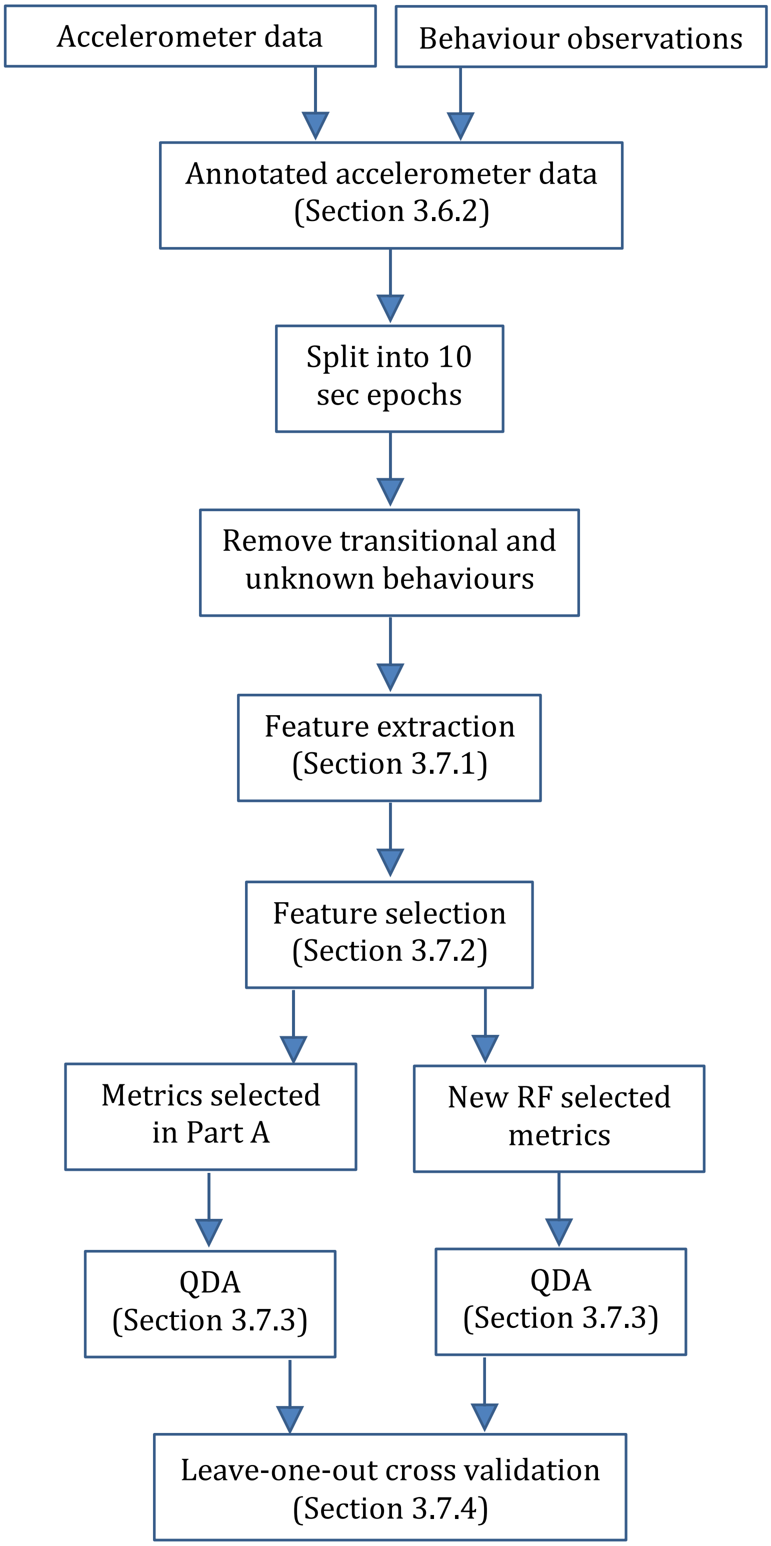


Figure 5-5. Schematic workflow of the steps used to develop the behaviour prediction models and compare the model performance using two subsets of metrics.

5.6 Results and discussion

5.6.1 Overview of observations and data

No apparent adverse effects on animal behaviour were observed in the present study due to sensor attachment. The collar mounted accelerometer failed to collect any data on one deployment. Observational periods were the same for all deployments as accelerometers were attached to the three locations simultaneously. Due to leg and collar accelerometer malfunction, fewer behaviour events were recorded for these two deployments (Table 5-11).

Table 5-11. Total number of 10 second, single behaviour epochs obtained. The number of animals for which behaviour data were collected within each deployment is shown in parentheses.

	Total # of 10 second epochs			
	Walking	Standing	Grazing	Lying
Leg	94 *(3)*	106 *(3)*	298 *(4)*	46 *(1)*
Collar	95 *(3)*	106 *(3)*	298 *(4)*	40 *(1)*
Ear	274 *(5)*	862 *(5)*	342 *(5)*	0*(0)*

Lying behaviour was only collected from one animal and no data were collected from the ear accelerometer for this activity. The collar and leg accelerometers failed to collect any walking and standing data during two deployments reducing the amount of data available for model training. This was not perceived to be a problem given there were still adequate data available to train the classifier. As data for lying behaviour were only collected from one animal, differences in acceleration signals between lying sheep was not observed or accounted for. Therefore this result should be interpreted with caution.

5.6.2 Collar deployment

The RF variable selection processes yielded the following order of importance of metrics as determined from the mean decrease in Gini value: *Az, Entropy, AI, Min-Z, Max-Z, MV, Ax, Energy, Min-X, Max-Z, Min-Y, Max-Y, Ay* and *SMA*. This differs to the RF selected metrics of importance in Chapter 5 where *MV*, *Energy* and *AI* were reported as the most important classification metrics.

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using the two feature subsets; Part A *(MV, Energy* and *AI)* and; Part B *(Az, AI* and *Entropy)* are presented in Table 5-12. Note that the dataset used in Part A did not include lying behaviour however those selected metrics have been applied to a datset here which contains lying events.

Table 5-12. QDA confusion matrices of the evaluation and leave-one-out cross validation analysis for the collar accelerometer data using Part A and Part B metric combinations. Correctly predicted events are shown in bold and misclassifications in red.

	Predicted behaviour (events)	Observed behaviour (events)			
		Grazing	Lying	Standing	Walking
PART A METRICS	**Model development**	QDA			
	MV, Energy, AI				
	Grazing	**281**	1	11	21
	Lying	1	**38**	22	0
	Standing	9	1	**70**	2
	Walking	7	0	3	**72**
	Prediction accuracy	*94%*	*95%*	*66%*	*76%*
	Cross validation	QDA			
	MV, Energy, AI				
	Grazing	**281**	1	11	22
	Lying	1	**37**	22	0
	Standing	9	2	**70**	2
	Walking	7	0	3	**71**
	Prediction accuracy	*94%*	*93%*	*66%*	*75%*
PART B METRICS	**Model development**	QDA			
	Az, Entropy, AI				
	Grazing	**287**	0	23	0
	Lying	2	**37**	22	0
	Standing	8	1	**59**	7
	Walking	1	2	2	**88**
	Prediction accuracy	*96%*	*93%*	*56%*	*93%*
	Cross validation	QDA			
	Az, Entropy, AI				
	Grazing	**286**	0	25	0
	Lying	2	**37**	22	0
	Standing	9	1	**57**	7
	Walking	1	2	2	**88**
	Prediction accuracy	*96%*	*93%*	*54%*	*93%*

Comaprison between the A and B metric combinations reveal grazing and lying were well predicted in both. Standing behaviour was poorly predicted in both A and B yet slightly lower classification success was obtained using B. Walking behaviour was well predicted with combination B (93%) yet only moderate prediction accuracy was obtained using combination A (75%).

In the leave-one-out cross validation matrix for metric combination B, results show that standing behaviour was misclassified with lying and grazing. In agreement with our findings, using collar mounted accelerometers to classify cattle behaviour Martiskainen et al. (2009) and González et al. (2015) found misclassification most often occurred with similar behaviours such as standing and lying. As mentioned previously in chapter 4, the position of the sensor during standing and lying is similar between these two behaviours making discrimination difficult. Differing to the present findings in section 5A, results in Section 5B suggest that standing behaviours were more readily distinguished than grazing activity from the collar accelerometer.

In addition to increasing the number of animals used to create the classification model, a possible explanation for the difference in classification results between those presented in Section 5A and here is sensor movement across different animals. One of the major challenges with behaviour modelling using data acquired from collar mounted accelerometers is the physical movement of the collar on the animal causing sensor reorientation (Dutta et al., 2015). It has been stated that even a slight tilt of the accelerometer can influence the classification results (Foerster, Smeja, & Fahrenberg, 1999). In cattle, Martiskainen et al. (2009) reported the neck collar on cows could turn from side to side to some extent, even though the attachment of the accelerometer case had been designed to prevent this as much as possible. Trotter et al. (2011) provides a detailed description of how the change in positioning or orientation of the accelerometer unit impacts on the recorded signal. Although it is not being proposed that the variation in sensor movement accounts for all the misclassification, it can be a contributing factor which must be acknowledged.

The three diagrams in Figure 5-6 demonstrate the clustering pattern of the four behavioural states which in turn affects the ability of the QDA model to discriminate between behaviours. Examining the three diagrams, it is evident there is no clear grouping for the standing and lying behaviours, with behavioural events for these two activities being intermingled. A clearer grouping of grazing events is evident hence it has been well predicted by the QDA model. Although walking events are widely dispersed, segregation from other activities, particularly shown along the *AI* axis, results in the high prediction accuracy of this behaviour.

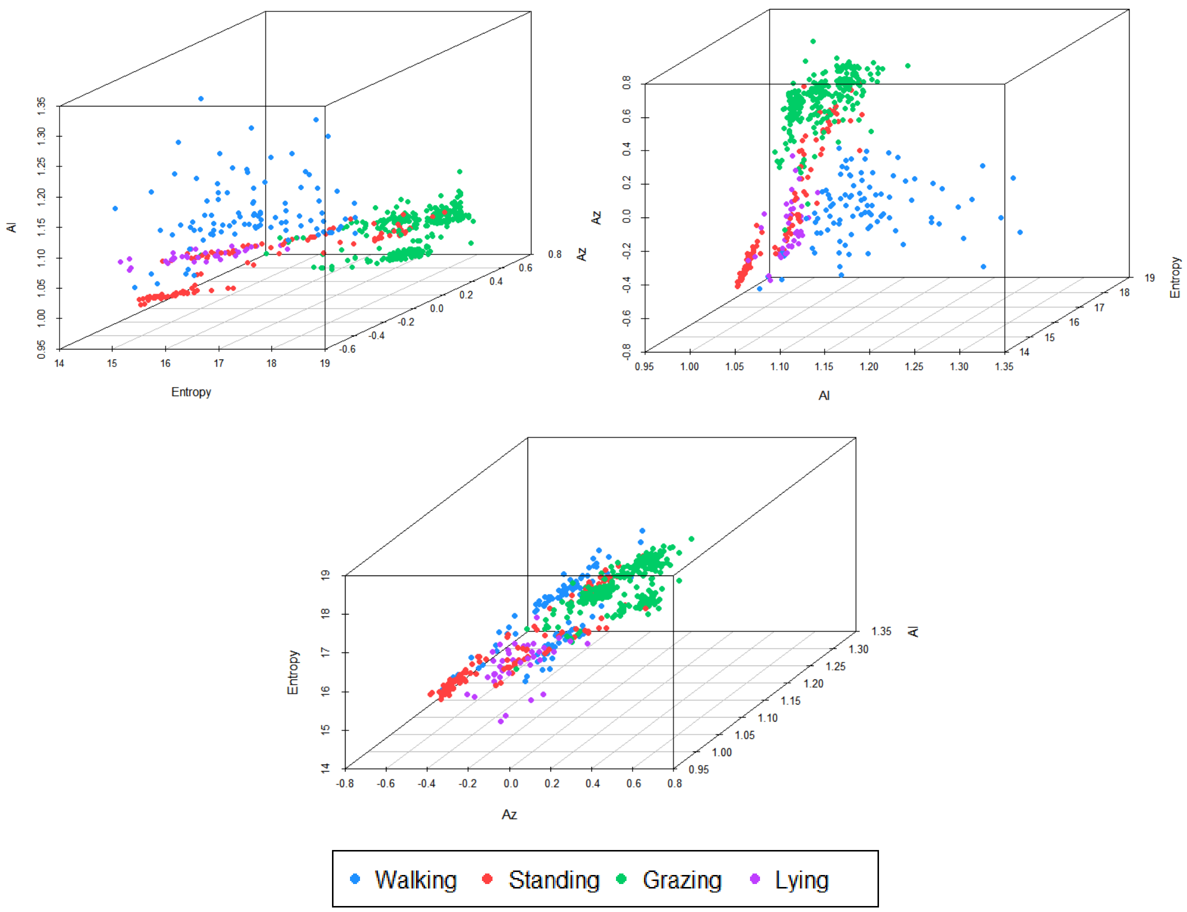


Figure 5-6. 3D scatterplot of mutually exclusive behavioural events extracted from the collar accelerometer using *Az, AI* and *Entropy* metrics.

5.6.3 Leg deployment

The RF variable selection processes yielded the following order of importance of metrics as determined from the mean decrease in Gini value: *Ax, SMA, MV, Max-Y, Max-X, Min-X, Energy, Max-Z, Ay, Entropy, Az, Min-Z* and *Min-Y*. This is similar to the RF selected metrics of importance in Chapter 5 where *MV*, *SMA* and *Energy* were reported as the most important classification metrics. As speculated in Section 5.4.3 the inclusion of lying behaviour makes *Ax* an important metric for discrimination between lying and upright behaviours due to the clear change in orientation of the *X* axis.

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using the two feature subsets; Part A *(MV, Energy* and *SMA)* and; Part B *(Ax, SMA* and *MV)* are presented in Table 5-13. Note that the dataset used in Part A did not include lying behaviour however those selected metrics have been applied to a datset here which contains lying events.

Table 5-13. QDA confusion matrices of the evaluation and leave-one-out cross validation analysis for the leg accelerometer data using Part A and Part B metrics. Correctly predicted events are shown in bold and misclassifications in red.

	Predicted behaviour (events)	Observed behaviour (events) Grazing	Lying	Standing	Walking
PART A METRICS	**Model development**	QDA			
	MV, Energy, SMA				
	Grazing	**204**	4	42	0
	Lying	66	**40**	4	0
	Standing	24	2	**58**	0
	Walking	4	0	2	**94**
	Prediction accuracy	*68%*	*87%*	*55%*	*100%*
	Cross validation	QDA			
	MV, Energy, SMA				
	Grazing	**202**	5	42	0
	Lying	68	**39**	4	0
	Standing	24	2	**58**	0
	Walking	4	0	2	**94**
	Prediction accuracy	*68%*	*85%*	*55%*	*100%*
PART B METRICS	**Model development**	QDA			
	Ax, SMA, MV				
	Grazing	**270**	0	45	0
	Lying	0	**46**	0	0
	Standing	26	0	**61**	0
	Walking	2	0	0	**94**
	Prediction accuracy	*91%*	*100%*	*58%*	*100%*
	Cross validation	QDA			
	Ax, SMA, MV				
	Grazing	**270**	0	47	0
	Lying	0	**46**	0	0
	Standing	26	0	**59**	0
	Walking	2	0	0	**94**
	Prediction accuracy	*91%*	*100%*	*56%*	*100%*

Comaprison between the A and B metric combinations reveal walking behaviour is well predicted by both. Grazing behaviour is better predicted using Part B metrics (91% vs. 68%) while standing behaviour was poorly predicted using both combinations due to missclassifctaion with grazing. Part B derived metrics were superior in predicting lying posture which is to be expected as the data used to derive feature importance in Part A did not include lying events. Therefore Part B derived metrics, *Ax*, *SMA* and *MV* are superior at classifying basic behavioural states across multiple animals.

The results obtained in Part A demonstrated grazing, standing and walking activities can be predicted with high accuracy in a single ewe using the QDA algorithm with *MV*, *SMA* and *Energy* metrics. In contrast, Part B results show standing behaviour was poorly predicted (56%) due to a high misclassification rate with grazing. Differing results were reported by Robert et al. (2009) who attached an accelerometer to the hind leg of cattle and reported a 98% prediction for standing behaviour. However, grazing activity was not measured in their trial. The misclassification between these two behaviours can be attributed to similar leg movement traits within standing and grazing activity yielding similar acceleration signatures with the additional animals adding further complexity. As there was ample feed available, sheep could walk (or ambulate) slowly whilst grazing, therefore within a 10 second epoch there was few total leg movements, resulting in similar metric values for grazing and standing behaviours. This is depicted in Figure 5-7 with grazing and standing events being tightly clustered. Furthermore, as alluded to by Blomberg (2011), animals standing still but lifting the instrumented leg can lead to an incorrectly registered behaviour, in this case most likely grazing.

The successful classification of lying is a function of the change in the *Ax* value between upright and lying behaviours. Due to the limited amount of data for lying, this should be interpreted with caution. Similar to the results in Section 5A yet differing to previous studies in cattle (Luu et al., 2013; Robert et al., 2009), walking behaviour was well discriminated from all other behaviours.

The diagrams in Figure 5-7 below highlight the groupings for each behaviour showing the clear separation of walking and lying events. Grazing and standing are misclassified in the QDA model and reasoning for this is reflected in Figure 5-7 as there is no clear differentiation between these two behaviours.

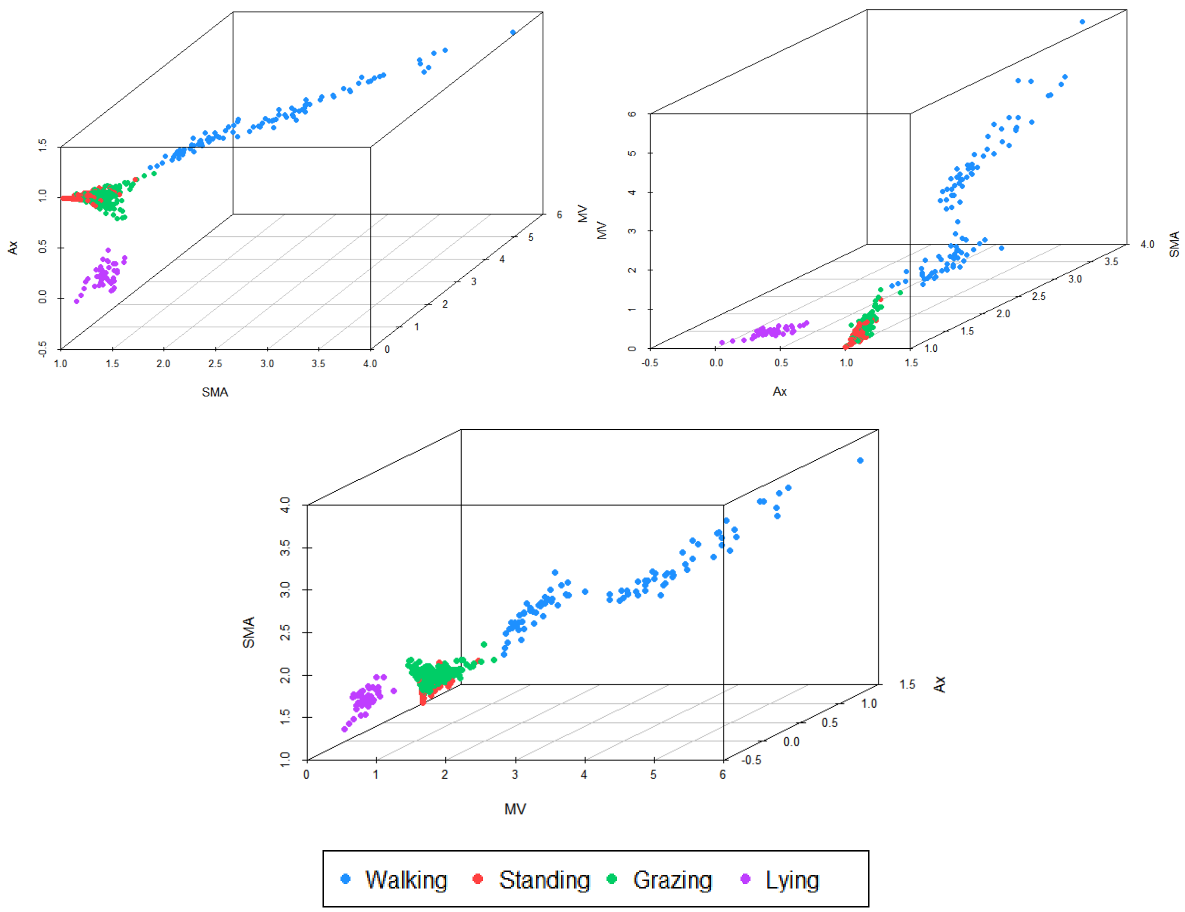


Figure 5-7. 3D scatterplot of mutually exclusive behavioural events extracted from the front leg accelerometer using *AI, SMA* and *MV* metric values.

5.6.4 Ear deployment

The RF variable selection processes yielded the following order of importance of metrics as determined from the mean decrease in Gini value: *MV, AI, Ay, SMA, Az, Energy, Min-Z, Min-X, Max-Y, Min-Y, Max-Z, Entropy, Ax* and *Max-X*. This is similar to the RF selected metrics of importance in Part A where *MV*, *AI* and *Energy* were reported as the most important classification metrics (note *Ay* was the 4th highest ranked metric). In Part A, *Ay* was shown to differentiate grazing and standing behaviour. Because of the sensor design and its movement within the ear (see Chapter 4) the left/right swing motion recorded by the *Y* axis was highly relevant in discriminating between activity intensity, particularly at identifying grazing behaviour.

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using the two feature subsets; Part A *(MV, Energy* and *AI)* and; Part B *(Ay, AI* and *MV)* are presented in Table 5-14.

Table 5-14. QDA confusion matrices of the evaluation and leave-one-out cross validation analysis for the ear accelerometer data using Part A and Part B metrics. Correctly predicted events are shown in bold and misclassifications in red.

	Predicted behaviour (events)	Observed behaviour (events) Grazing	Standing	Walking
PART A METRICS	**Model development**		QDA	
	MV, Energy, AI			
	Grazing	**305**	36	22
	Standing	32	**822**	1
	Walking	5	3	**250**
	Prediction accuracy	*89%*	*95%*	*92%*
	Cross validation		QDA	
	MV, Energy, AI			
	Grazing	**304**	36	22
	Standing	32	**822**	1
	Walking	6	3	**249**
	Prediction accuracy	*89%*	*95%*	*92%*
PART B METRICS	**Model development**		QDA	
	MV, AI, Ay			
	Grazing	**322**	26	1
	Standing	15	**830**	1
	Walking	5	5	**271**
	Prediction accuracy	*94%*	*96%*	*99%*
	Cross validation		QDA	
	MV, AI, Ay			
	Grazing	**322**	26	1
	Standing	15	**830**	1
	Walking	5	5	**271**
	Prediction accuracy	*94%*	*96%*	*99%*

Comaprison between the A and B metric combiantions reveal all behaviours are well classified using both metric combiantions however slight improvements are achieved when using Part B derived metrics. Metrics derived in Part B, *MV*, *AI* and *Ay*, were superior in predicting walking (99% vs. 92%), grazing (94% vs. 89%) and standing activity (96% vs. 95%). Some grazing events were misclassified as standing and vice versa, however the misclassification rate was not substantial. In contrast to our work, Bikker et al. (2014) reported a poor ability to predict active behaviour (kappa value of 0.47). Due to the SensOor system using proprietary algorithms comparison between classification methods is challenging. Potentially, the difference between walking classification in the present work and earlier studies of Bikker et al. (2014) is the effect of the sensor weight in the animal's ear (see section 5.4.4).

The strong clustering of grazing and standing events is highlighted in Figure 5-8. There is a clear clustering pattern of grazing and standing events along the *Ay* axis. Walking events are more widely dispersed due to the dynamic nature of sensor movement as the animal walks, creating a greater distribution of points.

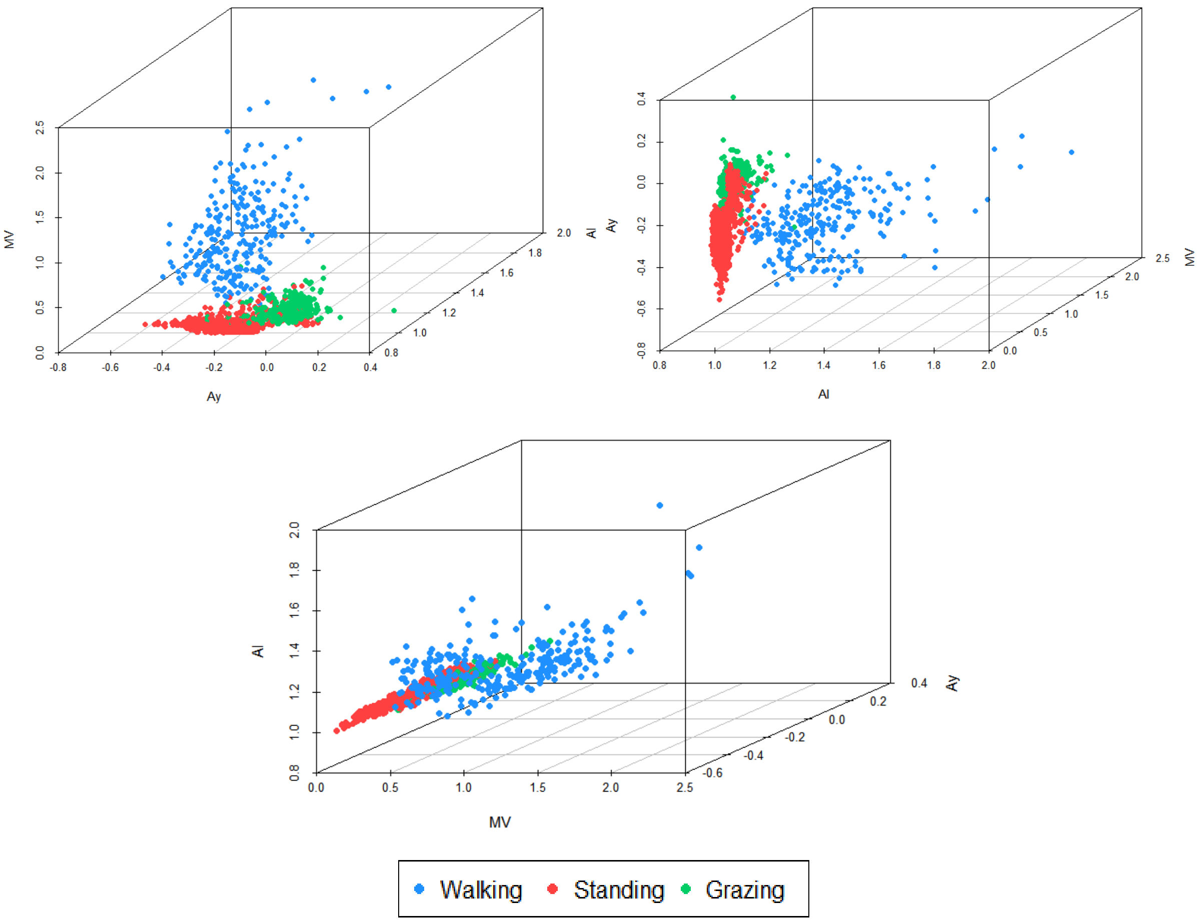


Figure 5-8. 3D scatterplot of mutually exclusive behavioural events extracted from the ear accelerometer using *AI, Ay* and *MV* metric values.

5.7 Conclusion

In Part A, *MV* and *Energy* metrics were rated in the top three in all deployments with *MV*, *Energy* and *AI* being featured in the top three for both the collar and leg deployments. In conclusion we found the leg deployment yielded the highest total accuracy followed by the ear and collar, however the differences between the three were negligible as all modes of deployment achieved a successful level of behaviour classification. We note our data set was very small and hence the results from Part A are inconclusive as to which attachment location provides the highest level of prediction. Therefore all three locations were evaluated further in Part B. Although excellent classification accuracy was achieved from the leg attached accelerometer, the impracticality for the sheep industry remains a downfall of this deployment mode. Deployment on the leg is labour intensive and leg sensors may also interfere with husbandry practices such as shearing. While the accelerometer was in a fixed position for the duration of the present study, it has previously been suggested that if the devices are attached so tight to the limb that it cannot move up and down or around the leg, injuries will develop within a few days. Development of algorithms capable of dealing with the variation in signal resulting from a loose attachment should resolve any misclassifications caused, however the process of deployment remains an issue. Furthermore animals may walk at such a low speed that the sensor is not registering any activity for some time. If only one leg is equipped with a sensor, the risk of missing registration of walking behaviour may become an issue. There is also a risk that animals standing still yet lifting their legs may be misclassified as moving.

Part B used a larger dataset endeavouring to capture any between-animal variation which may influence the discriminative ability of the classifier. The leg and collar deployments both yielded poor standing prediction accuracies due to misclassification with grazing and lying events respectively. The ear deployment yielded high classification success for standing, grazing and walking behaviours with the QDA model using *MV*, *AI* and *Ay* metrics proving to be superior. These results are encouraging as they provide proof of concept that behaviour can be predicted from an eartag deployed accelerometer, aligning with the conventional industry practice of using eartags for sheep identification.

Chapter 6

The application of a moving window classification algorithm to predict sheep behaviour from a tri-axial accelerometer

6.1 Introduction

Results found in Chapter 5 of this thesis demonstrate a highly accurate off-line, post event behaviour recognition algorithm can be developed. In a commercial deployment scenario, sensor systems must be able to monitor animal behaviour in real time. This will enable more accurate and timely management decisions allowing animal performance and welfare to be optimised (González et al., 2015). The advantages and possible uses of a real-time behaviour classification system for free ranging livestock have been widely acknowledged, however few studies have developed and implemented a practical system. Research has begun investigating ways of taking accelerometer technology and applying it to commercial operations, however this has predominantly been centred on the dairy and beef feedlot sectors (see for example, the IceTag3D™ and CowManager SensOor systems) with limited research conducted in the sheep industry to date.

The task of developing a real-time classification model is inherently more difficult than developing an off-line classifier. There are several constraints and challenges which must be acknowledged including (i) correlated time-dependent measurements, (ii) transitional states, and (iii) a rapid signal processing requirement with minimal computational energy and storage overhead (Trotter et al., 2011). As such, many studies have focused on the classification of data where the start and end times of each behaviour are known (as in Chapter 5). Epochs which contain more than one behaviour are classed as transitional events and often excluded from the analysis as these transitional periods have the potential to be misclassified (Robert et al., 2009). In a real time classification system, segregation of these transitional epochs is not possible as there is no knowledge of the animals' current or future behaviour since the start and end times of behaviour states are not known to partition the time series acceleration signal (Smith et al., 2016). Therefore, analysis methods which can handle the transition between behaviour classes must be developed. However, few studies have attempted this level of classification. The use of epochs which group data over a predetermined time period is a common data analysis step (Alvarenga et al., 2016; Robert et al., 2009; Smith et al., 2016; Trotter et al., 2012; Yoshitoshi et al., 2013). Previously, many studies have used a training and testing dataset. The training dataset usually contains mutually exclusive behaviour epochs (similar to Chapter 5). However it is commonly unspecified whether the testing dataset has transitional behaviour epochs excluded (Alvarenga et al., 2016; Robert et al., 2009) or whether transitional behaviours are included.

A simple approach using a moving window technique with overlap between epochs has been proposed to alleviate some of the classification issues associated with the transition between behaviours and this has previously been used in behaviour classification studies using accelerometer data (Alvarenga et al., 2016; Campbell et al., 2013; Marais et al., 2014; McClune et al., 2014) although these are often applied to clean data sets of mutually exclusive behaviours. Nielsen et al. (2010) used a moving average of 3 or 5 seconds of the motion index or step count values obtained from the IceTag3D™ device. Simply, if the moving average at a particular second was greater than the predetermined value it was classified as walking, otherwise it was classed as standing. Using a different approach, González et al. (2015) fitted mixed models to data obtained from a collar mounted accelerometer on cattle to calculate threshold values corresponding to periods where behaviours transitioned between different activity states. These threshold values were then applied to a decision tree to classify 10 second aggregated data into 5 mutually exclusive behaviours achieving an overall accuracy of 90.5%.

If accelerometers are to be utilised in commercial operations for remote health and welfare monitoring, there is a need to develop a system capable of classifying behaviour in sync with data acquisition. The potential accuracy of these devices to determine actual behaviours in near real-time influences the utility of this technique in future research and animal production systems. If behavioural states cannot be estimated from continuous accelerometer data then there is arguably little point pursuing this technology any further.

6.2 Research objectives

In this Chapter, the performance of a moving window algorithm to classify continuous ear, leg and collar accelerometer signals into four mutually exclusive sheep behaviour categories was evaluated. To achieve this, the following objective was investigated:

1. Evaluate the use of three moving window lengths (3, 5 and 10 seconds) to categorise approximately 2 hours of continuous accelerometer signals from three deployment locations (collar, leg and ear).

6.3 Materials & methods

The data for this chapter were acquired in conjunction with Chapter 5 Part B.

6.3.1 Animals

As per Section 5.5.1.

6.3.2 Instrumentation

As per Section 5.5.2.

6.3.3 Observations

As per Section 5.5.3

6.3.4 Behaviour prediction model

From Section 5.6 the following QDA model metric combinations were identified as yielding the highest prediction accuracies in their respective modes of deployment:

- Collar – *Az* + *Entropy* + *AI*
- Leg – *Ax* + *SMA* + *MV*
- Ear – *MV* + *AI* + *Ay*

6.3.5 Moving window classification

Following on from the development of a mutually exclusive behaviour prediction algorithm, the next step was to test the performance of the behaviour prediction algorithm (listed in Section 6.3.4 above) across a continuous accelerometer data stream including transitional behaviours and behavioural events shorter than 10 seconds. The data sets for each sheep within each deployment were fully annotated and contained a continuous stream of data across the entire observation period. The three metrics identified by RF analysis for variable importance were calculated on the collar, leg and ear data sets for each individual sheep. Using the behaviour prediction model developed earlier, activity for each sheep was classified using a 3, 5 and 10 second moving window epoch. The three moving window lengths selected (3, 5 and 10 seconds) were based on previously used epoch sizes applied to group accelerometer data (Alvarenga et al., 2016; Robert et al., 2009). The window was stepped by 1 row and used an overlap of post behaviour signals to classify behaviour at a specific point i.e. for the three second moving window, signal rows 1-36 are used to classify row 1. Similarly to classify behaviour in row 2, signal values from rows 2-37 are used and so on. Note, 1 row refers to a single row of raw accelerometer data which was recorded at 12 Hz. This moving window approach has a much larger degree of overlap than other studies and the advantage of this approach is that each row of the accelerometer signal receives a behaviour classification.

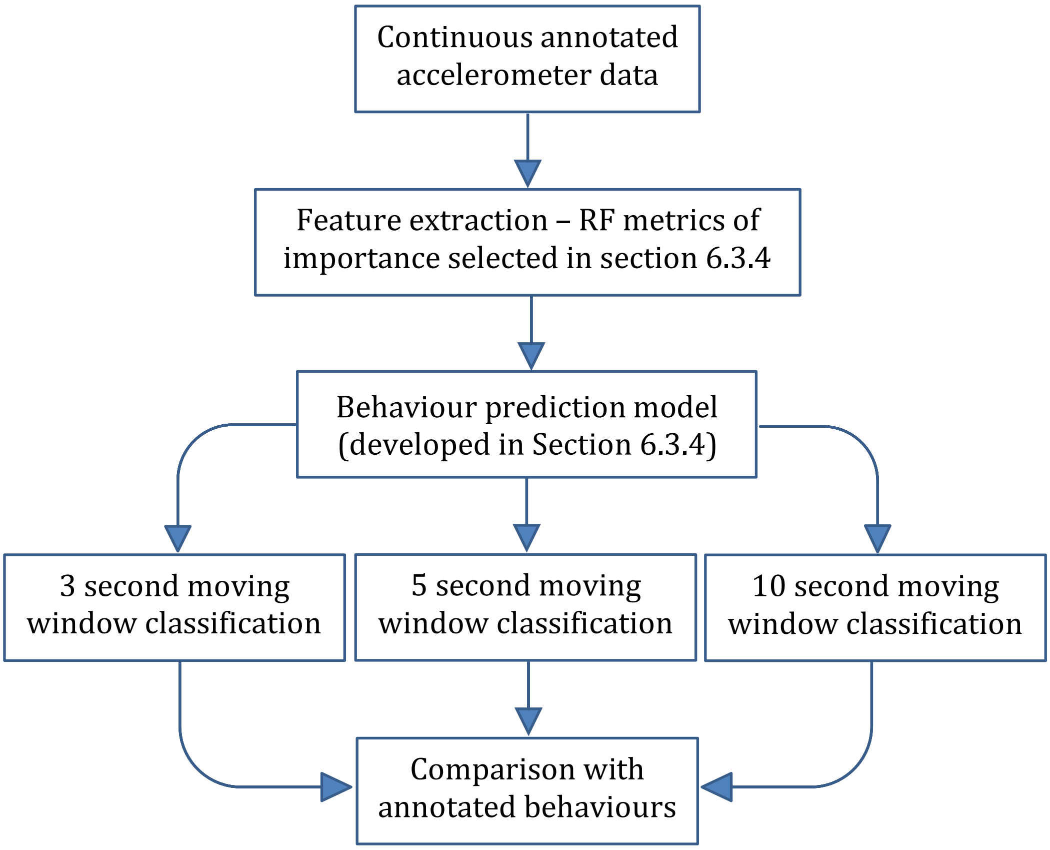


Figure 6-1. Schematic workflow of testing the behaviour prediction model across a continuous accelerometer stream using a 3, 5 and 10 second moving window.

To quantify the performance of the moving window classification algorithm, the following equation was used to calculate the total correct classification rate:

$$\theta = \frac{\#\ of\ model\ predicted\ behaviour\ events}{Total\ \#\ of\ annotated\ behaviour\ events}$$

For instance, the successful classification θ denotes the percentage of points correctly predicted (in agreement with the video observations). These classification rates were calculated separately for each sheep within each deployment.

Determining the most suitable moving window length

To test whether there was a difference between the three moving window lengths evaluated for predicting each of the four behaviours; grazing, standing, walking and lying, a linear mixed model (lmm) was developed. There was a total of 4 behaviours, 3 window lengths and up to 5 sheep included in the model (depending on the deployment mode). Number of sheep and behavioural observations differ between deployments (please refer to Table 6-1 for more detail). Deployment and Window size were fixed effects and Sheep ID was a random component. To compare and test for significance between the three window lengths, the statistical model *lsmeans* (Lenth & Hervé, 2013) with the interaction between Window and Deployment was used. Collar, leg and ear deployment modes were analysed separately.

6.4 Results & discussion

The work in Chapter 5 show the successful development of a highly accurate post event off-line prediction algorithm. To align this work with a commercial application, the next step was to determine if these algorithms could be adopted to a real-time classification scenario using continuous accelerometer signals across multiple animals.

In comparison with video observations there was considerable difference in the classification success across the four behaviours and between animals within each deployment (Table 6-1). Deployment location also had an influence on the between-animal classification accuracies with the leg and collar deployments showing a greater range in successful classification accuracies compared to the ear attachment, especially for standing behaviour. This is somewhat reflective of the original classification algorithm performance discussed in Section 5.6 above and the lower prediction accuracies for standing behaviour in these modes of attachment.

The accuracies across the three moving window sizes varied little within each accelerometer deployment. One of the main disadvantages of using a longer window is that it may contain a mixture of two or more activities of varying intensity and the average data may reflect an intermediate intensity. For example, if a sheep's activity abruptly changes from resting to walking, the moving average may identify an intermediate and faulty period of eating. This was not observed in the present study. Rather, rows at the beginning and end of the window were misclassified as the preceding or proceeding behaviour, respectively. Error in data annotation may also contribute to this misclassification. Furthermore if the activity bout is shorter than the window, the average value for that burst will differ from the actual activity intensity leading to misclassification. A longer window has the advantage of normal data-smoothing through time averaging and this was seen in the classification of walking behaviour from the collar deployment with the longer window length having higher classification accuracy. Consequently, window selection becomes a pragmatic trade-off to ensure the moving windows were sufficiently long to represent behaviours, while being short enough to reduce the likelihood of multiple behaviours being captured in the same window (Smith et al., 2016).

Table 6-1. The percentage of correctly predicted behaviours for individual sheep in each deployment mode across the three moving window lengths evaluated (3, 5 and 10 seconds). Percentage values derived from agreement between visual annotation and classification algorithm prediction. This highlights the large variation in classification accuracy between sheep within deployments and also within sheep across behaviours in the same deployment. This is clearly evident in the collar and leg deployment results for Sheep B.

Deployment	Sheep ID	3 sec window				5 sec window				10 sec window			
		Standing	Walking	Grazing	Lying	Standing	Walking	Grazing	Lying	Standing	Walking	Grazing	Lying
Leg	A	55%	95%	74%	95%	54%	95%	78%	95%	51%	94%	84%	94%
	B	1%	92%	83%		1%	92%	86%		0%	91%	90%	
	C			64%				66%				73%	
	E	79%	93%	83%		78%	96%	83%		79%	93%	78%	
	Mean prediction %	49%	93%	80%	95%	48%	94%	83%	95%	47%	92%	83%	94%
Collar	A	67%	65%	85%	10%	67%	68%	85%	10%	62%	74%	84%	9%
	B	30%	80%	85%		29%	84%	84%		27%	87%	85%	
	C			92%				92%				93%	
	E	96%	43%	94%		96%	47%	94%		95%	61%	94%	
	Mean prediction %	68%	67%	88%	10%	67%	71%	88%	10%	64%	77%	88%	9%
Ear	A	79%	89%	85%		78%	92%	86%		78%	94%	87%	
	B	97%	98%	55%		97%	99%	58%		97%	100%	52%	
	C	69%	91%	79%		70%	91%	84%		69%	89%	89%	
	D	96%	100%	76%		96%	100%	84%		97%	100%	92%	
	E	87%	98%	89%		86%	99%	92%		87%	98%	95%	
	Mean prediction %	89%	94%	83%		89%	95%	86%		89%	95%	89%	

6.4.1 Leg

There was little variation in classification across the three window lengths for predicting walking with all moving windows achieving greater than 90% accuracy for each sheep. Similar results were reported by Nielsen et al. (2010) in cattle with on average 10% misclassification rates in walking periods using the Icetag3D. Standing prediction accuracies were consistent across the three window lengths yet there was large variation between sheep with accuracies ranging from 0% to 79%. During model development, standing behaviour was often misclassified as grazing. Therefore this misclassification is also evident in the moving window classifier here. Grazing behaviour was best classified by the 10 second moving window with between-sheep values ranging from 73% to 90%. Lying behaviour was very well predicted with the 3, 5 and 10 second windows recording accuracies of 95%, 95% and 94%, respectively.

Window length was shown to have no significant effect on the behaviour prediction in any of the 4 behaviours recorded for the leg deployment. There was no significant difference in the standing prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the grazing prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the walking prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the lying prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds.

6.4.2 Collar

Classification for walking is improved through lengthening the window from 3 to 10 seconds with better classification success yielded by the 10 second moving window compared to the 3 and 5 second windows. However, there is a substantial variation between sheep with accuracies ranging from 61% to 87%. This classification success rate is higher than that reported for cattle by González et al. (2015) (~60%) who found travelling events were commonly misclassified with foraging behaviour. Standing was consistently classified across each moving window, again with substantial difference between sheep being observed with values ranging from 27 to 96%. Grazing behaviour was also consistently classified across 3, 5 and 10 second moving windows with high accuracy. Accuracies between sheep ranged from 84 to 94% with little variation between the three window lengths. Lying behaviour was very poorly predicted from the collar data with accuracies of 10%, 10% and 9% for the 3, 5 and 10 second moving windows, respectively with the small amount of data used for this behaviour in model training contributing to this poor classification.

Window length was shown to have no significant effect on the behaviour prediction in any of the 4 behaviours recorded for the collar deployment. There was no significant difference in the standing prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the grazing prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the walking prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the lying prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds.

6.4.3 Ear

The mean prediction percentages for the ear were the highest for all three deployment modes. Between-sheep variation was evident in the standing and grazing behaviour predictions and to a lesser extent in walking activity. Increasing the moving window from 3 to 10 seconds yielded a small improvement in classification agreement, particularly for grazing behaviour achieving a 6% improvement with the longer window. Walking behaviour was consistently predicted, yielding a between-sheep accuracy range of 11%. For the 10 second moving window, standing behaviour prediction accuracies ranged from 69% to 97%, walking prediction accuracies ranged from 89% to 100% and grazing behaviour predictions ranged from 52% to 95%. For the 5 second moving window, standing behaviour prediction accuracies ranged from 70% to 97%, walking prediction accuracies ranged from 91% to 100% and grazing behaviour predictions ranged from 58% to 92%. For the 3 second moving window, standing behaviour prediction accuracies ranged from 69% to 97%, walking prediction accuracies ranged from 89% to 100% and grazing behaviour predictions ranged from 55% to 89%. The longer moving window length of 10 seconds is superior given the slightly better mean prediction accuracies it provides compared to the 3 and 5 second windows.

Window length was shown to have no significant effect on the behaviour prediction in any of the 3 behaviours recorded in the leg deployment. There was no significant difference in the standing prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the grazing prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds. There was no significant difference in the walking prediction between any of the three moving windows; 3 & 5 seconds, 3 & 10 seconds or 5 & 10 seconds.

6.4.4 General discussion

An interesting finding was the substantial classification differences between animals within the same behaviour category, referred to here as between-animal variation. This is particularly evident in standing behaviour predicted from the collar and leg deployments. Similar results were found by Blomberg (2011) who reported accelerometers correctly classified behaviour in cattle with a relatively high rate of accuracy, but with large differences between individuals. It has previously been acknowledged that variability in feed intake and time spent eating between calves has been attributed to differences caused by breed, temperament, and social interactions (Shane, White, Larson, Amrine, & Kramer, 2016). While the current project did not investigate the specific causes of variability between sheep, it is speculated that the primary source of this between-animal variation in signals arises from two related causes; animal physical characteristics affecting how the sensor attaches to the animal and the sensor motion during activity. Wolfger et al. (2015) speculated that the inter-animal variation between estimates provided by observations and accelerometer recordings could be attributed to differences in ear movement between cattle.

Similarly, differences between sheep in physical (skeletal) structure may influence walking pattern (or gait) and thus sensor motion during measurement of motion (or activity). Consequently, the models' ability to discriminate between behaviour states may be adversely affected. González et al. (2015) also observed large differences between animals and collars for the fitted parameters of the probability density functions, threshold values and structure of the frequency distributions (e.g. overlap of populations) which clearly demonstrated the need for accounting for such differences. Further research should investigate the source of such variation to determine the proportion of observed variation between experimental animals that result from difference in animal movement patterns, differences in sensor attachment and differences in measurement between sensors (González et al., 2015). This has a huge implication for commercial adoption of this technology, as sensors will be deployed across a variety of animals of different age, breed, production status etc. and prediction algorithms need to account for this between-animal variation in their classification protocols.

6.5 Conclusion & future research

The automatic identification of sheep behaviour has many benefits for animal welfare and labour efficiencies. The current study showed the ear-borne tri-axial accelerometer to be the superior mode of deployment to discriminate behaviour in sheep using a QDA moving window classification algorithm. No significant difference was observed between the three moving window lengths evaluated, however slight improvements were seen using the 10 second window in the ear deployment. With the inclusion of transitional behaviours, a large between-sheep variation in classification rate was apparent, which must be considered in future work. The combining of behaviour states into "active" and "inactive" behaviour classes could potentially alleviate some of the misclassifications between different individuals.

Chapter 7

Can accelerometers be used to detect *Haemonchus contortus*-infected sheep?

7.1 Introduction

Gastro intestinal nematodiasis (GIN) affects many sheep producing countries around the world, with graziers investing significant labour and financial resources towards its control and treatment. In Australia, GIN represents the highest disease-related national cost with a large proportion of the expense being attributed to reduced income resulting from lost productivity (Sackett et al., 2006). Effective control of these parasitic infections is important given the increasing world population and the expectation of a rising demand for ruminant products (Jackson, Bartley, Bartley, & Kenyon, 2009). As such, parasite control and treatment plans are a necessary component of any flock management program.

The summer rainfall regions of Australia are dominated by three major species of the Trichostrongylidae family, *Haemonchus contortus*, *Teladorsagia circumcincta* and *Trichostrongylus colubriformis* (Kelly, 2011). These are more commonly referred to as Barber's pole worm, Small brown stomach worm and the Black scour worm, respectively (Brightling, 2006). The effect on the host is often species specific i.e. *H. contortus* infection leads to anaemia and weakness (Brightling, 2006) while the scour worms result in a depressed feed intake of the host. Broadly, parasites can have a profound effect on animal behaviour, including changing the amount of time individuals invest towards specific activities (Worsley-Tonks & Ezenwa, 2015). Although it is largely unknown exactly what movement-related behaviours are associated with parasite challenge and the rate at which they develop, some broad descriptions of behaviour changes during disease exist (Gougoulis, Kyriazakis, & Fthenakis, 2010; Hart, 1988; Kyriazakis & Tolkamp, 2010). Szyszka, Tolkamp, Edwards, and Kyriazakis (2012) infected beef cattle with a single dose of *Ostertagia ostertagi* and found the parasitised animals had less frequent but longer lying bouts which persisted for 30 days post infection. There was a slight increase in the average duration of feeding however, there was no treatment effect on overall activity measured by either the number of steps taken or total lying time. It was concluded that although parasitic challenge had significant effects on several behaviour aspects, these changes may be considered too subtle to be useful indicators of disease. In contrast, Szyszka and Kyriazakis (2013) found bull calves with a high infection of *Ostertagia ostertagi* had a 25% increase in lying time and a 22% decrease in standing time from day 29 post infection compared to controls. From day 34 – 46 parasitised calves had a 34% decrease in steps taken relative to controls, yet no effect on feeding behaviour was observed. A reduction of 56 minutes in daily grazing time was reported by Forbes, Huckle, Gibb, Rook, and Nuthall (2000) for treated heifers despite having low nematode infections (<300epg) with *Ostertagia spp*. dominating faecal cultures. This study offers support for the theory that parasite induced inappetance manifests as a reduction in grazing time and subtle changes in ingestive behaviour.

In sheep, many studies have demonstrated parasite induced inappetance with some showing evidence for a preferential selection for a higher protein diet (Kyriazakis, Anderson, Oldham, Coop, & Jackson, 1996; Kyriazakis, Oldham, Coop, & Jackson, 1994). Compared to controls, lambs infected with *Ostertagia circumcincta* spent less time grazing and had lower herbage intakes due to a reduction in the duration of feeding bouts, although the number of bouts was not reduced (Hutchings, Gordon, Robertson, Kyriazakis, & Jackson, 2000). Parasitised sheep also had lower rates of movement than controls. Kyriazakis et al. (1994) infected housed lambs with a daily dose of 2500 L3 *Trichostrongylus colubriformis* and found parasitized animals had a reduced feed intake and also consumed a higher protein ration. In a different study, *H. contortus* animals showed an increase in locomotor activity compared to control animals in an arena test (Fell et al., 1991). Using GPS tracking collars, Falzon et al. (2013) found a relationship between higher Faecal Egg Counts (FECs) and a greater distance per time step in sheep infected with a composition of *Haemonchus spp.* (12%), *Trichostrongylus spp.* (75%), and *Teladorsagia spp.* (13%). These studies offer support for the analysis of behaviour being used as a potential diagnostic tool.

The effects of health challenges that result in subclinical or clinical disease may lead to performance losses, an increase in treatment costs and compromise animal welfare (González et al., 2008; Quimby et al., 2001). To minimise the impact of health challenges treatment must be initiated early. To enable this, an early diagnosis of affected animals is required (Szyszka et al., 2012). Kyriazakis et al. (1994) and González et al. (2008) proposed that chronic health challenges such as parasite infection, may lead to gradual changes in behaviour differing from those behaviour symptoms associated with acute illness (Gougoulis et al., 2010).

Standard approaches to identify the level of infection within a flock include faecal egg counts (FEC), FAMACHAs (FAffa MAlan CHArt), blood packed cell volumes (PCV), blood haematocrit levels along with general health indicators such as weight loss (Pugh & Baird, 2012). These methods identify when an infection is present within the flock or individuals, and as such they do not measure the subtle changes which may occur leading up to the infection threshold. Therefore, these indicators may be susceptible to miss early behavioural changes and provide an incomplete description of parasite burden impacts especially in relation to behaviour (Falzon et al., 2013).

The relationship between-animal health and behaviour has gained attention (Weary et al., 2009) and several studies have highlighted the reliability of information provided by an animal's behaviour and physiological response in relation to its health and welfare status (Ahmed et al., 2016; Mepham, 2000; Nardone, Zervas, & Ronchi, 2004). As behaviour may be amongst the first responses affected by a health challenge (González et al., 2008; Huzzey et al., 2007; Kyriazakis & Tolkamp, 2010; Quimby et al., 2001), and the analysis of changes in behavioural activity can provide an assessment of animal wellbeing (Müller & Schrader, 2003; White et al., 2008), the possibility of using behaviour to aid in the early detection of disease should be investigated (Szyszka et al., 2012).

Accelerometers have the ability to monitor animal behaviour and document the percentage of time animals spend performing specific activities (Robert et al., 2009). Hence, they can potentially be used to diagnose disease symptoms based on quantification of the animal's behaviour. Accelerometers have been used previously to identify disease status in animals based on activity, with varied success. Using an activity count threshold based on the recorded acceleration in any axis, Smith et al. (2015) was able to identify steers that were subject to Bovine Respiratory Disease (BRD) as BRD infected animals had 25% fewer activity counts compared to their healthy counterparts. Tri-axial accelerometers attached to the back of piglets were successful in detecting early stage illness based on activity, with the movement of infected piglets being altered based on analysis of raw acceleration values (Ahmed et al., 2016).

In reference to accelerometers, Robert et al. (2009) stated "Research should be performed to evaluate the ability of the devices to monitor animal wellness status and the accuracy of the technology to diagnose disease will greatly impact the potential adoption in production systems". The use of accelerometers to detect movement related symptoms associated with internal parasitism in sheep appears to be a novel approach. The potential accuracy of the devices to determine actual behaviours has been investigated in previous chapters of this thesis as this influences the utility of such a technology in future animal health monitoring. The next step is to utilise this information for a commercial application.

7.2 Research Objectives

The overall aim of this chapter was to link the findings of previous chapters to a real-life case study of this technology. The potential use of ear tag deployed accelerometers to identify internal nematodiasis through a change in activity level was evaluated. To achieve this, the following objectives were investigated:

1. Develop a behaviour classification model using ear tag derived accelerometer signals to categorise "active" and "inactive" states.
2. Apply a 10 second moving window classifier to an entire 40 day, unclassified accelerometer dataset.
3. Determine the effect of *H. contortus* parasitism on the activity proportions of sheep based on indicators derived from traditional methods of determining parasitic infection.

7.3 Experimental procedures

This experiment was approved by the University of New England Animal Ethics Committee (AEC14-105) and followed the University of New England code of conduct for research in meeting the Australian Code of Practice for the care and use of animals. The study was completed in conjunction with a larger Sheep CRC project running from 14th April 2015 – 25th May 2015.

7.3.1 Study animals

A total of 200 mixed age ewes were used in this trial with a smaller number selected for sensor deployment. The breed was predominantly Merino with some Poll Dorset and Border Leicester Merino cross animals included. All instrumented animals were Merinos and all animals were drenched with 14mL Pyrimide 45 days before commencement of the study (day -45). Animals were divided into two groups of 100. On day 0, 30 ewes from each group were infected with a single dose of 10,000 L3 infective *Haemonchus contortus* larvae. The selection of treatment ewes was based on their social network connections. Baseline data were collected on movement order for 20 days (day -20 to day 0) after which social networks were analysed to assist with selection of animals to be treated. The degree, or number of 'immediate neighbours' for each animal within the two flocks was determined and 10 sheep with the highest, lowest and mid-range degree scores were allocated as treatment sheep in an alternating fashion i.e. in the high range degree scores sheep 1 was a control sheep, sheep 2 a treatment sheep, sheep 3 a control sheep and so on. All ewes were weighed, body condition scored, faecal sampled (Dever & Kahn, 2015), FAMACHA eye tested (Chylinski, Cortet, Neveu, & Cabaret, 2015) and had blood samples collected.

On days 21 and 31, all ewes were weighed and body conditioned scored. Control ewes were FAMACHA eye tested. All treatment animals and a random sample of 20 control ewes were faecal sampled. All infected ewes had blood samples collected. On day 41, all ewes were weighed, body condition scored, faecal sampled, FAMACHA eye tested, blood tested and drenched with TRIGUARD® (Merial).

7.3.2 Study area

This study was conducted at the University of New England's "Trevanna" property. Each replicate group was kept in adjacent paddocks of approximately 10 hectares. Experimental procedures were conducted in sheep handling facilities located 500 metres from the study paddocks. On day 0 and day 22 animals were moved to fresh paddocks.

7.3.3 Instrumentation

Five treatment and five control animals from each group were fitted with an Axivity AX3 accelerometer ear tag to the right ear on day 0. In total were 20 animals instrumented with accelerometers. Instrumented animals were randomly selected in an alternating fashion as they entered a race. Eight animals from each group were also fitted with a UNEtrackerII GPS collar. Accelerometers and collars were removed on day 41 and antiseptic spray was applied to the ear tag wounds. Further information on the mode of deployment is described in Chapter 3 of this thesis. Eight collars had a pair of visual cattle ear tags attached to the sides of the collar, with each collar having a different colour (Figure 7-1) to improve individual animal identification from the video recordings. To create the behaviour classification model, data were annotated from the video recordings.

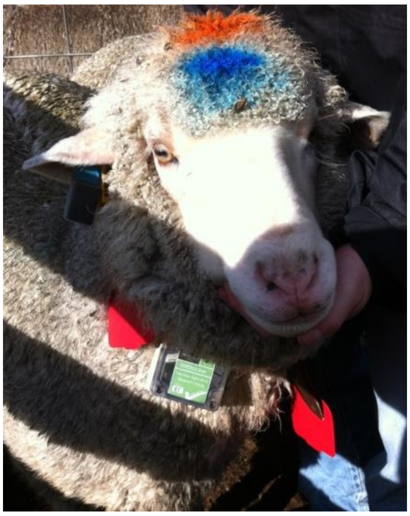


Figure 7-1. Study animal showing the eartag accelerometer sensor and GPS tracking collar with coloured visual tags used to identify individual animals for the annotation of accelerometer signals with visual observations.

7.3.4 Developing the behaviour classification model

Observations

Two observational periods were used to collect video recordings of the animals' behaviour. Session 1 was conducted on the 29th April 2015, recording normal daily behaviour in the study paddocks. Session 2 was conducted on the 15th May 2015 in a 0.4 ha paddock adjacent to the sheep yards. This provided a controlled environment with only the identifiable instrumented sheep so that grazing, resting and walking behaviours could be recorded. During both observational sessions, behaviours were classified according to those listed in Section 3.5.

Annotation

Behaviour observations were recorded for eight of the instrumented animals. The corresponding accelerometer streams for the time periods for which video observations had been recorded were extracted. These files were then annotated with their corresponding behaviours according to the protocol outlined in Section 3.6.2.

Feature extraction

Ten second epochs of mutually exclusive behaviours were extracted. For each epoch, *MV, AI* and *Ay* features were calculated. These were the only features calculated as they were previously shown to successfully classify behaviour for multiple animals (Chapter 6).

The behaviour model

There were three behaviour models tested which combined behaviour into different classes for the QDA classification. This was an attempt to improve the classification accuracy and minimise misclassifications between activity states. The models tested and their behaviour classes contained within each model were:

Model 1; grazing, standing, walking, lying.

Model 2; grazing, walking and inactive (standing and lying combined).

Model 3; active (grazing and walking) and inactive (standing and lying).

Validation

Model validation was achieved by using a leave-one-out cross validation analysis on each of the three models

7.3.5 Classifying continuous accelerometer streams for all sheep

Because of the size of each accelerometer file (~2GB) the data were stored in a PostgreSQL database. The accelerometer files were then clipped to the start and end of the experimental period. Based on the results of Chapter 6 of this thesis, a moving window of 10 seconds, stepped by 1 row was used to classify behaviour. Using this method, every row of accelerometer data was given a behaviour classification. Metrics *MV, AI* and *mean-Y* were calculated for each animal using PostgreSQL and R (R-Core-Team, 2015). The epoch length was 10 seconds.

7.3.6 Statistical Analysis

This section firstly investigated differences in the proportion of time spent performing the activity, based on the original experimental design (i.e. original treatment and control groups). Secondly, animals were re-assigned to 'healthy' and 'sick' groups based on individual health status using the biological measurements collected. Comparison in activity proportions between these two groups was investigated. Thirdly, as infection would take time to develop, animals selected based on individual health status were compared for differences in activity proportions between the beginning and end of the study.

Generalised additive mixed model (GAMM).

To examine if *H. contortus* had an effect on behaviour, the difference in activity proportion between animals was tested using a generalised additive mixed model (GAMM)(Wood, 2006). Three separate analyses were performed:

Analysis I - All animals

For the initial analysis, individual animals were left in their original treatment groups. There were a total of 37 days (data collection and paddock movement days were excluded) of repeated measures for all 16 sheep split into two groups; 8 sheep in Group 1 and 8 sheep in Group 2. Sheep in both groups were split between treatments (control and infected) with four sheep from each group receiving each treatment in Group 1, while Group 2 had 3 control animals and 5 treatment animals. Due to sensor malfunction, data were only available for these animals. The proportion of time spent active per day from those observations were analysed using a generalised additive mixed model (GAMM) with cubic smoothing splines to absorb the serial correlations associated with the repeated observations of each sheep and day. Group and treatment were fixed effects, while sheep within group and day, and splines for day and the interaction between sheep within group, were random effects.

The model used was:
Proportion ~ Treatment + Group + s(Day, bs = "re") + s(Sheep, by = Group, bs = "re")
Where *s* is the spine smoother and *bs="re"* indicate the random terms in the model.

Analysis II - Animals re-categorised based on EPG counts

Given there was a large variation in parasitological measurements within each group and there was no clear sign of an infection being established based on these measurements, two new categories were created using the EPG values to isolate the "healthiest" and "sickest" status animals, irrespective of the original treatment assignment. Each cohort consisted of four animals. Sheep were assigned to the "sickest" cohort based on an EPG count above 120 and the "healthiest" cohort animals were assigned based on an EPG count of 0. Similarly, there was a total of 37 days (analysis and paddock movement days were excluded) of repeated measures for each 8 sheep split into two groups, 4 sheep in Group 1 and 4 sheep in Group 2. Sheep in both groups were split between the two categories with 2 sheep from each group in the "healthiest" and "sickest" categories. The proportion of values marked as active per day from those animals were analysed using a generalised additive mixed model (GAMM) with cubic smoothing splines to absorb the serial correlations associated with the repeated observations of each sheep and day. Original "Group" was not included in the model. Fixed effects were Treatment (sick or healthy), while the random effects consisted of Sheep within Treatment and Day, and splines for Day and the interaction between Sheep within Treatment.

The model used was:
Proportion ~ Treatment + s(Day, bs = "re") + s(Sheep, by = Treatment, bs = "re")

Analysis III - Animals re-categorised based on EPG counts and data split into 2 periods

The data for these reassigned animals were then split into two periods: days 2-5 (period 1) and days 36-40 (period 2). This was done because any level of infection will take time to become established and hence have an influence on behaviour. The structure within the groups and categories remained the same as outlined above, however Period was added to the model as a fixed effect. The interaction of Sheep by Period replaced the interaction component from the model (ii) above.

The model used was:
Proportion ~ Treatment + Period + s(Day, bs = "re") + s(Sheep, by = Period, bs = "re")

7.3.7 Smoothing the data

Given the challenges associated with the lack of treatment effect, an alternative approach was applied. This section examined the relationship between the lengths of the activity periods of animals throughout the day and investigated differences between the lengths of activity for the treatment and the control groups, based upon the active/inactive classification produced from the IMU data logged across the entire study period. The first stage of this process involved filtering the activity time series data so that transitions between the active and inactive states are represented as clean, discrete events. In the raw classified data, transitions between these states, typically include very small (often miss-classified) intervals of activity that do not reflect the transition from one state to another. The filtering process removes these small, miss-classified events.

7.3.8 Survival analysis

The filtered time series data were then analysed using Matlab scripts to generate a dataset that contained the duration and start time (hour of the day) for every activity period for each animal within the study. The data sets for each of the individual animals were then combined to form control and treatment sets for a survival analysis. Activity durations from sheep 13, 19, 2 and 8 were used to create the control group (healthy animals) and sheep 11, 12, 18 and 16 where used to create the treatment group (sick animals). This is the same as the reclassification conducted in the previous section in analysis iii.

Survival analysis is typically used to analyse time periods related to failures and events, such as the death of organisms in response to treatment and disease or failures in equipment under differing stress levels or situations. It has also been applied to duration data in other areas relating to foraging behaviour in fish (Hansen, 2016), transportation analysis (Hencher & Mannering, 1994) and consumer purchasing behaviour (Bhat, 1996). The Kaplan-Meier (KM) method (Kleinbaum, 2005) was applied to estimate survival functions for the treatment and control group activity durations. To determine differences between survival functions, a log-rank test on the two survival functions was used.

7.4 Results

Because of sensor malfunction, four animals were excluded from the analysis. This left four control animals in Group 1, four treatment animals in Group 1, three control animals in Group 2 and five treatment animals in Group 2.

No adverse effects on animal behaviour were observed in the present study due to sensor attachment.

7.4.1 Behaviour classification model

Feature selection methods were not used in the present study. The QDA classification model results for the evaluation and leave-one-out cross validation analysis for models 1, 2 and 3 are shown in Table 7-1, Table 7-2 and Table 7-3, respectively. The progression of the behaviour grouping for model 1, model 2 and model 3 was conducted in an attempt to improve classification accuracy and reduce ambiguity of the classifier.

Model 1

No difference between evaluation and validation analysis was observed. The model correctly predicted grazing and walking behaviour (94% and 95% respectively). Standing and lying behaviour were predicted with reasonable accuracy, however, misclassification of standing events as lying and vice versa was high. Combining these two behaviours into an "inactive" class resulted in a reduction of this misclassification rate.

Table 7-1. QDA confusion matrices of the evaluation and leave-one-out cross validation analysis for model 1 using derived metrics: *MV, AI* and *mean-Y*. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)			
Evaluation data set	QDA			
MV, AI, Mean-Y	Grazing	Standing	Walking	Lying
Grazing	**509**	8	35	0
Standing	16	**483**	8	48
Walking	13	4	**748**	1
Lying	1	129	0	**183**
Prediction accuracy	*94%*	*77%*	*95%*	*79%*
Cross validation	QDA			
MV, AI, Mean-Y	Grazing	Standing	Walking	Lying
Grazing	**508**	9	35	0
Standing	17	**482**	8	48
Walking	13	4	**748**	1
Lying	1	129	0	**183**
Prediction accuracy	*94%*	*77%*	*95%*	*79%*

Model 2

No difference was observed between the evaluation and cross validation analysis. Combining standing and lying behaviours into a single behaviour class, 'inactive, substantially improved the prediction accuracy of this behaviour category, achieving 98% correct prediction. In comparison with model 1, there was no difference observed for grazing and walking behaviours.

Table 7-2. QDA confusion matrices of the evaluation and leave-one-out cross validation analysis for model 2 using derived metrics: *MV, AI* and *mean-Y*. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)		
Evaluation data set	QDA		
MV, AI, Mean-Y	Grazing	Walking	Inactive
Grazing	**509**	36	8
Walking	13	**748**	5
Rest	17	7	**843**
Prediction accuracy	*94%*	*95%*	*98%*
Cross validation	QDA		
MV, AI, Mean-Y	Grazing	Walking	Inactive
Grazing	**508**	36	8
Walking	13	**748**	5
Rest	18	7	**843**
Prediction accuracy	*94%*	*95%*	*98%*

Model 3

In model 3 grazing and walking behaviours were combined as "active" and standing and lying as "inactive". No difference was observed between the evaluation and cross validation analysis, similar to models 1 and 2. Very high prediction accuracy was achieved using this approach, with "active" and "inactive" having prediction accuracies of 97% and 99%, respectively. Because of the superiority of model 3 results, behaviours were classified as either 'active' or 'inactive' in future classification of the entire dataset using PostgreSQL.

Table 7-3. QDA confusion matrices of the evaluation and leave-one-out cross validation analysis for model 3 using derived metrics: *MV, AI* and *mean-Y*. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)	
Evaluation data set	QDA	
MV, AI, Ay	Active	Inactive
Active	**1296**	10
Rest	34	**846**
% predicted correct	*97%*	*99%*
Cross validation	QDA	
MV, AI, Ay	Active	Inactive
Active	**1296**	10
Rest	34	**846**
% predicted correct	*97%*	*99%*

7.4.2 Biological measurements

To monitor the level of infection and effect on the host, five biological measurements were taken; body condition score (BCS), weight, faecal condition score (FCS), haematocrit (hct) values and strongyle eggs per gram (EPG). The latter two measurements were considered of most value in identifying an infection and are summarised in Figure 7-2 and Figure 7-3 respectively.

It was evident that the mean haematocrit values for the control and treatment populations for both groups were greater than 31 with a low standard error (Figure 7-2). Little difference at the conclusion of the study (day 41) between control and treatment populations was evident. The haematocrit value is considered to be in the normal range therefore, and based on this measurement, a successful infection was not established in either treatment group.

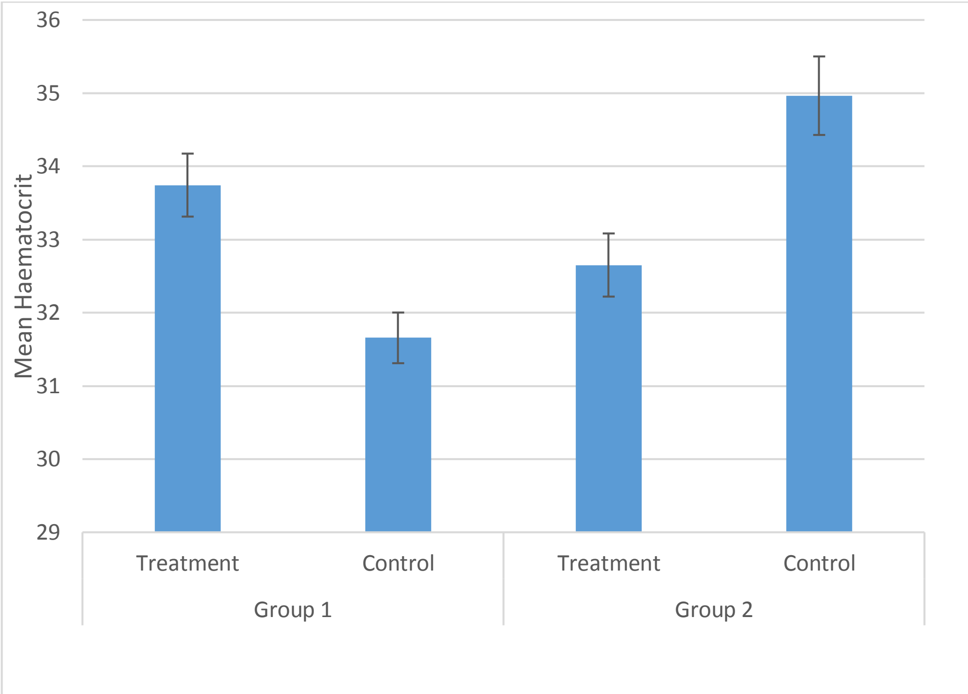


Figure 7-2. Mean +/- SE haematocrit values for the treatment and control populations in Groups 1 and 2, respectively on day 41.

The mean strongyle EPG counts for the control and treatment animals in Groups 1 and 2 are shown in Figure 7-3. Mean EPG counts were low for all populations and had a large standard error. The control animals in group 2 had a higher mean EPG count compared to the treatment animals in both groups. Similar to the haematocrit measurements, the low EPG counts offer support that a successful *H. contortus* infection was not established. Furthermore there was a large variation in the strongyle EPG values between animals across groups and treatments (Table 7-4).

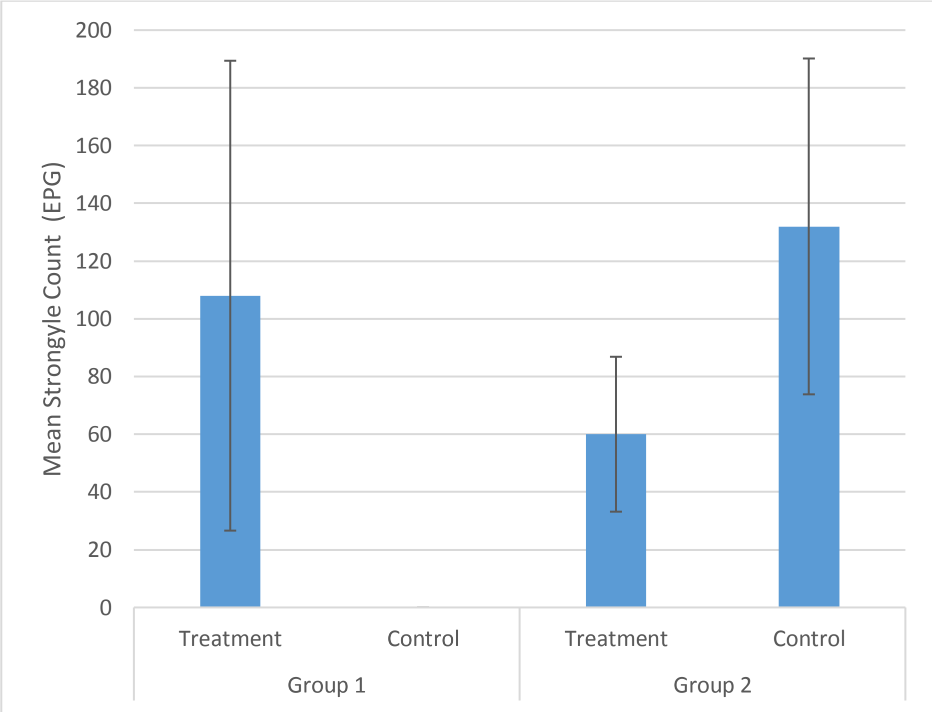


Figure 7-3. Mean ± SE strongyle egg count for the treatment and control populations in groups1 and 2, respectively on day 41. Group 1 control animals had a 0 EPG count.

Summarising Table 7-4, there was little change in the body condition score across all animals, indicating that that animals maintained relatively good condition throughout the study period. Only one animal lost weight from day 0 to day 41 with animals gaining an average of 2.1 kilograms over the study period. Faecal condition scores (FCS) remained relatively stable with all values being between 1.0 and 2.0. Haematocrit (hct) values also remained relatively stable with there being no clear differentiation between the treatment and control animals. Animals with a hct value below 20 were considered to require treatment. The lowest hct recorded was 30.5 for a control animal. The strongyle EPG counts varied across animals in both groups. Only two treatment animals in group 1 shed strongyle eggs while all other animals produced 0 EPG. In group 2, there were five animals which shed strongyle eggs although the highest count was only 120. Two control animals produced strongyle eggs within this group. Using the following definitions from Brightling (2006) of <200 EPG having little effect on production and 200-500 EPG having some effect on production, only one animal met the criteria of possibly being affected by haemonchosis.

Table 7-4. Summary of the biological measurements taken for the instrumented treatment and control animals within groups 1 and 2. There is little evidence of a substantial infection being established based on these 5 measurements.

Group	Treatment	ID	**BCS**			**Weight**			**FCS**			**Haematocrit**			**EPG - strongyle**		
			Day 0	Day 41	Change	Day 0	Day 41	Change	Day 0	Day 41	Change	Day 0	Day 41	Change	Day 0	Day 41	Change
1	Control	1	3.0	3.0	0.0	47.0	48.2	1.2	2.0	1.0	-1.0	33.8	30.5	-3.3	0	0	0
1	Control	2	3.0	2.0	-1.0	46.8	46.4	-0.4	1.5	1.0	-0.5	32.2	32.3	0.1	0	0	0
1	Control	3	3.0	3.0	0.0	44.2	44.6	0.4	1.0	1.0	0.0	33.0	31.3	-1.6	0	0	0
1	Control	5	3.0	2.0	-1.0	44.2	44.2	0.0	1.0	1.0	0.0	32.3	32.0	-0.3	0	0	0
1	Treatment	11	3.0	2.5	-0.5	50.4	50.8	0.4	1.0	1.0	0.0	35.4	35.2	-0.3	0	420	420
1	Treatment	12	3.0	3.0	0.0	53.6	57.6	4.0	1.5	1.5	0.0	33.3	32.9	-0.5	0	120	120
1	Treatment	13	3.0	3.0	0.0	50.8	51.2	0.4	1.5	1.5	0.0	33.0	33.7	0.7	0	0	0
1	Treatment	15	3.0	3.0	0.0	50.2	52.0	1.8	2.0	1.5	-0.5	35.1	34.0	-1.1	0	0	0
2	Control	6	3.0	2.5	-0.5	43.4	47.6	4.2	1.0	1.0	0.0	35.4	34.7	-0.7	0	60	60
2	Control	8	3.0	2.5	-0.5	49.8	51.8	2.0	1.0	1.0	0.0	33.6	34.2	0.6	0	0	0
2	Control	9	3.5	3.0	-0.5	44.8	48.4	3.6	1.0	1.0	0.0	30.9	34.1	3.2	0	60	60
2	Treatment	16	3.0	2.5	-0.5	42.8	46.0	3.2	1.5	1.0	-0.5	31.1	31.0	-0.1	0	120	120
2	Treatment	17	3.0	2.5	-0.5	50.8	54.2	3.4	1.5	1.0	-0.5	32.5	32.7	0.3	0	60	60
2	Treatment	18	2.8	2.5	-0.3	42.2	46.0	3.8	1.0	1.0	0.0	34.4	33.5	-0.9	0	120	120
2	Treatment	19	3.0	3.0	0.0	45.2	48.6	3.4	1.0	1.0	0.0	32.5	32.9	0.4	0	0	0
2	Treatment	20	3.0	3.0	0.0	42.2	44.4	2.2	1.0	1.0	0.0	34.4	33.1	-1.3	0	0	0

7.4.3 Activity classification

The average time individual animals spent active across the study period based on the activity predictions from the model 3 classifier is shown in Figure 7-4. Substantial between-animal variation was evident, particularly in the group 1 control animals. Average proportion active values range from ~28% to ~56%. Using the IMU behaviour classification model 3, most animals appear to spend on average approximately 38% of the day in an active state. The times of the day which animals were most active is further demonstrated through observation of the daily diurnal patterns as shown in (Figure 7-7 and Figure 7-8).

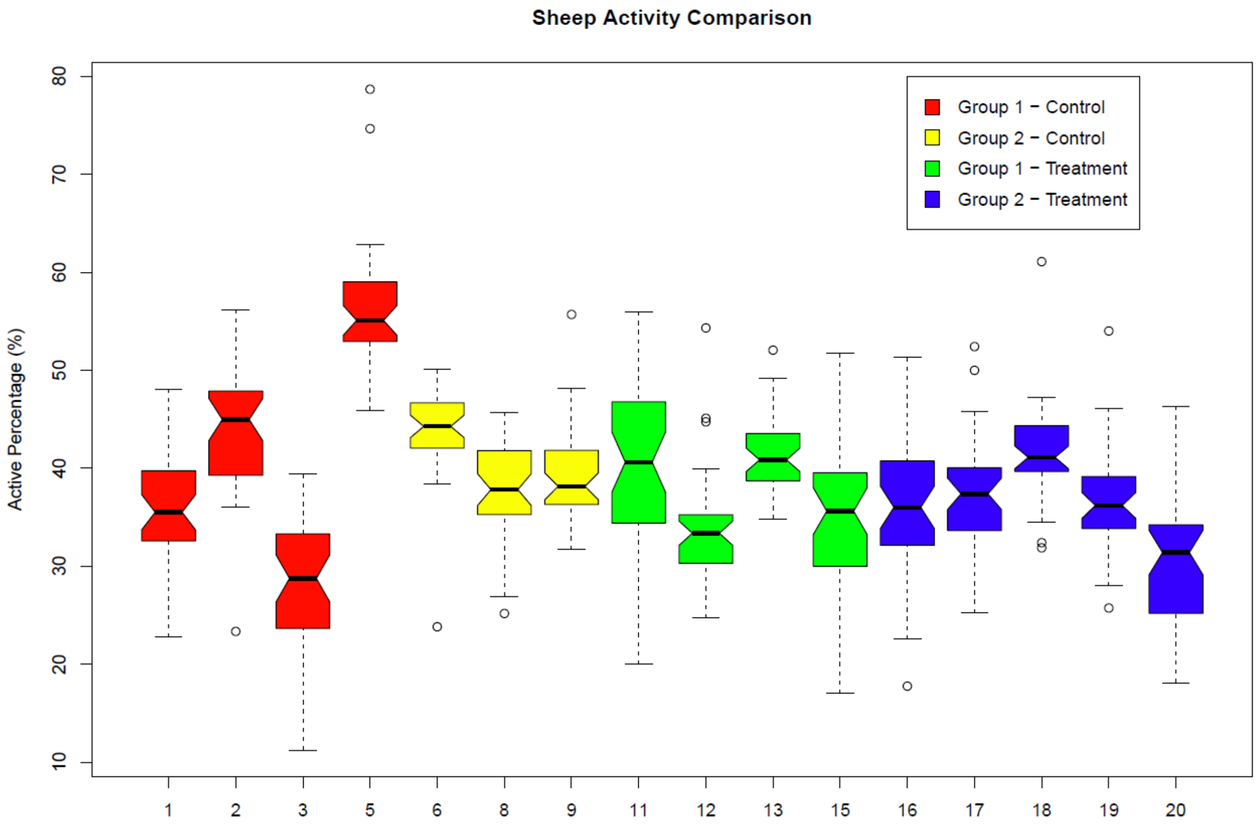


Figure 7-4. Mean time individual animals spent active across the study period based on the activity predictions from the model 3 classifier.

7.4.4 Testing for a change in activity proportion based on the level of parasitism

Analysis I - Comparing original treatment and groups over all days

Across the entire study period (excluding data collection days) this model indicates that there was no significant difference in the proportion of time spent active between the two treatments ($p = 0.615$) or between the two groups ($p = 0.394$). There was a significant difference in the proportion of time sheep were active between days ($p < 0.0001$) and also for the interaction of sheep within group, indicating that the activity proportions for sheep within Group 1 ($p < 0.0001$) and Group 2 ($p < 0.0001$) was different.

Analysis II - Comparing selected sheep based on individual health status over all days

From Table 7-4, it is evident there was no nematode infection, based on the strong biological measurements recorded. Therefore without regard to treatment, the 4 "healthiest" and 4 "sickest" animals were selected from the strongyle EPG counts. This reclassification was conducted to evaluate whether there was any difference in behaviour at disease state thresholds lower than previously reported as having an impact. The healthiest group was selected based on animals having a 0 EPG count. As more than 4 animals met this criteria, to balance the number of animals in each group, four animals were selected at random which were; 13, 19, 2 and 8. The sickest group was selected based on animals having an EPG count > 120 and this group consisted of animals: 11, 12, 18 and 16.

Irrespective of the study design and grouping of animals based on their individual health status, there was no significant treatment effect even by comparing the "healthiest" and "sickest" animals based on their corresponding EPG counts ($p = 0.288$). Day had a significant effect on the activity proportions ($p < 0.0001$). Sheep within each status were also significantly different ($p < 0.0001$).

Analysis III – Comparing selected sheep on start vs. end periods

Segregating the study into two separate periods, period 1 (2-5 days) and period 2 (36-40 days) failed to yield a significant treatment effect ($p = 0.236$). The activity proportions were also non-significant between the two periods ($p = 0.123$). This is supported by the minimal change in the average proportion of time spent active being 36.0% and 40.2% for period 1 and period 2, respectively across all animals. The minimal difference in the mean daily activity percentages for the healthy and sick animals across both periods are shown in Table 7-5. Activity proportions were significantly different between days ($p < 0.0001$) and within each period individual sheep were significantly different in their activity proportions.

Table 7-5. Mean and standard deviation daily activity percentages for the 'healthy' and 'sick' status animals for period 1 and period 2.

	Period	Mean daily % active	SD of daily % active
Healthy	1	37	0.021
	2	42	0.064
Sick	1	35	0.066
	2	39	0.05

7.4.5 Smoothing the data to analyse activity periods

The time series plot of the behaviour classified IMU data with many small intervals of active and inactive behaviour caused by transitions between periods of activity prior to the filtering process is shown in Figure 7-5 . The noise in the signal was problematic for analysing activity periods, as long activity sessions are not reflected correctly within the raw time series data. For example, most long periods of activity will contain noise, resulting in them being registered as multiple smaller activity periods. To remedy this issue, a moving average filter with a window size of 10 seconds (with rounding on the average) was used to remove this noise from the classified activity time series data. Figure 7-6 shows the filtered activity time series data with most of the noise removed.

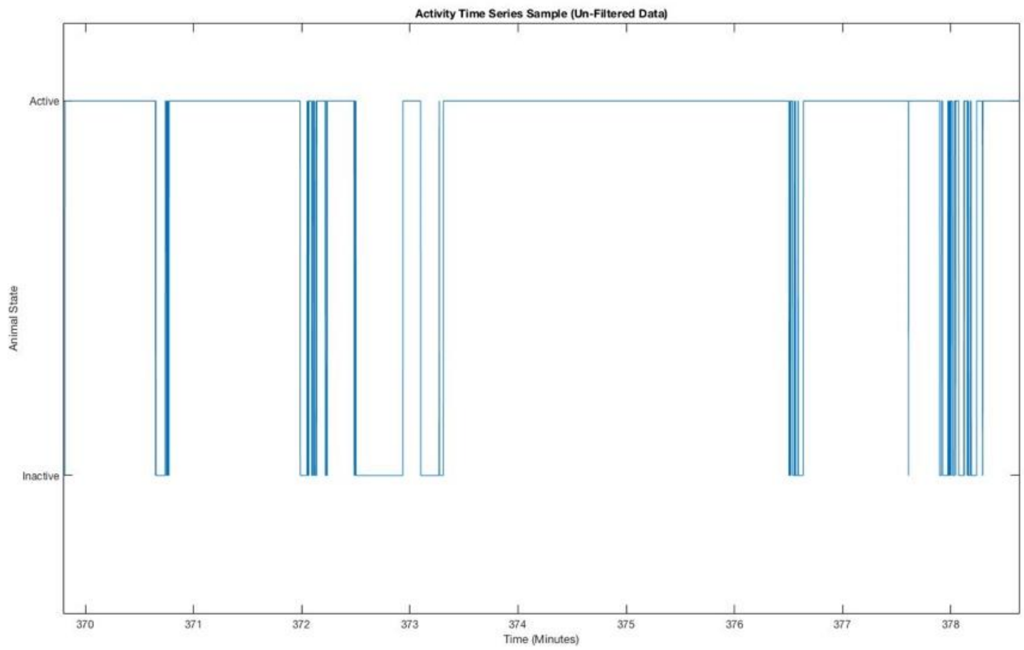


Figure 7-5**.** Unfiltered activity time series data sample from sheep 1, day 2 of the study.

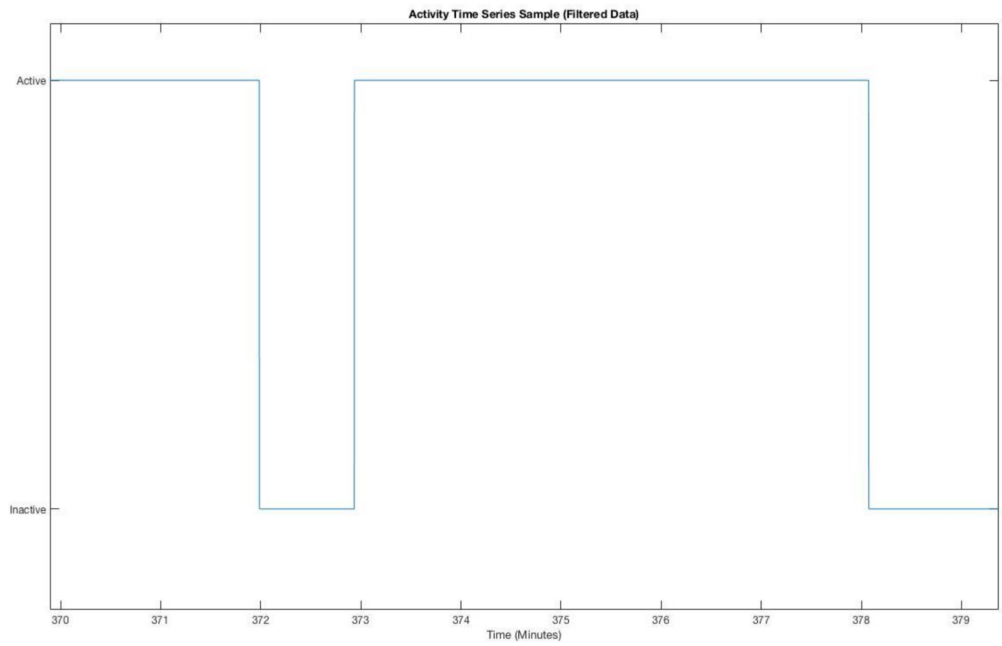


Figure 7-6. Activity time series data after a moving average filter has been applied on sheep 1, day 2 of the study.

7.4.6 Diurnal activities

Figure 7-7and Figure 7-8 show scatter plots of the individual bouts of activity for the control (healthy) and treatment (sick) groups, identifying their start and end times (i.e. hour of the day). These plots provide a good illustration of the diurnal patterns of activity for each group across the period observed. It is evident that there is no substantial difference in the pattern between the treatment and control groups, in terms of time of the day animals commence bouts of activity of specific durations. As expected, both groups engage in longer bouts of activity during the daylight hours, particularly in the early afternoon. The data suggest there was a lower proportion of bouts of longer duration within the "sick" group compared to the "healthy" group.

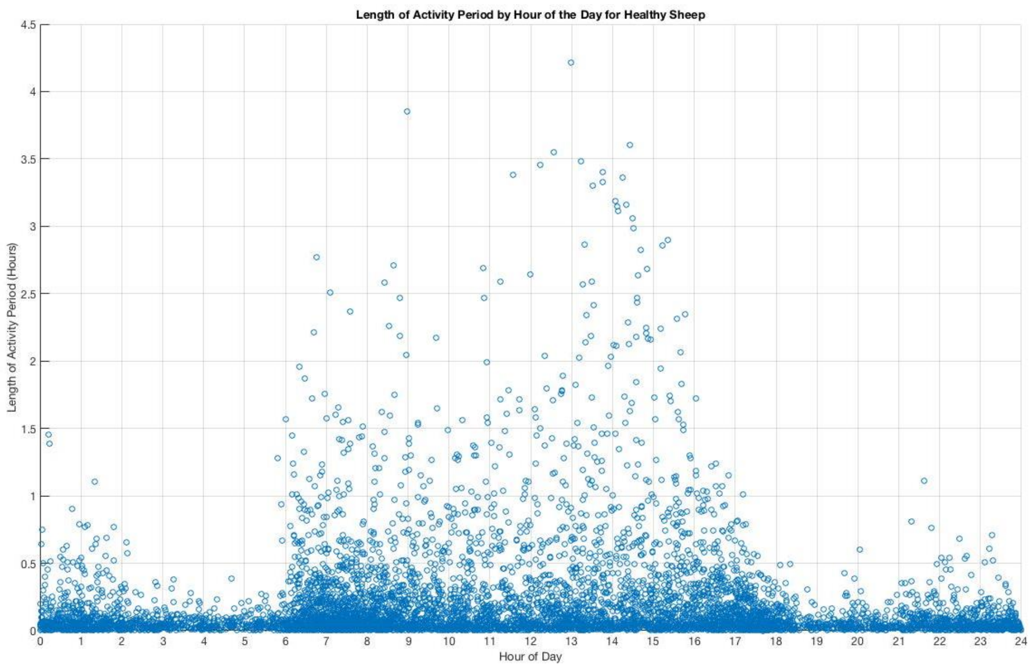


Figure 7-7. Activity period lengths vs. start time with the day for all four healthy sheep across the entire study period.

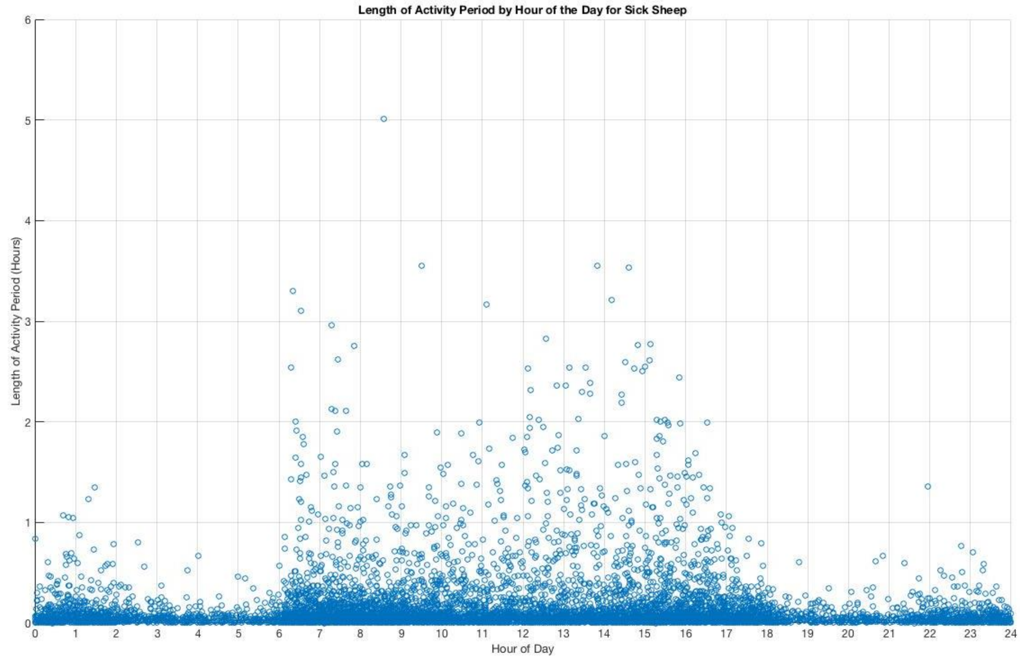


Figure 7-8. Activity period lengths vs start time with the day for all four sick sheep across the entire study period.

7.4.7 Testing for a difference in activity length engagement between 'healthy' and 'sick' animals

Figure 7-9 shows a plot of the survival functions, with the *Y-axis* being the probability and the *X-axis* plotting the activity period duration. There is a clear difference between the functions, with the estimated survival function for the sick animals showing lower probabilities for longer activity durations. This significant difference was confirmed through the use of a log-rank test on the two survival functions, which produced a Z-Score value of 12.63 ($p = 0.000$). This allows for the rejection of the (null) hypothesis that the survival functions are the same, indicating that there is a statistical difference between the distributions of activity durations between the two groups.

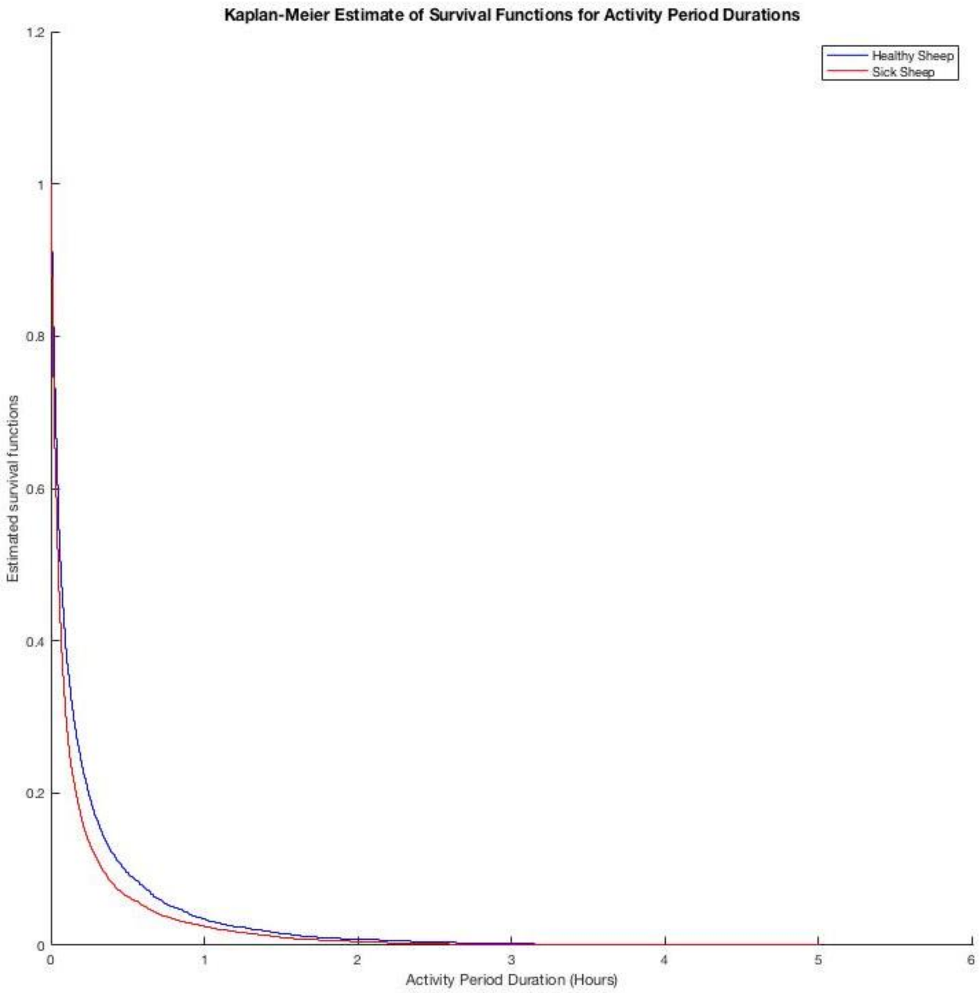


Figure 7-9. Kaplan-Meier Estimates for the survival function based upon the activity period durations for the healthy and sick groups.

From Figure 7-9, it can be concluded for a given period of activity, healthy sheep have a higher probability of engaging in that activity for a longer duration. In comparison sick animals have a lower probability of engaging in activities for the same period of time as their healthy counterparts.

7.5 Discussion

Observations of animal activity and behaviour have been used for hundreds of years to detect illness (Smith et al., 2015). The objective of this study was to investigate the potential of using accelerometer sensors to detect movement related symptoms of *Haemonchus contortus* infection in Merino ewes and as such quantitatively validate activity changes associated with infection. Based on previous studies by Worsley-Tonks and Ezenwa (2015) and Falzon et al. (2013), it was hypothesised that subtle changes in behaviour would manifest as an increase in activity in accordance with haemonchosis progression. It was anticipated these behaviour changes could be detected by accelerometers through documenting the proportion of time animals spent in an active and compared to an inactive state.

7.5.1 Behaviour classification and the value in simplifying basic behavioural states

A highly accurate mutually exclusive behaviour classifier was developed using *MV, AI* and *Mean-Y* features derived from ear mounted accelerometer signals in Chapter 6 of this thesis. One of the main differences between the data analysis in previous chapters (5 and 6) and this experiment, was the reduction of behavioural states to a simple active compared to an inactive state. This was done to maximise the overall prediction accuracy. A similar categorisation of behaviours as "active" and "inactive" was used by Umstätter et al. (2008). The "active" class combines grazing and walking as these behaviour types often occur in unison, with walking commonly performed during a grazing bout. The "inactive" class combined both lying and standing postures. Because of the similar orientation and motion experienced by the sensor within these behaviours, discrimination between the two was difficult, often leading to a high rate of misclassification. Using only two behaviour classes, it was possible to gain information on the percentage of time animals spent active and resting allowing the study of diurnal activity patterns. The diurnal patterns (Figure 7-7 and Figure 7-8) support previous research that the main period of activity occurs during daylight hours, except for a short grazing event around midnight which is similar to that reported by (Broom & Fraser, 2007). This provides confidence that the moving window behaviour classifier was able to identify sheep's active and inactive states successfully.

Over the entire study period, animals spent on average 37.6% of the day in an active state, as calculated from the classification model. This was similar to total grazing times previously reported for ruminants (Gregorini, 2012). Comparing the moving window results in Chapter 6 of this thesis, grouping behaviour into an "active" and "inactive" class substantially improves the classification success and this approach is recommended in future studies to reduce ambiguity between similar acceleration signals. Having only two behaviour classes also improves the simplicity and energy efficiency of the classification algorithm, making it more suitable for an embedded processing system classifying behaviour in real time.

7.5.2 Sensing behavioural changes related to worm infestation

The common diagnostic indicators of *H. contortus* infection, Haematocrit, FAMACHA and strongyle EPG count demonstrated a successful *H. contortus* infection was not established over the 41 day study period. The high condition score of test animals, frost and weather conditions across the study period may have contributed to this. The strongyle EPG counts show that some animals were infected, however these counts were very low. Based on these EPG counts, the threshold where an effect on production may commence varies within the literature. However, drenching is often recommended for EPG values in the range of 500-2000 (Brightling, 2006). Based on this recommendation, no animals within this current study would require anthelmintic treatment. It is well known that a threshold parasite level within the host needs to be reached in order for any effects on the host performance to become evident (Brightling, 2006; Sandberg, Emmans, & Kyriazakis, 2006). Therefore, because of the lack of infection, any documented activity changes between treatment and control animals would be minimal and this is reflected in the analysis comparing activity proportion between "healthy" and "sick" animals.

The analysis of total activity times supports the biological measurements indicating that there was no significant treatment effect. In all three scenarios modelled, treatment did not have a significant effect on the proportion of time animals spent active. Proportion of time spent active was significantly affected by day in each model which highlights the substantial variation in activity within sheep between days. Reasons for differences between days is unknown but a possible explanation could include environmental and ecological effects with wind, rain and heat all affecting the length of grazing activity (Fraser, 1974; Gregorini, 2012; Ratner & Hafez, 1975). Changes in feed composition may also account for some of this variation. Although the methods used to analyse the data differ from traditional approaches, given the very mild infection level, having all the original treatment animals in the model, even though they were showing no signs of infection, may have been masking some of the subtle changes in daily activity between the "healthy" and "sick" animals. The aim was to identify animals which, based on the biological measurements, were candidates for showing signs of being affected by internal *H. contortus*. Therefore, this approach seemed appropriate and justifiable, although a significant treatment effect was not identified.

The survival functions illustrate a clear visual difference between "healthy" and "sick" animals based on EPG counts, with the estimated survival function for the "sick" animals showing lower probabilities for longer activity durations. There is consistent evidence that feed intake is reduced during gastrointestinal parasitism in ruminants (Forbes et al., 2000; Hutchings et al., 2000; Kyriazakis, Tolkamp, & Hutchings, 1998). The findings of the present study support those of Hutchings et al. (2000), that *Ostertagia circumcincta* infected lambs had shorter grazing bouts than controls, even though there was no difference in total grazing events. Similarly, studies with cattle have revealed no significant effect of parasitism on overall activity distribution (Szyszka & Kyriazakis, 2013; Szyszka et al., 2012). Other studies with cattle have described a reduction in grazing time (Forbes et al., 2000) with this being the proposed dominant reason for the reduction in animal performance (Kyriazakis & Tolkamp, 2010). The findings of this current study contradict those of Falzon et al. (2013) in which parasitised sheep had a greater distance per time step. This current study has demonstrated that infected animals were less likely to engage in active bouts of similar lengths compared to their uninfected "healthy" counterparts. Given there was no change in body weight or condition score, it is unlikely total herbage intake was reduced in the "sick" animals.

7.5.3 Inter-animal and inter-day variation in behaviour

A key finding was the large inter-animal variation in activity proportions. The first model included all animals across all experimental days, indicated the significance of individual sheep for a difference in activity proportions and is also evident in Figure 7-4. It has previously been found that individual animals differ greatly in their behaviour (Theurer et al., 2013) which is supported by the current findings. Possible explanations for this variation include: (1) the behaviour classification accuracy of the classifying model used. Either the model is correct and there is a large variation between animals or the model is incorrectly classifying behaviour in some circumstances and, (2) differences in the ear structures between animals resulted in a slightly different sensor orientation which ultimately influenced the recorded acceleration. This will affect the behaviour classification given the different metric values resulting in those behavioural events falling into the incorrect behaviour class when using the QDA. Some sources of signal variation between animals (González et al., 2015) and additional discussion on this inter-animal variation was provided in Chapter 6 of this thesis.

To date there have been limited studies which have quantitatively validated the movement related symptoms associated with *H. contortus* infection in sheep. Comparison of studies with either cattle or sheep with different infecting parasites must be viewed with caution as effects on the host are often parasite species specific and the physiological effects may also result from the level of animal resistance and resilience to that specific parasite. An obstacle of using this approach is its dependency on establishing normal baseline activity levels and as highlighted by Theurer et al. (2013), individual animals differ greatly in behaviour. Accelerometer derived algorithms used for the detection of BRD infected cattle cannot be easily generalised across years and herds with health status requiring comparison of activity counts of all animals of the herd at the same point in time (Smith et al. 2015). Also, it is possible that behaviours other than those addressed here such as social behaviour and spatial movement patterns could be captured by automated means and used for the purposes of monitoring health status (Szyszka et al., 2012). This was beyond the scope of the current study, however further research should address this possibility.

7.6 Conclusions & future research

The current study demonstrates preliminary research into the application of using accelerometer sensors to detect changes in behaviour associated with internal parasitism. Given the small level of established infection in the present study, the sample size was small and observed behaviour changes were mild. Based upon using EPG as a determinant for infection level with animals regrouped into "healthy" and "sick" categories, survival analysis indicated that animals with a moderate EPG count had a lower probability of performing an active bout for the same length of time compared to their uninfected 'healthy' counterparts. A greater sample size may allow for better understanding of the host behaviour adaptations to varying levels of infection. Future research should focus on identifying the host-behaviour changes which occur with increasing parasitic load. This will allow the development of algorithms which will trigger an alert when these behaviour changes occur, substantially enhancing the commercial applicability of this technology.

Chapter 8

Predicting lameness in sheep using tri-axial acceleration signals

8.1 Introduction

Lameness is known to be a painful condition. Pain is defined as "an unpleasant sensory and emotional experience associated with actual or potential tissue damage" (Merskey, 1986). One approach for assessing pain in animals is to examine their behaviour (Weary et al., 2009). Until recently, behavioural assessments of illness have relied on subjective clinical evaluation based on the accumulated experience of livestock handlers which is prone to poor reliability (Weary et al., 2009). Sheep behaviour is frequently monitored to determine the health and wellness state of the animal. Identifying lame behaviour requires analysis of the animal's gait. There are several methods available to analyse gait characteristics including visual observation, pressure measuring devices (Besancon, Conzemius, Derrick, & Ritter, 2003; Kim & Breur, 2008; Lascelles et al., 2006; Oosterlinck, Pille, Huppes, Gasthuys, & Back, 2010; Rajkondawar et al., 2006; Seebeck et al., 2005), video signals (Maertens et al., 2007; Pluk et al., 2009) and accelerometer systems. A visual based numerical rating scale to assess sheep locomotion comprising of five categories (0 = normal movement, 1 = occasional limping, 2 = lifting foot when standing, not lame when moving, 3 = carrying foot, but lame on movement and 4 = carrying foot at all times) was developed by Ley, Livingston, and Waterman (1989). A similar rating system was developed by Welsh, Gettinby, and Nolan (1993). These and similar visual locomotion scoring systems require the observer to distinguish normal from abnormal walking behaviour. An in-depth description of sound and lame locomotion is provided in Section 2.3.2 and Section 4.4 of this thesis. As these scoring systems are based on observer judgment, they are open to some degree of subjective interpretation (Van Nuffel et al., 2015).

In the field, the categorisation of an animal as lame is subjective, being based on farmer opinion and the inherent level of lameness which is accepted before treatment is required. This differs across farms (Kaler, 2008). Reliant on subjective visual observer rating, Kaler (2008) reported the greatest disagreement between observers occurred between scores 0 and 1 (using numerical rating scales developed by Welsh et al. (1993) and Ley et al. (1989)). This indicates that some observers could not differentiate between a normal and occasional limping gait. Therefore, subtle signs of lameness could potentially be missed through visual observation in the early stages when detection and the commencement of treatment are valuable to limiting production losses. Additionally, the average overall exact agreement between and within observers was 68% which indicates a difference in how observers objectively categorise animals as being lame (Kaler, 2008). This bodes well for the adoption of a subjective detection system.

Whilst visual locomotion scoring has the advantage of being implemented on any farm at any given time, practical considerations should be taken into account. In addition to the inconsistency of locomotion scoring, assessing the gait of individual sheep in a flock can be practically challenging. Sheep being a prey species and stoic in nature, lame animals may mask the signs of vulnerability, because this would make them an easier target for predators (Weary et al., 2009). Therefore, animals may tend to only show lame locomotion and behaviour when the lameness is at an advanced stage. Also, any scoring of the entire flock only provides prevalence information for that specific moment and daily monitoring of locomotion and behaviour on farm by a trained observer is too time-consuming and thus very cost inefficient (Van Nuffel et al., 2015).

There is no gold standard to assess locomotion as each approach has its own advantages and disadvantages (Kaler, 2008). Currently, approaches used to define locomotion include the observation of stride length, duration of weight bearing on both affected and unaffected limbs, body posture and joint movement (Sprecher, Hostetler, & Kaneene, 1997). The main disadvantage of these methods is the requirement for a visual appraisal of each animal. Utilization of technology to automatically record behaviour allows for collection of objective values without the need for human observation. However, systems need to be developed that allow reliable and repeatable measurements of behaviours capable of indicating animal wellness state (Robert et al., 2009; Weary et al., 2009). Martiskainen et al. (2009) stated that an automated monitoring system capable of observing several detailed behaviour patterns would be welcomed in animal production as an aid to assess health and welfare and measures of activity may be useful to assess welfare and health (De Passille et al., 2010). Monitoring systems must be able to recognize behavioural signatures associated with normal behaviour and with non-normal behaviour indicative of compromised welfare status or the onset of specific diseases (Greenwood et al. 2014).

Accelerometry systems monitoring activity can also be used for lameness estimation (Kokin et al., 2014). Accelerometers have previously been used to detect lameness in horses (Keegan et al., 2001; Keegan, Yonezawa, Pai, Wilson, & Kramer, 2004; Scheibe & Gromann, 2006), beef cattle (Scheibe & Gromann, 2006) and dairy cows (Chapinal et al., 2010; Higginson et al., 2010; Kokin et al., 2014; Martiskainen et al., 2009; Pastell, Tiusanen, Hakojärvi, & Hänninen, 2009). In cattle, lameness has commonly been detected via a change in daily activity or a change in recumbent posture (Blackie et al., 2011; Chapinal et al., 2010; Kokin et al., 2014; Callaghan, Cripps, Downham, & Murray, 2003). Few studies have attempted to identify lameness through a difference in acceleration signal. Lame and sound cows from four leg deployed accelerometers using variance and wavelet variance for each axis along with total leg acceleration were distinguished by Pastell et al. (2009). Similarly, Blomberg (2011) identified differences in the acceleration across all gait phases between normal and lame cows. Raw acceleration differences between lame and sound animals were not evident but differences in symmetry between the legs were detected. Using SVM classification models, Martiskainen et al. (2009) achieved a reasonable recognition of standing (80% sensitivity, 65% precision), lying (80%, 83%), ruminating (75%, 86%), feeding (75%, 81%), walking normally (79%, 79%), and lame walking (65%, 66%) in dairy cows using collar deployed accelerometers. Using a decision/regression tree algorithm, Al-Rubaye, Al-Sherbaz, McCormick, and Turner (2016) proposed using a wither mounted accelerometer to detect lameness in sheep. The results from this work are yet to be published.

Automatic measurement of activity related to normal and abnormal behaviour characteristics would allow for daily activity measurements and compared to the traditional approaches, could therefore be a better option (Van Nuffel et al., 2015). Previous experiments have validated the ability of accelerometers to consistently and reliably describe sheep behaviour patterns in a controlled environment. The ability of such devices to detect changes in movement symptoms related to lameness is yet to be evaluated.

8.2 Research Objectives

Improving lameness detection at pasture is constrained by labour availability and costs. Therefore, the aim of this experiment was to determine the potential for using collar, leg and ear deployed accelerometers to differentiate between normal and lame behaviour based on a change in acceleration signature. To achieve this the following objective was investigated:

1. Develop an ear, leg and collar behaviour prediction model to discriminate between mutually exclusive sound and lame related movement behaviours using accelerometer signals obtained from multiple sheep.

8.3 Materials & methods

This experiment was conducted immediately following the experiment described in Chapter 5, Part B. The quantification of normal behaviour in animals (described in Section 5.5) will be referred to as "Phase I" and the recording of lame behaviours described below will be referred to as "Phase II". Phase II comprises of 2 different levels of classification, referred to here as "Analysis I" and "Analysis II".

This experiment was approved by the University of New England Animal Ethics Committee (AEC14-066) and followed the University of New England code of conduct for research in meeting the Australian Code of Practice for the care and use of animals.

8.3.1 Animals

Please refer to Section 5.5 of this thesis.

8.3.2 Observations

Observations were conducted using the same process described in Section 5.5.3.

8.3.3 Instrumentation

Accelerometers were attached to animals as described in Chapter 5, Section 5.5.2. Following this period of "sound" behaviour observations (Phase I), accelerometers were removed and animals were allowed to rest for approximately 20 minutes. The same animal was then re-instrumented with accelerometers and released with 2 companion animals and the "lame" behaviour observations (Phase II) commenced. Each observation session lasted approximately 2 hours. Accelerometer and video observation files were downloaded after the recording event was completed on individual sheep. This process was repeated for 5 animals.

8.3.4 Lameness simulation

To simulate lameness, the sheep's front leg was tied up using VETFLEX bandage. The hoof was bent backwards and tied back near the fetlock joint (Figure 8-1). This method allowed the leg to remain straight however the animal was unable to bear any weight on the restrained limb. Using the visual rating scale developed by Ley et al. (1989), this restraint method would be regarded as a category 4 (carrying leg at all times).

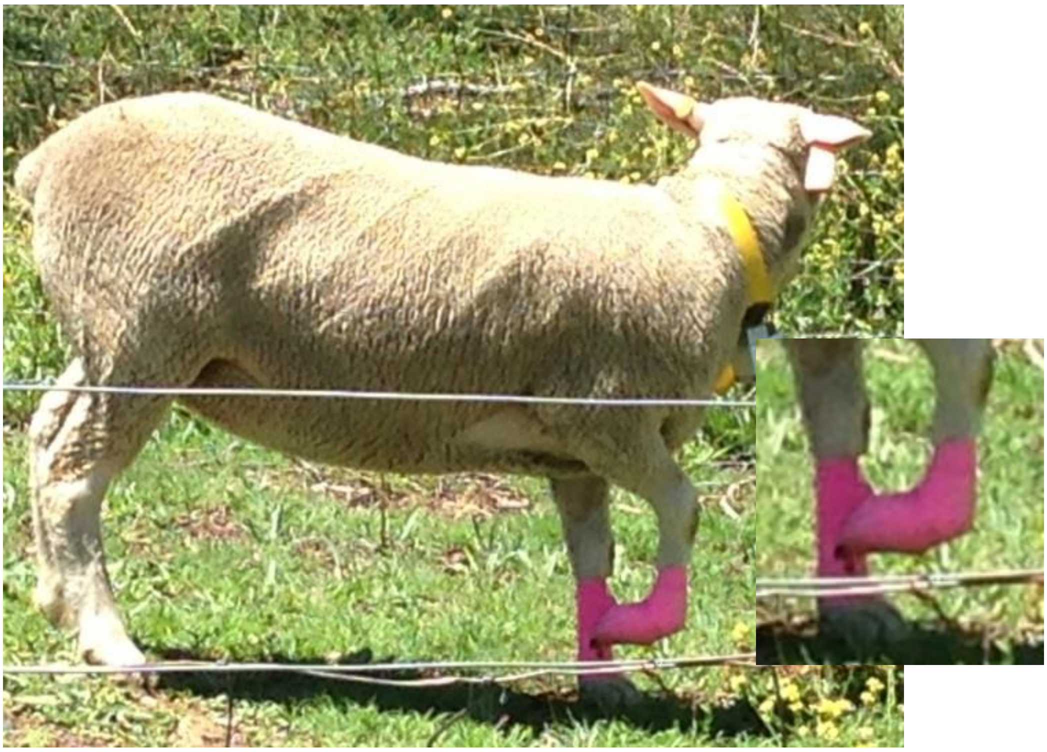


Figure 8-1. Experimental animal showing the method used to simulate lameness behaviour. The method of restraint prevented any weight bearing on the restrained limb.

8.3.5 Developing the behavioural classification model

The steps to building the classification model were the same as that described in Chapter 5, Part B (refer to Figure 5-5). Lame recordings were analysed as a mirror image of the sound behaviours creating four behaviour classes for classification: lame walking, lame standing, lame grazing and lame lying. Lame lying and lame standing were excluded from the analysis as these behaviours confused the classifier and were misclassified with their corresponding sound behaviours, due to similarities between the two signals (data not shown). This left the following six behaviour classes for discrimination using the QDA: lame walking, lame grazing, sound walking, sound grazing, sound standing and sound lying (where available).

Accelerometer data were downloaded and annotated with the corresponding video recordings (refer to Section 3.6.1). The following features were extracted for each

10 second epoch; *Ax, Ay, Az, MV, SMA, AI, MI, Entropy*, *Energy Min-X, Min-Y, Min-Z, Max-X, Max-Y* and *Max-Z,* using equations 1 to 15. Data files within each deployment were combined following metric calculations creating a single file for each deployment.

Metrics were selected using Random Forest variable importance analysis. Given the similarities between some "sound" and "lame" behaviours, the data were separated into two analyses. Analysis I included sound walking, sound standing, sound grazing, sound lying (where data were obtained), lame walking and lame grazing. Analysis II excluded lame grazing in an attempt to reduce the level of misclassification between lame and sound grazing events. As this experiment classified lame behaviour based on a change in acceleration signal (creating new behaviour categories), feature selection was required to select the subset of metrics of most importance. As additional behaviour classes were included, the same metric combination identified in Chapter 5 may not be relevant here. Feature selection using Random Forest was performed on Analysis I and Analysis II separately and the three highest ranked features were used as the discriminating metrics for the QDA classifier.

Leave-one-out cross validation was performed on the QDA model for each deployment. Accuracy, sensitivity, specificity, precision and total accuracy were calculated for the cross validated results using equations 16 to 19.

8.4 Results & discussion

This study was divided into two phases: Phase 1 (sound behaviour which was analysed in Chapter 5 Part B) and Phase 2 (lame simulation behaviour). Observation periods for each phase lasted approximately 2 hours per animal allowing enough time for the animals to perform recorded behaviours. The sound events reported in Chapter 5 Part B were needed for comparison with the lame observations. This minimised the between-sheep variability as lame and sound movement data were recorded for the same animals.

8.4.1 Observations

Observational periods were the same for all deployments as accelerometers were attached to the three locations simultaneously. Because of accelerometer malfunction the recorded behaviour events differ between deployments. Only 10 second epochs containing mutually exclusive behaviours were used in this analysis. That is, all transitional behaviours were removed. The total number of 10 second epochs of mutually exclusive behaviour obtained for each recorded behaviour within the three deployments for both Phase 1 and Phase II observation sessions are shown in Table 8-1.

Table 8-1. Total number of 10 second mutually exclusive behaviour epochs. The number of animals for which behaviours were collected within each deployment is shown in parentheses.

		Total # of 10 second epochs		
		Collar	Leg	Ear
Phase I	Sound walking	95(3)	94(3)	274(5)
	Sound standing	106(3)	106(3)	862(5)
	Sound grazing	298(4)	298(4)	342(5)
	Sound lying	40(1)	46(1)	0(0)
Phase II	Lame walking	88(3)	92(4)	98(4)
	lame standing	62(3)	93(4)	97(4)
	Lame grazing	171(3)	181(4)	182(4)
	Lame lying	236(3)	279(4)	279(4)

8.4.2 Ear deployment

Analysis I

For the ear deployment data set including behaviour categories sound walking, grazing, standing and lame walking and grazing, the RF variable selection yielded the following order of importance of metrics as determined by the mean decrease in Gini value: *MV, Ay, Energy, SMA, AI, Min-X, Max-Y, Max-X, Min-Z, Az, Min-Y, Max-Z, Ax* and *Entropy.*

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using features *MV, Ay* and *Energy* is presented in Table 8-2

Table 8-2. QDA confusion matrices of the evaluation and leave-one-out cross validation analysis for the ear deployed accelerometer data using derived metrics *MV, Ay* and *Energy* for mutually exclusive sound (grazing, standing and walking) and lame (walking and grazing) behaviours. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)				
	Sound grazing	Sound standing	Sound walking	Lame walking	Lame grazing
Evaluation data set			QDA		
Sound grazing	**287**	42	5	6	131
Sound standing	44	**812**	2	3	11
Sound walking	1	4	**242**	9	3
Lame walking	0	0	13	**78**	2
Lame grazing	10	3	11	2	**35**
Prediction accuracy	*84%*	*94%*	*89%*	*80%*	*19%*
Cross validation			QDA		
Sound grazing	**287**	42	5	6	131
Sound standing	44	**812**	2	3	11
Sound walking	1	4	**241**	9	3
Lame walking	0	0	14	**78**	3
Lame grazing	10	3	11	2	**34**
Prediction accuracy	*84%*	*94%*	*88%*	*80%*	*19%*

Little difference was observed between the evaluation and cross validation results for any of the five behaviour categories. Sound standing and walking behaviour events were well classified (94% and 88% prediction accuracy) while lame walking had slightly lower prediction accuracy (80%) due to misclassification with sound and lame grazing. A number of grazing events were misclassified as normal standing (44) and this reduced the overall prediction accuracy of normal grazing (84%). Lame grazing events were often misclassified with sound grazing, therefore the prediction accuracy of lame grazing was poor (19%).

Analysis II

For the ear deployed data set including behaviour categories sound walking, grazing, standing and lame walking, the RF variable selection yielded the following order of importance of metrics as determined by the mean decrease in Gini value: *MV, AI, Ay, SMA,* *Energy, Min-Z, Min-X, Az, Max-Y, Min-Y, Ax, Max-Z, Entropy* and *Max-X.* These are the same features selected in Section 5.6.4.

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using features: *MV, Ay* and *AI* are presented in Table 8-3.

Table 8-3. QDA confusion matrices for the evaluation and leave-one-out cross validation analysis for the ear accelerometer data using derived metrics; *MV, Ay* and *AI* for mutually exclusive sound (grazing, standing and walking) and lame (walking) behaviours. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)			
	Sound grazing	Sound standing	Sound walking	Lame walking
Evaluation data set	QDA			
Sound grazing	**321**	26	1	6
Sound standing	15	**830**	1	3
Sound walking	2	5	**262**	9
Lame walking	4	0	9	**80**
Prediction accuracy	*94%*	*96%*	*96%*	*82%*
Cross validation	QDA			
Sound grazing	**321**	26	1	6
Sound standing	15	**830**	1	3
Sound walking	2	5	**262**	9
Lame walking	4	0	9	**80**
Prediction accuracy	*94%*	*96%*	*96%*	*82%*

Removing lame grazing from the model improved the prediction accuracy of all remaining behaviours. Lame walking events were still misclassified as sound walking while fewer grazing events were misclassified as standing, increasing grazing prediction accuracy from 84% to 94%. Fewer sound walking events were misclassified.

The head position provides valuable information for the detection of different behaviours including disturbed behaviour patterns (Scheibe & Gromann, 2006). Discriminating lame walking from other behaviours, predominantly sound walking, relies on the increased range of motion experienced by the sensor created from the 'head bobbing' action characteristic of abnormal quadruped gait movement (Distl & Mair, 1993; Flower et al., 2006; Nordlund et al., 2004). The increased acceleration experienced by the sensor during lame walking in shown in Figure 8-2. In comparison with normal walking, during lame walking the *X* and *Y* axes record a greater acceleration amplitude, indicative of the increased swinging motion the sensor experiences resulting from the uneven weight distribution during lame locomotion.

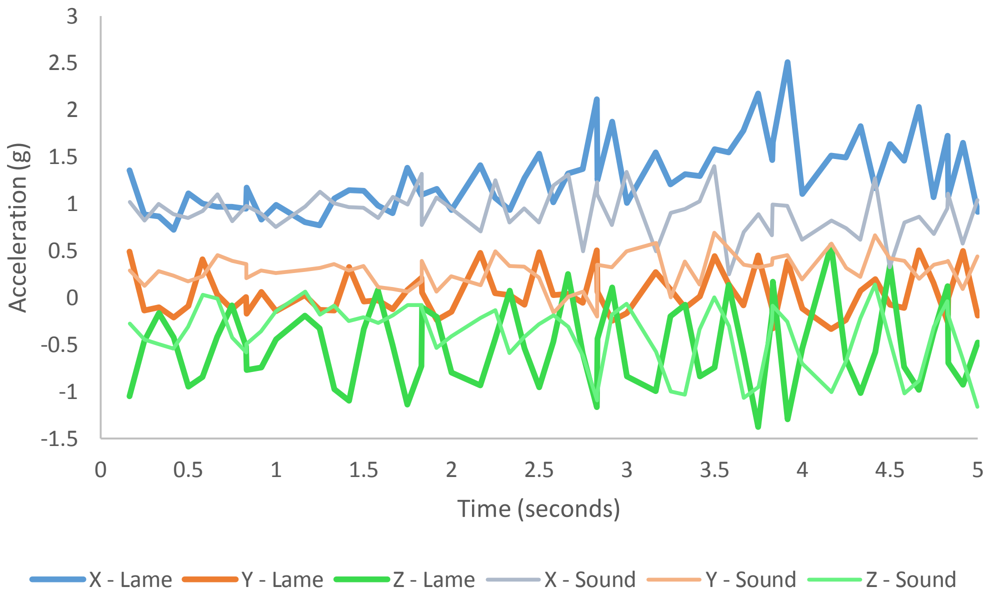


Figure 8-2. Raw ear acceleration signals for sound and lame walking. Note the increased amplitude of lame walking.

This is further reflected in the higher *AI, MV* and *Ay* metric values for lame walking compared to sound walking (Figure 8-3). The extent of this difference was much lower between sound and lame grazing (data not shown), hence the poor classification of lame grazing events.

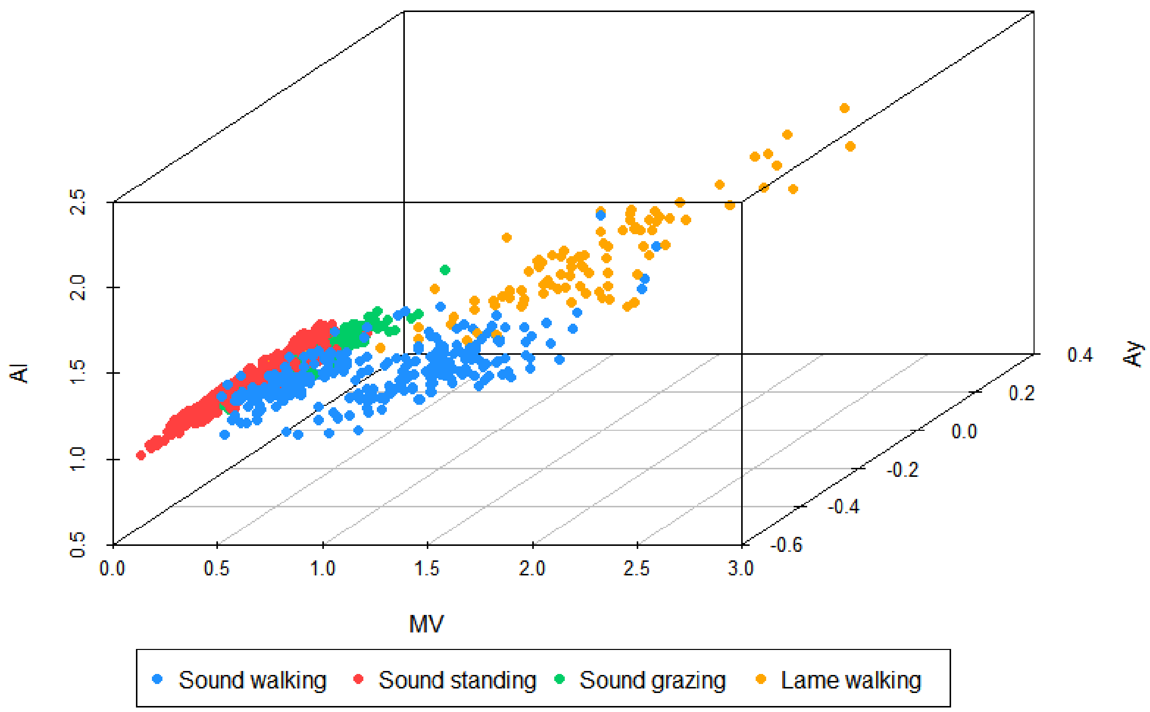


Figure 8-3. 3D scatterplot of mutually exclusive behavioural events extracted from the ear deployed accelerometer using *AI, Ay* and *MV* metric values.

The clustering of behavioural classes is shown in Figure 8-3. As the same metrics were selected as in Chapter 5 Part B, this plot is very similar to Figure 5-8. Crossover between lame walking and sound walking is apparent which is reflected by the misclassifications in the QDA matrices (Table 8-3). Lame walking events show a greater spread in all three planes which reflect the head bobbing motion observed with abnormal locomotion creating a higher range in sensor in motion. The uneven weight distribution in lame animals (Flower et al., 2006) further distorts the sinusoidal acceleration signal associated with sound walking activity, shown here by the higher values for metrics measuring the intensity of movement (*AI* and *MV*). This hobbling action resulting from an uneven weight distribution on the fore and hind limbs is one of the first signs of lameness identified by sheep farmers (Ford & Brian, 2016) highlighting the potential advantages of using such technology to aid in detection.

Using the change in ear motion to provide information on health status in ruminants has previously been proposed. Accelerometer tags attached to feedlot cattle to quantitatively measure ear drooping as “droopy ears” can potentially indicate illness

(Nagely, 2012). Whilst this is different to the objective investigated in the present study, it highlights an application of using ear motion to provide information on animal health status.

The agitation and discomfort associated flicking of the head which has previously been linked with lameness (Kaler, 2008) was not observed in the present study. The simulated lameness system employed in this current study did not result from the animal experiencing pain. Rather the method of restraint simply prevented the animal from bearing any weight on the restrained limb. Future work may investigate alternate methods of lameness simulation i.e. turpentine injection (Colditz, Paull, Hervault, Aubriot, & Lee, 2011) as this excessive movement of the head potentially holds classification value for the detection of individuals with early signs of lameness.

The performance statistics of the leave-one-out QDA classification matrix from Analysis II (Table 8-3) is presented below in Table 8-4.

Table 8-4. Performance values of the QDA leave-one-out cross validation model using metrics *MV*, *AI* and *Ay*.

	Sound grazing	Sound standing	Sound walking	Lame walking
MV, AI, Ay				
Sensitivity	94%	96%	96%	82%
Specificity	97%	97%	99%	99%
Accuracy	96%	97%	98%	98%
Precision	91%	98%	94%	82%
Total accuracy		*97%*		

The overall performance of the QDA model was high. Accuracy values for all behaviours were greater than 95% and the overall total accuracy of the classifier was high (97%). However, the unbalanced structure of the data makes this measure difficult to interpret (Kubat, Holte, & Matwin, 1998) and therefore other measures of model performance are more informative. Specificity for all behaviour categories was high (>96%). Sensitivity values were good for all sound behaviours but slightly lower for lame walking resulting from 18 events being misclassified for this behaviour class. Similarly, precision for this behaviour was moderate (82%) as 13 behaviour events were incorrectly predicted as lame walking. Similar to the model used by Martiskainen et al. (2009), this indicates the classifier had difficulty in predicting positive cases for the lame walking category, suggesting that this behaviour pattern is most easily confused with other behaviours.

8.4.3 Leg deployment

Analysis I

For the leg deployed data set including behaviour categories sound walking, grazing, standing and lying and lame walking and grazing, the RF variable selection processes yielded the following order of importance of metrics as determined by the mean decrease in Gini value: *Ax, SMA, Az, AI, MV, Max-Y, Max-X, Max-Z, Energy, Entropy, Ay, Min-Y, Min-X* and *Min-Z.*

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using features *Ax, Az* and *SMA* are presented in Table 8-5.

Little difference was observed between the evaluation and cross validation results for any of the six behaviour categories. Sound grazing, sound walking, sound lying and lame walking were well classified. Sound standing events were misclassified with sound grazing (similar to Section 5.6.2). Lame grazing had a poor prediction accuracy due to many events being recorded as sound grazing and standing (55 and 105 events, respectively). As lame animals tend to move less, the stepping motion when grazing may have been reduced, resulting in more misclassifications as standing.

Table 8-5. QDA confusion matrices for the evaluation and leave-one-out cross validation analysis for the leg accelerometer data using derived metrics; *Ax*, *Az* and *SMA* for mutually exclusive sound (grazing, standing, walking and lying) and lame (walking and grazing) behaviours. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)					
	Sound grazing	Sound standing	Sound walking	Sound lying	Lame walking	Lame grazing
Evaluation data set	QDA					
Sound grazing	**263**	33	0	0	5	55
Sound standing	33	**72**	0	0	6	105
Sound walking	0	0	**82**	0	2	0
Sound lying	1	0	0	**46**	0	8
Lame walking	1	0	12	0	**80**	6
Lame grazing	0	1	0	0	0	**7**
Prediction accuracy	*88%*	*68%*	*87%*	*100%*	*86%*	*4%*
Cross validation	QDA					
Sound grazing	**262**	34	0	0	5	55
Sound standing	33	**71**	0	0	6	105
Sound walking	0	0	**81**	0	2	0
Sound lying	2	0	0	**46**	0	8
Lame walking	1	0	13	0	**80**	6
Lame grazing	0	1	0	0	0	**7**
Prediction accuracy	*88%*	*67%*	*86%*	*100%*	*86%*	*4%*

Analysis II

For the leg data set including behaviour categories sound walking, grazing, standing and lying and lame walking, the RF variable selection processes yielded the following order of importance of metrics as determined by the mean decrease in Gini value: *Ax, SMA, AI, Max-X, Az, MV, energy, Max-Y, entropy, Min-X, Ay, Max-Z, Min-Y* and *Min-Z*

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using features: *Ax, SMA* and *AI are* presented in Table 8-6.

Table 8-6. QDA confusion matrices for the evaluation and leave-one-out cross validation analysis for the leg accelerometer data using derived metrics; *Ax*, *SMA* and *AI* for mutually exclusive sound (grazing, standing, walking and lying) and lame (walking) behaviours. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)				
	Sound grazing	Sound standing	Sound walking	Sound lying	Lame walking
Evaluation data set			QDA		
Sound grazing	**267**	42	0	0	3
Sound standing	26	**63**	0	0	6
Sound walking	0	0	61	0	3
Sound lying	0	0	0	**46**	0
Lame walking	5	1	33	0	**81**
Prediction accuracy	*90%*	*59%*	*65%*	*100%*	*87%*
Cross validation			QDA		
Sound grazing	**266**	44	0	0	3
Sound standing	26	**61**	0	0	6
Sound walking	0	0	**60**	0	3
Sound lying	0	0	0	**46**	0
Lame walking	6	1	34	0	**81**
Prediction accuracy	*89%*	*58%*	*64%*	*100%*	*87%*

Again, little difference was observed between the evaluation and cross validation results. Sound grazing and lying and lame walking were well predicted, however sound walking prediction accuracy was substantially reduced in this model with 34 events being misclassified as lame walking. Also, sound standing was slightly reduced with more events being misclassified as grazing. Due to the reduced stepping action observed during grazing behaviour in lame animals, the recorded signals between these two behaviours are similar resulting in the high misclassification rate. As the instrumented limb was bearing all the forequarter weight of the animal, a reduced amount of movement when grazing was evident. Further work is required to validate overall change in activity levels of lame animals in the field.

Alternating the instrumented limb between the fore and hind legs could potentially change the recorded acceleration signals thereby affecting the behavioural classification. Differences have been reported in the measured variance value between the hind and foreleg of cattle for the forward and vertical axes (Pastell et al., 2009). Also, when cows are lame on both hind limbs, weight is seldom transferred to the front limbs in an attempt to reduce pressure on the painful limbs. In contrast, cows that were lame on both front limbs were found to transfer some of the weight to the hind limbs. This work demonstrated the ability to discriminate between normal and unhealthy legs of dairy cows using wavelet variance and sensor axis symmetry to associate gait changes. Therefore, the instrumentation of normal and lame legs has the potential to highlight further acceleration differences due to the abnormal movement pattern of the lame limb. Whilst successful, the additional instrumentation of all limbs is impractical for long-term use in a commercial operation. However, instrumentation of multiple limbs should be a focus of future research to validate the acceleration signatures between the fore and hind limbs of sheep.

Similar to the scatterplot shown in Figure 5-7, the close clustering between sound grazing and standing is evident, substantiating the misclassification between these two behaviours (Figure 8-4). The misclassification of sound walking with lame walking is further justified in Figure 8-4 as there is no clear differentiation between these two behaviours making it difficult for the classifier to discriminate between them. Similarly, based on leg acceleration signals, Scheibe and Gromann (2006) found acceleration patterns differed only slightly between healthy and lame cows with the main differences being detected on the basis of power spectra of the resulting forces created by healthy and lame limbs.

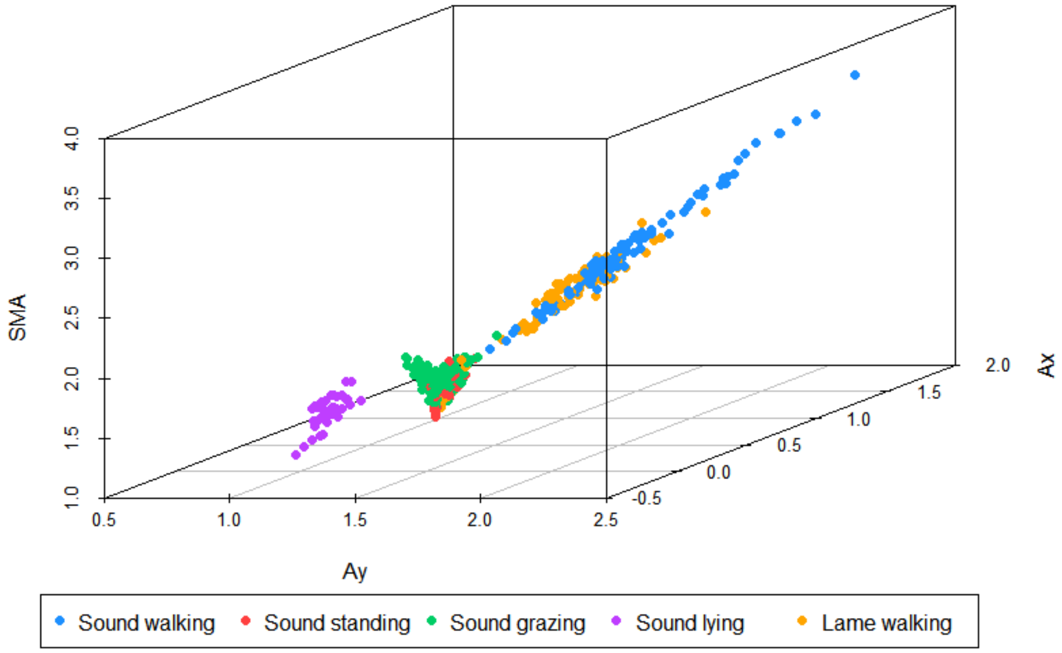


Figure 8-4. 3D scatterplot of mutually exclusive behavioural events extracted from the leg accelerometer using Ax, AI and SMA metric values.

The performance statistics of the leave-one-out QDA classification matrix from Analysis II (Table 8-6) is presented below in Table 8-7.

Table 8-7. Performance values of the QDA leave-one-out cross validation model using metrics *SMA*, *AI* and *Ax.*

	Sound grazing	Sound standing	Sound walking	Sound lying	Lame walking
Ax, SMA, AI					
Sensitivity	89%	**58%**	**64%**	100%	87%
Specificity	83%	94%	99%	100%	98%
Accuracy	86%	88%	94%	100%	96%
Precision	85%	**66%**	95%	100%	87%
Total accuracy			*93%*		

The overall performance of the leg QDA model was moderate. Accuracy was above 85% for all behaviours. Sensitivity for lame walking was high (87%), however misclassification rates for sound standing and walking behaviour categories resulted in these behaviour classes having a low sensitivity value (58% and 64%, respectively) suggesting a number of negative cases were misclassified as positive. Precision for all behaviours except sound standing was high. This suggests the standing behaviour was easily confused with other behaviours, namely grazing. Overall, the achieved classification of lame walking was similar to the ear accelerometer.

8.4.4 Collar deployment

Analysis I

For the collar deployed data set including behaviour categories sound walking, grazing, standing and lying and lame walking and grazing, the RF variable selection processes yielded the following order of importance of metrics as determined by the mean decrease in Gini value: *Ax, Az, Entropy, AI, Energy, Max-Z, MV, Max-X, Min-Z, Min-X, SMA, Min-Y, Ay* and *Max-Y*.

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using features *Ax, Az* and *Entropy* is presented in Table 8-8. There was little difference between the evaluation and cross validation results for any of the six behaviour categories. The biggest change was sound lying prediction decreasing from 60% to 56%. The prediction accuracies of sound grazing and sound walking were relatively good. However, sound standing, lying and lame walking and grazing predictions were poor. Lame grazing was predominantly misclassified with sound grazing (39 events), with sound standing being misclassified as sound grazing and walking (similar to Table 5-12). Lame walking was very poorly predicted (14%) because of misclassifications with sound standing and walking and lame grazing.

Table 8-8. QDA confusion matrices for the evaluation and leave-one-out cross validation analysis for the collar accelerometer data using derived metrics: *Ax, Az* and *Entropy* for mutually exclusive sound (grazing, standing, walking and lying) and lame (walking and grazing) behaviours. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)					
	Sound grazing	Sound standing	Sound walking	Sound lying	Lame walking	Lame grazing
Evaluation data set	QDA					
Sound grazing	**281**	25	1	1	0	39
Sound standing	0	**54**	11	1	29	14
Sound walking	12	22	**78**	13	13	2
Sound lying	2	5	5	**24**	15	4
Lame walking	0	0	0	1	**12**	3
Lame grazing	3	0	0	0	19	**109**
Prediction accuracy	*94%*	*51%*	*82%*	*60%*	*14%*	64%
Cross validation	QDA					
Sound grazing	**281**	26	0	0	0	39
Sound standing	12	**53**	12	3	29	14
Sound walking	0	22	**77**	13	13	2
Sound lying	2	5	5	**22**	4	4
Lame walking	0	0	0	1	**11**	4
Lame grazing	3	0	0	0	20	**108**
Prediction accuracy	*94%*	*50%*	*82%*	*56%*	*14%*	63%

Analysis II

For the collar deployed data set including behaviour categories sound walking, grazing, standing and lying and lame walking, the RF variable selection processes yielded the following order of importance of metrics as determined by the mean decrease in Gini value: *Entropy, Az, Max-Z, Energy, AI, MV, Ax, Min-X, Min-Z, Max-X, Ax, Min-Y, SMA, Ay* and *Max-Y*.

The confusion matrices obtained from the QDA evaluation and leave-one-out cross validation analysis using features *Entropy, Az* and *Max-Z* are presented in Table 8-9.

Table 8-9. QDA confusion matrices for the evaluation and leave-one-out cross validation analysis for the collar accelerometer data using derived metrics E*ntropy, Az and Max-Z* for mutually exclusive sound (grazing, standing, walking and lying) and lame (walking) behaviours. Correctly predicted events are shown in bold and misclassifications in red.

Predicted behaviour (events)	Observed behaviour (events)				
	Sound Grazing	Sound Standing	Sound Walking	Sound Lying	Lame walking
Evaluation data set			QDA		
Sound grazing	**283**	25	2	0	0
Sound standing	13	**54**	9	11	9
Sound walking	2	15	**63**	6	42
Sound lying	0	12	21	**21**	6
Lame walking	0	0	0	2	**31**
Prediction accuracy	*95%*	*51%*	*66%*	*53%*	*35%*
Cross validation			QDA		
Sound grazing	**283**	26	2	0	0
Sound standing	13	**53**	10	12	9
Sound walking	2	15	**60**	8	42
Sound lying	0	12	23	**18**	6
Lame walking	0	0	0	2	**31**
Prediction accuracy	*95%*	*50%*	*63%*	*45%*	35%

Removing lame grazing from the model increased the prediction accuracy of lame walking but reduced sound walking prediction accuracy. This resulted from an increase in sound walking events being misclassified as lying. Sound grazing and standing prediction accuracies were similar across Analysis I and II, however more lying events were misclassified as standing in Analysis II. Similar to the description for cattle (Krohn & Munksgaard, 1993), the main lying posture for sheep does not differ much from their standing posture which explains the mutual misclassifications of lying as standing in the current study. In cattle, Martiskainen et al. (2009) reported the misclassification of lame walking often occurred with either standing, feeding or sound walking (in 32% of cases) based on an SVM classification model. This misclassification of behaviours is comparable to the present study where lame walking was misclassified either as sound walking or standing.

Justification for the poor misclassification presented in Table 8-9 above can be seen in Figure 8-5. With the exception of sound grazing, there is considerable overlap between the other four behaviours making it difficult for the QDA to differentiate between multiple behaviours. A cluster of lame walking events is apparent in the bottom right which highlights the variation in acceleration signals between sheep. Figure 8-5 also indicates there is little difference in the acceleration signatures between lame and sound walking obtained from a collar mounted device (denoted by the clustering of lame and sound walking events). The lack of deviation from a normal signal suggests the collar attachment location dampens any change in signal which may be associated with the uneven weight distribution (Ford & Brian, 2016) and head bobbing action exhibited by lame animals.

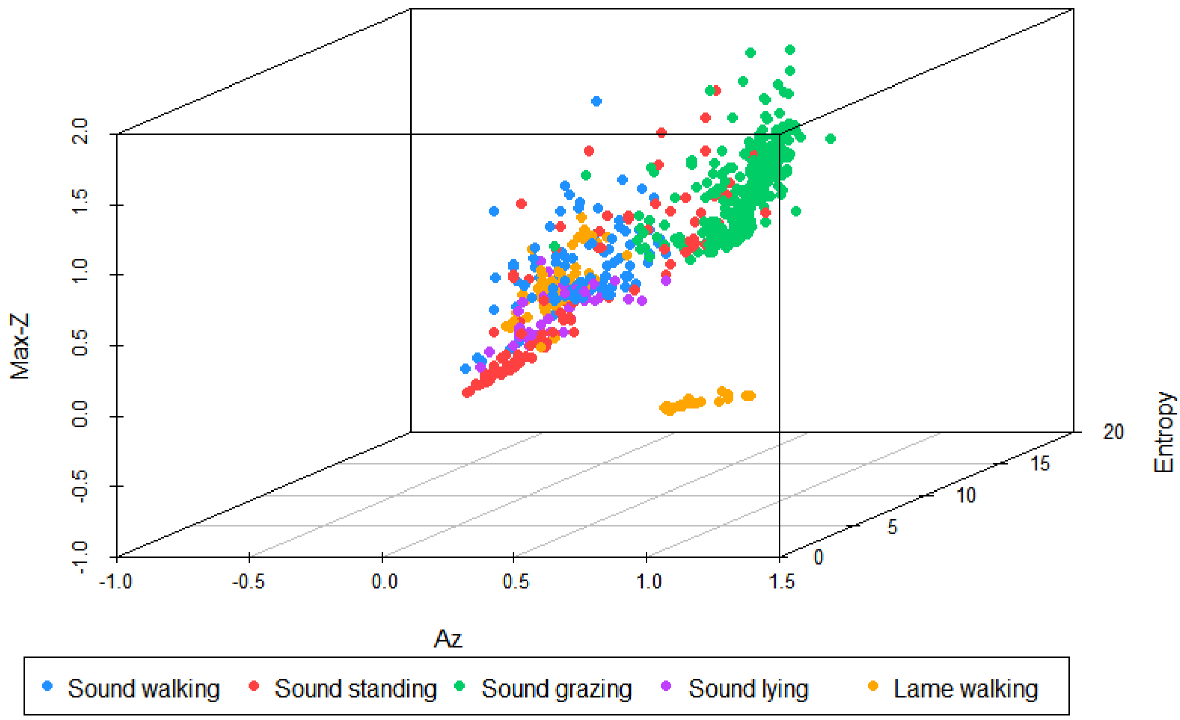


Figure 8-5. 3D scatterplot of mutually exclusive behavioural events extracted from the collar accelerometer using *Az, Max*-Z and *Entropy* metric values.

The performance statistics of the leave-one-out QDA classification matrix from Analysis II (Table 8-9) is presented below in Table 8-10.

Table 8-10. Performance values of the QDA leave-one-out cross validation model using metrics *Entropy*, *Az* and *Max-Z*.

	Sound grazing	Sound standing	Sound walking	Sound lying	Lame walking
Entropy, Az, Max-Z					
Sensitivity	95%	50%	63%	45%	35%
Specificity	90%	92%	87%	96%	90%
Accuracy	92%	85%	84%	93%	83%
Precision	91%	55%	47%	45%	35%
Total accuracy			87%		

The overall performance of the QDA classification model was poor. The performance statistics for sound grazing behaviour was high, however the sensitivity and precision rates for all other behaviours was low. With the exception of sound grazing, results suggest that the classifier had difficulty in predicting positive events for the majority of behaviour classes. The accuracy, sensitivity and precision values (83%, 35% and 35% respectively) for lame walking differ to those reported in the earlier work of Martiskainen et al. (2009) in cattle who reported corresponding values of 98%, 65% and 66%. The low performance statistics obtained indicate a collar deployed accelerometer holds little value for classifying lame walking behaviour in sheep using the classification model employed here. Since reducing the number of lame behaviour categories to only include lame walking failed to substantially improve the classification success, other techniques need to be evaluated in an attempt to improve the prediction results.

8.4.5 General discussion

Lameness has traditionally been identified through visual inspection of individual animals within a flock. A sensor based detection method using a tri-axial accelerometer deployed in three different locations (leg, ear and collar) was developed and evaluated across multiple animals with the aim to identify lameness behaviour through a change in acceleration signal. The approach used to categorise lame walking from normal behaviours in the present study is similar to that used by Martiskainen et al. (2009), whereby lame behaviours are added to the classifier as an additional class of behaviour. Other studies conducted on dairy cattle have used a change in the proportion of behaviours (predominantly lying) to infer a lameness state (Higginson et al., 2010; Kokin et al., 2014; Pastell et al., 2009). This approach has shown that around 92% of cows which developed clinical lameness also had a decrease in pedometric activity of at least 15% (Mazrier, Tal, Aizinbud, & Bargai, 2006). Additionally, extreme lying times, observed through increases or decreases in the amount of time spent lying, have been shown to be predictive of lameness events in cattle (Ito, Weary, & von Keyserlingk, 2009). Similar detail on the association between lameness and lying behaviour is lacking for sheep, however a decrease in activity of lame animals has been previously indicated (Hodgkinson, 2010). Further validation to quantify total lying time to detect lameness in sheep should be investigated. Using a behavioural state proportion approach, lameness could be categorised based on a change in activity proportion, similar to the methodologies employed in Chapter 7.

The novel method used to simulate lameness in this present study was extreme and prevented any weight bearing on the restrained limb. The lameness action created by this method of restraint is severe and more excessive than a naturally occurring lame gait pattern. Due to lameness activities being grouped as a different class for classification, this method was preferred to create a distinct difference in the acceleration signals compared to normal behaviour. If a difference in acceleration pattern could not be detected with an extreme gait change as investigated here, there would be little hope of detecting a mildly lame gait. Additional approaches should be investigated which would also allow for alternate methods of detection such as walking speed, distance travelled, stride length and stride duration which have been suggested to be valid indicators of lameness in other species (Chapinal et al., 2010; Flower et al., 2006). A question which has not been explored here however, may hold diagnostic value is when lame sheep are grazing, do they alter the vertical angle of the 'good' foreleg while grazing to avoid over-balancing? For example, when the head is lowered so they can eat grass, compared to a normal (non-lame) sheep. Perhaps less tilting of the remaining leg occurs away from the vertical although is unlikely this adjustment would be detected by an ear mounted accelerometer sensor.

There is evidence from the dairy industry that dairy farmers underestimate the proportion of lame cattle in their herds with values as low as 25% awareness (Whay, Main, Green, & Webster, 2003). Two hypotheses have been proposed for this under estimation. Either farmers cannot identify lame cows, or farmers only consider a cow lame when it is “lame enough” (in their opinion) to require treatment. A similar scenario may also be true for sheep farmers (Kaler, 2008). Given the intensity of dairy farming and the frequent inspection of individual animals, and the polarising opposite of extensive sheep farming, one would expect the level of under diagnosis of lameness in sheep flocks to be high. There is little information on the ability of sheep farmers to identify lame sheep or on the decision for when a sheep farmer decides to investigate a lame sheep (Kaler, 2008). In a questionnaire survey, Kaler (2008) found that although most farmers and sheep specialists considered that a sheep with a locomotion score as low as 2 (based on the above mentioned rating systems) was lame, a proportion of them did not catch individual lame sheep until the locomotion score was 4. Similar results were reported in a questionnaire survey of Dwyer (2009). As farmers attribute the majority of their flock lameness to two foot lesions: interdigital dermatitis (ID; caused by *F. necrophorum*) and footrot (FR; caused by *D. nodosus*) (Kaler & Green, 2008), not catching and treating sheep with a lower locomotion score may be a result of an inherent assumption among farmers that sheep with lower locomotion scores do not have foot lesions, are not in pain, will recover without treatment or will become more lame and then require treatment (Kaler, 2008). A valid question to ask here is - what is the value of detecting lameness earlier and initiating treatment sooner? Further research is required in this area to quantitatively describe the advantages of an electronic detection system in terms of overall productivity and animal welfare benefits.

8.5 Conclusions

The identification of animals with abnormal gait patterns could aid in the detection of many diseases which have lameness symptoms. The daily monitoring of locomotion or behaviour visually on farm is time-consuming and hence cost inefficient. Automatic measurement of lameness-related, animal-based characteristics would allow for daily measurements and could therefore, be a better option. This current study has shown that a tri-axial accelerometer deployed in the ear tag can discriminate lame walking activity from normal grazing, standing and walking behaviours. The collar and leg deployed accelerometers failed to successfully classify both sound and lame walking activity. This could be a function of sensor placement and the simulation not being a true representation of lameness. Further research investigating a commercially suitable accelerometer based, automatic identification system as lameness develops is warranted. Also, future work should investigate a detection system based on changes in indicators over time rather than on the deviation from the group mean. Gait characteristics should also account for variations in normal and abnormal patterns in terms of animal age, sex and breed.

Chapter 9

General Discussion

The objective of the research presented in this thesis was to evaluate the use of accelerometer sensors to improve sheep health and welfare through behaviour monitoring. Animal behaviour was quantifiably measured using these animal-borne IMU devices and variations in measured signal was linked to animal health status. A sub-aim of this research was to ensure industry applicability, hence sensors were primarily evaluated in an ear tag form factor to reflect the deployment mode required for commercialisation of these systems. The overarching hypothesis was that through behaviour classification algorithms, ear-mounted accelerometers would detect different activity states that would enable inference of health status. This hypothesis was tested through a series of experiments ranging from simple proof of concept to more studies designed to detect specific disease states:

The preliminary study presented in Chapter 4 analysed the acceleration signals obtained from a collar, leg and ear deployed tri-axial accelerometer sensor for three behaviours: walking, grazing and resting (standing and lying postures). The aim was to investigate how accelerometer signals relate to sheep movement and activity and identify key differences in acceleration signatures between behaviours within each deployment. The information obtained from this experiment examining the fundamentals formed the basis of interpreting behaviour patterns from accelerometer sensors, and assisted in the development of hypotheses which were examined in the ensuing chapters. This foundational work was critical to understanding the relationship between-animal movement and the potential activity classification value of the three modes of sensor deployment (collar, leg and ear). This is a key understanding required for the commercialisation of such technologies.

The proof of concept experiment presented in Chapter 5 explored the application of collar, leg and ear deployed accelerometers to classify three mutually exclusive behaviours. Here the classification models were evaluated. Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Principal Component Analysis (PCA) and Random Forest (RF) analysis methods were trialled to determine the most successful classification model. Eight summary features, or metrics, were calculated from the raw acceleration signal values which were shown to vary in their importance between each deployment. Principal component analysis (PCA) failed to improve the classification accuracy and was therefore excluded from further analysis in subsequent chapters. Walking behaviour was successfully classified from all deployment modes. Grazing behaviour was better classified by the ear and collars deployments, while standing behaviour was poorly predicted from the collar and leg modes of deployment when tested across multiple animals. Overall the QDA classifier was determined to be the most suitable classification algorithm for discriminating between the three mutually exclusive behaviours measured. As per the other limited research efforts that have been made in this area (Alvarenga et al., 2016; Robert et al., 2009) this chapter determined that different behaviours could be classified from an IMU. Of most significance was the discovery that the ear tag form factor could well prove to be a suitable location of sensing behaviour in sheep. Although this has been proven for cattle (Bikker et al., 2014), this remains the first work carried out to prove IMU signals for a device attached to the animals ear (which moves independently of the body) can be used to categorise basic sheep behaviours. Adding to the suitability of QDA as an accurate predictor was its relatively low computational demand, a valuable data processing asset for commercialisation. Previous research has successfully classified ruminant behaviour using IMU sensors (for example Martiskainen et al., 2009) however, often the algorithms used are computationally demanding and less feasible for embedded processing. A key finding from Chapter 5 was the capability of sheep behaviour to be predicted from an eartag deployed IMU sensor using a simple prediction algorithm. These findings show promise for this technology to align with the conventional industry practice, excluding the need for such sensors to be deployed in a collar or leg bracelet form factor as accepted by other industries.

A critical issue identified during this project was how continual time series data were to be treated. Previous researchers have largely ignored this component, focussing mainly on set interval tracking (Alvarenga et al., 2016; Marais et al., 2014; Mason & Sneddon, 2013; McLennan et al., 2015; Trotter et al., 2012). In a proof of concept trial this is acceptable however I believe prior to commercial acceptance methods which are capable of classifying behaviour in sync with data acquisition must be explored. The latter was investigated in Chapter 6, which explored the hypothesis that accelerometer data can be used to identify behaviour through the implementation of a moving window classifier applied to the time series accelerometer data stream. This is a fundamental hurdle for commercial adoption of these devices as there is no known state of animal behaviour hence, transitional periods of activity cannot be excluded from the prediction algorithm as was the case in Chapter 5. The previous research in this field has avoided this level of classification or, have used devices with proprietary algorithms to delineate between behaviour states. Multiple moving window lengths were evaluated within each deployment mode, with results showing no significant difference between the three window lengths evaluated. However, there were substantial differences in the classification prediction accuracies between individual animals. This highlighted extreme inter-animal variation, namely the way similar behaviours exhibited by individual animals can influence accelerometer signals differently. This is attributed to the differences between sheep in their physical structure which influences the movement patterns and hence, sensor motion during measurement of motion (or activity). This further signifies the need for a "robust" classification model able to predict sheep behaviour across multiple animals.

The 10 second QDA moving window classifier was able to classify a time series accelerometer stream, including transitional behaviours with reasonable accuracy. For the ear deployment, using metrics *MV*, *AI* and *Ay*, the 10 second moving window classifier successfully classified 89%, 95% and 89% of standing, walking and grazing events, respectively. The leg and collar deployments yielded inconsistent behaviour predictions between the different activities. These findings show great promise for the potential application of ear mounted IMU sensors for sheep behaviour monitoring in near real time, as a successful method for dealing with the transitional behaviours was demonstrated.

The results in the preceding chapters suggested that basic sheep behaviours could be detected. The next challenge was to determine if actual disease states could be detected (Chapters 7 and 8). Chapter 7 integrated the knowledge gained in the previous chapters by applying this technology directly to a highly challenging disease case study, namely, internal parasitism resulting from *H. contortus* infection. This study quantitatively validated activity changes associated with infection based on the proportion of time animals spent in an active compared to an inactive state. Animal movement was recorded for 40 days and based on acceleration signals, sheep movement was classified as either 'active' or 'inactive' using a 10 second QDA moving window classification algorithm calibrated for this group of animals. An unfortunate limitation of this study was the lack of a successful *H. contortus* infection in treatment group animals resulting in an absence of clinical illness at the conclusion of the 40 days. Initial analysis showed no significant treatment effect on the proportion of time animals spent in an active state. Based upon health status using EPG as a determinant for infection level, animals were regrouped into 'healthy' and 'sick' categories, where survival analysis found that animals with an EPG count >120 and <420 had a lower probability of performing a longer grazing bout compared to their uninfected 'healthy' counterparts. Given the extremely mild level of infection, which previous work has indicated will have little effect on productivity, and the small sample size, the differences in observed behaviours was limited. A significant variation in activity proportions between sheep within the two groups and also between days ($p < 0.0001$) was shown. This result also signified the necessity for specifically calibrated behaviour prediction models when dealing with isolated mobs and individuals, which will present a challenge for future commercial applications. Furthermore, an obstacle of using this approach to monitor individual health status, is its dependency on establishing normal baseline activity levels, from which deviations can be identified. As highlighted by Theurer et al. (2013), individual animals differ greatly in behaviour and therefore, the development of a standardised behaviour model applicable to multiple animal across many environments is challenging.

The final experimental chapter (Chapter 8) evaluated accelerometer technology as a means to detect a disease related symptom, lameness. Differing to Chapter 7, this work attempted to identify lameness based on a change in the acceleration signal rather than a change in activity proportion. The method used to simulate lameness was severe, resembling an extreme scenario in order to create an altered acceleration signal which could be segregated from sound behaviours acceleration signatures. However, in this instance, lame grazing events were often misclassified with sound grazing events in both the collar and ear deployments and as sound standing in the leg deployment. Therefore, lame grazing and lame standing activity classes were excluded from the model to remove the ambiguity and improve the prediction accuracy. In the final classification model which only included lame walking (along with all sound activity classes), lame walking events were predicted with 82%, 35% and 87% from the ear, collar and leg deployments, respectively. These results showed a collar deployed accelerometer was unsuitable to detect lame gait characteristics in sheep and further research should focus on using leg and ear modes of deployment. Misclassification of sound walking with lame walking using the leg accelerometer highlighted the superiority of the ear mode of attachment. However, whilst promising, this initial study requires further validation for the detection of lameness as the symptom progresses from subtle to severe gait changes as this study only investigated an extreme example of lame locomotion. Lameness simulation should also look at the difference between having lame fore and hind limbs as this will affect the acceleration signal obtained, ultimately influencing the classifiers ability to discriminate between sound and lame gaits.

There are a number of limitations of the research presented in this thesis. The issue of the small sample size of animals which does not capture all of the individual movement variation present between animals was clearly identified in Chapters 6 and 7. Individual animals differ greatly in their activity (Theurer et al., 2013) and this is particularly evident from the initial analysis in Chapter 7 showing significant variation in the proportion of time individual sheep spent active within each group and across different days. The frequency of grazing bouts is flexible, interacting with the external environment, animal husbandry and grazing methods (Gregorini, 2012). As these factors vary from farm to farm and also across production seasons, this signifies the requirement for some type of on-board learning system capable of storing individual animal baseline activity levels, from which deviations can be recognised. It is envisaged some form of data repository may be required, where sheep behaviour and accelerometer signals have been correlated to the many factors which can influence activity and grazing patterns including breed, age, environment, production status, landscape, pasture quality and quantity, weather and management practices.

A limitation of the continuous video recording method used to annotate accelerometer recordings with behaviour observations, is its susceptibility to some level of intra observer variation. The accuracy of the classification model is reliant on the observers ability to time synchronise video observations with their corresponding accelerometer recordings. As a minor time deviation potentially having a large effect on the interpretation of the data (Blomberg, 2011), protocols were developed to minimise the occurrence of incorrect annotation. However, the shortfalls of this approach must be acknowledged.

Future Research

The findings of this current thesis have identified a number of future research opportunities to further enhance behaviour classification and disease detection in sheep using accelerometer sensors. The variation in sensor orientation between animals is an issue with the ear tag form factor. This arises due to physical differences in ear structures between animals which influences the dynamic motion experienced by the sensor. Future studies should investigate difference in sensor design and placement on the ear to minimise the between-animal variation. However it is unrealistic to expect sensors can be placed in exactly the same location for all animals, therefore algorithms which can account for this appear to be a more practical option.

The transfer of data from the animal to a server is currently limited by technology capable of streaming this quantity of information across large distances. This research took into account the need for the lowest possible processing power through simple algorithms, however future research needs to further consider the use of embedded processing, reducing the quantity of data to be transferred across a wireless sensor network. This could improve energy efficiency and reduce power requirements.

Incorporation of this technology into an automatic livestock monitoring system (ALMS) will require the categorisation of accelerometer signals into behaviour observations in near real time. Further development of the classification processes presented here should be acknowledged to streamline the steps involved, allowing graziers to be notified via a form of alarm if their animals are displaying ill-health symptoms.

The suitability of the behaviour prediction model has not been tested across different flocks. Therefore, generalisations should be made with caution. Further studies are required that investigate factors influencing overall activity patterns, which include climactic, seasonal, geographic, sheep breed, host age and management effects. The previously suggested research into understanding individual baseline activity will provide some resolution to this, however more studies using larger cohorts of animals are necessary before the commercialisation of these systems on farm is a reality.

Comparison of traditional health detection systems versus systems based on remote activity monitoring must be evaluated. This includes costs and labour associated with setup, maintenance and training which may be seen by the traditional sheep industry as potential challenges when considering such a system. The economic advantages of these systems needs to be very clearly determined before producers can begin to consider the adoption of ALMS as they become a commercial reality.

This thesis has only investigated two disease case studies with behavioural symptoms. Behaviour data should be examined carefully as the commonly monitored behaviours are only specific for one type of illness or pain response. Whilst it is unrealistic to expect this system to replace the requirement for a differential diagnosis before treatment, future studies should investigate the potential for using accelerometers across a range of diseases to see if individual diseases can actually be detected rather than a simple "there's something wrong" alert. There is enormous scope for investigation into specific finger printing of diseases.

One of the main challenges is developing a commercial device small enough to be deployed as an ear tag, yet robust enough to withstand the harsh conditions it will encounter in the field (Trotter, 2013) with a suitable amount of energy storage. In terms of technology, advances should focus on reducing sensor size, developing a more power efficient system and incorporating energy harvesting to allow long term deployments, reducing animal intervention. Opportunities may exist in the use of photovoltaics and kinematics, harvesting energy from body movement, to power the devices.

Concluding remarks

Remote animal behaviour monitoring can offer advantages in terms of labour efficiencies and animal health and welfare. As a greater cost is placed on improved animal welfare, producers will be driven to improve practices. The challenge will always be working with sheep, being an animal of low economic value where there is inevitably a small margin between economic investment and return. The cost of sensors in extensive sheep farming is even a more critical issue than for other farm enterprises, because of the low value of individual animals and the typically large flock sizes. If not completely viable today, on-animal sensors for monitoring health and production status will inevitably become a commercial reality. Therefore, there is a need for this technology to be developed in a way to ensure it is accurate, non-invasive, usable and cost effective. The sheep industry both within Australia and internationally is a traditional industry, which does not assimilate change rapidly, adding further complication. The penalties for early adoption of a new technology can be financially severe for producers if the promises are not demonstrated on the farm. This has implications for the adoption of other research and development in the future. Therefore, continued thorough research and development of accelerometer technology for monitoring livestock behaviour and health status and educating potential adoptees of proven benefits is required before commercialization. If research can meet these challenges then these diagnostic sensor systems have the potential to improve, in terms or welfare and production, the way livestock are managed in the future.

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