MASSEY UNIVERSITY
ENGINEERING

SCHOOL OF ENGINEERING AND
ADVANCED TECHNOLOGY

DEVELOPMENT OF AN AUTOMATIC LAMENESS DETECTION SYSTEM FOR DAIRY CATTLE

A thesis presented in partial fulfilment of the requirements
for the degree of

Master of Engineering
in
Mechatronics

at Massey University, Manawatu, New Zealand.

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2016

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Abstract

Lameness in dairy cattle negatively effects the welfare of affected cows and is the third biggest cause of economic loss to the dairy industry in New Zealand. As the cost and frequency of lameness continues to increase, profitability will further decrease, unless a more effective and efficient method of detecting cattle lameness is found.

The main objective of this study was to investigate whether differences between healthy and lame cattle could be identified by capturing ground reaction forces when the dairy cattle walked over the designed platform. The designed walkover platform (WoP) has four independent platform segments, with each segment containing four ASB1000 shear beam load cells, a 24 bit sigma-delta analogue-to-digital converter and an ATmega328 microcontroller. Software was developed in Python 2.7 to record the captured load cell signals and process them to determine the three basic kinematic variables associated with lameness: force, position and duration. Based on these variables a wide range of typical gait parameters such as stride length, abduction, stance time, etc. were calculated. Laboratory testing of the positional and weight accuracy of a platform segment found a maximum weight error of 0.4%, a X-position mean error of 1.0 ± 2.2 mm and a Y-position mean error of 0.8 ± 1.8 mm.

The WoP was tested on two farms during the winter of 2015. During this period approximately 9500 hooves landed on the platform from 200 cows. 95% of all hoof falls were captured implying that the segment length and lead on platform were the correct dimensions for an averaged sized herd of dairy cattle. The dynamic weighing of the cattle on the WoP showed a mean deviation of -13.7 ± 7.5 kg. On farm and video analysis lameness scoring was conducted by a trained observer. The lame and healthy cows were compared to see the differences in variable values and signal signatures. Two-sample t-tests proved that the most significant variables are a combination of weight, position and duration parameters with these being: asymmetry in front limb weight, asymmetry in rear limb weight, asymmetry in diagonal weight, asymmetry in side weight, average step overlap left-side, average step overlap right-side, asymmetry in step overlap L Vs R, average step overlap, average abduction left-side, average abduction, asymmetry in stance time left-side, asymmetry in stance time L vs. R, asymmetry in stance time front hoof and asymmetry in stance time hind hoof. Statistical techniques were used to build classification models based on significant variables associated with lameness. The model that demonstrated the most promise is logistic regression using six predictor variables; this technique correctly classified all 86 cow trials in relation to the observer score. Although there is still much work to be done to provide an automated solution to lameness detection, this research provides novel contributions towards the architecture of a commercial low cost system that can determine cattle lameness in any limb.

Acknowledgements

I would like express my very great appreciation to Associate Professor Gourab Sen Gupta and Ken Mercer from the School of Engineering and Advanced Technology at Massey University for their valuable and constructive suggestions during the planning and development of this project. The willingness of my supervisors to give their time so generously has been very much appreciated. Weekly meetings were very helpful and the discussions on and off topic steered me in a positive direction.

I would like to thank Johann Nel who also completed his Masters working on this project during an earlier phase. His assistance towards software and hardware development has been a valuable contribution. The platform mechanical manufacturing and Python software development would have taken a considerable amount of time without your help. The team work and comradery shared throughout my time on the project was an added bonus.

I could not have achieved (or survived) without the financial assistance of Callaghan Innovation, C. Alma Baker Trust, Massey University and Ken & Elizabeth Powell Postgraduate Scholarships that I received, so thank you very much.

Massey University production veterinarians Associate Professor Richard Laven and Dr Lisa Hine helped immensely freely giving their time and expertise towards the project. Without the cattle anatomy lessons or the locomotion scoring reports the project outcome would not have been as confident, so thank you. Also from Massey University, Dr Russell Wilson provided commercialisation and IP knowledge during meetings which was very helpful.

I would like to thank Matthew Collis from Palmerston North for free access to his farms milking shed to set up the walkover platform. The data captured from the 400 + cows over the two month period was essential. The farm employees were also very helpful which contributed to the high quality of data that was captured.

I would also like to thank Tru-Test Limited for being the industrial sponsor and providing all the resources necessary to develop a system that is suitable for an industrial application. In particular, Dr Ross Nilson, Brendan O'Connell and Lawrence Blount who regularly provided technical knowledge and industrial mentoring.

Finally, I wish to thank my family and friends for their support and encouragement throughout my project, namely my parents, Briahna Dalbeth, Tobin Hall and Brendan Taylor. Last but not least, my amazing girlfriend Karin Sievwright who is always willing to edit my work and keep me on track.

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List of Abbreviations

NGRF	Normalised ground reaction force
RF	Right front hoof
LF	Left front hoof
RH	Right hind hoof
LH	Left hind hoof
StDev	Standard deviation
DA	Discriminant analysis
LS	Locomotion scoring
WoP	Walkover platform
PCB	Printed circuit board
COP	Centre of pressure
BLG	Binary logistic regression

Platform background – one main platform called WoP separated into four individual platform sections/segment

Chapter 1: Introduction

The work presented in this thesis was carried out in collaboration with Tru-Test (Auckland, NZ) and the School of Engineering and Advanced Technologies (Massey University, Palmerston North). Tru-Test is an agricultural manufacturing company that specialises in milk meters, livestock scales and electric fencing. Funding for the project was provided by Callaghan Innovation, Alma Baker Trust, Massey University and Ken & Elizabeth Powell Scholarships.

The New Zealand dairy industry is the country's top merchandise export earner and in 2014 contributed $13.2 billion of export earnings (29% of the total value that New Zealand earned from its merchandise exports). The industry directly contributes approximately 3% of New Zealand's GDP (Ministry for Primary Industries, 2013) and has continued to grow over the last 30 years, with an average herd size of 419 cows per farm. The third biggest cause of economic loss to the industry (behind mastitis and sub-fertility) is lameness; this costs the New Zealand dairy industry approximately $250 million per annum (DairyNZ, 2015). Of concern is that the incidence of lameness is increasing.

Traditionally, the identification of lame cattle has involved passive observation with the farmer noticing a cow walking slower and with irregular steps. This identification method is very time consuming and labour intensive and is not particularly efficient as it often results in a significant delay between the onset and detection of lameness. This problem has been exacerbated by the introduction of milk shed automation as the contact time between the farmer and the animal (during which detection can occur) has become significantly reduced, thus in modern sized herds it is difficult to identify lameness using this traditional method. As the cost and frequency of lameness will continue to increase into the future, this problem will become worse, unless a more effective and efficient solution is found to detect cattle lameness.

The idea to measure lameness electronically is a fairly recent concept and currently there is only one commercial system available. The United States based company Bou-Matic has developed the StepMetrix system which is an automated solution to cattle lameness detection. The StepMetrix system generates scores based on the captured ground reaction forces produced by an array of load cells as the animal walks over the platform. The score is then displayed to the farmer who decides whether to take action and examine the cow further or let her keep walking. The system supposedly averages over 85 % accuracy in detecting lameness in individual cattle (BouMatic, 2015). The disadvantage of this system is that it only detects lameness in the hind limbs and it requires reference data from each cow before it can compare differences. Consequently, all animals need to walk over the system at least once when they are healthy before lameness detection can occur. A study involving the StepMetrix system found that although the system had a high specificity rate, the sensitivity rate was low, ranging between 20 – 35 %.

This means that many lameness cases are not being detected which lowers the farmers' confidence in the system (Bicalho *et al*. 2007).

The major goal of this project is to calculate and determine the variables of significance in detecting lameness in order to build an accurate classification model to identify lame and healthy cattle. The work in this thesis includes the design and manufacture of a ground reaction force based platform using an array of load cells to capture the three main kinematic parameters associated with detecting lameness, with these being force, position and duration. From the three parameters, gait variables can be found, such as stride length, to analyse differences in each hoof of individual cattle. The hypothesis that a lame cow will produce a distinct signal signature that will be distinguishable from a healthy cow firstly needs to be tested. The significance of the variables will determine the role in which they are applied to statistical models.

The designed platform is intended to replace the current Tru-Test walkover weighing scales so it has to be able to find the total cow weight as well as lameness related variables. The system would ideally be low cost to manufacture in order to successfully commercialise it.

Testing the performance of the manufactured platform is an exciting development towards an automated solution for lameness detection in New Zealand. The test data is to be captured from a farm without any intervention to the natural flow of the cows leaving the milking shed. The system needs to provide numerical information to access acute daily changes in the front and hind limbs to monitor the health and wellbeing of dairy cattle.

Chapter 2: Background Information

This chapter provides an overview of lameness research, current automated solutions and requirements for a practical system. The first subsection explains the significance of lameness in the New Zealand dairy industry and how it is currently identified. The second subsection provides background information on current lameness detection systems and the variables used to associate lameness.

2.1. Lameness Research

2.1.1. The New Zealand Dairy Industry

Currently, New Zealand has over five million dairy cattle with an average herd size of 419 cows per farm (DairyNZ, 2015). Figure 2.1 shows that although there has been a reduction in the number of dairy herds in New Zealand, the average herd size has linearly increased over the last 30 years. The increase in herd size can be attributed to farm area expansion (largely due to South Island growth) and automation technologies (DairyNZ, 2015).

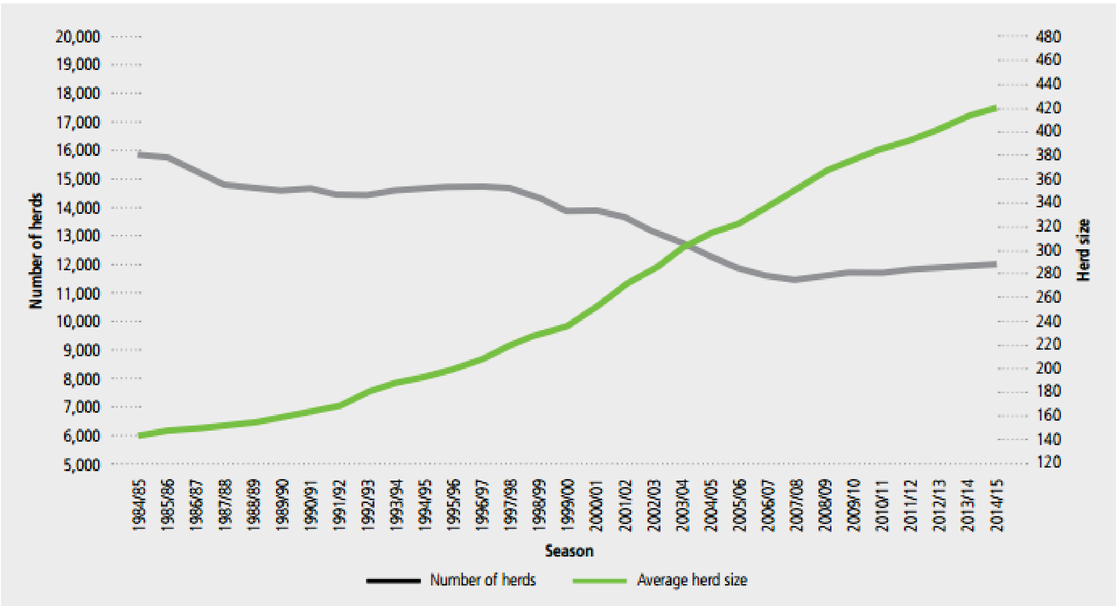

Figure 2.1: Trends in the number of dairy herds (DairyNZ, 2015)

2.1.2. Cause of Lameness

Lameness is due to trauma accompanied by secondary infection, with claw disorders accounting for approximately 90% of lameness (Malmo *et al*, 2011). One of the main causes of lameness is white line disease. This disease is related to the handling of cattle in yards/races and results in abscess formation mainly in the lateral claw of the hind limb and often at the area just cranial to the heel bulb. This occurs due to the penetration of stones into the claw resulting in infection of the soft corium and significant discomfort to the cow (Malmo *et al*, 2011). The handling of cattle has worsened in recent years as increased farm sizes have resulted in herds having to walk further to the milking shed every day; this increases the wear on the cows' feet and likelihood of inflicting damage.

Another main cause of lameness relates to the maintenance state and surface structure of yards/races. Yards are made of concrete, which can be rough and very abrasive resulting in damage to the hooves and high incidences of lameness. Race surfaces which lead to the milking shed can also be very uneven and stony resulting in additional hoof damage and further development of lameness. Furthermore, if the stock herder is impatient and pushes the cattle too hard incident rates will increase (Malmo *et al*, 2011).

2.1.3. Identifying Lameness – Point Scoring System

Presently lameness is categorised using the Locomotion Scoring (LS) System which is based on observing cattle walking, with the emphasis on head bob and stride length. The scoring system in New Zealand ranges from 0 to 3 (shown in Table 1), with 0 being normal and 3 being severely lame. This method of visual scoring is very subjective and environment conditions such as a sloped or muddy raceway can alter the natural walking rhythm of the cattle, which leads to an incorrect score. Generally, trained large animal veterinarians are employed to score an entire herd of cows, although the majority of farmers also know how to identify lame animals.

Table 1: Locomotion Scoring Criteria (Zinpro, 2015)

Score	Description
0	Cow walks with a level back and long strides. Walks rapidly, confidently and no apparent signs of lameness. The hind hoof lands in a similar location to the front hoof.
1	Cow shows no apparent signs of limping; however the cow will take shorter strides and have a slightly arched back.
2	Cow's head carried low or bobbing up and down. Signs of obvious arched back and an obvious limp which favours the affected limb(s).
3	Cow has a very noticeable arched back, difficulty turning; moves slow and applies little or no weight to the affected limb(s)

2.1.2.1 Accuracy and Consistency

LS between trained individuals scoring the same cows display a degree of variation. An experiment involving seven experienced European observers viewing 58 video recordings of cows was conducted. The distribution of healthy and lame cows was approximately equal to represent the five level European LS system. A cow with score 1 walks normally whereas a cow with score 5 is an extremely lame cow. The observers were asked to score all 58 cows on two different occasions, separated by four days or more. Within and between observer agreement was investigated. Within observer agreement is the percentage of all the cows that were given an identical score by an individual observer on both occasions. Between observer agreement is the percentage of cows given the same LS by all seven observers (Schlageter-Tello *et al*, 2013). It can be seen from Table 2 that both categories of observer agreement are less than conclusive. Within observer agreement averaged 69.3% across the five levels and between observer agreement averaged 55.3%. This makes designing an automated system even more important considering that each observer has a different perspective on separate days. There is currently no clear or accurate numerical information that can be given to compare a healthy and abnormal cow gait, which frankly in this day and age is less than ideal.

Table 2: Locomotion Scoring - Within and between observer agreement (Schlageter-Tello *et al*, 2013)

Locomotion Score	Within Observer Agreement, % (95% confidence interval)	Between Observer Agreement, % (95% confidence interval)
1	72.5 (64.4 - 80.6)	63.9 (60.3 - 67.6)
2	63.9 (56.9 - 70.9)	58.9 (55.9 - 61.6)
3	60.0 (51.7 - 68.2)	53.1 (49.6 - 56.5)
4	74.5 (67.2 - 81.9)	62.1 (58.6 - 65.5)
5	75.6 (60.2 - 91.9)	38.7 (30.5 - 46.9)

Another example of varying locomotion scoring was witnessed during the scoring sessions of this project. An experienced large animal locomotion scorer was employed to score the entire herd of dairy cattle while they exited the rotary milking shed. A video camera (GoPro 3) recording at 1080p (60fs) captured the same animals walking out of the milking shed. Some discrepancies were noted in the original scoring data so the same veterinarian was given snippets of particular cow videos to re-score. It was very interesting to find that some of the originally scored lame cows were re-scored as healthy.

2.1.4. Cost of Lameness

Early identification and prevention of lameness would not only save farmers money but would also improve animal health and performance for the rest of the season. According to Malmo *et al* (2011), the world-wide incidence rates of lameness indicate that as many as 60% of cows in a given herd may become lame at least once in a year. Estimated instances of lameness diagnosed in New Zealand dairy farms are between 10% and 15% depending on the herd size and districts at any one time during the year. Surveys based on cases treated by veterinarian's state that only around 25% of total cases of lameness are dealt with by professionals directly. Farmers and stockpersons generally deal with lameness incidences so the rate of lameness is expected to be a lot greater than reported (Malmo *et al*, 2011).

The estimated cost of a single case of lameness in New Zealand is $350; this is based on treatment costs, increased chance of culling, loss of production and reduced reproductive performance (Franklin Vets, 2013). This cost however can be considerably higher depending on the season of the year and if the lameness negatively affects mating. Based on the estimated instances of lameness in New Zealand dairy cattle (between 10% and 15%), it can be expected that in a normal sized herd of 413 cows between 41 and 62 cows would be diagnosed with lameness per year, resulting in an annual cost to the farmer of approximately $14350 to $21700. This demonstrates the importance of individually monitoring each cow so that those displaying mild lameness can be quickly detected and treated before the lameness becomes more severe and the associated cost of lameness increases. Consequently, the relevant solution for the project is to develop a lameness detector that could cost up to $3000 to manufacture and could sell for at least $8000 if it lasted numerous years. The direct financial implications highlight the significance of lameness and the need for a detection system to be developed.

2.1.5. Weight Distribution Patterns

Non-lame dairy cattle distribute 55 - 60% of their weight to the front limbs and 40 - 45% to the hind limbs during walking (Van Nuffel *et al*, 2015). Even though the front feet carry a higher percentage of the total weight, lameness is predominately in the hind limbs (80%) (Malmo *et al*, 2011). When an animal becomes lame, they tend to shift their body weight onto non-affected limbs to reduce pain. According to Van Nuffel *et al*, (2015) the average ground reaction force was found to decrease on the affected limb with an increase in locomotion score. A cow standing with discomfort in one hoof primarily transfers this weight to the contralateral hoof. This suggests that a cow showing signs of lameness in one limb would show a greater asymmetry in weight applied to the pair of limbs (Singh *et al*, 2012).

Not surprisingly, other studies also agree with the finding that more weight is applied onto the limb that is contralateral to the affected limb. Rushen *et al*, (2007) found that the greater the severity of lameness, the clearer the relationship with the body weight distribution was. However, if lameness occurred symmetrically (often with painful lesions), the detection of asymmetric weight shifting was difficult to notice. When a cow is lame on both front limbs, it was found that some of the weight was able to be transferred to the hind limbs (Neveux *et al*, 2006). Interestingly, weight is seldom transferred from the hind limbs to the front limbs when both hind limbs are lame. By using these findings of weight distribution it may be possible to distinguish between a healthy and lame cow in this project.

2.1.6. Severity for Intervention

Treating lame cows takes a great deal of time and physical effort. Farmers try to keep the cost-to-benefit ratio for treatment as low as possible; hence the majority of farmers in New Zealand follow the guideline given below (Veterinary Clinic Morrinsville, 2015).

- *Score 0*: The cow is healthy, no further action is required.
- *Score 1*: The cow is slightly lame, closely monitor to detect the lame leg and ensure further lameness does not develop. The farmer or foot trimmer may lift the leg and check for signs of lameness if problems persist.
- *Score 2*: The cow is moderately lame and should be drafted and examined as soon as practical to identify the lame hoof and treat accordingly. Depending on the farm management the farmer/hoof trimmer or veterinarian will carry out the treatment.
- *Score 3*: The cow is severely lame and needs immediate treatment, usually by a veterinarian. The lame cow should be kept on pasture close by and not be made to walk far.

The focus for this project is to detect cattle with a score of 2 or above which is within industry practise for treatment. Detecting lameness before it occurs (subclinical) is impractical since there are no definitive clinical signs of laminitis.

2.2. Current Lameness Detection Systems

Currently there are only three systems that provide an automated solution to detect cattle lameness using force measurement techniques. The only commercial system and the first to develop the idea was a US based dairy automation company called Bou-Matic. The device they developed is known as StepMetrix and is based on a ten year study with the help of the University of Maryland (BouMatic, 2015). The second system is called the GAITWISE system and was based on a development project with several Belgium institutes contributing to the findings. The third system is a research/trial system developed by the Royal Veterinary College in London with the intended purpose of early lameness detection.

2.2.1. The StepMetrix System

The StepMetrix system shown in Figure 2.2 comprises of an array of single axis load cells embedded into a platform which is permanently installed in the return lane of a milking shed. The platform has two parallel platform segments, one for left hand side legs and one for right hand side legs. The advanced controller reads the radio frequency identification device (RFID) of individual cattle and analyses their steps. The software then compares previous records of the cows gait such as force, location and duration to the current signals detected. The StepMetrix management software which is installed on a PC then generates lameness scores based on determined ‘normal’ gait variables. This system has consistently averaged over 85% accuracy in detecting lameness in individual cattle and retails for approximately $30,000 USD (BouMatic, 2015).

Figure 2.2: StepMetrix system components

The granted US patent for the StepMetrix system (Tasch *et al*, 2004) provides excellent information regarding experimental setup. The physical concept they developed uses a load cell in each corner of the two active platforms which is shown in Figure 2.3. The platform layout consists of eight load cells sampling at 100Hz at known X, Y distances which makes it possible to find the location of a force anywhere on the plate.

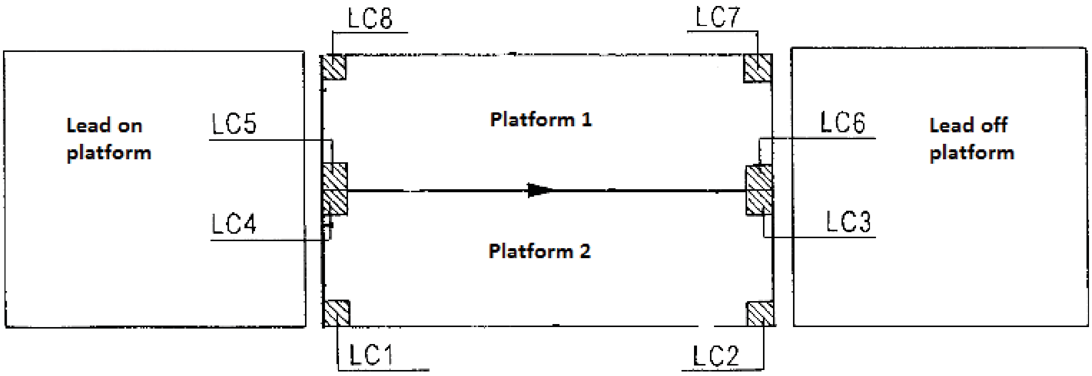

Figure 2.3: StepMetrix platform layout found in patent (Tasch *et al*, 2004)

Currently, the StepMetrix system only detects lameness in the hind limbs and it requires reference data from each cow before it can compare differences. For each limb, the system displays a daily SMX score as well as a weekly graph to show how that particular cow is trending. The SMX score is a numeric value calculated from the significant gait variables (these variables have not been published). It is then up to the farmer to react to the daily scores and decide if the cow should be examined further. A Cow Snapshot Report lists all the cows SMX scores in the herd in descending order from severely lame to healthy (BouMatic, 2015). A study involving the StepMetrix system found that although the system had a high specificity rate, the sensitivity rate was low, ranging between 20 – 35 %. This means that many lameness cases are not detected, therefore lowering the farmers' confidence in the system (Bicalho *et al*. 2007).

2.2.2. The GAITWISE System

The second lameness detection system is called the GAITWISE system and was developed by Maertens *et al* (2011) in Belgium. It is yet to become a product on the market although it has displayed promising results over the seven year period of the project. The system uses a pressure sensitive walkway incorporated into a platform to monitor the cow's gait using variables in four dimensions (two spatial, one temporal and one force). The recorded data is then analysed against 10 basic gait kinematic variables with the use of MATLAB, with these variables being stride length, stride time, stance time, step overlap, abduction, asymmetry in step width, step length, step time, stance time and force. The system operates fully automatically and in real time and has been extensively tested to 84 % accuracy in correctly classifying lame cattle (Maertens *et al*, 2011).

The pressure mat has an array of 384 sensor elements covering 1266 cm^2 and is 610 mm wide by 4880 mm long. To protect the sensitive pressure mat multiple protective layers are required. The first layer is a "1 mm thick ethylene propylene diene monomer flexible water and manure proof cover," (Maertens *et al*, 2011) followed by a second layer of a 10 mm thick rubber top surface to provide skid resistance and mechanical protection. Measurements from the pressure mat are output at 60 Hz.

The method of testing the system involved using a sample herd of 80 dairy cows milked twice daily on a Belgium farm. A video camera (sampling at 30 frames per second) was mounted to monitor the cows walking over the pressure mat platform. A trained observer then viewed the recorded information and assigned a gait score of 1, 2 or 3. The results were compared to the output of the GAITWISE system which also indicated scores in the same range. A gait score of 1 indicated the cow did not show any sign of lameness, 2 signified slight lameness, and 3 indicated severe lameness. Van Nuffel *et al* (2009) also uses the gait scoring on a 3 point scale to assess lameness via a video recording and evaluates against kinematic gait variables using a pressure mat. For the GAITWISE system, the flow of the cows walking over the pressure mat is controlled by a gate to only let one cow walk over the platform every 30 seconds. Reducing the natural flow would not be appealing to managers of large farms in New Zealand who milk over 1000 cows each session.

An important discovery made by this study was that out of all the gait variables used to decide if a cow was lame, four variables contributed the most to the correct classification. The variables were 'asymmetry in step length', 'asymmetry in stance time', 'asymmetry in step time' and 'asymmetry in step width' (Maertens *et al*, 2011). These variables resulted in a sensitivity of 85, 76 and 90 % using linear regression, for gait scores of 1, 2 and 3 respectively. According to Van

Nuffel *et al* (2009) the four identical kinematic variables mentioned above showed a strong correlation for detecting lameness.

2.2.3. Royal Veterinary College Lameness System

A London-based research team have recently developed an automated early lameness detection system for dairy cattle (Royal Veterinary College, 2015). The system uses five force plates to analyse the gait of dairy cattle. Over a two year period they collected over 500,000 foot strikes from dairy cows exiting the milking shed. Of interest is that only 7.5% of the foot strikes (67,000) could be used to extract data from. This was found to be the case when using a platform to measure ground reaction forces; if the cow was not walking with a constant speed then the data collected would be invalid. The StepMetrix and GAITWISE system also mentioned this finding.

The results of the Royal Veterinary College study (2015) found there was no single discriminatory feature when identifying lameness. Using advanced statistical techniques it was found that vertical forces were not as closely related to identifying lameness as stride variables. This result is surprising considering that when a cow shows signs of lameness they try to shift their weight distribution from the affected leg to ease the pain. Flower, Sanderson & Weary (2005) found similar results with multiple variables contributing to lameness detection. They also found that stride variables showed a higher correlation than vertical forces alone and that compared with lame cows, healthy cows had shorter stride durations (1.26 ± 0.03 s vs. 1.48 ± 0.05 s), longer strides (139.5 ± 2.1 cm vs. 130.0 ± 3.2 cm) and walked faster (1.11 ± 0.03 m/s vs. 0.90 ± 0.05 m/s) (Flower *et al*, 2005).

2.2.4. Common Variables Indicative of Lameness

An amalgamation of common gait variables that were found in the lameness detection systems mentioned above is shown in Table 3. The variables are divided into three sections; force, spatial and temporal. The definition of the variables is based on lameness parameters from Maertens *et al* (2011) and Tasch *et al* (2004). Variables that are used by the StepMetrix System (SM) and GAITWISE System (GW) are noted.

Table 3: Description of gait variables calculated from kinematic measurements (Maertens *et al*, 2011. Tasch *et al*, 2004)

Gait variable	General definition	Significance for lameness detection	Variable used by system
Force			
Individual limb weight	The mean ground reaction force exerted by an individual leg	Reluctance to bear weight	SM, GW

Total weight	The total weight of the cow	Reducing weight overtime	SM, GW
Normalised ground reaction force (NGRF)	The individual limb weight divided by the total weight	A comparable weight variable (always between 0 – 1)	SM
Asymmetry in limb weight	Mean difference in relative force exerted by the limbs between left and right hoof imprint	Asymmetrical gait, tenderness	SM, GW
Asymmetry in diagonal weights	Mean difference in relative force exerted by the diagonal limbs between LF,RH and RF,LH	Asymmetrical gait, tenderness	SM, GW
Asymmetry in side weights	Mean difference in relative force exerted by the limbs on the opposite sides	Asymmetrical gait, tenderness	SM, GW
Spatial			
Front step length	Step length between front left and right hoof imprints	Asymmetrical gait, arched back	GW
Hind step length	Step length between hind left and right hoof imprints	Asymmetrical gait, arched back	GW
Front step width	Step width between front left and right hoof imprints	Asymmetrical gait	GW
Hind step width	Step width between hind left and right hoof imprints	Asymmetrical gait	GW
Stride length	Distance between two consecutive imprints of the same hoof	Speed, arched back	SM, GW
Asymmetry in step length	Mean difference in step length between left and right hoof imprints (separate front and hind limb)	Asymmetrical gait	GW
Asymmetry in step width	Mean difference in width between left and right hoof imprints	Asymmetrical gait	GW
Step overlap	The lengthwise distance between the front hoof and the hind hoof on the same side	Speed, arched back	GW
Abduction	The sideways distance between the front hoof and the hind hoof on the same side	Reluctance to bear weight, tenderness	GW
Temporal			

Stance time	Time during one step that hoof is on the platform	Speed	SM, GW
Asymmetry in stance time	Mean difference in time that hoof is on the ground between left and right sides	Favouring a particular side	SM, GW
Stride time	Time between two consecutive imprints on the same hoof	Identify limb that has least contact with platform	SM, GW
Velocity	Hoof speed (m/s) is stride length divided by stride duration	Speed	SM, GW

2.2.5. Requirements for a Practical Lameness Detection System

The required outcome of the project is the ability to detect lameness as well as being able to weigh the cattle as they walk over the platform. Since this project is being developed with the aim of a commercial application to replace a current product, it must be able to weigh the cattle if it is to be successful. The system must also be cost effective so that farmers consider purchasing it. Moreover, the designed system should ideally fit into the main stakeholder's current manufacturing abilities.

The main kinematic measurements that need detecting are:

- Weight
- Position
- Duration

The weight measurement relates to individual limb weight and total body weight of the cow which will be displayed in kilograms. The intended accuracy is to be 5 – 10 kg for an individual limb, which is deemed reasonable considering that an average sized dairy cow weighs 450 kg (DairyNZ, 2015). The position variable determines the central location of each foot fall within an accuracy of 30 mm (Maertens *et al*, 2011) in vertical and horizontal directions. The duration of each foot fall is measured in seconds with a resolution of milliseconds in order to determine precise differences between limbs.

2.2.5.1. Tru-Test Products

Tru-Test Limited is the main stakeholder for this project, as well as funding all hardware components. A technical meeting took place during the project concept development stage to gather technical knowledge about their current walkover weigh system and how it works. A typical walkover weigh system consists of the following:

- Platform: The platform has two load bars with each bar having a half-bridge strain gauge. These two bars are then wired together to form a full bridge.

- EID Antenna and EID Reader: The EID Reader has an ARM Cortex M3 microcontroller. This interfaces with a single channel 24-bit ADC with a sampling rate of 50 Hz.

An important piece of information the engineers mentioned was that the cows could generate signals up to five times their average weight when walking over the platform. For this reason they recommended using 1000 kg rated single-point shearbeam load cells, specifically the ASB-1000 by PT Global. The engineers also suggested waterproofing the electronics, and to ensure that no high pressure water came into direct contact with the load cells as this has caused load cell failure in the past. It is interesting to note that although the load cells are IP-67 rated, these failures still occurred.

2.2.5.2. Ground Reaction Forces

Current lameness detection systems measure ground reaction forces produced from the walking cattle. Force transducers are required to determine ground reaction forces, with the following options investigated:

- Load cell (used in the StepMetrix system by Bou-Matic)
- Load bar (used in walkover weigh platforms by Tru-Test)
- Pressure-sensitive mat (used in the GAITWISE system)
- Tactile sensors (piezoresistive and piezoelectric)

Load bars and load cells use strain gauges to measure an applied force. The difference between them is that load bars are used to span a larger width, whereas load cells are designed for point loads. There is no fundamental reason why a pressure-sensitive mat or tactile sensors could not be used, although it would be more challenging to implement into the current walkover weigh scales that Tru-Test offer. As stakeholders, Tru-Test has indicated they would prefer a load cell based system due to the robustness and current use of strain gauges in production of scales.

2.5.5.3. Load Cell Principle of Operation

A load cell is a force transducer and is used to transform an applied force into an electrical signal. A load cell system typically comprises of three elements including: the load cell, which is a mechanical arrangement; the strain gauge (a planar resistor); and a load cell amplifier (Bailey & Gilman, 2005). When a force is applied to the load cell the strain gauge deforms/stretches which changes the electrical resistance of the wire by an extremely small amount in proportion to the force. The load cell amplifier takes the output of the strain gauge in the range of a few millivolts and amplifies or converts the signals into a more useful voltage. The most common arrangement for a load cell is a Wheatstone bridge configuration which consists of four strain gauges. Cheaper and less accurate load cells are available with half bridge or quarter bridge strain gauges. For best performance, a stable voltage reference source is supplied to both the bridge excitation and the ADC reference (ratio-metric). The bridge output is directly proportional to the voltage reference and hence any drift in this produces a corresponding drift in the output voltage. The ratio-metric arrangement removes the effect of drift and noise in the excitation source.

The selection of the type of load cell for the application is vital to make sure that the capacity and structure is appropriate for the intended environment. Load cells can be divided into four main types:

- "S" load cell
- Beam load cell
- Column load cell
- Diaphragm load cell

The load cells used in this project are shearbeam full bridge load cells rated to 1000 kg. ASB1000 load cells were purchased as they were a low cost option ($56 NZD) for a full bridge strain gauge. The load cells were tested in the laboratory for reaction to vertical and horizontal forces before being used on the project. It was found that this type of load cell only reacts to a vertical force and not a horizontal force which what is required for the application.

2.5.5.4. Intellectual Property

As mentioned, various universities and agricultural related development companies have realised the opportunity to develop a lameness detection system. A handful of patents have been filed worldwide; therefore it is very important to research current patents in order not to infringe any.

In the New Zealand patent register two patents exist in regards to lameness detection. The first is an international patent for the granted (June 2006) StepMetrix System (PCT/US2001/017322). This system was discussed in Chapter 2.2.1 and is a similar concept to this project by making use of multiple load cells. However, the claims of this patent relate more to the computer based diagnostic system and do not protect the use of multiple load cells; as a result the patent will not be infringed (under my understanding).

The second patent is also protected internationally and is held by Delaval Holdings Ab (filed in 2012). The claims from this patent relate to image processing and positioning of video cameras to detect lameness. Image processing is not within the scope of this project and no cameras will be used to develop processing algorithms, therefore the patent will not be infringed.

Chapter 3: System and Hardware

3.1. Project Phases

The project involved multiple phases which can be seen in the block diagram in Figure 3.1. The three main sections were the design and manufacture of the walkover platform (WoP), capturing data and designing algorithms to deduce variables indicative of lameness, then using these variables in conjunction with the manual locomotion scoring to find statistical models that correctly classify the selected cows.

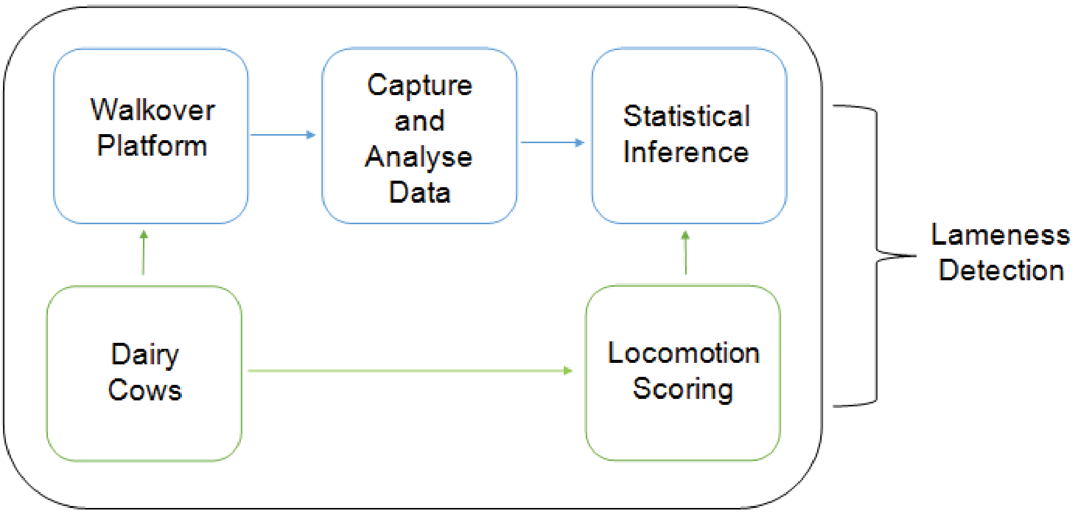

Figure 3.1: Project phases block diagram

3.2. Prototype Scales

The main concept of the project revolves around having a platform that is able to capture ground reaction forces that are produced when cattle walk over the structure. The platform has four individual platform segments which can be seen in Figure 3.2. For simplicity the sections were labelled as A, B, C and D (please see 3.2.3 for the reason behind four individual segments).

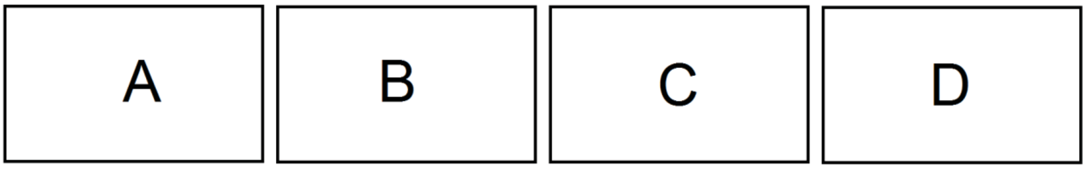

Figure 3.2: WoP concept with four sections

3.2.1. Requirements

The general mechanical design specifications that were established during the concept development stage that the platform had to comply with include:

- The platform has to be capable of supporting at least 500 kg as the weight of the three most common dairy cattle breeds in New Zealand is between 400 kg and 490 kg (DairyNZ, 2015).

- Each platform segment must be adjustable and easily moved to find the optimal stride length between the gait ranges of 700 mm ± 50 mm (Stephenson, 2006).
- The entire platform needs to fit within the standard width of a cattle race in a milking shed.
- The overall height of the platform must be kept as low as possible so the cattle do not have to raise their legs higher than usual as this could alter the signals produced.
- The platform needs to be dimensionally similar to the current Tru-Test weight scales (700 mm overall width, 400 mm walking surface width, 100 mm high).
- There are to be no protruding bolts on the walking surface and no small crevices for stones or foreign objects to accumulate.
- The platform needs to be manufactured for the intended environment (milking shed). For example it needs to be able to handle high pressure wash down twice a day.
- The load cells and electronics need to be enclosed to give a degree of waterproofing and protection from direct high pressure water.

3.2.2. System Block Diagram

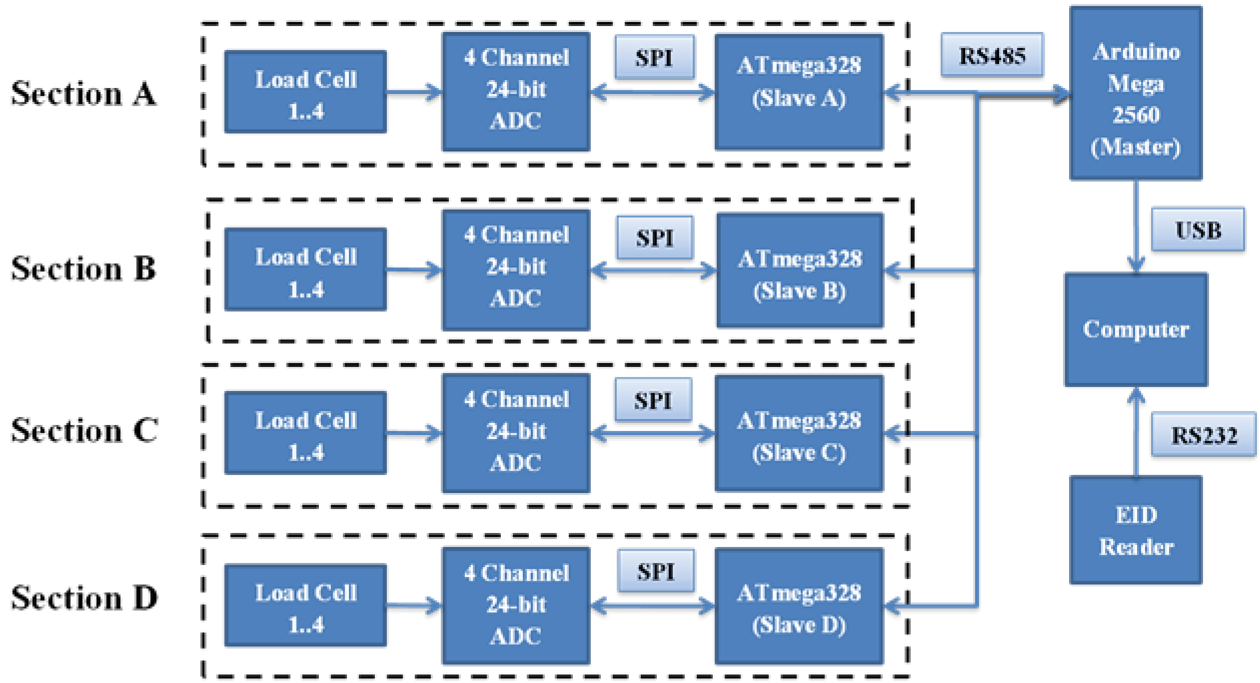

Figure 3.3: Functional block diagram of system

The system block diagram (Figure 3.3) shows four independent platform sections, with these sections labelled as A, B, C and D. Each platform section has three generic function blocks; these consist of four ASB1000 shearbeam load cells (one in each corner), a 24 bit four-channel AD7193 ADC to interface the load cells and an ATmega328 microcontroller acting as a slave device. The inter-block SPI communication between the ADC and the slave microcontroller is multi-directional meaning that the ADC is able to be programmed (register based) and also transmit digitised load cell data to the microcontroller. The master microcontroller (Arduino Mega) controls when to request and receive information from the four slave microcontrollers via the RS485 communication bus. This information is then sent serially to the PC running the analysis and plotting software. The EID reader identifies which cow has walked over the platform and transmits this data to the PC serially.

3.2.3. Mechanical Platform Development

The mechanical arrangement of the platform was designed in two stages; the initial prototype platform segment then the conjunction of multiple segments to form a walkover platform. The number of segments and the spacing between them is a critical component of the project. The concept of having four separate segments should theoretically make the data analysis easier knowing that only one foot will be on the segment at any one time. At least four segments are needed for accurate walkover weighing to make sure there is enough time to get the cow's total weight. This was found to be the case in the Royal Veterinary College study where five segments were needed to capture the total weight.

3.2.3.1. Platform Prototype

An initial full sized single segment was designed and manufactured to test how the load cell signals responded and to test that centre of pressure could be accurately determined. The prototype segment was designed to be 700 mm long by 500 mm wide so that it would fit within a standard sized race. According to Stephenson (2006) the natural step distance of a dairy cow is 700 mm; this was found by measuring the 'ruts' that remained in the ground on farm raceways. Consequently the initial platform was made to be the same distance that a healthy cow would potentially step. The initial prototype included adjustable sliders to move the load cells to find the optimal position. The optimal position was to have the load cells adjusted to be as close to the corners as possible as this gives the most surface area. Figure 3.4 shows the manufactured steel platform segment framing with one load cell bolted into each corner. See Appendix 1 –ASB1000 for a diagram and information about the load cells used.

Figure 3.4: Constructed prototype platform

After completion of the initial prototype testing (See Chapter 6.1.1) a number of design changes were implemented based on what had been learnt and observed. The main changes include:

- Removal of load cell sliders as they were not needed. The load cells were instead positioned at a fixed location.
- The load cell sockets were welded onto the top sheet metal platform tray. This removed the need for the top structural frame used in the initial prototype.
- The material used for the bottom structural frame that the load cells mounted to was changed from 5 mm angle iron to 5 mm C-channel. This was done to increase the torsional strength and provide waterproofing protection for the load cells.
- The section length reduced from 700 mm to 650 mm to meet the specification that the gait distance could be optimized between the ranges of 700 mm ± 50 mm so the cattle's natural gait was not altered.

The final prototype platform consisted of a 3 meter long mainframe which supports the four sections at designated positions. The main reason for the mainframe is to easily attach the sections at pre-determined spacing positions, with these being 650 mm, 700 mm and 750 mm respectively. Further reasons for a main frame as opposed to single supporting sections was that the side rails could be one continuous length and be attached to the main frame without interfering with the load cell signals from each section. A single main structure was also easier to level at the cow shed and required only 8 support feet instead of 16 if the platform sections were independent units.

Figure 3.5 shows the platform segment spacing diagram for the 650 mm setup. The reference location for the measurements is the bottom left corner centred on the load cell. A clearance of 10 mm was used between first the segment (A - B) and 20 mm on the following segments. The reason for the larger clearance was only realised after manufacturing and positioning the first segment. The extra 10 mm was added to make sure that neighbouring segments would not 'jam up' when used in farm conditions of mud and manure. A 340 mm blanking spacer was inserted before the first segment to fill in the gap in the main frame. The spacer was placed at the beginning rather than the end of the platform as it was observed that the cattle took a large stride when stepping up onto the platform. This location therefore yields the lowest disturbance to the captured data.

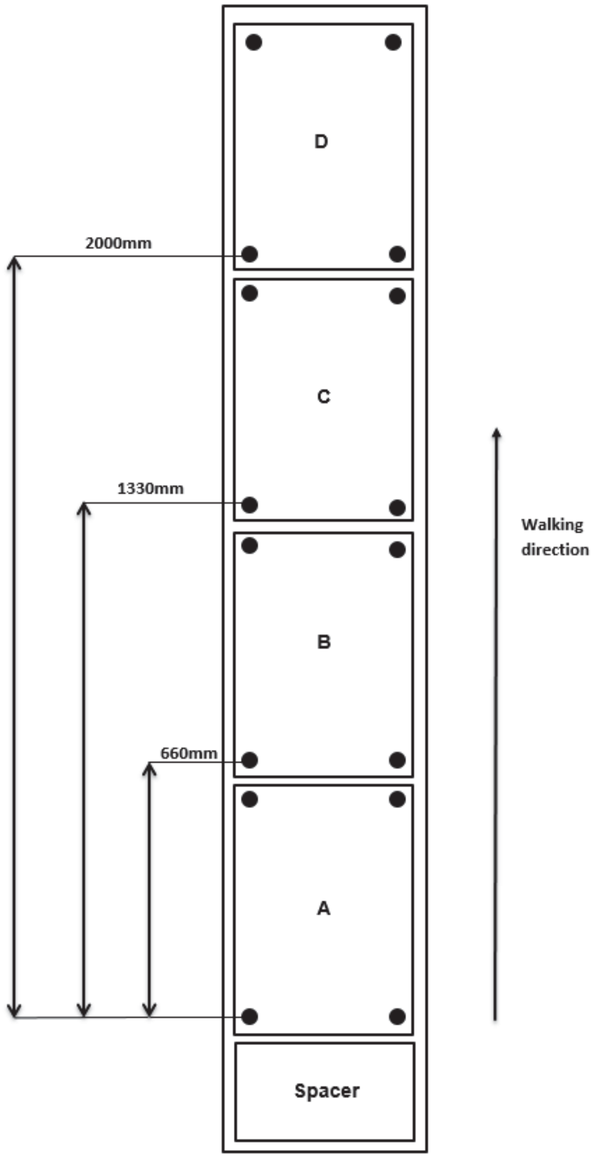

Figure 3.5: 650 mm platform segment spacing

Key design aspects of the CAD model seen in Figure 3.6 include:

- The main frame is able to accommodate four platform sections at a maximum spacing of 750 mm.
- The 3 m long side rails are a safety feature and also guide the cows along the platform. The side rails overlap the platforms by 50 mm to make sure that a cows hoof cannot venture inside the load cell mounting positions otherwise the platforms could flip.
- The 3 dividing bars seen between the platform sections are needed when the spacing's are 700 mm or 750 mm. This stops the cows hoofs getting trapped in the small gap left by the platform sections and also encourages them to step over the gap which may alter their gait.
- The electrical boxes are mounted underneath the platform trays which will protect them from direct high pressure water blasting.

- The overall walking surface width is 400 mm and the height is 100 mm.

Figure 3.6: CAD model of final platform design

3.2.4. Signal Conditioning

The electronics for the project are based on taking the analogue signal that the load cells produce and directly interfacing with an ADC. The digital signal is then communicated via SPI to an Arduino microcontroller for processing. The aim of the initial prototype was to design a break-out board that fits an Arduino Uno and is able to directly interface four load cells with a high precision multichannel ADC. The required data is then able to be transmitted serially to a computer for further processing.

3.2.4.1. Component Selection

The two main components required for the breakout board design was a highly stable voltage reference for the load cells and an ADC. For compactness, surface mount components were selected to ensure that the breakout board fitted within the header pins of the Arduino Uno microcontroller. A small range of voltage reference devices existed that would provide a highly stable reference voltage for the load cells. The AD7193 required an analogue voltage reference between 3 V and 5 V and the ASB1000 load cell recommended a voltage between 5 and 12 volts; consequently a reference voltage of at least 3 V was needed. A voltage of 4.096 was found to be the closest to what was required and a common reference used by precision voltage devices. Before looking for a suitable voltage reference device, the current drawn from each load cell was calculated with ohms law, with V being the precision voltage reference and R the input resistance of the ASB1000.

$$I = \frac{V}{R} = \frac{4.096}{410} = 10mA$$

Therefore four load cells require 40 mA supplied from the voltage reference device.

All manufacturers that produced a 4.096 voltage reference were explored and it was found that the highest current that could be supplied was 30 mA. To increase the current a basic analogue electronics voltage follower circuit was employed. Consequently the output current of voltage reference devices was an unimportant factor as the op-amp supplied the necessary current at the same voltage. Compared to other similar voltage reference devices the Texas Instruments REF5040 had superior characteristics with the lowest temperature drift (3 ppm/°C) and lowest noise (3 μV_{PP}/V). This made the REF5040 the most desirable and precise reference even though it was only capable of sourcing 8 mA.

The voltage follower circuit required a high-precision op-amp that had low offset voltage drift characteristics and was able to supply enough current. An AD8656 precision CMOS amplifier by Analog Devices was chosen as it was able to retain a low offset voltage drift (0.4μV/°C) and supply 220 mA which was more than suitable for the application.

3.2.4.2. AD7193 ADC Investigation

A considerable amount of time was spent on understanding the AD7193 and all the features associated with it. These features include:

- 24-bit sigma-delta ADC with 4 differential input channels
- Very low gain drift (±1 ppm/°C) and offset drift (±5 nV/°C)
- Multiplexor with automatic channel sequencer which simplifies communication
- Simultaneous 50 Hz/60 Hz rejection and programmable filters
- Variable output data rate between 4.7 Hz and 4.8 kHz
- Programmable gain (up to 128)
- Averaging (up to 16)

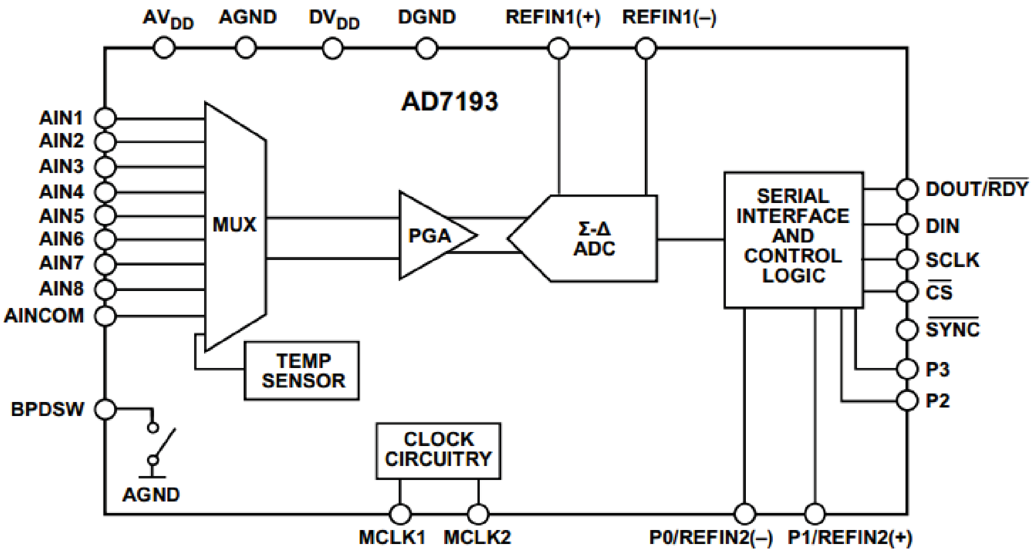

Figure 3.7: Functional block diagram of AD7193 (Analog Devices, 2015)

An internal block diagram of the AD7193 is shown in Figure 3.7. The AD7193 features a temperature sensor, an internal clock, programmable gain array, multiplexor, and SPI interface. The output of the 4 load cells are connected to AIN1 through to AIN8 and powered from REFIN1(+) and REFIN(-) which is the analogue reference voltage of 4.096V.

The AD7193 communicates via the SPI bus which requires four wires, these being:

- DOUT/$\overline{\text{RDY}}$: Master In/Slave Out (MISO). It functions as a serial data output pin to access the output shift register of the ADC. The output shift register can contain data from any of the on-chip data or control registers. In addition, DOUT/RDY operates as a data ready pin, going low to indicate the completion of a conversion.
- DIN: Master Out/Slave In (MOSI). This receives data from the microcontroller to configure internal registers.
- $\overline{\text{CS}}$: Chip Select (active low). This is used to select the AD7193. In this case this line will always be low to have this component selected.
- SCLK: The serial clock which can be internal or external. The serial clock input is for data transfers to and from the ADC.
- The $\overline{\text{SYNC}}$ pin is tied high as no synchronisation with other devices is required for this application.

3.2.4.3. Schematic Diagram and PCB

After thoroughly understanding the AD7193 datasheet an Altium schematic was designed for the purpose of creating a compact and highly accurate break-out board.

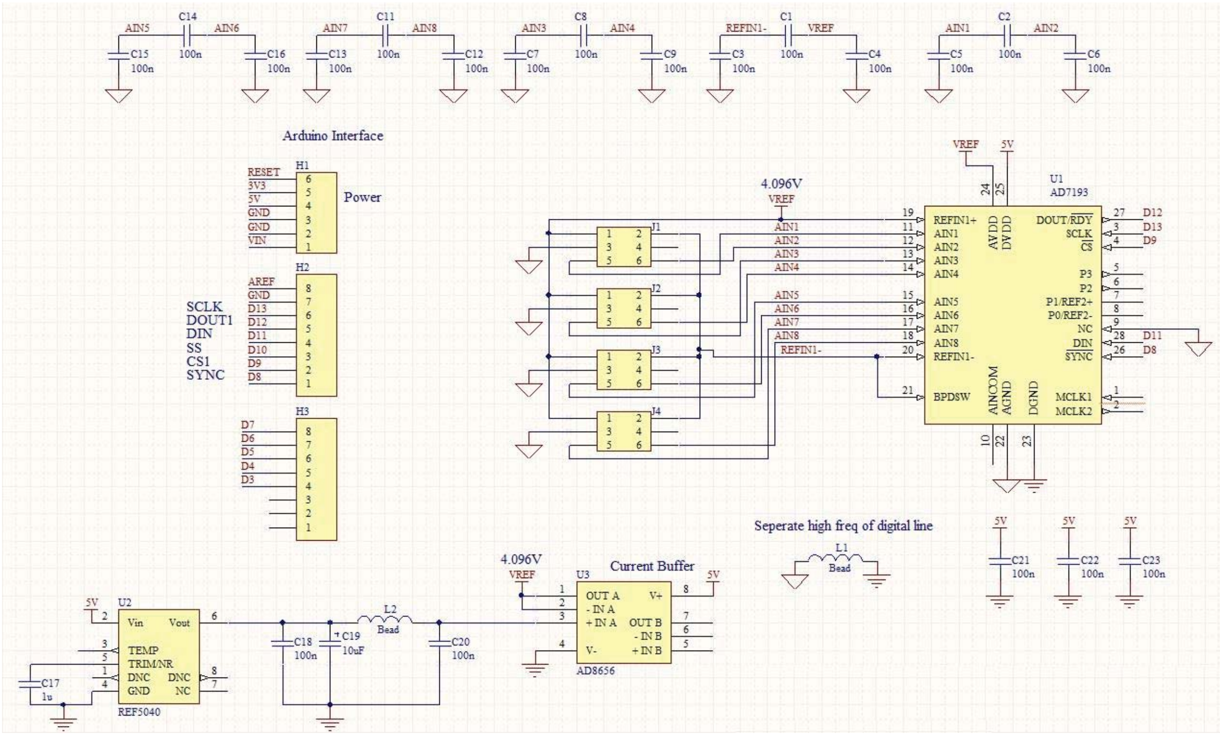

Figure 3.8: Schematic diagram of initial prototype

The circuit schematic shown in Figure 3.8 includes:

- The voltage reference (REF5040) to supply a stable 4.096 V.
- The voltage follower circuit using an AD8656 to boost the current supplied to the load cells.
- The 24 bit AD7193.
- 100 nF filtering capacitors on all input channels to the ADC (AD7193 datasheet recommendation).
- A low impedance bead - used between the digital and analogue ground to separate the high frequency switching on the digital line which helps smooth the input analogue signal.

3.2.4.4. Communications

As the overall system consists of four individual sections, some form of communication needed to take place. Two types of communication interfaces were investigated that would allow for connecting multiple devices, with these being I^2C and RS-485.

RS-485 was chosen over I^2C for this system mainly because RS-485 has superior noise immunity, faster data transfer speeds, further data transfer distances and is an industrial standard. RS-485 line drivers/receivers were required for each device operating on the data lines. The MAX487 by Maxim Integrated were found to be suitable for the task at hand. The MAX487 transceiver had two communication lines (A and B), two switchable pins to set whether the transceiver should be in transmit or receive mode, and two serial data lines.

The RS485 communication circuit recommended using fail-safe biasing to terminate the line at the furthest most point. Fail-safe biasing uses three resistors connected in series. The reason for the resistors was to remove the undefined state on a standard RS485 bus and replace this with a differential voltage between ±200 mV so no false triggering could occur.

3.2.4.5. Final Prototype PCB

Successful testing of the communication protocol and initial PCB prototype meant that a 'final' PCB was able to be designed. It was decided that the PCB would be housed inside each platform section because:

- This makes repairing and fault finding easier as each section has its own unique ID.
- Sections could be assembled and tested individually.
- There would be less redesign work compared to a single PCB interfacing 16 load cells.

The final manufactured prototype PCB (shown in Figure 3.9) was designed to incorporate an ATmega328 microcontroller acting as a slave device. The load cells are connected to the PCB via waterproof cable glands; and a 4-wire power and communications cable was connected with an IP-68 plug and socket for easy removal. The separate units were connected with a daisy chained parallel configuration; meaning only one cable was needed for each PCB.
The schematic of the final prototype can be found in Appendix 7.

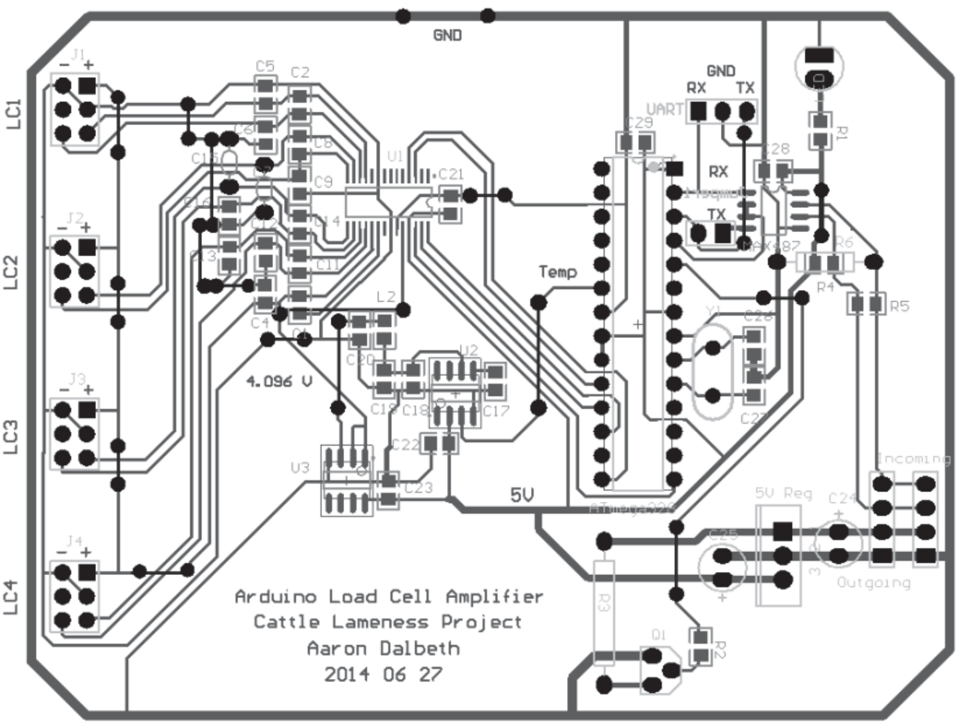

Figure 3.9: Final prototype PCB (Dalbeth, 2014)

3.2.5. Embedded Software

The microcontroller programming was done in the Arduino IDE, and is hardware-orientated. The main purpose of the microcontroller programming was the capability to interface with the AD7193 (get a digitized signal of the load cell) and the MAX487 (transmitting the data via RS-485) devices. There were three types of communication interfaces used with these being SPI (communication between ATmega328 and AD7193), RS-485 to communicate between master and slave devices, and serial communication between the master and computer. The Arduino Uno was used to program the ATmega328 microcontroller before inserting it into the constructed PCB.

3.2.5.1. RS485 Communication Protocol

The master microcontroller queries each slave segment in turn i.e. A, B, C, D, A, B, C etc. (this is also known as round-robin) as only one device was able to communicate on the RS-485 bus at a time. The individual sections were always in receiving mode (once the master transmits a packet, it goes into receive mode). The corresponding section received the packet, went into transmitting mode, responded to the master with the corresponding data, then went back into receive mode. It can be seen therefore that it was important to have some protocol between the master and slave devices (Nel, 2015).

Each slave section had four load cells connected to it; the master would query the section and the slave responded to the master with the corresponding data. The master had to be capable of selecting individual slaves that were able to:

- Set a sampling rate of the AD7193.
- Request data from the slave device. This could be the digitized values of the load cells, or the current temperature the REF5040 was reporting.
- Turn on the heating circuit.

Various pre-existing RS-485 protocols were investigated but were found to be complex. Consequently, it was decided to make a custom data transfer protocol, as this allowed a specific protocol to be designed for this system. The designed protocol was named the AJ convention (Aaron and Johann) and a packet consisted of three characters (Nel, 2015).

A diagram of an AJ packet transmitted by the master microcontroller to the slave microcontrollers is shown below and is transmitted as ASCII characters:

Slave ID	Command	Termination

Where:

- Slave ID is either, A, B, C, D or E, with E being all slaves selected

- Command
- R = Read data (Slave will respond with digitized values).
- Fx = Change frequency (set the sampling rate of AD7193), x specifies the sampling rate.
- T = Read REF5040 temperature.
- Termination is simply a new-line character ‘\n’

A diagram of an AJ packet transmitted by a slave microcontroller to the master microcontroller is shown below and is transmitted as ASCII characters:

Slave ID	Data	CRC-32	Termination

Where:

- Slave ID is the ID of the device that is responding to the master.
- Data, this is either the digitized values of the load cells (CH1:xxx CH2:xxx CH3:xxx CH4:xxx), where xxx is the AD7193 values or the temperature of the REF5040.
- CRC-32 used for data integrity.
- Termination is simply a new-line character ‘\n’.

Every time a slave responds to the master, it also transmits the character ‘M’. The master microcontroller uses this as a mechanism to query the next slave device. The designed protocol was extensively tested in the laboratory making use of the four PCB’s (see Figure 3.10). A bench-top power supply was set to 12V; the current limit was set to 400mA and connected to the incoming power terminals of slave A. The 12V and ground is looped in parallel to the other three PCB boards’ power terminals which is how the final system is powered. The RS-485 communication lines (A and B) are also connected in parallel on the PCB boards. The Arduino Mega has its own MAX487 connected to it, and simply connects in parallel to the A and B lines. It was decided to make use of an Arduino Mega as it has more than one serial port on it. One serial port was used to send and receive data from the slave devices; another serial port was then used to send the data from the microcontroller to the computer for further processing.

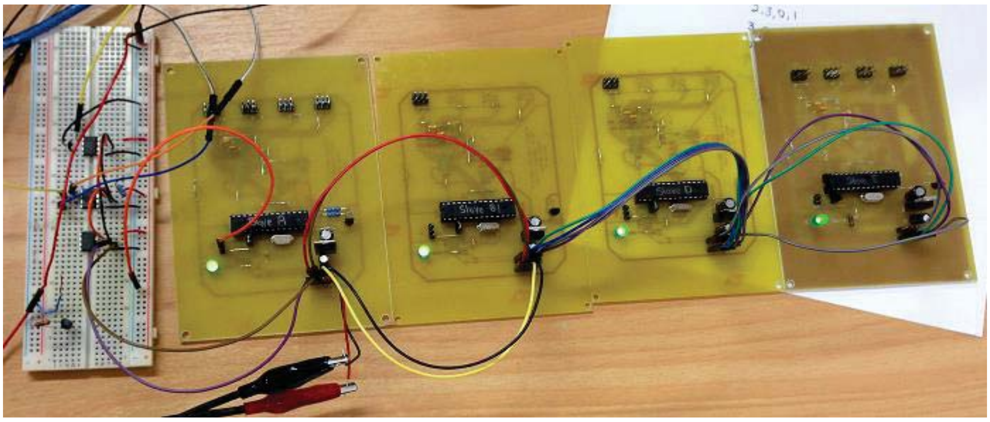

Figure 3.10: RS-485 Test setup of master/slave

3.2.5.2. AD7193 Programming and Sampling Rate

The complete process of configuring, reading and communicating with the AD7193 is detailed in Appendix 4. The overall layout of the program to capture data from the load cells can be seen in Figure 3.11. When the program starts, there are multiple initializations that take place. The first being the serial initialization, this is where the baud-rate is set for serial data transmission. When the SPI initialization takes place, SPI communication is started, the data mode is set, which was found to be mode 3 after inspecting the datasheet. The clock divider was set to 4 MHz, and the bit order was set to output the most significant bit first.

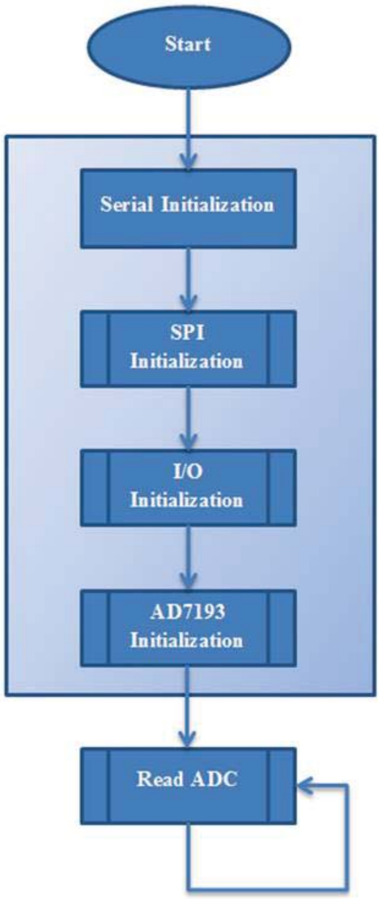

Figure 3.11: Program layout of AD7193

The sampling rate of the AD7193 can be configured to one of seven following modes shown in Table 4. The true sampling rate when multiple channels are used depends on the number of enabled channels. For example when four load cells are connected to the ADC all the available channels are being occupied. Equation 1 is used to determine the output frequency per channel:

$$Sampling\ Rate = \frac{AD7193\ Data\ Rate}{Number\ of\ Enabled\ Channels} \tag{1}$$

Table 4: Sampling rate modes of AD7193

Mode	Sampling rate of AD7193
A	50Hz
B	60Hz
C	150Hz
D	300Hz
E	960Hz
F	2400Hz
G	4800Hz

The RS-485 communication operates in half-duplex mode (data can't be transmitted and received simultaneously). The master has to request data from one slave device at a time, as only one device can use the data bus at a time. For this reason the overall sampling rate at which data is being received from each section is significantly reduced when multiple slaves are connected on the RS-485 bus. The rate of which data is ideally received from the system is given in equation 2:

$$Data\ Rate_{IN} = \frac{AD7193\ Data\ Rate}{No.of\ Enabled\ Channels\ \times No.of\ Slave\ Devices} \tag{2}$$

Where:

- AD7193 data rate is the sampling rate the AD7193 is set to.
- No. of enabled channels is the number of load cells being interfaced (usually four).
- No. of enabled slaves is how many platform segments are active (usually four).

During testing it was found that the actual communication frequency per platform segment was not consistent when sampling at higher frequencies. The data from the slave platforms at 4.8 kHz and a baud rate of 115200 oscillated between the period of 0.008 s – 0.005 s. Figure 3.12 shows the data received from the four platform sections plotted against frequency. It can be seen that there are spikes every 4-5 readings which is partially due to the ADC's not being synchronised to a common clock during initialisation. At an ADC frequency of 4800Hz the settling time per channel using the Sinc 4 filter is 0.83 mS per channel. This equates to 3.32 mS for all four load cells to complete the conversion. As the ADC for each platform is continuously cycling each channel and polling for end of conversion there is an inherent delay depending on when the slave has a request for data from the master.

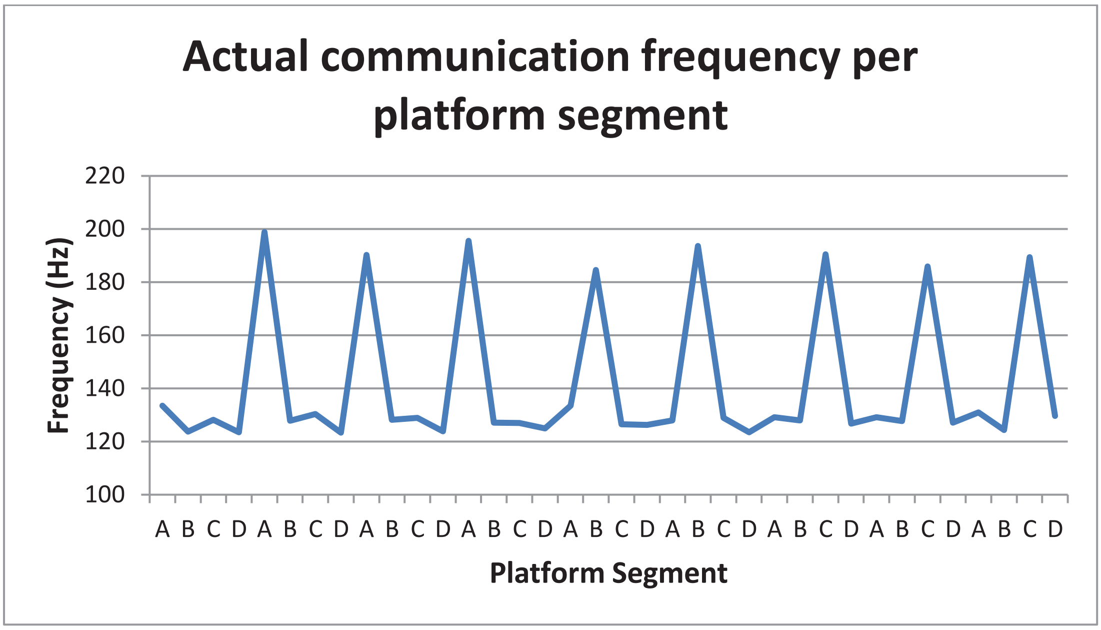

Figure 3.12: Actual data rate received per slave segment

A pin on the Arduino Mega (master) was programmed to toggle each time data was being received to verify the incoming data rate. The results are shown in Table 5. At sampling speeds of 2.4 kHz and 4.8 kHz the measured frequency of the incoming data was less than the theoretical speed given in equation 2. The time between switching slaves and waiting for new data to arrive was longer than the time to send the data. Equation 2 does not take into account the 4 ms switching delay of the slave devices at this frequency. Using a baud rate of 250kb/s increased the overall data communications speed but at the cost of system reliability. Therefore at the highest sampling speed of the ADC, each load cell is being sampled at 568 Hz (142 multiplied by 4). To increase the sampling frequency and reach the theoretical values in equation 2 full duplex RS485 would need to be engaged. It was decided that the current sampling rate would be sufficient for the project's needs (nearly 10 times faster than the GAITWISE system sampling).

Table 5: Comparison of calculated and measured incoming data frequencies

AD7193 Data Rate (Hz)	Calculated Frequency (Hz)	Measured Frequency (Hz)
50	3.13	3.72
60	3.75	4.84
150	9.40	10.05
300	18.75	20.47
960	60.00	60.50
2400	150.00	142.90
4800	300.00	198.40 Peak

3.3. PC Software Test Harness

Various software tools were created using Python 2.7 programming language to help detect lameness, these include: capturing the load cell values, processing them and calculating the basic kinematic variables. The main tasks the test harness software had to perform were:

- Able to capture the ADC values from each section and translate it into useful data.
- Remove offset on individual load cells.
- Transfer data from the master microcontroller to the computer.
- Plot the force vs time signal.
- Plot centre of pressure on the platform.
- Record data to a file for post-processing.

3.3.1. Load Cell Calibration

When a new load cell is purchased from the manufacturers a load cell calibration certificate accompanies it which states the tested strain gauge characteristics. One of the main characteristics on this certificate is the full scale output voltage factor which is used to determine the scale factor. Each load cell certificate contains a serial number of the load cell which is unique to that load cell. From the 16 load cells purchased it was found that the full scale output varies from 1.998 mV/V to 2.002 mV/V. A scale factor based on the median (2.000 mV/V) could be used throughout the load cells but this could create an error of 8.2 μV when a 1000 kg load was applied. Although this error sounds very small it would equate to at least a 5 kg difference between the lowest and highest full scale output load cells. Consequently, five separate scale factors were determined to make the system as accurate as possible. See Appendix 5 for experimental setup and results of the load cell calibration.

3.3.2. Calculating Load Cell Weight

An issue encountered after calibrating the load cells was that each load cell had different offset values due to the slight differences in the strain gauges. This meant that the offset value when no load was applied had to be individually calculated then removed from the respective incoming channel before an accurate force could be determined. An algorithm was designed to tare the load cells so that the initial readings were zero. The algorithm works by taking a sample of 100 data points per platform segment and averages each channel by the incoming data. This effectively zeros the entire platform and any weight associated with the rubber mat or accumulation of manure.

To calculate the weight being experienced on each section, the mean of each channel is deducted from the current channels ADC value and multiplied by the scaling factor, see equation 3.

$$LC = (ADC_{Value} - LC_{Mean}) \times Scaling\ Factor \tag{3}$$

Where:

LC is the load cell value scaled in kilogram

ADC_{Value} is the raw incoming ADC value of a specific channel

LC_{Mean} is the mean value calculated from the raw ADC values under no load

Scaling Factor is the calculated factor to convert to kilograms

The resultant force experienced on each load cell in each segment is now scaled in kilograms. To calculate the total weight being experienced on a section, the force experienced on each load cell is summed together, see equation 4.

$$\sum_{n=1}^{4} Total\ Weight = LC_n \tag{4}$$

3.3.3. Calculating Centre of Pressure

One of the most significant variables to correctly classify lameness is related to the position of the force applied. The position variables can be used to determine irregularities in stride length, step overlap and step abduction. These variables provided a strong correlation for classification in Maertens *et al* (2011) study.

To determine the centre of pressure (COP) location on the platform an algorithm was designed to find the X and Y positions using the four load cell signals. When the load cells are under pressure, reaction forces are generated. These forces, F1, F2, F3 and F4, are shown in Figure 3.13. This figure also shows how the reaction forces correspond to the position of the load cells, with LC1 representing load cell 1. The distance between LC1 and LC2 or LC3 and LC4 on the x axis is the width measurement and the distance between LC1 and LC3 or LC2 and LC4 on the y axis is the length measurement. The total force (F_T) on the platform is found using the previously calculated summation of the four load cell signals, with these being F1 + F2 + F3 + F4. The COP is a coordinate (X, Y) that can occur at any position within the dotted line perimeter and is calculated using equations 5 and 6 (Nel *et al*, 2015).

$$X = \frac{(F2 + F4)}{F_{Total}} \times Width \tag{5}$$

$$Y = \frac{(F3 + F4)}{F_{Total}} \times Length \tag{6}$$

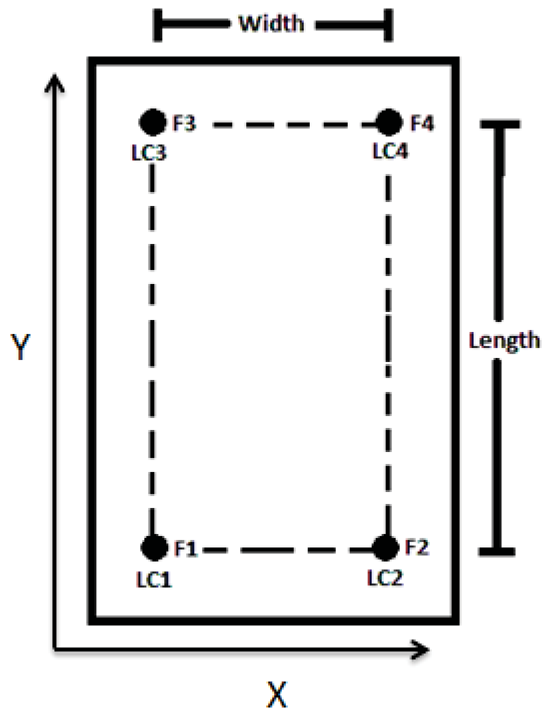

Figure 3.13: Centre of pressure calculation diagram

Using these equations a force applied anywhere inside the dotted line perimeter can be located with x, y coordinates given in mm from the origin, which is the point occupied by LC1. The value of 435 mm was the width between the load cells and 575 mm was the length between the load cells for the four platform segments. The testing of the algorithm and the accuracy of the coordinates can be found in Chapter 6.1.1.

3.3.4. Recording Data

The software records relevant data received from all four platform segments and writes it to a text-file using the following format:

TIME, SLAVE, CH1, CH2, CH3, CH4, Total Weight, X-Position, Y-Position, Peak

Where:

- TIME is the timestamp that the data was captured in microsecond resolution
- SLAVE is the ID of the section
- CH1 – 4 is the force (kg) experienced on each load cell rounded to 2 decimal places
- Total Weight is the total weight experienced on the section (kg)
- X-Position/Y-Position is the centre of pressure on the section (mm)
- Peak indicates whether a new peak weight has occurred or not. A ‘P’ is written to indicate a new peak occurred, otherwise an ‘o’ is written to the file.

An example is given below of how the data is stored in the text-file.

TIME,SLAVE,CH1,CH2,CH3,CH4,WEIGHT,X,Y,PEAK

10:32:06.692000,A,2.48,3.78,1.79,0.02,8.08,339.39,303.67,P

10:32:06.723223,A,3.99,9.62,4.08,1.00,18.71,318.80,247.95,P

10:32:06.770478,A,11.42,20.10,4.72,3.26,39.52,349.44,234.47,P

10:32:06.801198,A,17.91,30.00,5.99,6.55,60.47,347.13,226.93,P

Examining the first line from the example it can be seen that data was captured in the morning at 10:32:07, it was coming from section A, the total weight was 8.08kg and the centre of pressure was at 339 mm (x) and 303 mm (y). Data will only be recorded if more than 5 kg of force is experienced on any segment. This is to ensure that any build-up of mud or manure will not cause the program to start recording.

3.3.5. Plotting Weight and Position

A script was created that plotted the data from the text-file displaying the four load cell signals and the location of that force in the same graph. The program reads the text-file, determines whether the data belongs to section A, B, C, D then simply extracts the time, weight, x and y positions and plots it. Figure 3.14 shows an example of the plotted data; the signal signature seen is the author's natural walking pattern. It can be seen that the weight signals correspond to the same colour positional signals shown in each segment. The beginning peak seen on each segment is the heel landing and the second peak on the segment is the toe pushing off. The first foot was placed on segment A on the left side and the next foot is the right foot shown in green. A pattern of left-right, left-right can be seen in the positional segment which shows the movement of the author with the straight lines being drawn on each segment. These positional points are not clustered together in a single point as the weight on each foot is shifting. This reveals the 'walking signal signature' of the author and the inherent characteristics of a heel-toe movement in humans.

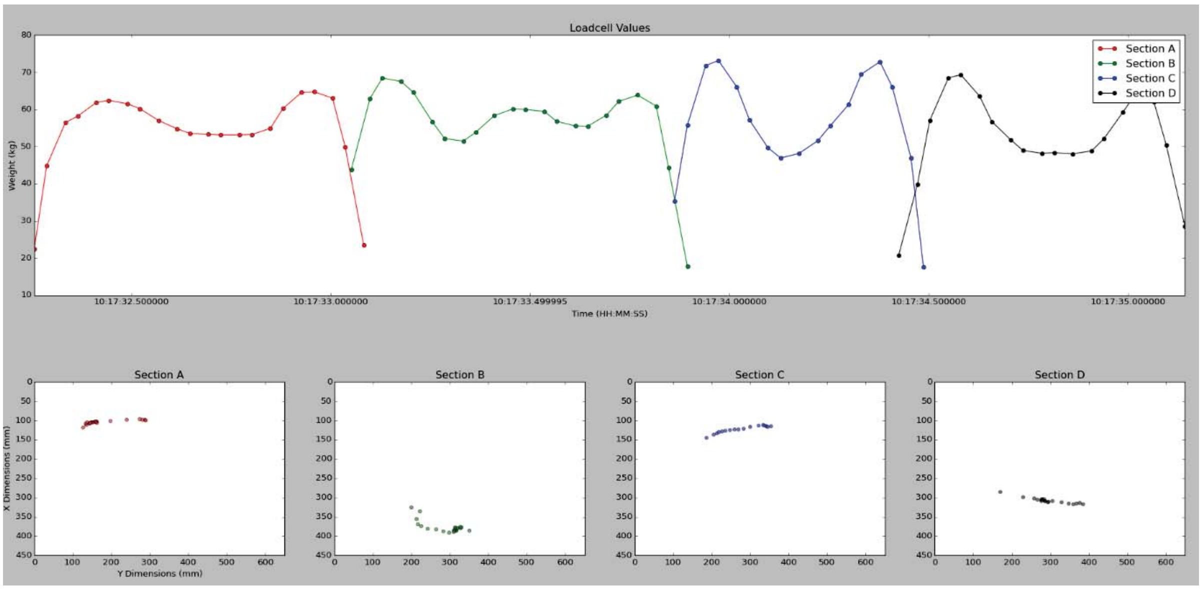

Figure 3.14: Author walking across platform - load cell signals and positions

To find the steady state noise that exists in the system, the author stood on one platform section and stayed as motionless as possible to capture the static weight. The processed weight signal was zoomed into at steady state (approximately 63.2 kg) and is shown in Figure 3.15. The signals are fluctuating between 62.7 kg and 64.2 kg as marked by the dashed black lines (1.5 kg range). The reason for this is from the noise induced by the inherent nature of the sigma-delta ADC as it converts the analog signal using pulse density modulation to a digital signal.

It was found that with a gain of 128 at 4.8 kHZ using the Sync 4 digital filter, the ADC has a peak-to-peak noise of 2.6 μV and an effective resolution of only 15 bits (Analog Devices, 2015). Therefore, to find the noise in kilograms the full scale output voltage is divided by the noise ratio and multiplied by the scale factor of the load cell.

$$Noise\ (kg) = \frac{load\ cell\ full\ scale}{peak{-}to{-}peak\ noise} * scale\ factor = \frac{8.192\ mV}{2.6\ \mu V} * 0.0004724 = 1.48\ kg$$

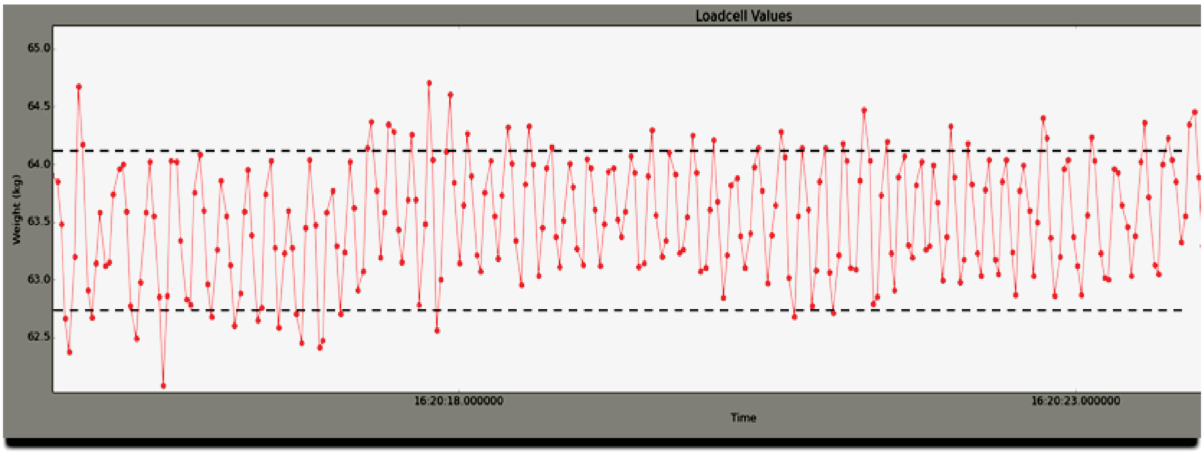

Figure 3.15: Steady-state noise

Chapter 4: System Integration and Methods

This chapter describes the statistical techniques that were used to reduce variables and classify the cows. Dairy cattle identification and locomotion scoring are discussed. The final section describes the experimental setup and methods used during the on-farm testing.

4.1. Statistical Analysis Techniques

To determine lameness, reference data from healthy and lame cows is needed to compare differences in variables. As a starting point, basic statistics of averages, standard deviations, correlations etc. were used to form an understanding of the expected data to be observed and processed. Further statistical techniques were investigated in order to reduce redundant variables to help build models to classify lameness. These techniques included:

- Two sample T-test
- Novelty Detection
- Principal Component Analysis
- Discriminant Analysis
- Logistic Regression

4.1.1. Two Sample T-test

A two sample t-test is used to determine whether the means of two independent groups are significantly different from each other, in this case healthy vs. lame. A confidence interval is calculated by testing the hypothesis of the difference between two sample means. A value is significant if the P-value is less than 0.05 (5%). The procedure is based on the t-distribution which assumes that the drawn samples come from a normal or close to normal distribution (Minitab, 2015). The significant variables found from the T-test will later be used in models to classify lameness.

Using this technique Van Nuffel *et al* (2013) published a paper using the GAITWISE System to find the variables that were the most significant in determining lameness. A healthy group of 10 non-lame cows' variables were evaluated with 10 lame cows noticed by the farmer. The significant variables were stance-time RH, stance-time RF, force LH, step-overlap and total time. Applying this technique by itself does not determine lameness unless threshold values are set and a smart algorithm is written. In my opinion, the mentioned study is biased and the cows were most likely selected to alter the results to make their system perform better than it actually is. See Chapter 6.4.2 for T-test results from the farm trials.

4.1.2. Novelty Detection

Novelty detection is a machine learning system that can identify new or unknown data that the system was not previously aware of through the aid of statistical based approaches. This technique is commonly used in signal processing, pattern recognition, data mining and disease detection. In this project, novelty detection was investigated using the raw weight signals from the load cells (signal signatures) that each cow produces when they walk over the platform. A training set of healthy cow hoof falls from each platform segment were used to form a ‘healthy boundary’ based on the mean ± X standard deviations, where X was found so that all healthy cows fell inside the boundary. Lame cow signals were then added to the model and the percentage of time outside of the boundary was found which would determine the amount of outliers and the severity of lameness. See Chapter 6.4.1 for novelty detection results from the farm trials.

4.1.3. Principal Component Analysis

Principal Component Analysis (PCA) is a variable reduction method which reduces the data set of the matrix to a smaller number of variables called principle components. The purpose of PCA is to reduce the number of original variables by deleting redundant information. PCA is a very powerful method and is used as a tool in exploratory data analysis and industries such as the medical field. For example it is very helpful for a doctor to be able to narrow down 15 symptoms of a disease to three basic variables for quicker diagnoses. In the context of the project, PCA was used to reduce the number of variables associated with detecting lameness into a combination of new variables.

Using Minitab 17 statistical package it was found that from the 32 main variables PCA could reduce these to 10 new variables which could explain 90% of the variance of the original data. Although using ten variables would make the algorithms easier to develop, the computation power that modern day computers possess makes it not worthwhile to reduce variables if information is being lost in the process. PCA was therefore not required to be investigated further for this project.

4.1.4. Discriminant Analysis

Discriminant analysis (DA) is a statistics tool used to characterise two or more classes of objects or events. This method looks for linear or quadratic combinations of variables which best explain the data, with the assumption that independent variables are normally distributed. It is very similar to regression analysis and PCA, although DA explicitly attempts to model the difference between the classes of data and produce an outcome for each observation (Eberly College of Science, 2015). This type of classification method is exactly what is needed for the project; to be able to take an unspecified number of variables and generate a result of healthy or lame for that particular animal.

Minitab 17 statistical package was used to find the discriminant functions and classify the cows based on the significant variables indicated from the t-test. Models with all the variables and combinations of selected significant variables were examined to try and find a model that gave the best results. A prior probability can also be used to increase the model accuracy. In this case, it is known that on average 90% of a herd will be healthy and 10% will be lame at any given time in New Zealand (Malmo *et al*, 2011). Minitab also uses cross validation to estimate misclassification probabilities (false positive and false negative) which is a more robust model validation technique. The program finds the equations for the categories by systematically leaving one data point out of the calibration model and then adds this data point back to the model to see what classification it would be. This is basically finding a model with the supplied calibration data then testing the model by removing each data point at a time. An example of an equation for a linear discriminant function for a healthy and lame cow is shown below. The equation consists of a constant and multiplication factors for each predictor variable in the model. In this case, seven variables associated with weight are used in the equation. A linear score function is obtained from each equation to find a single value (202.3 and 205.2).

$$Healthy\ (x) = -6633.6 + 6650.9 * NGRF\ LF + 7002 * NGRF\ RF + 7092 * NGRF\ LH + 5539 * NGRF\ RH + 0.1 * frontlimb + 6.7 * rearlimb + 1.3 * diagonal = 202.3$$

$$Lame\ (x) = -6716.3 + 6762 * NGRF\ LF + 6919 * NGRF\ RF + 7183 * NGRF\ LH + 5573 * NGRF\ RH + 0.2 * frontlimb + 6.6 * rearlimb + 1.3 * diagonal = 205.2$$

Minitab then uses decision rules to compare the two values to determine the classification. In this instance Lame > Healthy, therefore the cow belongs in the lame category. See Chapter 6.4.3 for discriminant analysis results from the farm trials.

4.1.5. Logistic Regression

Binomial logistic regression (BLR) is a statistics tool used to predict the probability that an observation falls into one of two categories, such as win/lose, pass/fail or healthy/lame. The BLR model is used to estimate the probability of a binary response based on one or more predictor variables by using a cumulative logistic distribution (Artificial Intelligence in Motion, 2013). The model is a very similar method to DA, although BLR makes no assumption of the distribution of the independent variables; consequently the model will predict the probability more accurately for a skewed distribution. It is commonly used in many fields, including engineering and medical (Laerd Statistics, 2013). SPSS 23 statistical software was used to categorise the cattle into healthy and lame groups based on a combination of significant predictor variables. See Chapter 6.4.4 for logistic regression results from the farm trials.

4.2. Cattle Identification

In the New Zealand Dairy Industry all animals are required to have a National Animal Identification and Tracing (NAIT) Radio Frequency Identification (RFID) tag to comply with regulations. This allows farmers to keep track of their animals and to enhance New Zealand's ability to respond quickly to biosecurity outbreaks. To read the tag, an RFID reader is used to identify the unique electronic identification number which is a 12 digit number. An RFID system on the farm consists of:

- Tag: small transponder located in the right ear that holds and sends information.
- Antenna: energises the transponder of the tag to receive information.
- Reader: processes and stores the information from the antenna and provides an output of data visually and externally.

An XRP2 EID reader and a large RF antenna were supplied by Tru-Test to read the ear-tags from cows as they walked over the system. In the farm trials, the RF antenna was positioned near the middle of the platform as this is the most common mounting place for walkover weigh scales (see Figure 4.1). The EID reader was connected serially (RS-232) to a computer at a baud rate of 9600 and it transmitted 8 data bits with no parity and one stop bit.

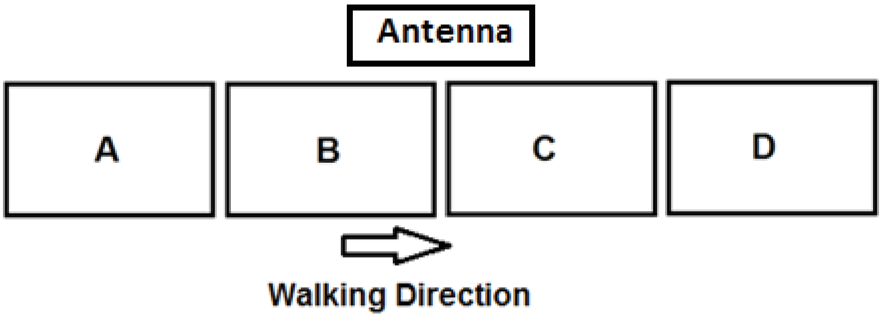

Figure 4.1: RF antenna positioned in middle of platform

4.2.1. Video Recording

To capture each milking session a waterproof sports camera (Go Pro Hero 3+) was used to record a video at 1080p 60fs with a wide angle lens. The video camera was positioned 2 m from the platform on a 1 m high rail which was located centrally so that it could see the cows walking towards the platform and also exiting. Each cow was videotaped from her right side and at least four strides per cow were captured every day. The videos were stored for gait scoring of the cows by a trained observer afterwards.

4.3. Farm Trials

Three separate on-farm trials were conducted with the aim of capturing data to test how the system performs. The initial trial was carried out at a farm with a control group of 10 cows to test the weighing algorithm. The system was moved to a large farm with a rotary shed to capture three weeks of data from an entire herd in the aim to determine lameness. The final trial involved one week of data capturing and analysis of a control group of cows.

4.3.1. Trial 1 Setup

The WoP was installed in the exit race of a 20 aside herringbone milking shed operated by Massey University in Palmerston North (see Figure 4.2). The 160 strong dairy herd was made up of an assortment of breeds of cows including Holstein-Friesian, Holstein-Friesian / Jersey crossbreed and Jersey. 10 cows were randomly selected from the herd after milking to form a control group to test the walkover weigh algorithm. Each cow was carefully moved to stand on the platform and wait with minimal movement for at least 3 seconds before they were allowed to walk off. The static weight of each cow was then found and recorded against the EID tag number. The group of cows were then made to walk over the platform as naturally as possible by an approved stock handler at least 10 times. This task was completed as quickly as possible before the cows became agitated and sick of walking around in circles. The captured dynamic data was post-processed to find the walkover weight compared to the static weight. See Chapter 6.2 for testing results.

Figure 4.2: WoP installed at milking shed

4.3.2. Trial 2 Setup

The WoP was shifted to a large farm located in Kairanga, Palmerston North, which milked between 200 and 800 cows everyday throughout the year. When the WoP was installed in July 2015, approximately 200 cows were being milked twice a day in the winter milking herd, with more being added each day due to calving. During calving the incidence rates of lameness are higher due to additional stresses being placed on the cows' body (R. Laven, personal communication, March 20, 2015). The 2015 winter season was particularly wet and muddy which also increased the lameness likelihood; consequently it was a perfect time to capture data for the project. Cows walked out of the 60 bail rotary milking shed individually along a 20 m raceway to feed sheds which accommodated 200 cows per shed (four in total). Figure 4.3 shows a feed shed which has concrete flooring with a herd of cows eating down both sides. The majority of the herd were Holstein-Friesian or Holstein-Friesian / Jersey crossbreed, which are the two most common breeds (34% and 46% respectively) in New Zealand (DairyNZ, 2015). After half an hour of being in the feed shed the herd were moved to pasture, sometimes a walk as far as 3 km one way.

The WoP was installed in the middle of the 20 m raceway under a structure with an arched tin roof. An existing chicane made of metal tubing was 2 m before the platform which helped slow down and single out the cows. A continuous rubber mat was laid over the length of the platform to hide the platform segments so that it seemed like one long platform to the cows (see Figure

Figure 4.3: Herd of cows in feed shed

4.4). The most suitable time to conduct on-farm assessments of dairy cattle gait is after milking (Flower, 2006) therefore data from the entire herd was captured at this time continuously over a three week period. The morning milking data was not captured (driving to the farm twice a day was not feasible), although the herd still walked over the platform. The cows were not pushed or disturbed while walking over the platform as the idea of this trial was to capture data as naturally as possible without any intervention.

Figure 4.4: WoP during use in raceway

The platform was calibrated each day before data was captured to make sure that the correct weight was being displayed. This simply involved the author standing on each section and making sure the static weight was constant and approximately 62 kg. Half way through the three week data gathering trial, Lisa Hine, who is a trained lameness scorer from the Massey University Large Animal Veterinarian Department, visited the farm. Eight final year vet students accompanied her to help with tag reading, writing scores and commenting on particular issues. Each cow was scored after walking over the WoP and down the raceway to the feed shed. A video camera also recorded the scoring session in case particular cows needed to be examined further. See Chapter 6.3.1 for scoring results.

4.3.3. Trial 3 Setup

Three weeks after the initial analysis of trial 2, a further week of data was captured and analysed from the herd, with the focus being on a control group of cows. The control group contained 25 cows - 10 randomly selected healthy (level 0) cows, 3 randomly selected level 1 cows and all identified lame (level 2) cows (12 in total). No level 3 cows were found in the herd during the video analysis scoring. The main reason to focus on a small group of cows instead of the entire herd was to be confident that the scored cows were ‘gold standard’ for their lameness level. Specifically, the lameness scorer was certain that the selected animals’ scores would be a good representation of the population to base the statistical calibration models around. See Chapter 6.4 for results.

Chapter 5: Data Exploration

This chapter describes the algorithms developed in this project and how the data is written to a file. Numerous post-processing algorithms are discussed as well as how the gait variables are determined.

5.1. Post Processing Algorithms

The post-processing software tools were created using Python 2.7 programming language. The main tasks this software had to perform were:

- Splitting the peaks in the weight signal to distinguish between front and rear legs
- Determining left and right hoof
- Calculating the dynamic weight on individual legs
- Calculating the total walkover weight
- Determining the gait variables and associated lameness variables
- Writing the variables to an Excel file

5.1.1. Splitting Peaks

One of the first algorithms designed was the ability to split the two weight signals that occurred on each platform segment. The platform was designed to capture two separate signals of the cow on the same side under normal walking conditions. The first signal is therefore recognised as the front leg and the second signal is the rear leg.

The method developed makes use of the weight of the peak that occurs (y-axis) by setting an arbitrary threshold value. Figure 5.1 gives an example of how the algorithm works with a threshold level set at 100 kg. Any weight above the threshold is true and any weight below is set as false. The algorithm makes use of the fact that at the start of a peak the transition from false to true occurs and on the way back down true to false occurs. Two Boolean values are used to hold the current value and the previous value to determine when a valid signal occurs. This gives the ability to individually keep track of each weight value assigned to a limb in an array which will be used in future algorithms to calculate dynamic limb weight. Another advantage is also removing false peaks that can occur when a cow half steps onto the platform and then steps off again if the threshold weight is set at a reasonable value. Acknowledgements to Johann Nel for designing this algorithm.

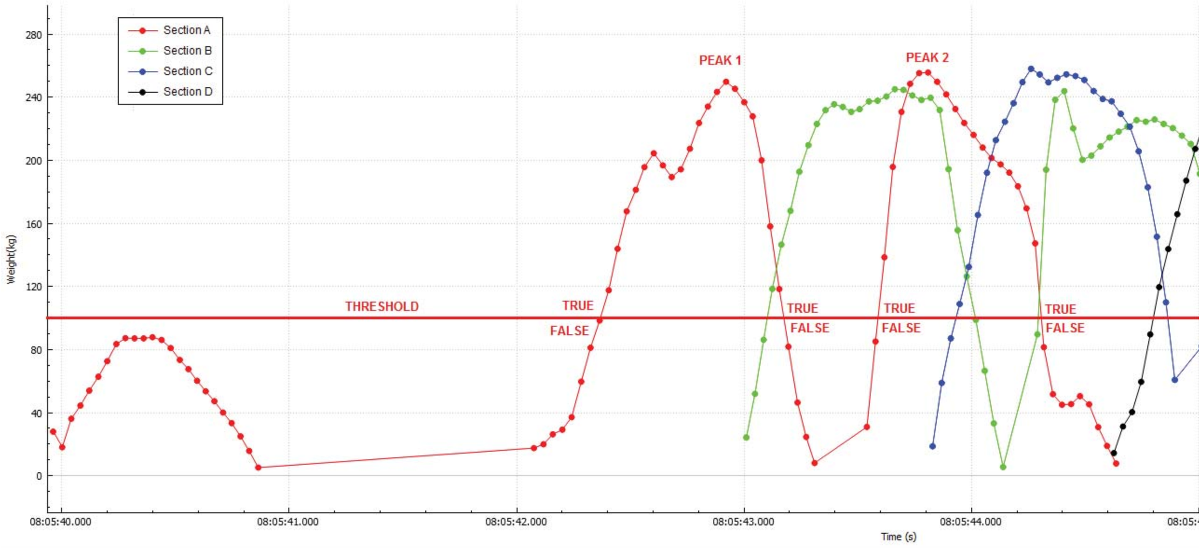

Figure 5.1: Example of splitting peaks on segment A (Nel, 2015)

5.1.2. Detecting Hoof Side

A simple algorithm was developed to determine whether a left or right hoof is on a segment. This was achieved by comparing the front hoof placements on the beginning two segments by taking the average X-position data on segment A and the average X-position data on segment B. An example of the positional data experienced when a cow walks over the platform is shown in Figure 5.2. If segment A X-position data (shown in red) is less than segment B X-position data (shown in blue) then the left hoof must stand on segment A first. The comparison is only tested on the first two segments as the cow will continue to stride in the same pattern on the remaining two segments. Only the front hooves are considered as the rear hooves should land in a similar position as the front. The weight signals experienced anywhere on the platform can now be assigned to either hoof (front/rear) on either side (left/right).

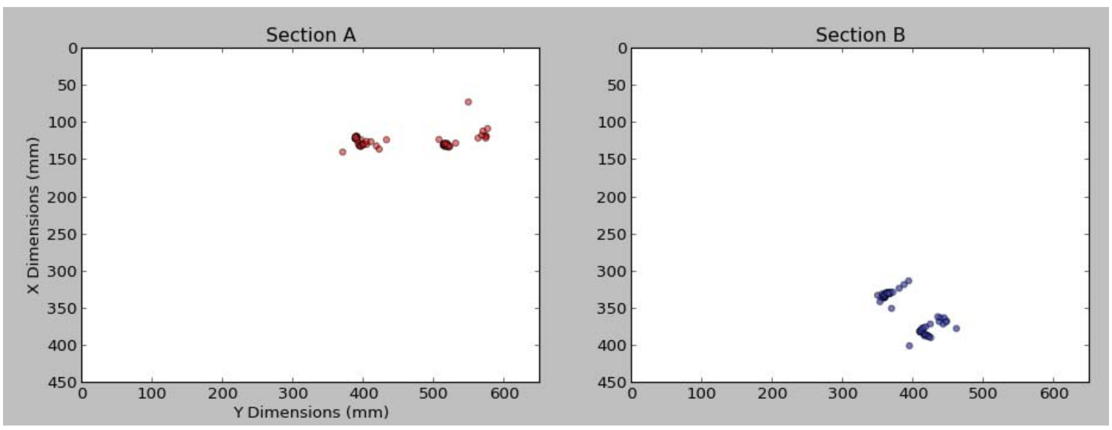

Figure 5.2: Positional data from walking cow on segments A and B

5.1.3. Walkover Weigh Algorithm Development

In order to calculate the total weight of a cow while moving across the platform an algorithm had to be developed to find the dynamic weight. Various filtering algorithms were examined with the most common techniques of moving average and weighted average being explored.

A moving average (or running average) is calculated by taking the arithmetic mean of a given set of values. The moving average 'window size' determines how much of the data is being examined for each calculation. For example a moving average with a window size of 6 will take the previous 5 data points and the current data point and average them to form one value. This averaging technique is commonly used with time series data to smooth out short-term fluctuations and can be considered as a low pass filter (Statistics How To, 2016).

A weighted average is similar to a moving average apart from a multiplying factor that assigns different weights to data depending on the importance of each data point. Mathematically it is the convolution of the data points with a fixed weighting function, usually between 0 and 1. The weighted average technique responds faster than the moving average technique using the same sample data. For the purpose of this project it was decided that the data would be most stable and closest to the correct weight at the centre of the data set, therefore the data in the middle of the dataset was given the most weight and that on the edges the least weight. To calculate a weighted average the following steps are performed:

- Multiply each value by its weight.
- Add up the weighted values.
- Add up the weights for each value.
- Divide the total of the weighted value by the total of the weights.

The two techniques were developed using inbuilt functions in Python's Numpy mathematical package. The moving average window size was experimentally evaluated and set at 3. The weights for the weighted average increased in incremental values depending on the array size from 0 – 1 – 0, with 1 being the central data point. The algorithms were tested in the laboratory by statically weighing myself then walking over the platform ten times at varying speeds to capture the dynamic signals. The static weight was found to be an average of 62.3 kg. The total weight will always be on one segment or between two segments at any one time, therefore the total weight between sections AB, BC, and CD needs to be resolved to find an average weight.

A graphical example of the signals experienced on sections B and C is shown in Figure 5.3. This shows two steps taken on the platform, with the red signal and blue signal showing the raw values experienced on section B and section C respectively. The green signal is the summation of both raw signals at each point in time and the magenta signal is the moving average of the combined weight. Notice how smooth the magenta signal is compared to the other three signals.

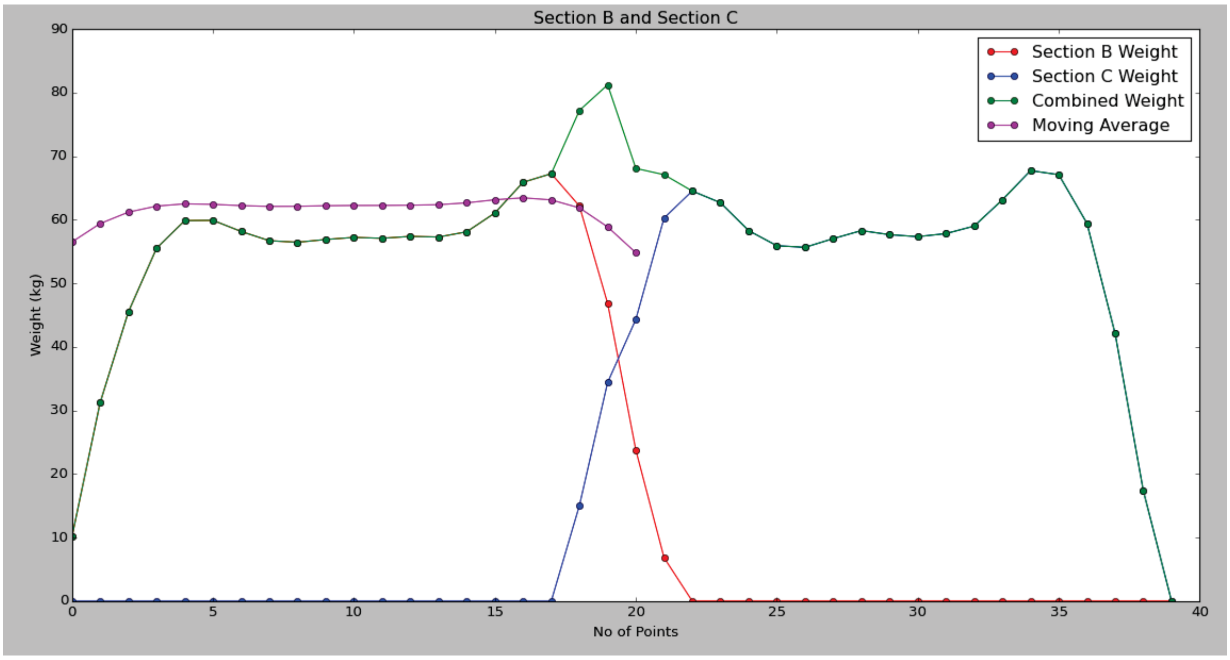

Figure 5.3: Signal showing moving average while author walking over platform

Overall, the weighted average technique produced the best results with an average of 61.8 ± 0.2 kg which is half a kilogram less than the static weight. Figure 5.4 illustrates the average calculated weights of the two techniques across the 3 sections. The running average is approximately 700 g less accurate than the weighted average. See Appendix 2.3 for full results of each test.

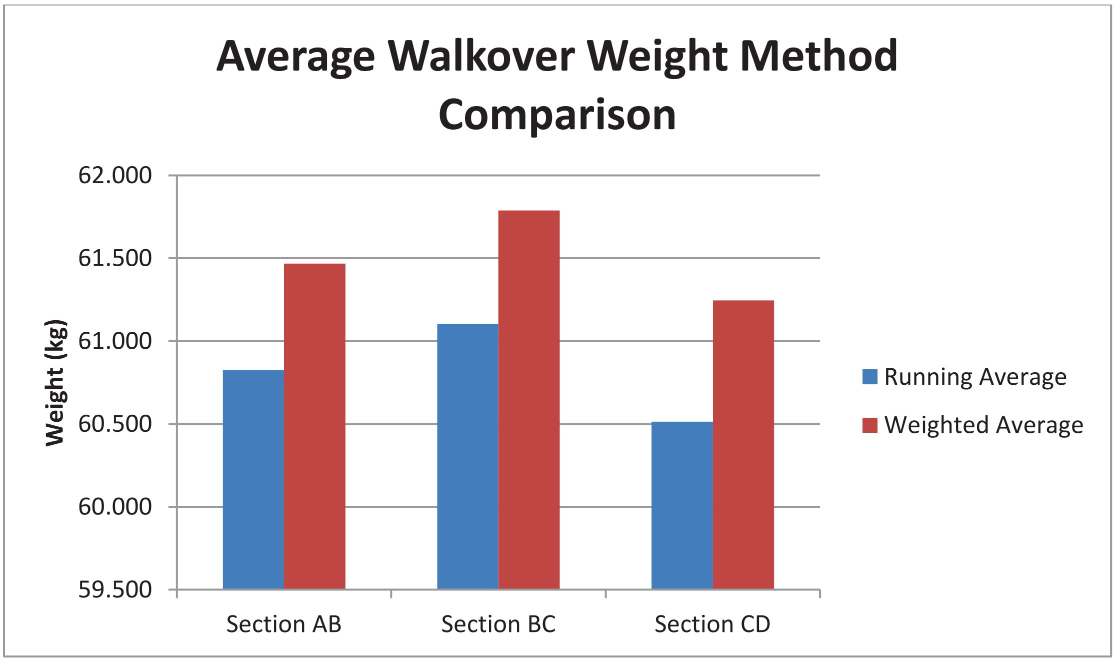

Figure 5.4: Walkover weight method comparison

Three methods to calculate the average weight of the cow on any two sections were developed. The methods are very similar, although each one uses a different combination of signals that occur between the platform segments. All three methods were tested making use of the running average and weighted average techniques to see what differences could be identified. The methods are explained below:

The first method looks at the two peaks that occur on each section i.e. section A and section B. The first peak that occurs on section A is added with the first peak that occurs on section B (both front legs). The second peak that occurs on section A is added with the second peak that occurs on section B (both rear legs). A running/weighted average of the combined first peak is taken and a running/weighted average of the second peak is taken. The results are added together and divided by two as the load is shared over two sections.

The second method takes the two peaks that occur on the first section (front and rear legs) on section A and adds them together and takes the two peaks that occur on the next section i.e. section B and adds them together. A moving/weighted average of section A's result and a moving/weighted average of section B's result is added together and divided by two as the load is shared over two sections.

The third method is to simply take a running/weighted average of the whole signal that occurs on section A and a running/weighted average of the whole signal on section B, with the resultant signals being added together.

To simulate how the algorithm would respond when a cow walked over the platform, two heavier people were used to 'move like a cow' and place two feet onto each platform segment. The moving/weighted average only considers weights above a certain threshold in order to remove the noise in the rising and settling time of each signal. The threshold limit for this application was set to 90 kg and above as the combined static weight was found to be 233.4 kg (approximately 115 kg per person). Ten walkover trials were conducted at varying speeds to determine which algorithm and method produced the closest results to the static weight. Figure 5.5 illustrates the weight signals and positional data of one trial run with the threshold level used by the algorithm shown by the dashed black line.

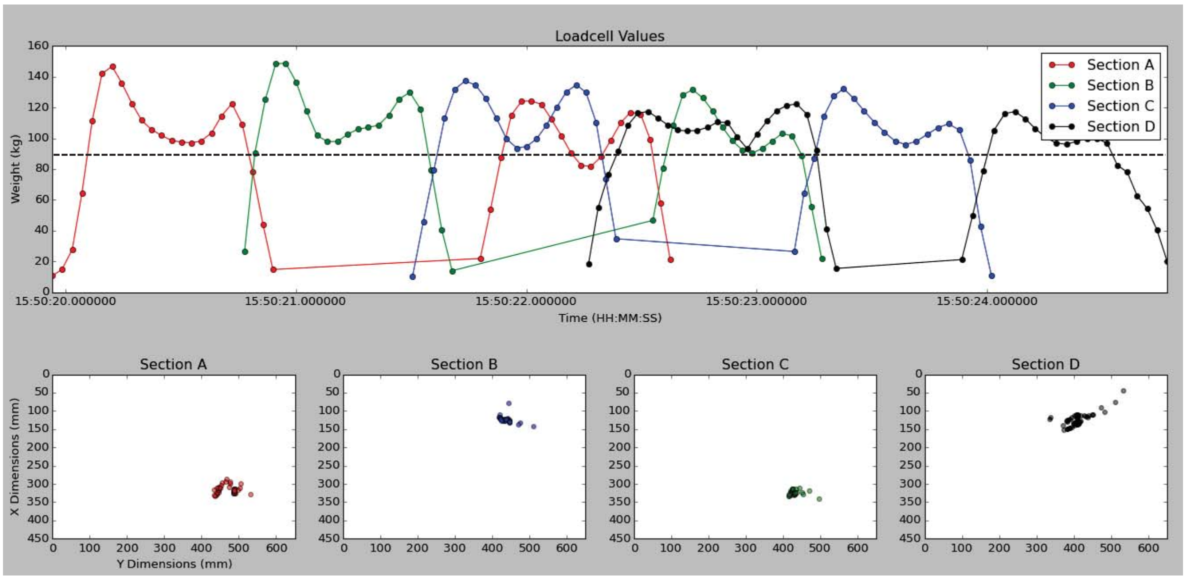

Figure 5.5: Simulating a cow walking pattern to test algorithm

The average result from the ten trials using the three methods described above is displayed in Figures 5.6 and 5.7. It is quite obvious looking at Figure 5.6 that method 3 produces the results closest to the static weight, with the section BC average of 228.4 kg being 5 kg less than the static weight. The weighted average results in Figure 5.7 show that the methods are very similar, although method 3 is slightly more accurate. The mean error and StDev of section BC is -4.7 ± 1.9 kg. It should also be noted that in both the running/weighted average results that section BC weight is higher compared with AB and CD. The reason for this is that section BC is a level walking surface, whereas AB contains a step onto the platform and CD a step off the platform which alters the weight distribution slightly.

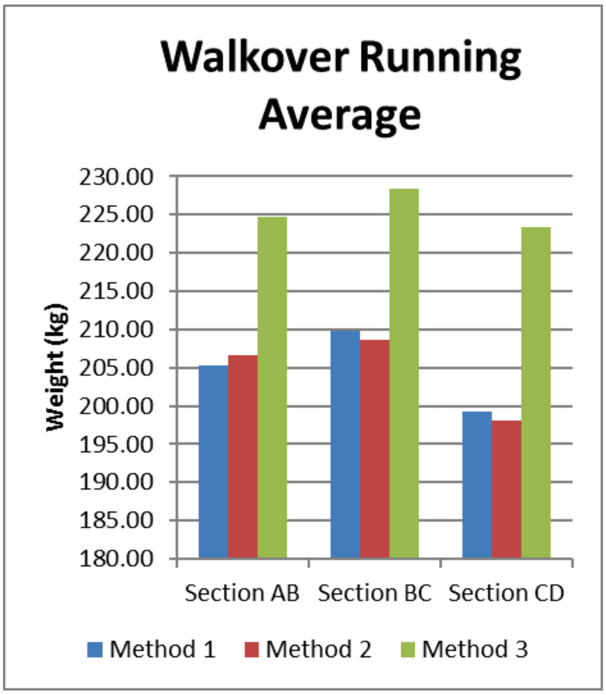

Figure 5.6: Walkover running average method comparison

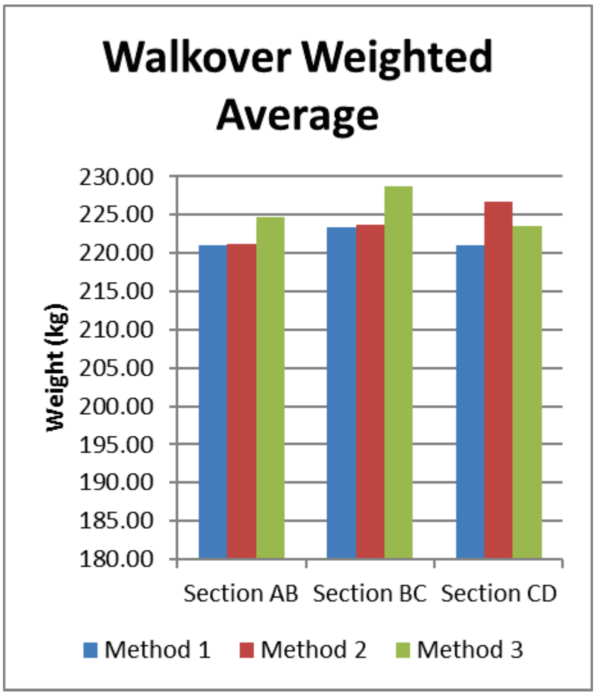

Figure 5.7: Walkover weighted average method comparison

A field trail was conducted (see Chapter 6.2) to test the accuracy of the algorithms on actual dairy cattle. It was found that the fixed threshold did not perform well when dynamically weighing the dairy cattle. In most instances the calculated walkover weight was at least 100 kg less than the static weight of the animal, which is not accurate enough for the required task. It was noted from the field trial data that the weighted average technique is a poor representation of the original signal, as can be seen in Figure 5.8. This figure shows blue signals which are the raw combined weight signals and green signals which are the weighted average output signals. These triangle shaped output signals are a poor interpretation of the original signal, which is why, when averaged, they produce a value which is far less than the desired amount. Consequently, an algorithm using dynamic thresholds and running averages was developed to optimise the acquired cattle signals.

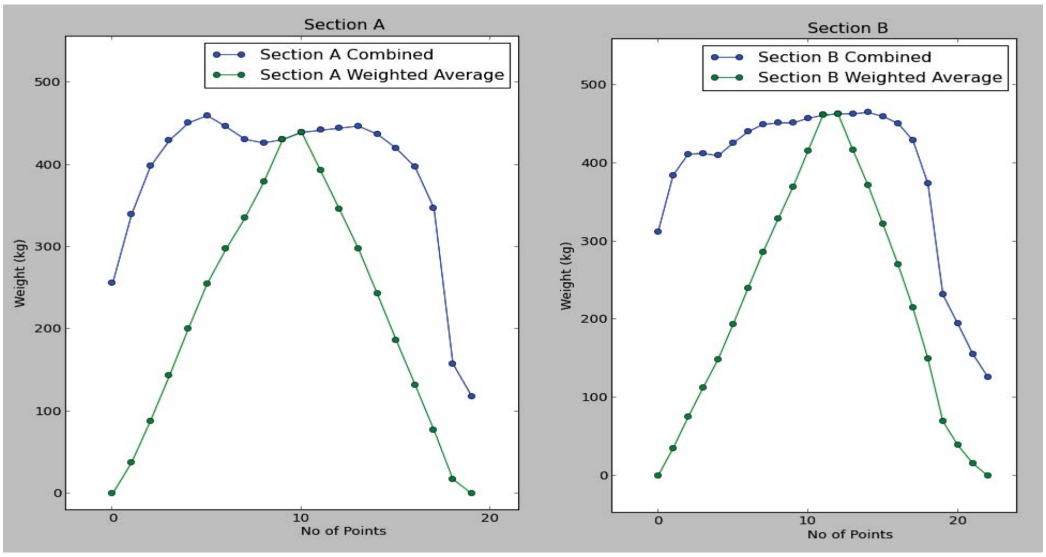

Figure 5.8: Example of how weighted average signal behaves

5.1.3.1. Dynamic Threshold Algorithm

The progression and optimisation of this algorithm came from observing the shape (peaks/troughs) of the captured field trial data and modifying the parameters to suit. Experimental testing of different window sizes and scale factors was explored to smooth the output signal to an acceptable level before finding an average value. The steps involved for each individual signal are listed below:

- Find the mean of the original signal and use this value as the dynamic threshold (at 100% of calculated average).
- Use all the data above the threshold and find the moving average of these points (new array) with a window size of 3.
- Find the average of the new array to calculate the weight value for each individual limb.
- Do this for both limbs (front /rear) on same segment to find a combined average weight.
- Repeat steps 1 – 4 for the next platform segment and divide the combined results by 2.

A graphical example of how the algorithm works is given below. The accuracy of this method was found to be within 15 kg of the static weight which was deemed acceptable for the project. For testing results see Chapter 6.2.

Figure 5.9 illustrates the signals experienced while calculating the weight of an individual limb, in this case the front right. The blue signal is the original data (mean = 249.1 kg), the brown signal is taking the running average (mean = 256.6 kg) of the original signal and the green signal is the running average after thresholding, shifted to the left (mean = 278.0 kg). The brown signal demonstrates why a threshold level is needed to get more stable and accurate results.

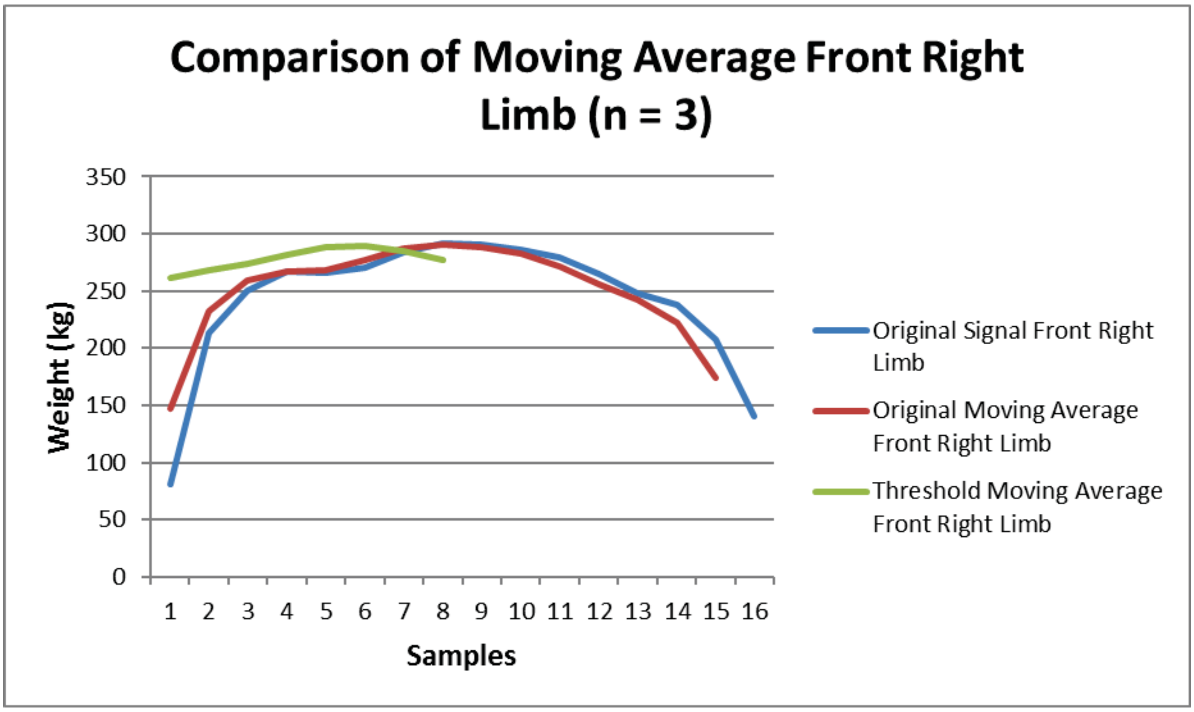

Figure 5.9: Example of front right limb signals

Figure 5.10 illustrates the signals experienced while calculating the weight of a right rear limb. The blue signal is the original data (mean = 206.3 kg), the brown signal is taking the running average (mean = 211.9 kg) of the original signal and the green signal is the running average after thresholding (mean = 273.3 kg).

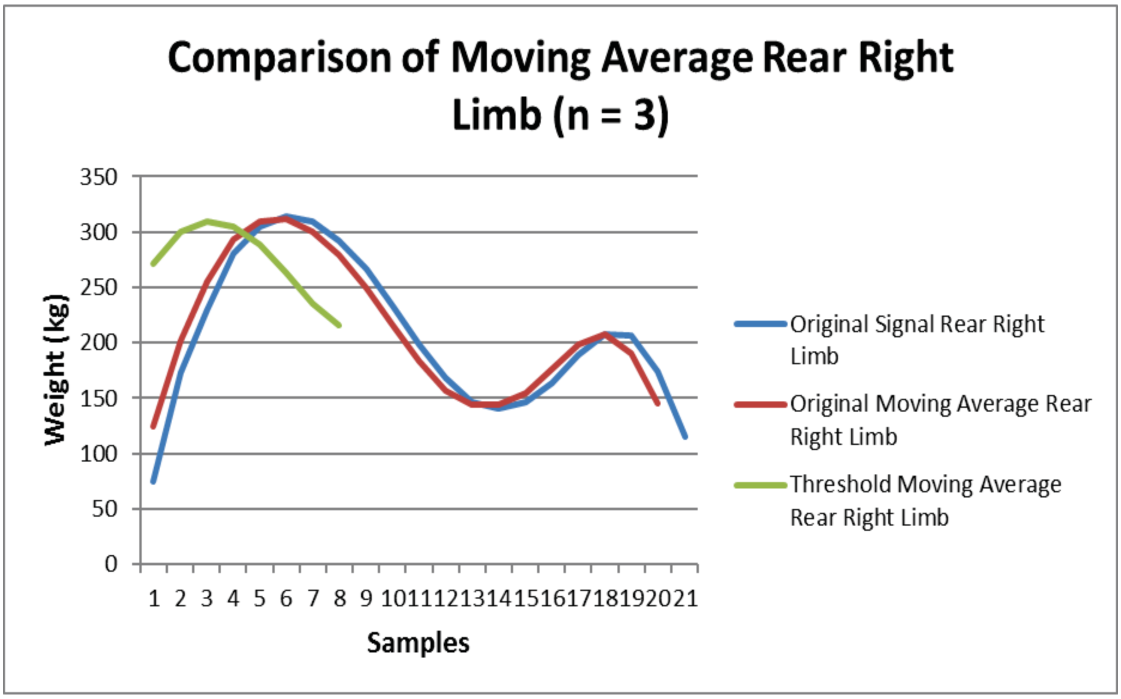

Figure 5.10: Example of rear right limb signals

Figure 5.11 shows the previous two signals on the same graph as well as the combined moving average signal (section A). The light blue signal shows the filtered data from combining the green and purple signals; the average weight is 551.7 kg (static weight 562 kg).

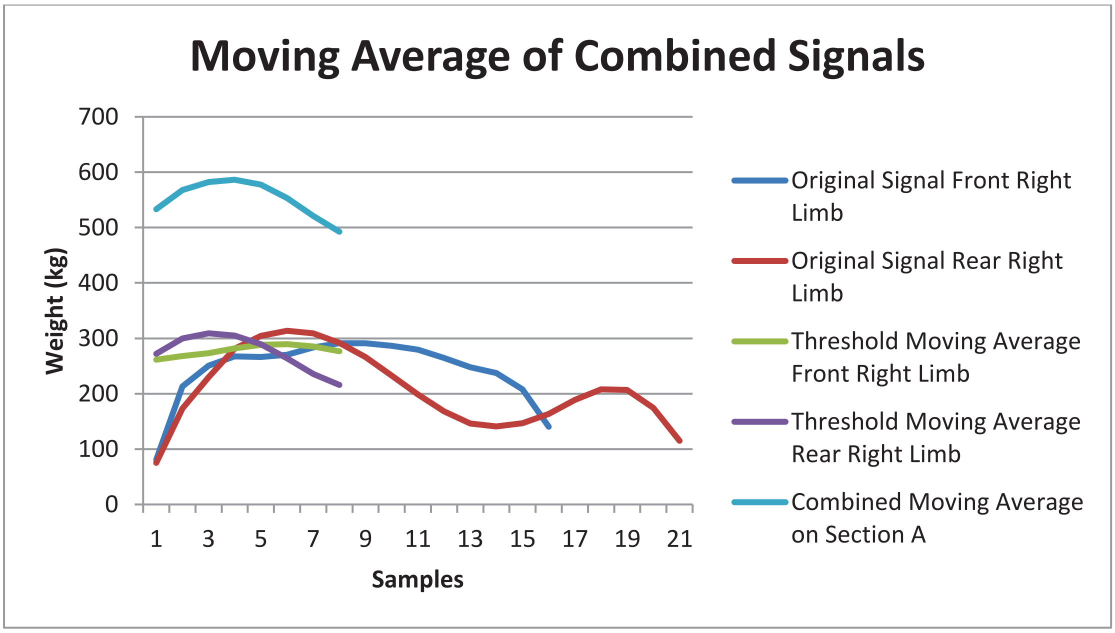

Figure 5.11: Moving average of combined signals

5.1.4. Calculating Variables Indicative of Lameness

Python scripts were developed to deduce the required variables that may be associated with discovering lameness. All the variables were found using the three main kinematic parameters of weight, position and time.

5.1.4.1. Force Related Variables

Individual limb weight and total weight: Explanation of these can be found in the previous chapter.

Normalised ground reaction force (NGRF): The individual limb weight divided by the total body weight.

$$NGRF = \frac{Limb\_x1}{total\ weight} \tag{7}$$

Asymmetry in limb weight: Absolute difference in relative force exerted by the limbs between left and right hoof imprint.

$$Asymmetry\ in\ limb\ weight = |RF - LF| \tag{8}$$

Asymmetry in diagonal weights: Absolute difference in relative force exerted by the diagonal limbs between LF,RH and RF,LH.

$$Asymmetry\ in\ diagonal\ weights = |(RF + LH) - (LF + RH)| \tag{9}$$

Asymmetry in side weights: Absolute difference in relative force exerted by the limbs on opposite sides.

$$Asymmetry\ in\ side\ weights = |(RF + RH) - (LF + LH)| \tag{10}$$

5.1.4.2. Spatial Related Variables

Figure 5.12 illustrates the positional locations of a cows walking pattern, with coordinate definitions for each platform section. These definitions will be used to explain how different variables are calculated.

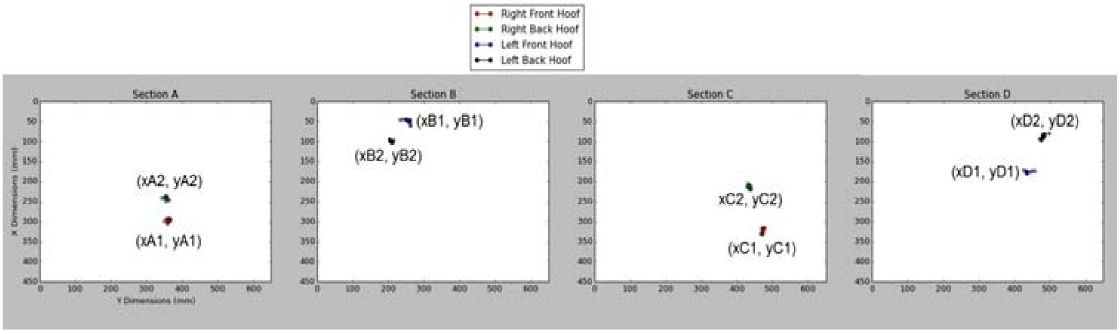

Figure 5.12: Positional data with coordinate definitions

Front step length: Step length between the front left and front right hoof imprints (see Figure 5.13).

$$Front\ step\ length = yB1 - \ yA1 \qquad (11)$$

Hind step width: Step width between hind the left and right hoof imprints (see Figure 5.13).

$$Hind\ step\ width = |xB2 - \ xA2| \qquad (12)$$

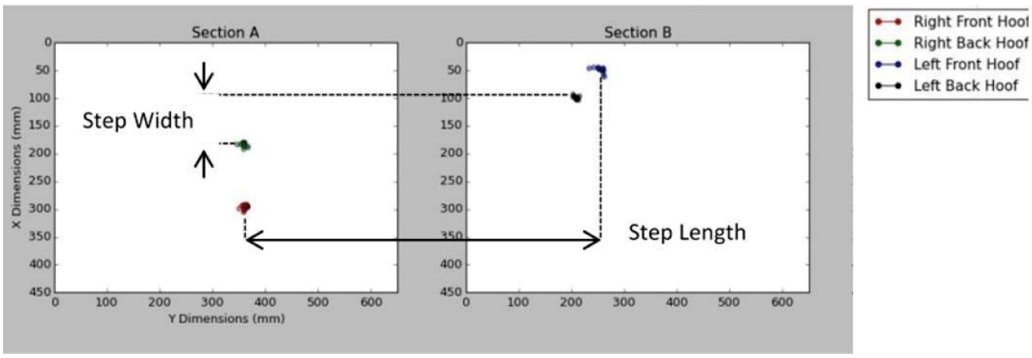

Figure 5.13: Example showing step length and step width

Step overlap: The lengthwise distance between the front hoof and the hind hoof on the same side (see Figure 5.14).

$$Step\ overlap = yA1 - \ yA2 \qquad (13)$$

Abduction: The sideways distance between the front hoof and the hind hoof on the same side (see Figure 5.14).

$$Abduction = |xA1 - \ xA2| \qquad (14)$$

(A positive value indicates that the rear hoof lands on the outside
of the front hoof which is 'normal')

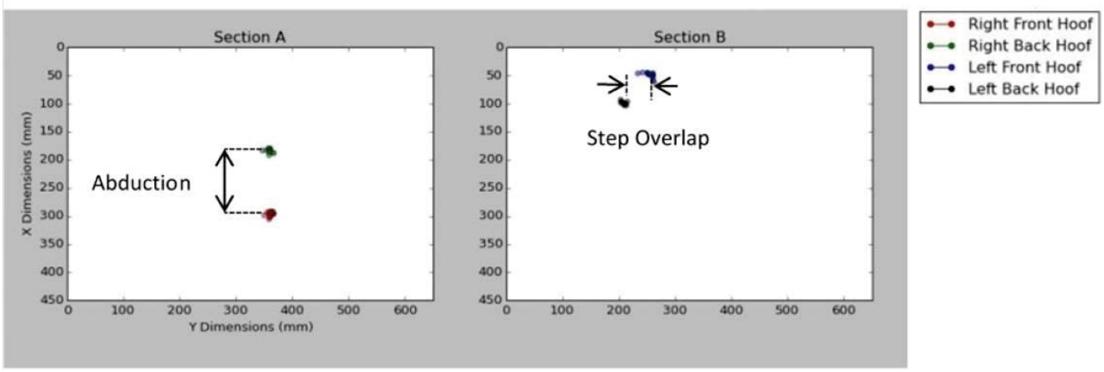

Figure 5.14: Example of step overlap and abduction

Stride length: Distance between two consecutive imprints of the same hoof (see Figure 5.15).

$$Stride\ length = yC1 - \ yA1 \qquad (15)$$

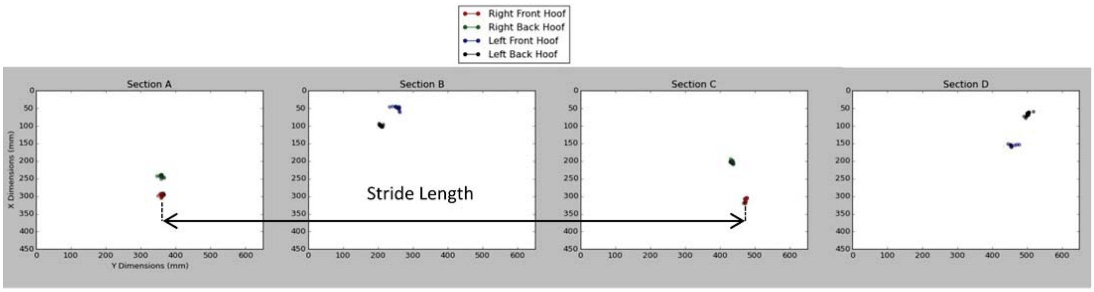

Figure 5.15: Example showing stride length

Three methods to filter the positional coordinates were developed to find the actual location of the hoof when the maximum pressure is applied. These methods of threshold, peak and radius are explained below.

Threshold method – The most obvious method is to set a weight threshold and remove any points that fall below this level. The threshold must be set high enough so that it eliminates the outliers created from placing and removing the hoof but low enough to capture the most stable part of the signal. An average of the remaining data points above the threshold is taken to find the centre of pressure (mm). The disadvantage with this method is that an accurate threshold limit needs to be established to get adequate filtering of the data points.

Peak method – This method finds the peak weight value that occurs in each signal and takes a certain number of points either side of the peak. The corresponding positional coordinates are then averaged to find the centre of pressure at the maximum weight. The number of points used depends on how many samples are in the signal and what spread needs to be examined to get a reasonable interpretation of the position. If too many points are used, then the next peaks signal will be combined into the average location which will yield incorrect results. Depending on where the peak value was found, if there are an insufficient number of points, a completely wrong position may also be calculated.

Radius method – The final method works by calculating the average location of the signal and then setting a specified radius around this location. All the data points inside this will be averaged again to find the centre of pressure. This method should be the most reliable as only outliers outside the radius will be removed from the data set; there is no bias as to whether the data was from the peak weight or the minimum weight.

5.1.4.3. Temporal Related Variables

Stance time: The time during one step that the hoof is on the platform (see Figure 5.16).

$$Stance\ time = \frac{(T_2 - T_1) + (T_4 - T_3)}{2} \tag{16}$$

Asymmetry in stance time: Mean difference in time that the hoof is on the ground between the left and right sides (see Figure 5.16).

$$Asymmetry\ in\ stance\ time = |(T_2 - T_1) - (T_4 - T_3)| \tag{17}$$

Stride duration: Time between two consecutive imprints on the same hoof (see Figure 5.16).

$$Stride\ duration = (T_2 - T_1) + (T_4 - T_3) \tag{18}$$

Velocity: Hoof speed (m/s) is stride length divided by stride duration.

$$Velocity = \frac{Stride\ length}{Stride\ duration} \tag{19}$$

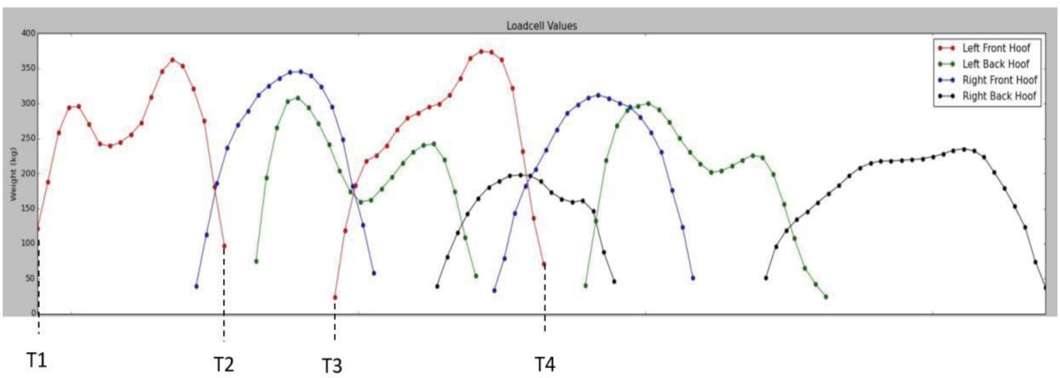

Figure 5.16: Example of hoof duration variables

5.1.5. Writing Variables to Excel File

In order to focus on an individual cow the text file recorded for each milking session had to be manually examined to split the data correctly. Attempts were made to automate this process with the aid of state machines but the variability and natural flow of the cattle made this a time consuming task outside the scope of this project. Therefore the decision was painfully made to manually search for the required EID tag, validate the data to see if it would be useful (i.e. check that not more than one cow was on the scale at a time) and copy and paste the data into a new text file. These individual text files were processed by the main Python program to produce an Excel File that contained the 82 desired variables. The inbuilt functions inside the xlsxwriter library were used to write the variables into the preferred locations. Other variables included in the Excel sheet were the leading leg (left/right), location in herd (%) and asymmetry of the majority of the variables to compare (left/right and front/rear). The main reason the data was organised in Excel rather than Python is that data in Excel spreadsheets are quicker and easy to arrange, format and graph. Statistical information such as, average, StDev, max, min and range could be effortlessly found for each variable, or a combination of variables. An example of an Excel spreadsheet with actual data can be found in Appendix 6.

Chapter 6: Experimentation and Results

This chapter presents the results from the laboratory testing and the results obtained during the farm trials. Section 6.1 presents the laboratory testing of the weight and positional accuracy of the platform. Section 6.2 describes how accurately the dynamic weight of cows can be found from the first on-farm trial. Section 6.3 reports on the findings from the second farm trial including lameness scoring and variable correlations. Section 6.4 presents the statistical findings from the controlled case study and the classification results. Section 6.5 discusses practical considerations and the findings from the farm trials.

6.1. Laboratory Testing

A series of tests were conducted on the assembled platform to measure its response and accuracy before installation in the milking shed. These tests included:

- Positional coordinate accuracy
- Calculating the total weight on the platform
- Step length accuracy
- Determining how a rubber mat affects the dynamic response

6.1.1. Positional Coordinate and Weight Accuracy

This test involved determining how accurately the system could measure the weight of an object placed anywhere within a platform section and whether the centre of pressure could be calculated correctly. A 20 kg calibration weight and a manufactured 25 mm circular point load stand were used as the test weight (see Figure 6.1). A laser cut test jig was made with 25 mm cut outs at 50 mm spacings so the point load stand could be placed accurately across the entire segment (Figure 6.2). The weight and positional coordinates were recorded at each test point location. Please see Appendix 3.1 for all the results that were recorded while conducting the experiment.

Figure 6.1: Calibration weight on point load stand

Figure 6.2: Laser cut test jig

The statistical results of the centre of pressure and weight accuracy can be seen in Table 6 and Table 7 respectively. The overall X-position accuracy was calculated to be within 1.0 ± 2.2 mm and the Y-position accuracy was calculated to be within 0.81 ± 1.8 mm. This is remarkably accurate considering that such a small signal (0.005% of full load) was experienced by the load cells.

Table 6: Mean and standard deviation of X & Y Position errors

X-Position			Y-Position	
Mean Error	1.005mm		Mean Error	0.814mm
Standard Deviation	2.172mm		Standard Deviation	1.788mm
Minimum	-4.279mm		Minimum	-2.437mm
Maximum	5.377mm		Maximum	3.512mm

Table 7: Mean and standard deviation of Weight errors

Weight	
Mean Error	20.087kg
Standard Deviation	0.034kg
Minimum	20.024kg
Maximum	20.180kg

It can be seen from Table 7 that the weight accuracy was calculated to be 20.08 ± 0.03 kg, with the mean weight error calculated to be 0.44 % of the 20 kg weight. The slight variation in weight could be due to the contribution of the RMS noise of the ADC, the load cell signal output (2mV/V ± 0.1 %) and the voltage reference drift (4.096 V ± 0.05 %). Only one segment was tested as it was assumed that the other three would behave in a similar way.

6.1.2. Step Length Accuracy

An investigation was conducted to determine how accurately known step lengths could be measured with the three methods discussed in Chapter 5.1.4.2. Three step lengths of 600, 650 and 670 mm were used as the test lengths as these are values between the expected cattle step length of 600 – 700 mm. Four 50 mm circular blocks were positioned at the measured locations on alternating sides to act as point load representations of cows' hooves (see Figure 6.3). Five walkover runs for each step length were simulated (two humans moving like a cow), giving two foot falls per platform segment. For each run, six measurements were calculated using the three methods, with these being the front footsteps of AB BC CD and the rear footsteps of AB BC CD.

An example of the measurements produced by the three methods for the same test run is shown in Figure 6.4. The 50 mm circular blocks were spaced at 600 mm distances to each other which are illustrated in Figure 6.5. It can be seen that the three methods yield similar results for each step, although the distance between steps is as much as 30 mm in this case (between AB front and BC front). When comparing like steps (front/rear of same platform segment) the result is very similar which is to be expected as the same circular block takes both the feet at the same location.

Figure 6.3: Step length testing setup (GoPro 3 wide angle lens)

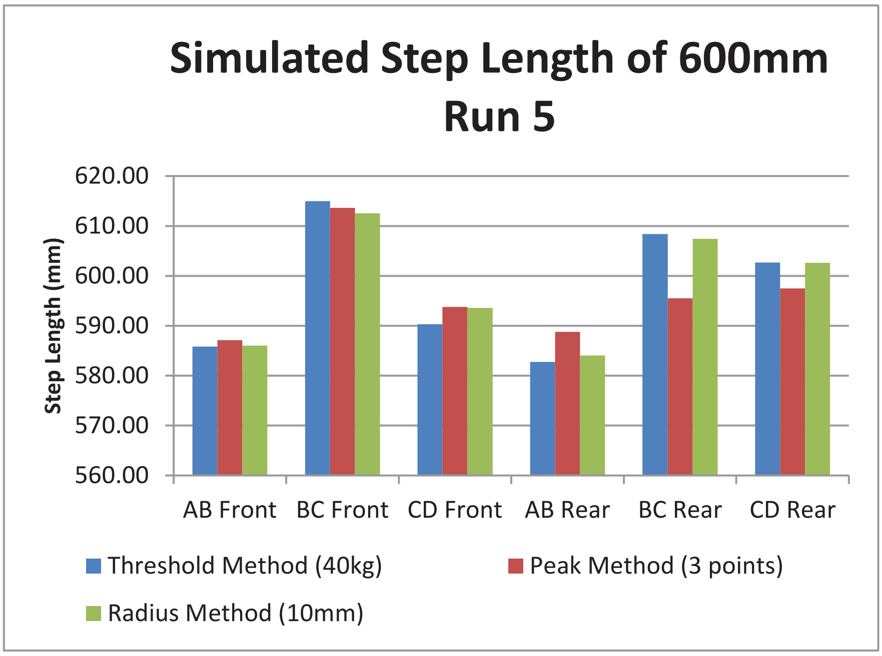

Figure 6.4: Test results from one trial of 600 mm step length

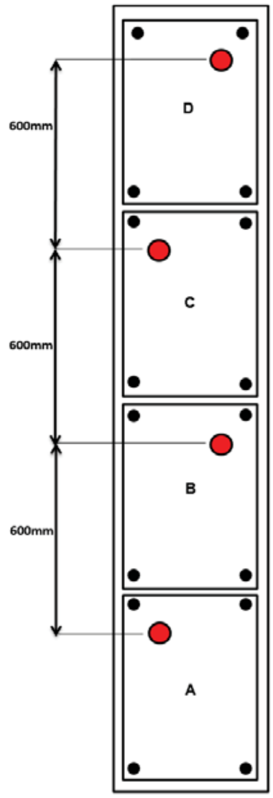

Figure 6.5: 600 mm layout

The results from the three step lengths were averaged over each trial run and can be seen in Figures 6.6, 6.7 and 6.8. The main point of interest between the figures is that the measurements between runs seem to vary by an average of 5 mm; the most logical reason for this is that the person did not always stand centrally or squarely on the block which would shift the centre of pressure. The overall result between tests is very similar, with Table 8 showing the average mean deviation and standard deviation across the three step lengths. In summary, on average, the measured step length was approximately 3 mm less than the actual measurement. The threshold method produced the largest standard deviation and range, whereas the peak method was the closest of the three algorithms. Therefore, it was found that using the peak or radius method for future filtering of positional data would deliver more accurate results. Please see Appendix 3.2 for the full test results.

Table 8: Summary of step length testing

	Mean Error (kg)	Standard Deviation (kg)
Threshold	-2.66	10.25
Peak	-2.40	8.95
Radius	-2.57	9.70

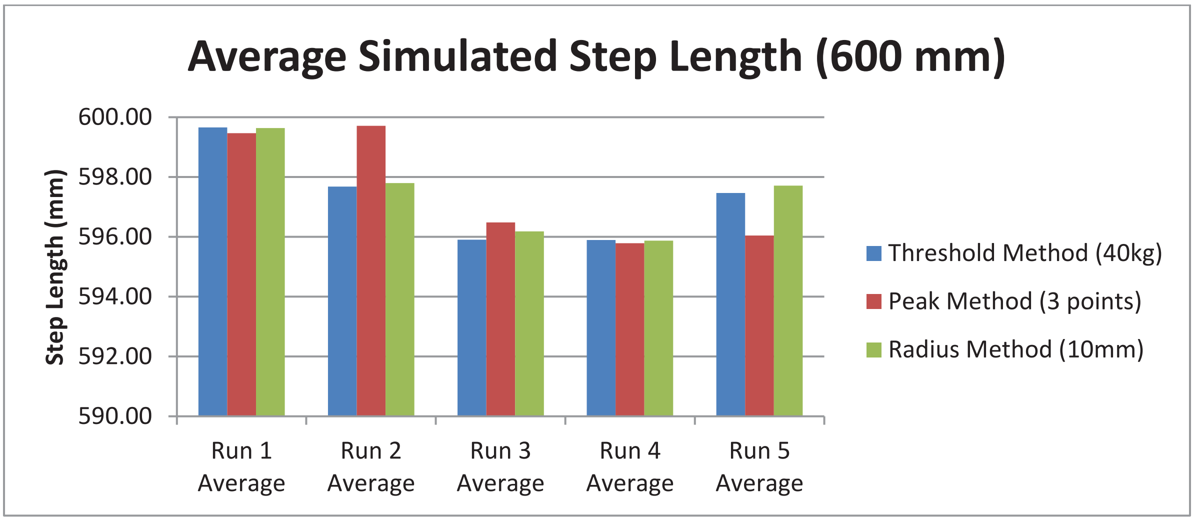

Figure 6.6: Average simulated step length (600 mm)

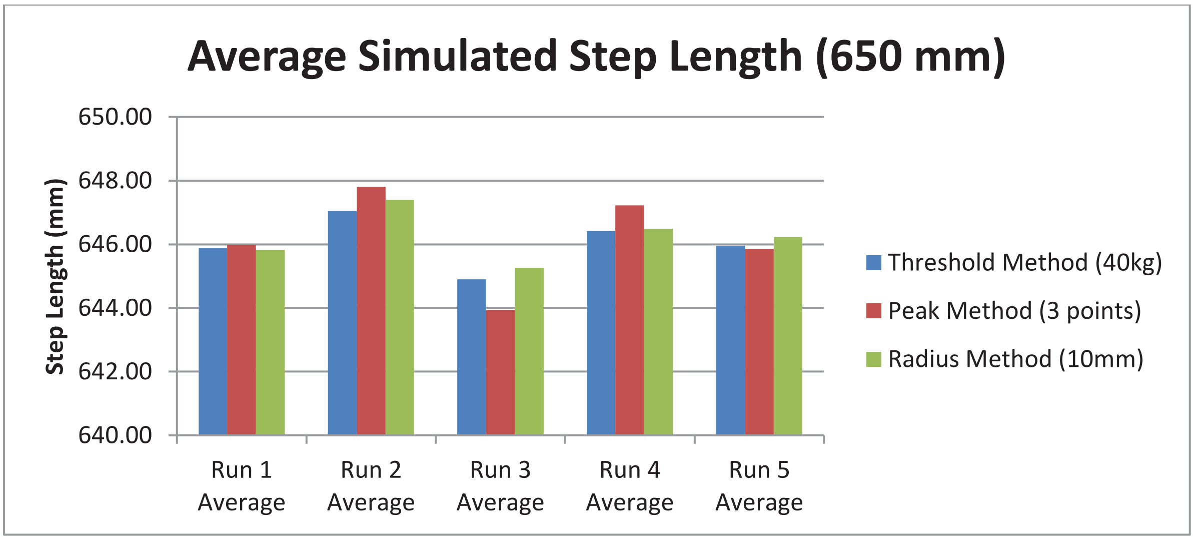

Figure 6.7: Average simulated step length (650 mm)

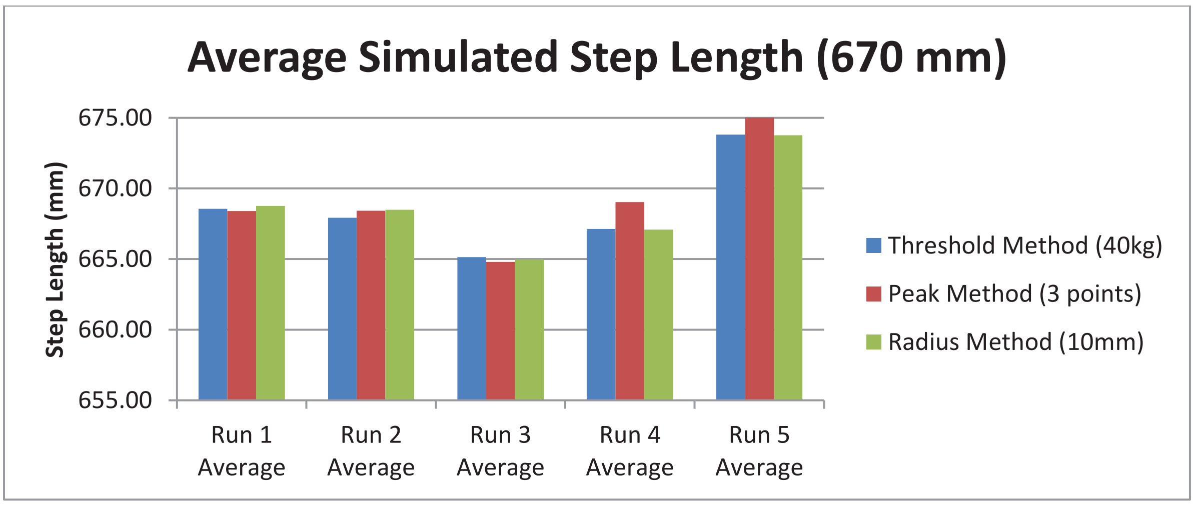

Figure 6.8: Average simulated step length (670 mm)

The step length experiment was not ideal in terms of accuracy, although it gave a fair idea of how the algorithms compare for the same controlled data. Of concern was the large standard deviation between step lengths which could be due to the following reasons:

- Measurement error in combination with human error to incorrectly mark out the stride positions, approximately ± 2 mm
- The assumption that each platform has exactly the same load cell spacing – this was found to be incorrect and was mainly due to manufacturing errors and human error when aligning the platforms square with the main frame; these factors contributed an error of approximately ± 3 mm.
- When standing on the front of the feet to act as point load, it was sometimes hard to always stand on the circular blocks squarely in the centre.

These aforementioned factors could contribute an error of approximately 10 mm during some movements which may be why some steps fluctuate more than others during testing.

6.1.3. Dynamic Response

A test was performed to assess the dynamic response of the load cells on one section and compare the signals that were produced when a rubber mat was attached to a section. The aim was to see whether the rubber mat would affect the signals and by how much. Figure 6.9 shows the signals that were produced by the section when stepping onto the section without a rubber mat attached. It can be seen that the total weight (black signal) has two spikes of 70 kg (which is 8kg above the average weight) when stepping onto, then off of the section. Note the y-axis scale in this figure goes from 0 – 80 kg.

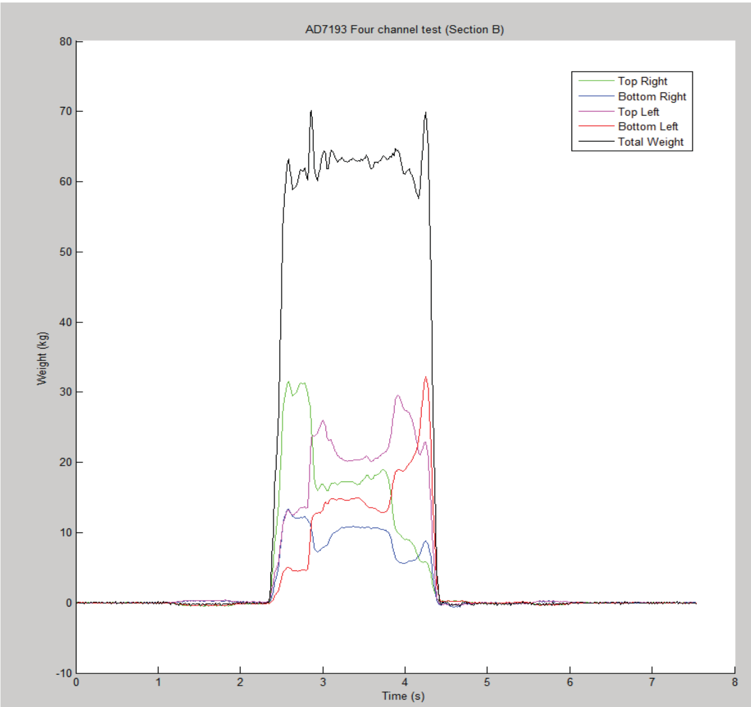

Figure 6.9: Dynamic response without rubber mat

When the same test was conducted with a rubber mat attached the two peaks were reduced to some extent. Figure 6.10 shows the signals produced by the section with a rubber mat when stepping onto, then off of the section. The key difference compared to the previous figure is that the peaks are reduced by 5 kg, therefore it was noted that the rubber mat dampens an impulse by approximately 8 %. As well as providing more grip for the cows while they walked over it, the rubber mat would also help smooth the signals which would help with the accuracy of the total weight algorithm.

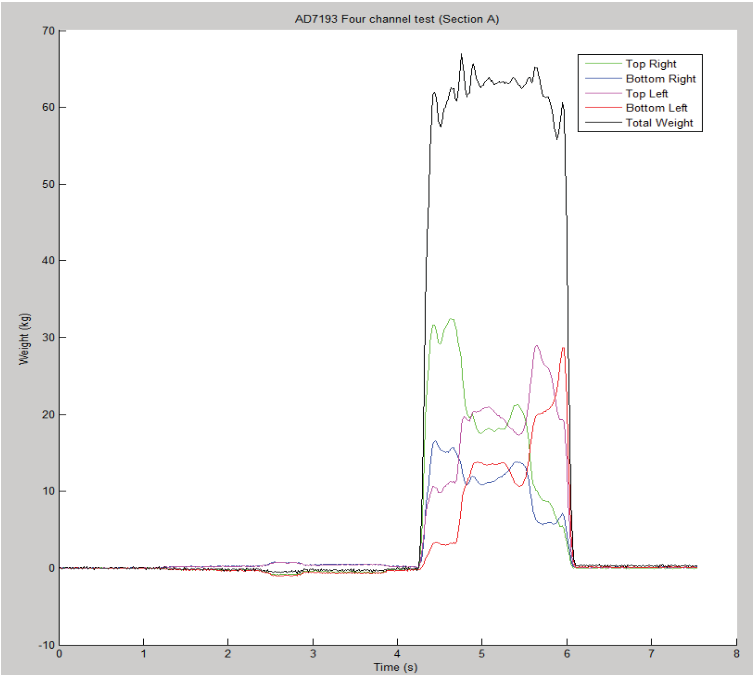

Figure 6.10 Dynamic response with rubber mat

6.2. Farm Trial 1 Results

The ten walkover trials were done with ten cows with body weights of 388, 455, 501, 522, 550, 550, 552, 562, 595 and 616 kg, respectively. The cows were weighed statically before dynamic weighing. Table 9 displays the static weights, average dynamic weights calculated from each of the trials and the average error compared to the static weight. Taking an overall average of all the cows' trials combined, it was found that the mean error and standard deviation were:

- Section AB = -20.14 ± 13.78 kg
- Section BC = -10.69 ± 10.57 kg
- Section CD = -10.15 ± 12.36 kg
- Combined Sections = -13.66 ± 7.52 kg

The closest resultant arrangement of platform sections is taking an average of all three sections (Combined Sections); this provides the lowest StDev and also contains the smallest range of 17.2

kg. Section BC gives the next best results with an average error closer to the static weight but with a larger spread of values. Section AB performs the worst out of the four arrangements with an average error of 20 kg less than the static weight. Therefore using the Combined Section weight, it would be considered that the total weight of the cow is within 15 kg of the static weight. See Appendix 3.3 for further results.

Table 9: Comparison of dynamic weight to static weight of 10 dairy cows

Cow EID	Static Weight (kg)	Average Dynamic Weight (kg)	Error (kg)
982 091001734424	550.00	534.70	-15.30
982 091001734362	552.10	536.20	-15.90
982 000124839853	562.00	549.60	-12.40
982 091001734048	500.70	491.30	-9.40
942 000015200296	455.10	440.50	-14.60
982 123464531778	387.60	376.20	-11.40
982 000091411599	550.20	535.60	-14.60
982 000091482234	594.60	580.70	-13.90
982 091001734420	522.10	512.80	-9.30
982 000091411587	616.00	596.20	-19.80

The walkover weight algorithm depends highly on how the animal walked over the platform. On clean runs when the cow walked normally without stopping or swinging her head then the weight calculated was closer to the static weight. When a cow walked slower than normal the signals captured displayed a longer plateau which made the algorithm find a weight closer to the static weight. When a cow was skittish, the signals were more erratic which reduced the peak times and hence the dynamic threshold would be set lower which affected the weight calculated.

It was interesting to see that on individual trials Section AB always found a weight that was approximately 10 - 20 kg less than the next two sections. The main reason for this is that the cow had to step up 100 mm onto the platform which slightly alters her weight distribution; more weight is spread to the hind legs which are placed on the ground. Section BC and CD produced similar results as the cow is walking on a level surface, although the step down from the platform on Section CD slightly increased the weight during some trials.

To compare how well the WoP and algorithm performs an industrial equivalent walkover platform would have ideally been tested. This was not possible at this location as no weigh scale was present. Further work could be focused in the area of walkover weigh algorithms to calculate the dynamic weights more accurately. Although this is only a small part of the project it has a huge significance on determining differences in weights applied to limbs compared with total body weight.

6.3. Farm Trial 2 Results

Three weeks of data was captured from the herd of dairy cows and subsequently analysed and compared to the manual lameness scores for each animal. During the first week after the installation of the WoP the cows were apprehensive about walking over it as they were not used to walking over a platform as the farm had no scales. The cows continually stopped on the platform and walked over in large groups which made it very hard to separate the data captured for each cow. Consequently the data captured during the first week was not used in the analysis. From this observation it should be noted that the settling period of a week needs to be applied for new farm installations.

6.3.1. Lameness Assessment

Each cow in the herd was individually scored for lameness by a trained observer, with the resultant scores being displayed in Figure 6.11. The majority of the herd were scored as healthy (0, n = 141), 33 were scored as level 1 (slightly lame), 21 were scored as moderately lame, and 3 were scored as severely lame. Therefore, 12% of the herd were classified as lame and were examined further. This is within New Zealand's expected lameness incident rate of 10 – 15% at any given time (Malmo *et al*, 2011).

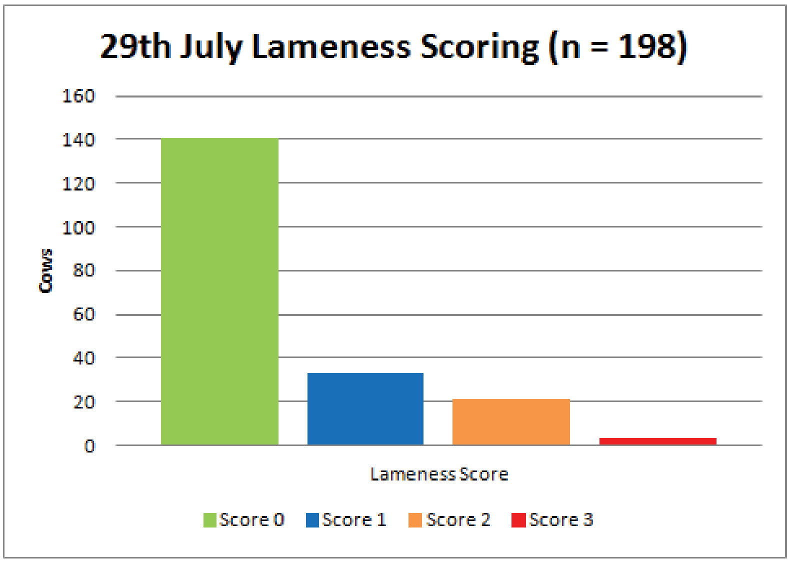

Figure 6.11: Manual lameness scoring results from trained observer

6.3.2. Data Analysis

All of the cows with a lameness score of 2 and above were identified and each day of clean data was manually extracted from the recorded text file. Clean data is classed as a successful measurement, meaning the animal walked over the WoP at a natural speed without stopping. A total of five days of data per cow were analysed (if possible) centred about the lameness scoring date, i.e. two days before scoring and two days after. The reason this time period was analysed is because the lameness level of a cow can change quickly and using two week old data may provide invalid results. During analysis, the plotted raw weight and position signals for each day gave a fair visual indication of whether each cow was healthy or showing signs of lameness. For example, Figure 6.12 displays a signal signature of a healthy cow (ID: 55) and Figure 6.13 displays

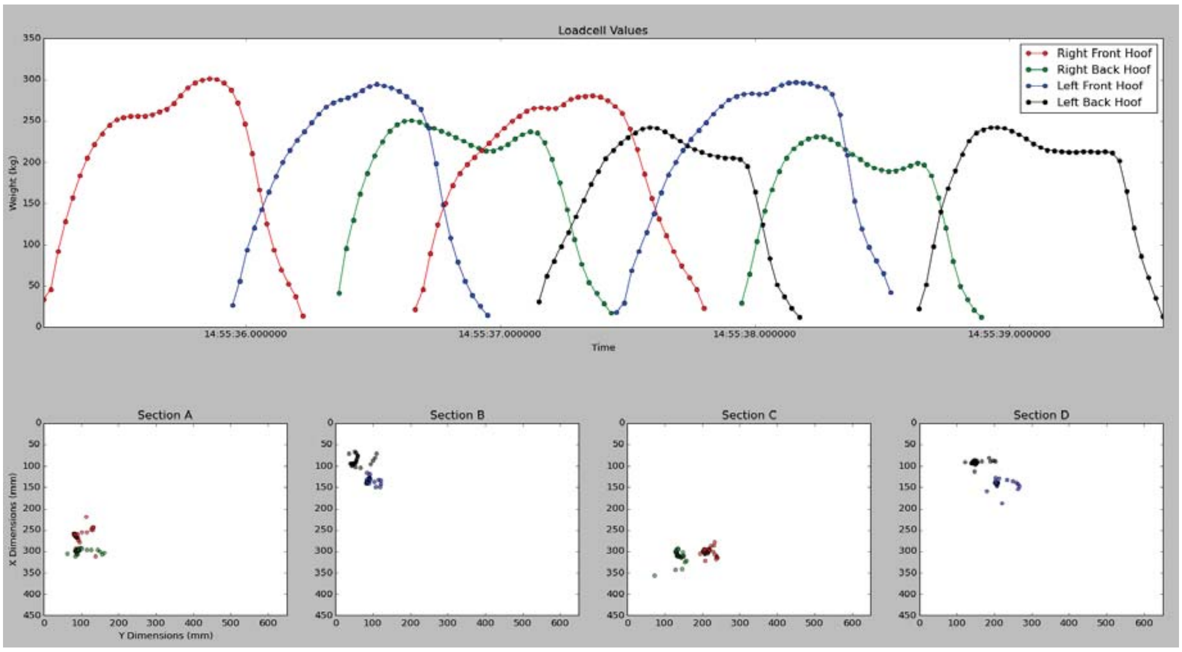

Figure 6.12: Weight and positional signal signature of a healthy cow (ID: 55)

a signal signature of a lame (level 2) cow (ID: 123).

The differences between Figure 6.12 and Figure 6.13 are fairly obvious. Figure 6.12 shows clean signals that reach the same peaks (front and rear) with the same duration in time, which are symmetrical to the contralateral limb. Conversely, Figure 6.13 illustrates weight signals that are dispersed and erratic with the front and rear hoof signals reaching the same peaks. The black

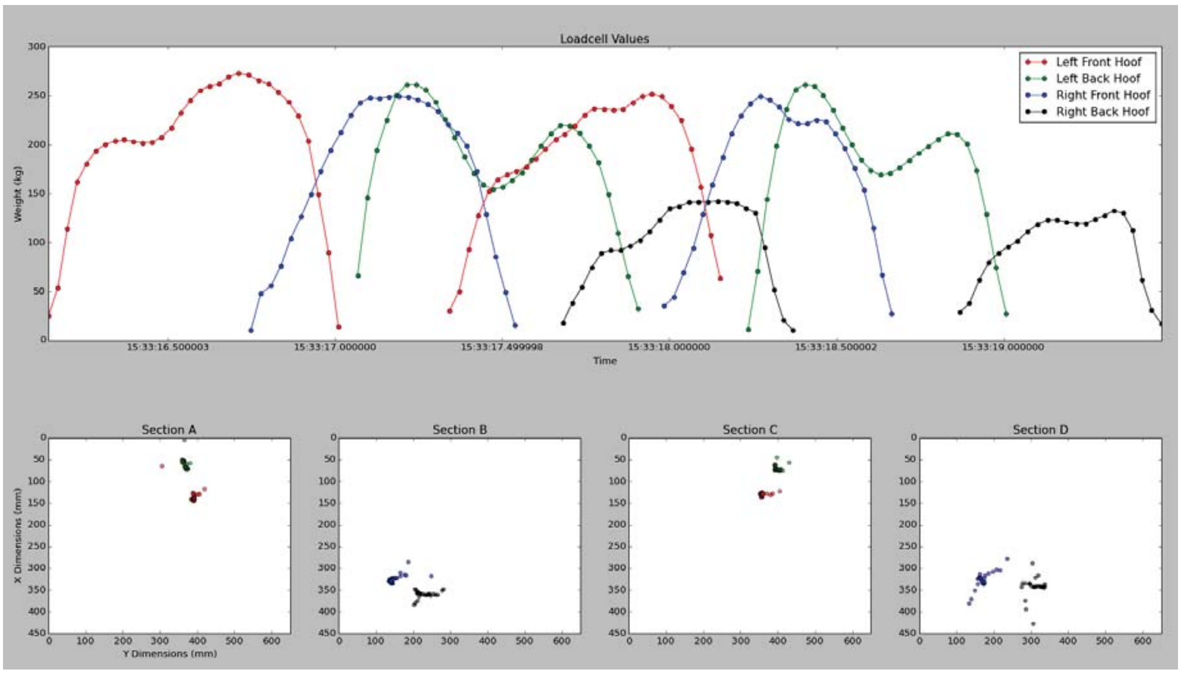

Figure 6.13: Weight and positional signal signature of a lame cow, RH (ID: 123)

signal (RH) has less weight being applied for a shorter duration of time compared to the LH hoof which indicates reluctance to bear weight.

Taking the previous two cows as examples, the differences in lameness related variables on the same day is graphically shown in the figures below. Cow 55 is the healthy cow ID and Cow 123 is the lame cow.

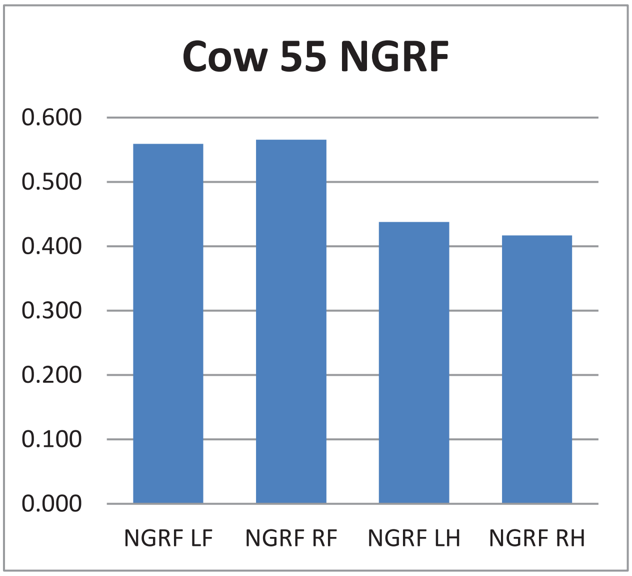

Figure 6.14: NGRF of a healthy cow

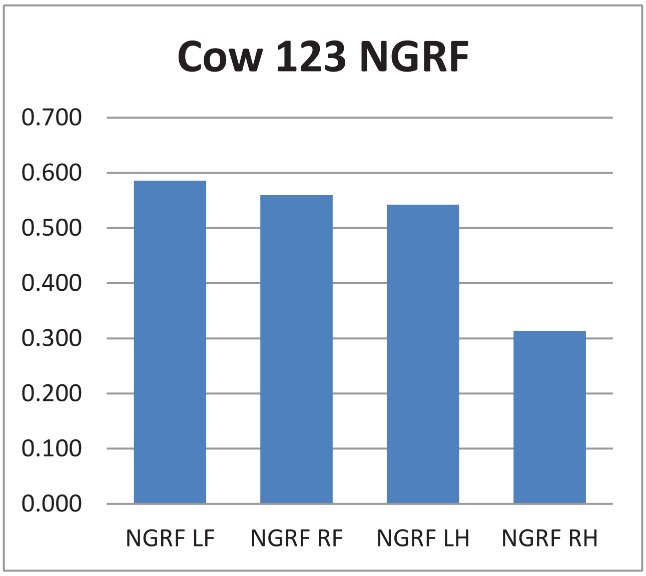

Figure 6.15: NGRF of a lame cow (RH)

Figures 6.14 and 6.15 illustrate the NGRF of each limb, with Cow 55 showing front leg distributions of 56 % of body weight and rear leg distributions of 41 – 43 %; this is considered to be a normal

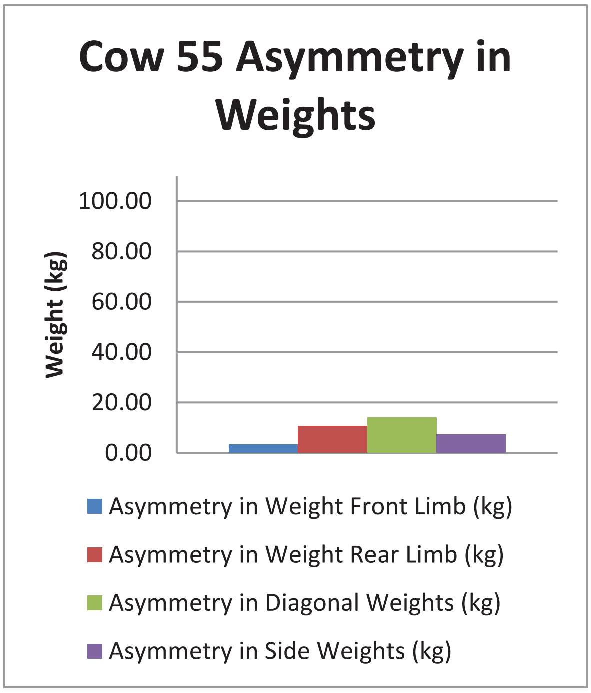

Figure 6.16: Asymmetry in weights of healthy cow

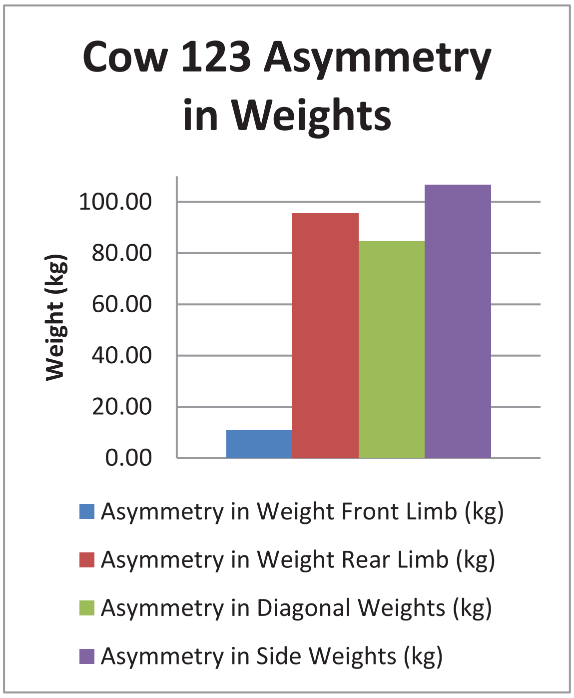

Figure 6.17: Asymmetry in weights of lame cow

weight distribution (Van Nuffel *et al*, 2015). Cow 123 is showing front leg distributions of 56 – 59 % and hind limb distributions of 54% on the LH limb and only 31% on the RH limb (lame leg). The contralateral hind leg is now taking 10% more of the total body weight than the healthy cow equivalent.

Figures 6.16 and 6.17 show the asymmetry in weight with four different variables. Cow 55 shows that all the variables have a difference less than 20 kg with the largest being asymmetry in Diagonal Weights at 14 kg. On the other hand, Cow 123 presents large asymmetry in weights, with the total difference in Side Weights being over 100 kg. The weight difference shown here is an extreme example; the usual average is a 35 kg difference. Further illustrations comparing variables can be found in Appendix 3.4.

6.3.3. Score 3 Cows

The signal signatures of the three level 3 cows were observed and their variables were found when possible. In most cases though it was very hard to find the variables due to the way the algorithms were designed to split the peaks and also wanting two foot falls per segment. When two foot falls were not observed, the algorithms were not able to produce a result and subsequently crashed. An example of what a lame level 3 cow signal signature looks like is shown in Figure 6.18. Looking at the first section (red signal) there is only one peak captured which last for four seconds at a peak weight over 350 kg. This is showing that the cow placed her first foot onto the section then without moving that foot the next front foot landed on the same section. The same shape signal can also be seen on section D. The positional data on sections A, C and D also shows significant fluctuations. This may have been caused by the cow dragging her hooves along the platform due to discomfort or the algorithm trying to resolve the COP when two hooves are on the same sections. Sections B and C have two distinct foot falls, although section C (blue signal) portrays tenderness in both limbs (lame side). The second blue signal shows the hoof was

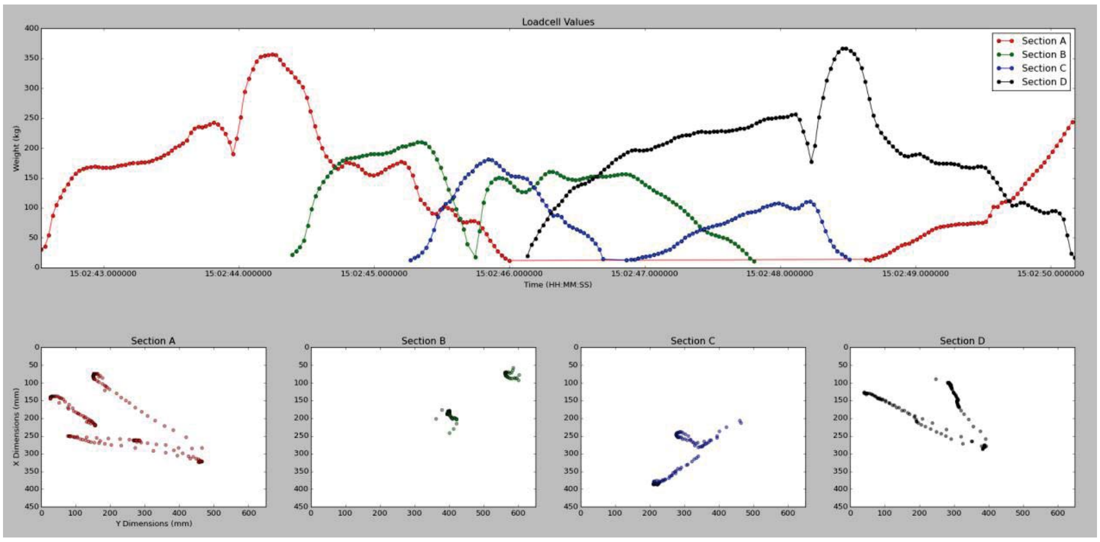

Figure 6.18: Lame level 3 cow signal signature

placed onto the platform very slowly judging by the slope of the signal. There is currently no variable that looks at the slope of the signal, therefore in the analysis and modelling in future chapters no level 3 cows' data is included. Such a variable could be found by taking the derivative. Implementing an algorithm to find this in future improvements may prove to be a useful tool.

6.3.4. Lameness Assessment – Part 2

During the analysis of the scored lame cows some discrepancies were noticed with at least half of the group. The signal signatures and calculated variables of 12 of the cows appeared to be reasonably healthy. This observation of healthy signals compared to lame signals could be made due to the scale of data that had been observed. It was also found that one of the scored healthy cows produced results similar to a lame cow which suggests that it may actually be lame and was misclassified during scoring. For these reasons, the recorded video of the lameness scoring day was used to find and snip the 21 level 2 cows as well as a selection of level 0 and level 1 cows. The mixed recorded files were given to the same trained locomotion scorer, who had no knowledge of my findings, and they scored all the cows. Not surprisingly, the rescored results differed from the original scores. Only 9 cows scored as moderately lame after the video analysis which is an adjustment of over 50%.

After mentioning these differences to the trained observer the response was that when the cows were scored on the farm the viewing location was not ideal. The raceway was slightly downhill over a muddy surface with small stones which shortened the strides of some of the cows, giving the appearances of lameness. With the aid of the video however, each cow could be analysed in slow motion and replayed multiple times to make sure the assigned score was correct. The video was also taken when the cows were walking on a level and clean section of the raceway which was water blasted twice a day, hence no stones were present. Given that there were no certainties that all the other cows were scored correctly, another trial was conducted to make sure the confidence level was high in order to calibrate models.

6.4. Farm Trial 3 Results

The third farm trial involved collecting one week's worth of data and analysing a control group of cows selected by the trained observer. Video assessment of the control cows' condition was analysed daily by the trained observer to make sure that the given score closely matched the lameness level selected. It was hoped that by focusing on a small group of cows with the aid of video playback that the lameness scorer could be confident in their decision. The control group contained 25 cows - 10 randomly selected healthy (level 0) cows, 3 randomly selected level 1 cows and all identified lame (level 2) cows (with this being 12). From the lame group of cows 3 were lame in the LF, 4 were lame in the RF, 3 were lame in the RH, and 2 cows were not in any obvious group.

6.4.1. Novelty Detection Results

After calculating the variables of all the control cows, the first technique attempted was novelty detection. This is essentially a method where a boundary envelope is placed around the mean of a healthy set of cows and this is used to characterise a cow as healthy. Exceptions are detected when individual readings fall outside this envelope. It is a useful method to show the shape and spread of data visually by overlapping many signals by normalising weight and time.

Using the 10 healthy control cows, the first two days of data were taken from each cow and a file was built with 20 independent trials in total (2 days X 10 cows). Figure 6.19 shows the plotted weight signals of the 20 trials which were normalised to be a maximum of one and all start at the same time on section A. The green signals are from section A, blue are section B, black are C and red are section D. Even though the signals start at the same point in time the finishing locations are different as they depend on the speed of the cow (4 – 5 s average).

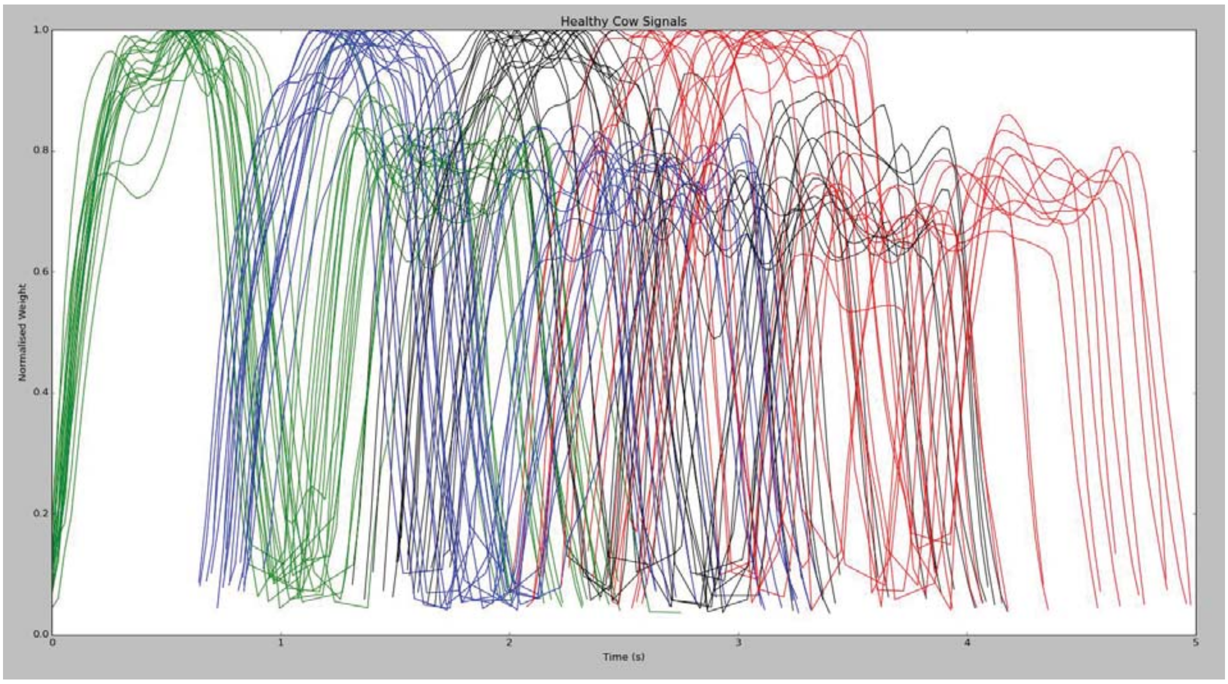

Figure 6.19: 20 independent healthy cow trials (weights normalised)

The time signals were normalised by applying linear interpolation to 100 points to make all the signals start and end at the same point. Each platform section was made to start at the same time, therefore 80 individual front/rear hoof falls overlap one another. Figure 6.20 displays the 80 healthy normalised signals, with the green signals indicating the left side of the cow and the blue signals indicating the right side of the cow. Large proportions of signals overlap and follow the same shape which is promising, although a number of outliers still exist.

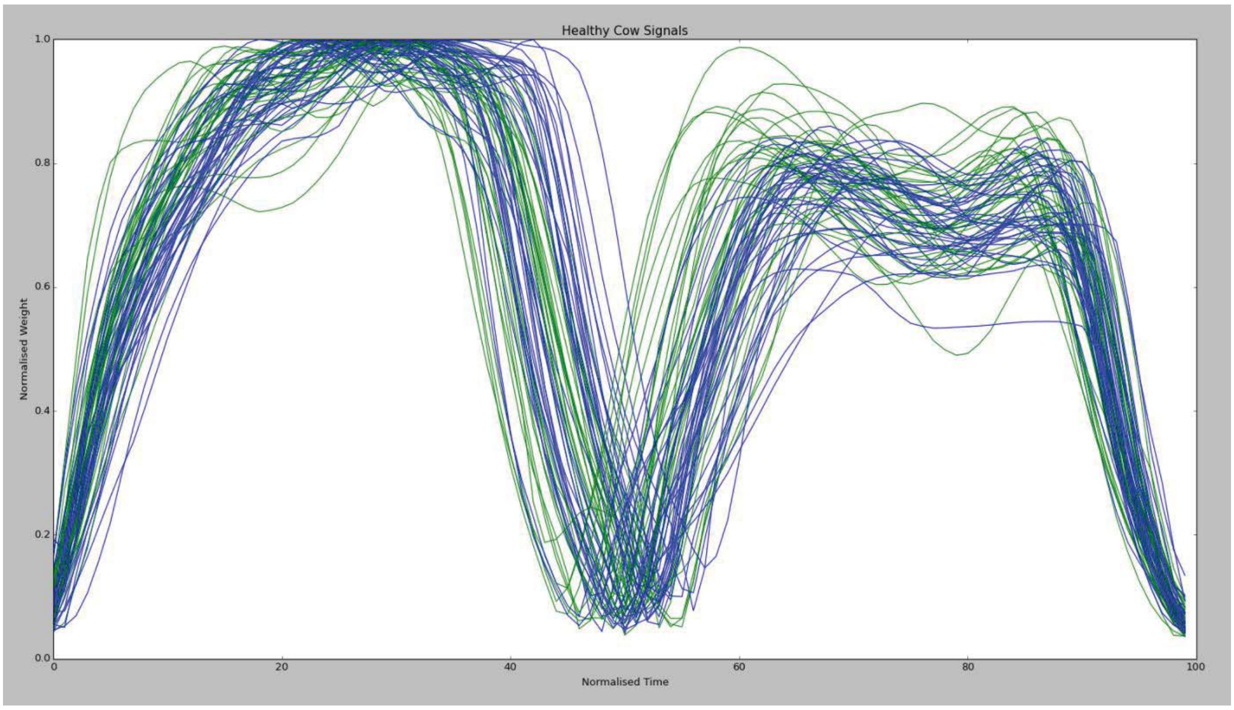

Figure 6.20: 80 independent healthy cow signals normalised

The mean of all 80 signals in Figure 6.20 was calculated and one standard deviation either side of the mean was plotted. These two limits form the boundary of the healthy set of data. The scaling factor on the standard deviation was increased until the majority of the signals were inside the envelope. Figure 6.21 illustrates what the boundary (red signal) looks like compared to the data at ± 5 standard deviations. The shape of the envelope is interesting; it is very thin near the top of the peak as all the signals tend towards one and it is reasonably wide during the transition from the front hoof to the back hoof where the data are spread.

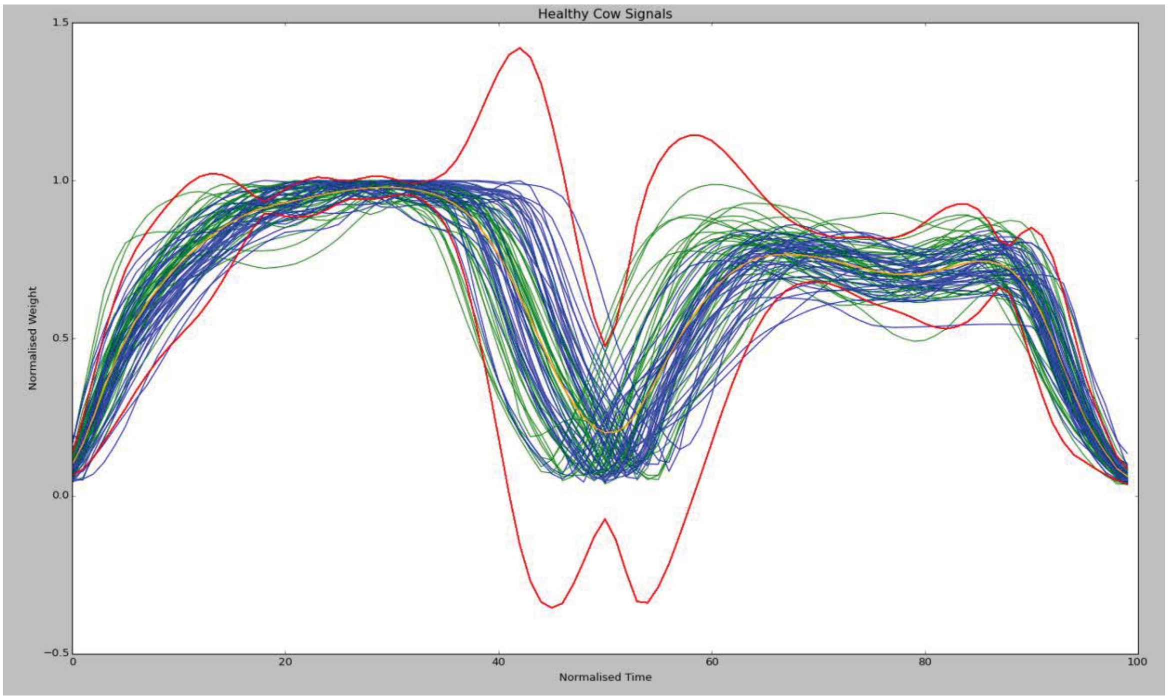

Figure 6.21: Healthy signal boundary envelope

To calculate the optimum boundary condition and the percentage of time the signals were inside the boundary a script was written that incremented the standard deviation between the ranges of 1 to 6. Each signal at all 100 time intervals was tested to see if it was inside the boundary at the given standard deviation. An example of the healthy signals experienced outside the boundary on platform B is shown in Figure 6.22. At 1 StDev approximately 60% of the signals fall outside the envelope which is less than ideal. At 4 StDev and beyond the slope flattens out showing that only 20% of the time the signal would be outside the boundary. On average at 6 StDev, 95% of the healthy signals were within the boundary at all times.

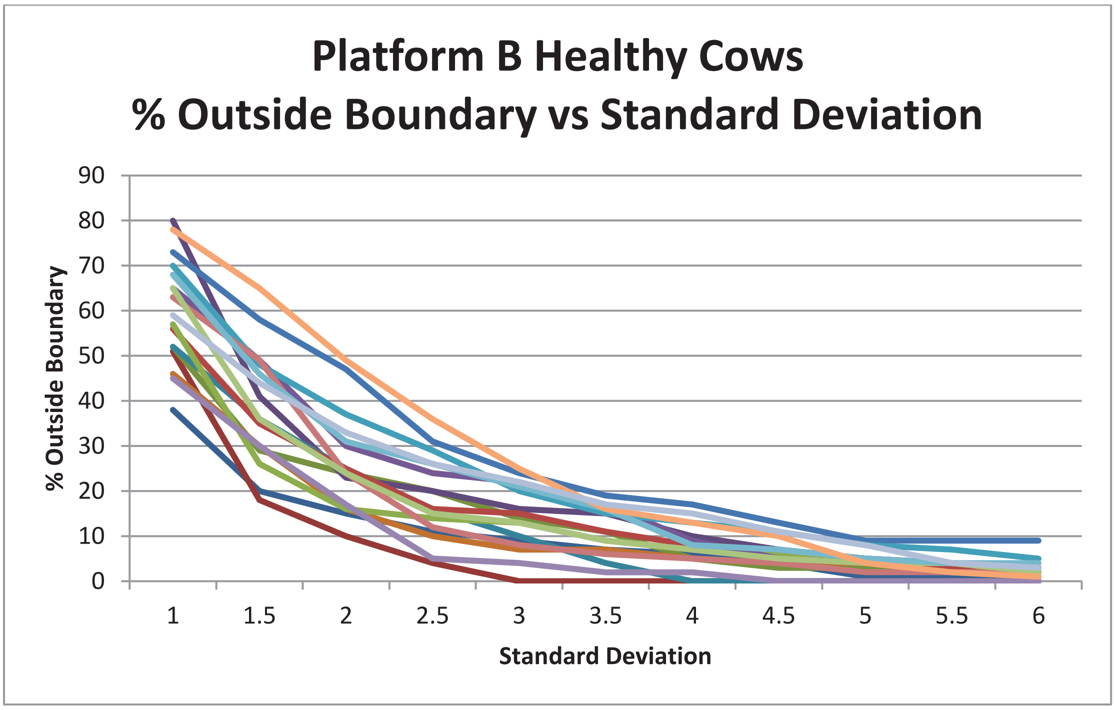

Figure 6.22: Healthy cow signals percentage of time outside boundary

The 12 lame cow signals from the same day were added to the healthy cow boundary which can be seen in Figure 6.23. The red signals are the lame cows and the blue signals are the healthy cows. There are a number of red signals which do not follow the shape of the healthy envelope which shows that there is a difference between healthy and lame signal signatures. On the other hand, there are also a number of lame signals within the healthy envelope. This reduces the percentage of time the signal is outside of the boundary and hence will likely produce a false negative.

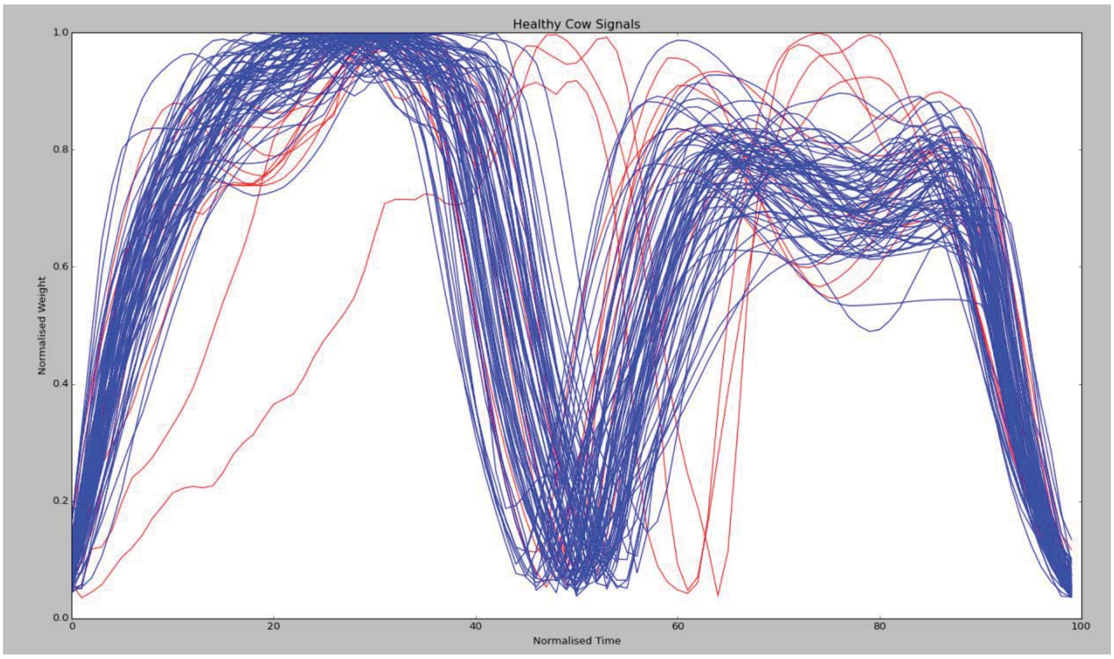

Figure 6.23: Lame cow signals (red) with healthy cow envelope

The amount of time outside the healthy boundary envelope on all platform sections for the lame cows is shown in Figure 6.24. Compared to the healthy cows in Figure 6.22 the lame cows have a reasonable linear relationship and the data were spread further. This indicates that there are considerable differences in profiles between the signal signatures of each lame limb. At 6 StDev the percentage of time outside the boundary is approximately 20%, although the range of signals is largely spread (2% - 70%).

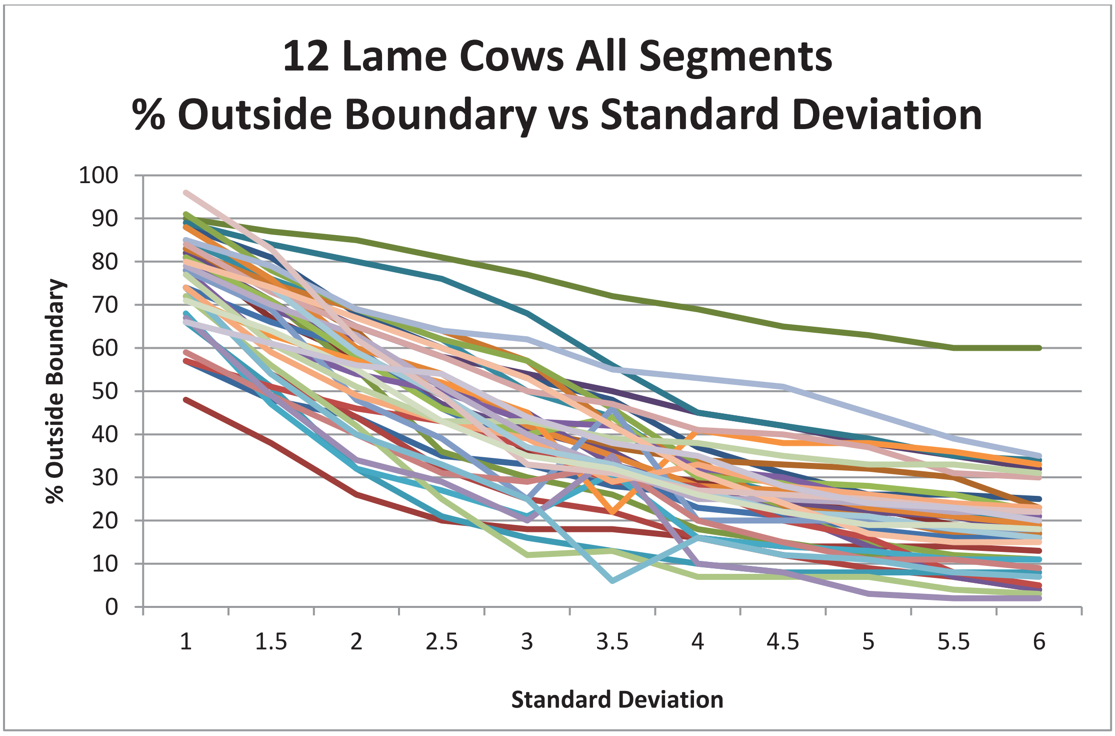

Figure 6.24: Lame cow signals percentage of time outside boundary

The average percentage of time outside the healthy envelope from each platform segment is compared between the healthy and lame group in Figure 6.25. The healthy signals are grouped tightly illustrating no significant differences between segments, whereas the lame signals are spread which is to be expected from Figure 6.24. The area between 4 standard deviations shows the largest separation between the two groups. Therefore taking this value, approximately 24 % of the lame cow signals would be classed as healthy (false negative) and 12 % of the healthy signals would be classed as lame (false positive). For this method to function more effectively the difference between the two groups of signals needs to show more separation over the standard deviation range. Large amounts of overlap exist between signals consequently making the implementation of this method not very effective.

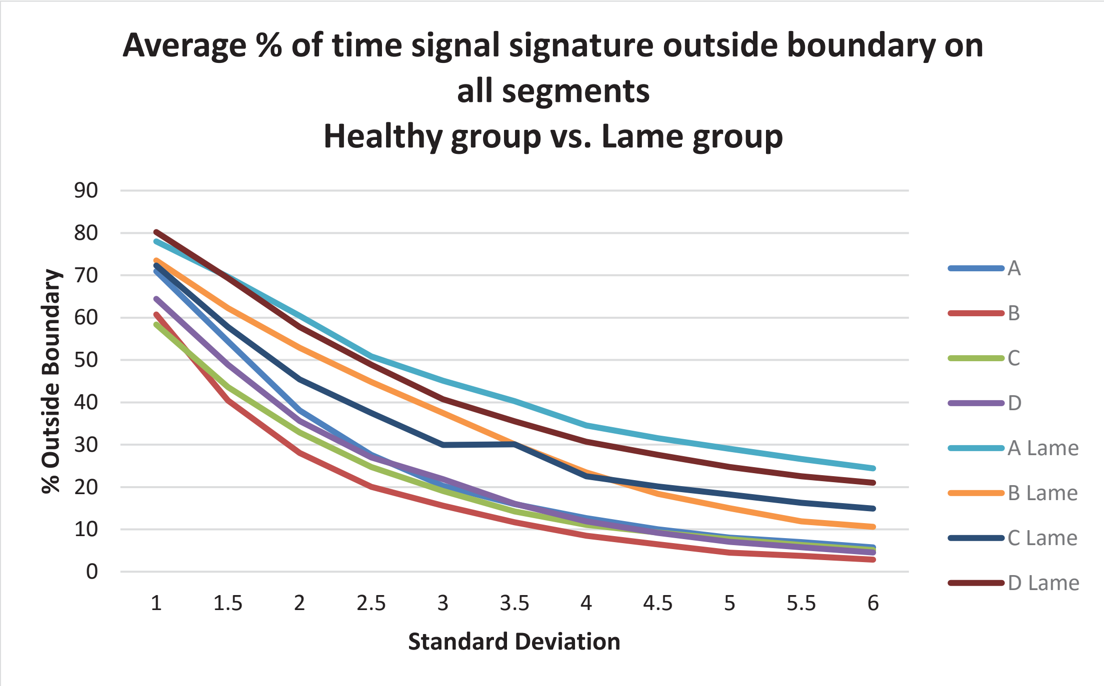

Figure 6.25: Average percentage of time outside of boundary

6.4.2. T- Test Results

Minitab 17 statistical software was used to find the p-values in two sample t-tests between the healthy and lame cows in the control group. The calculated 82 variables associated with lameness were reduced to 29 variables by averaging or removing multiples related to the same kinematic measurement. For example, strong correlations between the variables of front step AB, front step BC, front step CD and step overlap were found and reduced to step overlap solely. The averaged variables were double ups due to two sets of hoof falls per cow on the platform. Table 10 displays the results from the two sample T-test using all 50 trials of healthy cow data and all 36 trials of lame cow data. In total there were 15 variables of significance, with these being:

- *Force*: NGRF LH, asymmetry in weight front limb, asymmetry in weight rear limb, asymmetry in diagonal weight, asymmetry in side weight.

- *Spatial*: Average step overlap left-side, average step overlap right-side, asymmetry in step overlap L Vs R, average step overlap, average abduction left-side, average abduction.

- *Temporal*: Asymmetry in stance time left-side, asymmetry in stance time L vs. R, asymmetry in stance time front hoof, asymmetry in stance time hind hoof.

Table 10: Two sample T-test between all healthy and lame cows

Variable	Healthy Cow (N = 10)		Lame Cow (N = 12)			
	Mean	*StDev*	*Mean*	*StDev*	*P-value*	*Significant*
NGRF LF	0.561	0.017	0.563	0.052	0.847	NS
NGRF RF	0.557	0.015	0.549	0.046	0.336	NS
NGRF LH	0.442	0.017	0.462	0.037	0.006	Yes
NGRF RH	0.441	0.016	0.423	0.049	0.114	NS
Asymmetry in Weight Front Limb (kg)	7.4	5.6	33.8	21.1	0.000	Yes
Asymmetry in Weight Rear Limb (kg)	7.8	6.0	23.9	23.3	0.000	Yes
Asymmetry in Diagonal Weights (kg)	10.9	7.2	43.2	28.8	0.000	Yes
Asymmetry in Side Weights (kg)	11.5	8.0	42.1	30.4	0.000	Yes
Average Stride Left Side (m)	1.430	0.075	1.419	0.080	0.558	NS
Average Stride Right Side (m)	1.403	0.085	1.439	0.085	0.085	NS
Asymmetry in Stride Length L Vs R (m)	0.068	0.050	0.082	0.062	0.285	NS
Average Stride Length (m)	1.417	0.069	1.429	0.065	0.444	NS
Average Step Overlap Left Side (mm)	8	34	-24	48	0.002	Yes
Average Step Overlap Right Side (mm)	15	37	-12	49	0.010	Yes
Asymmetry in Step Overlap L Vs R (mm)	32	26	49	39	0.042	Yes
Average Step Overlap (mm)	12	29	-18	37	0.000	Yes
Average Abduction Left Side (mm)	2	24	20	36	0.012	Yes
Average Abduction Right Side (mm)	31	30	44	40	0.119	NS
Asymmetry in Abduction L Vs R (mm)	39	27	44	37	0.550	NS
Average Abduction (mm)	17	20	32	28	0.007	Yes
Average Stance Time Left Side (s)	0.994	0.133	1.009	0.175	0.685	NS
Average Stance Time Right Side (s)	1.004	0.130	0.956	0.154	0.161	NS
Asymmetry in Stance Time Left Side (s)	0.054	0.043	0.094	0.100	0.036	Yes
Asymmetry in Stance Time Right Side (s)	0.073	0.058	0.087	0.052	0.273	NS
Asymmetry in Stance Time L Vs R (s)	0.034	0.033	0.079	0.073	0.001	Yes
Asymmetry in Stance Time Front (s)	0.046	0.035	0.096	0.101	0.007	Yes
Asymmetry in Stance Time Hind (s)	0.045	0.037	0.081	0.065	0.006	Yes
Walking Duration (s)	4.366	0.488	4.372	0.696	0.967	NS
Walking Velocity (m/s)	0.482	0.055	0.497	0.089	0.398	NS
Number of trials	**50**		**36**			

The four differences in weight variables show a strong significance level at 0.000. This is most apparent in diagonal and side weights with the lame cows being on average 30 kg different. The NGRF LH variable is showing as significant because there are no cows in the group that are lame in the LH limb. When all the trials of the lame cows were averaged the cows that were lame in RF, LF and RH were shifting the balance of the remaining LH limb, giving the appearance that it was lame. See Appendix 3.5 for tables of lame cows that were filtered into groups by which leg was lame so as to not balance out the average value of the variables.

The four step overlap variables showed strong significant differences between the healthy and lame cows. On average, a healthy cow's hind hoof would land 12 mm behind where the front hoof had previously been, which is basically landing in the exact same position. Conversely, with a lame cow the hind hoof would land on average 18 mm in front of the front hoof.

The average abduction on the left hand side and the overall average abduction showed strong significance indicating that a lame cow tends to walk with their back legs slightly further apart. A healthy cow's hind leg would be an average of 20 mm outside of the front hoof placement, compared to 30 mm for a lame cow's leg. Although 10 mm does not seem like much of a difference, it is noticeable when watching a lame cow walk with that abduction amount.

The differences in stance times were also significant which was expected. The lame cows produced differences of 80 – 90 ms between limbs while the healthy cows showed differences between contralateral limbs of approximately 45 ms. On average, the tender limb of a lame cow was in contact with the ground for 30 – 40 ms less than the opposite limb. The overall walking velocities of the lame cows were not significant which is odd considering that lame cows walk slower in general. It should be noted that most of the healthy cows in the herd appeared to walk slowly, i.e. they were never in a rush and walked naturally at their own pace.

6.4.3. Discriminant Analysis Results

Minitab 17 was used to classify each trial from the control group of cows using the variables that had been calculated. Each trial was considered as a separate cow in terms of data that Minitab was using, therefore a total of 86 cows were used to build the model. Different combinations of predictor variables were trialled in order to find models which produced the best classification results. Combinations of variables included:

- All 82 variables
- All T-test variables
- Weight variables only
- Spatial variables only
- Temporal variables only
- Statistically significant variables

The result when all the T – test variables were used as predictors is shown below in Table 11. All the outputs from the Minitab software are classified using a cross validation technique discussed in Chapter 4.1.4. Table 11 shows that 48 of the 50 healthy cows passed as healthy and 2 were classified as lame, giving a 96 % success rate. Out of the 36 lame cows, 15 were classified correctly and 21 were said to be healthy, giving a 58 % success rate. Considering that 86 cows were used in the model and 69 were correctly classified, the proportion correctly classified was 80.2 %.

Table 11: Linear discriminant analysis classification (29 variables)

	Healthy	Lame
Healthy	48	21
Lame	2	15
Total N	50	36
N Correct	48	21
Proportion	0.96	0.583

When all weight related variables were used to predict the model the proportion correct was found to be 76.9 %. It was found that when fewer predictor variables were used in the model, the proportion correct became higher (to an extent). Using the six predictor variables of asymmetry in weights front/rear, asymmetry in side/diagonal weights, average step overlap and average abduction, the proportion correctly classified was 84.6 %.

The most accurate model found using linear discriminant analysis involved five predictor variables. These were: asymmetry in weights front limb, asymmetry in weights rear limb, asymmetry in step overlap L vs. R, asymmetry in abduction L vs. R, and walking velocity. Table 12 shows the classification output using these predictor variables. There is only one false positive but nine false negative classifications, giving a proportion correct of 88.4 %. One third of the lame cow group is being misclassified which is fairly high considering the application is aimed towards commercialisation. It was interesting to find that time/stance variables were not featured in the classification models that provided the highest proportion correct.

Table 12: Linear discriminant analysis classification using five predictors

	Healthy	Lame
Healthy	49	9
Lame	1	27
Total N	50	36
N Correct	49	27
Proportion	0.98	0.75

Quadratic discriminant analysis was explored using the same combinations of predictor variables to see what effect quadratic equations would have. The prior probability conditions of 10 % lame and 90 % healthy at any given time are still valid in this model. It was found that a quadratic model with the same predictor variables as the best performing linear model was more accurate. Table 13 below shows the output of the quadratic model with only three misclassifications from all 86 cows. Only one false positive and two false negatives occur in this model, giving the proportion correct at 96.5 %. The five predictor variables were:

- asymmetry in weights front limb
- asymmetry in weights rear limb
- asymmetry in step overlap L vs. R
- asymmetry in abduction L vs. R
- walking velocity

Table 13: Quadratic discriminant analysis classification using five predictor variables

	Healthy	Lame
Healthy	49	2
Lame	1	34
Total N	50	36
N Correct	49	34
Proportion	0.98	0.944

6.4.4. Logistic Regression Results

Binomial logistic regression was examined with the aid of SPSS 23 to see if more accurate models could be developed to classify the cattle as healthy or lame. The benefit of BLG is that the variables do not have to be normally distributed, which in some instances was necessary as predictor variables were skewed. The same combinations of predictor variables were trialled as DA to compare which method produced the best model. It was found that BLG is more successful and could handle a greater number of predictor variables to correctly classify the cattle. Using all the T-test variables resulted in a 100 % correct classification in both healthy and lame groups even though some of the predictor variables were not significant. Table 14 shows the significance of each variable calculated by SPSS during analysis of the model, with this being similar to the two sample T-test results. Seven variables are not seen as significant to the equations and have therefore been given less importance.

Table 14: Significance of predictor variables in the Binary Logistic Regression model

			Score	df	Sig.
Step 0	Variables	RatioNGRFFront	38.231	1	.000
		RatioNGRFBack	15.909	1	.000
		AsymmetryFront	39.360	1	.000
		AsymmetryRear	18.748	1	.000
		AsymemetryDia	35.656	1	.000
		AsymmetrySide	31.538	1	.000
		AsymmetryStrideLvsR	1.811	1	.178
		AverageStride	.018	1	.894
		StepoverlapLeft	12.621	1	.000
		StepoverlapRight	6.447	1	.011
		AsymmetryStepOverlap	5.614	1	.018
		AverageStepOverlap	13.718	1	.000
		AbductionLeft	2.827	1	.093
		AbductionRight	1.657	1	.198
		AsymmetryAbduction	.789	1	.374
		AverageAbduction	3.989	1	.046
		StanceLeft	4.473	1	.034
		StanceRight	.409	1	.522
		AsymmetryStaceLvsR	10.159	1	.001
		AsymmetryStanceFront	9.860	1	.002
		AsymmetryStanceRear	4.814	1	.028
		WalkingVelocity	.667	1	.414

The predictor variables were reduced to see what combinations still gave 100 % classification with the least number of variables required. It was discovered that using six predictor variables gave the desired outcome of correct classification, with these variables being:

- Asymmetry in front weights
- Asymmetry in rear weights
- Asymmetry in diagonal weights
- Asymmetry in stance L vs. R
- Average step overlap
- Average abduction

Table 15 illustrates the classification table that is produced by SPSS for the six predictor variables. The variable that had the most influence in the equation is asymmetry in stance L vs. R, which is interesting considering that no time-based variables were used in the DA models. The model was able to predict the classification with certainty as the probabilities tended towards the boundary of the logistic curve. This meant that there were obvious differences between the two groups for the equation to identify and hence the lame cow probabilities were in the order of 0.99, whereas the healthy cows were around 0.01. Very few values were located in the 'S' region of the logistic curve meaning that the cows were assigned into the respective groups without any chance of false positives.

Table 15: Classification table summary of Binary Logistic Regression (SPSS output)

Classification Table

Observed			Predicted: Classify Healthy	Predicted: Classify Lame	Percentage Correct
Step 1	Classify	Healthy	50	0	100.0
		Lame	0	36	100.0
	Overall Percentage				100.0

6.5. Farm Trial Discussion

The aim of the farm trials was to see if the designed WoP would be able to capture the required data in the intended environment over a period of time. The second goal was to use the data and calculate the variables associated with lameness in order to classify between healthy and lame cows.

The WoP successfully endured the harsh environmental conditions that are inherent of milking sheds and was tested on two farms during the winter of 2015, capturing approximately 9500 hoof falls on the platform. The WoP was cleaned daily with high pressure water and calibrated to make sure the load cells and electronics were functioning correctly. It was discovered during a calibration test near the end of the farm trials that one platform segment was displaying aberrant results. The farm trial for that day had to be cancelled and the WoP had to be taken apart to investigate what was causing the issue. Figure 6.26 shows the behaviour of the signals that were captured during calibration, with section C showing increasing weight even when no load was being applied. It was found that the top metal platform tray on section C had moved slightly which nicked two load cell cables and allowed water to enter. The water made its way to the strain gauge which negatively affected it. The two load cells had to be removed and replaced with new ones before the system was operational again.

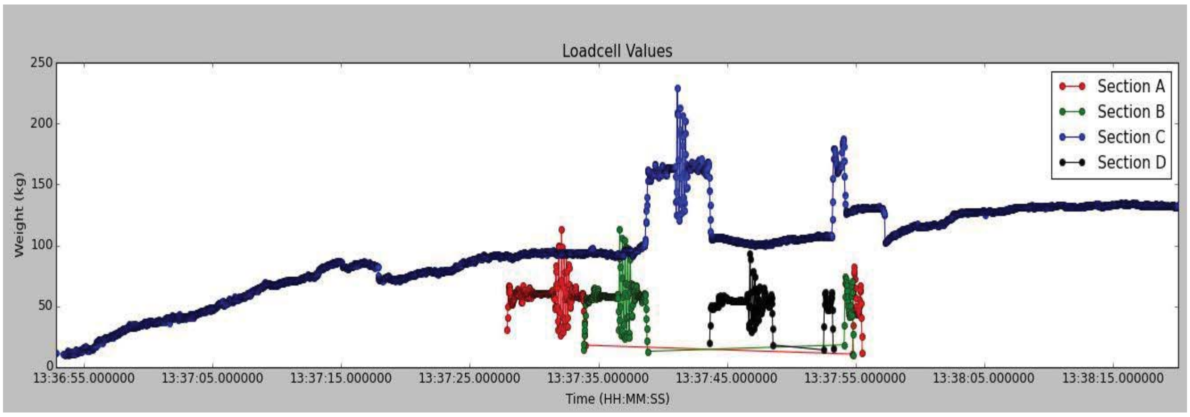

Figure 6.26: Load cell calibration issue (platform C)

It was observed during the first farm trial that when the cows exited the herringbone shed they would bunch together and have to be manually persuaded to walk over the platform. This caused a number of issues as the group of 20 - 40 cows would walk/run over the platform closely following each other creating an unnatural flow. This made it very difficult and sometimes not possible to split data manually, especially if the cows were in a hurry as the EID reader would occasionally miss tags. A practical solution would need to be developed or the cows would need to be trained to walk individually if the system was to be commercialised. A possible solution would be to develop an algorithm to decode the hoof falls and track where the cow is and how many cows are on the platform. A state machine could be used to track where each leg is at any time, although this would not solve the issue of cows bunching and consequently stopping on the platform.

The method of finding the individual limb weights worked reasonably well although the calculated weight was always less than the static weight. Acceleration and deceleration forces were not taken into account when designing the algorithm and should not be neglected as they contribute properties to the signal. In future designs, a simpler method to calculate the total cow weight should be considered by taking the summation of weight of all sections at the same point in time. Figure 6.27 illustrates the shape of the resultant signal (similar to current Tru-Test walkover weight signal) for a cow as she walks over the platform. The total weight of the cow is experienced on the platform along the second plateau and a filter could simply be applied between the two red marks to smooth out the signal, possibly producing more accurate results.

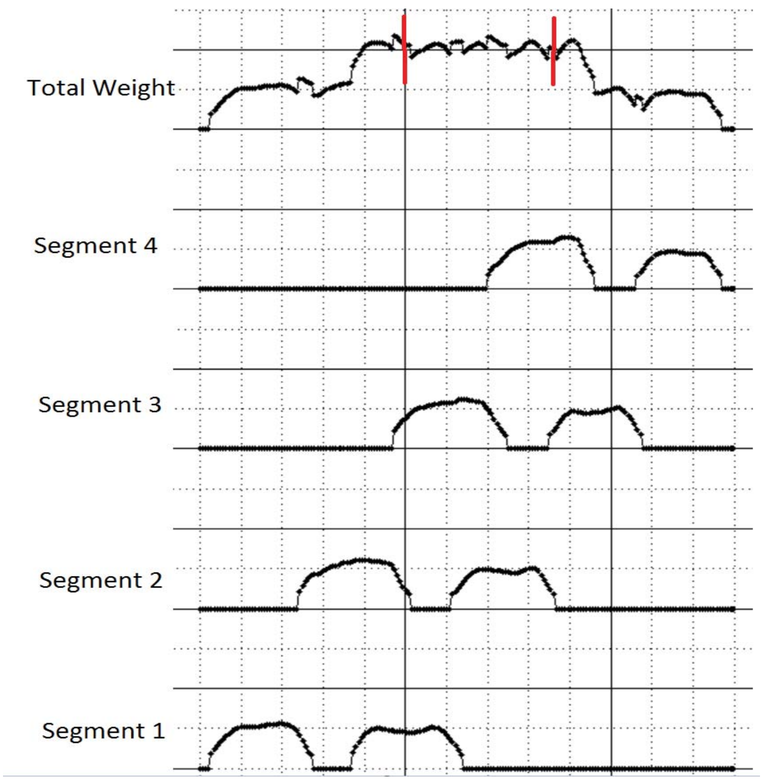

Figure 6.27: Total cow weight signal by taking summations of platform segments

On farm and video analysis lameness scoring was conducted by a trained observer with varying results. The visual observation method of scoring is very subjective and often results in missing symptoms or misclassifying the level of lameness. The scorer only has a short period of time to view the cow before the next one exits the milking shed. The observation area of the herd was along the raceway to the feed shed which was sloped slightly downhill causing the cows to shorten their stride. In future testing situations, more trained observers need to be used to average out the scores which could be influenced by environmental factors and individual opinions.

The findings from the data analysis and T-test results make it possible to draw conclusions about the usefulness of the variables and what the expected averages should be. For example the stride length variables did not show any significance which is not surprising considering that from weekly time series graphs of healthy cows the values fluctuated daily. The fluctuations could be due to natural variation depending on which leg was leading onto the platform and the speed of movement. A healthy cow average stride length was found to be 1417 ± 69 mm, whereas a lame cow tended to have a longer stride length of 1429 ± 65 mm. This finding is contrary to (Van Nuffel *et al*, 2013) who found that the stride length of a lame cow tended to decrease on average. The average step length of 697 ± 37 mm for a healthy cow is in agreement with an experiment at Massey University conducted by Stephenson (2006) who found that ruts in raceways made by dairy cows were 700 mm. Further investigation of the positional data discovered that 95 % of the hoof falls landed on a platform section, the other 5 % were between the segment gaps in the 'dead zone'. The high success rate implies that the lead on (blank) platform and the actual segment lengths are the correct dimensions for capturing foot falls of an average sized herd of dairy cattle.

The findings of the T-tests are in agreement with studies conducted by Maertens *et al* (2011) and Van Nuffel *et al* (2013), which also found that asymmetry in step length (step overlap), asymmetry in stance time and asymmetry in step width (abduction) were significant variables. The significance of the asymmetry in weight variables could not be verified with other studies as the data provided by the StepMetrix system was limited.

One of the main difficulties and time consuming tasks was manually validating and splitting the raw data based on where the EID tag was captured in the recorded text file. This had to be done to ensure that the analysed data was true and that the algorithms would actually be able to function. Basing the algorithms around capturing two hoof falls per segment was not ideal, particularly for severely lame cows which sometime struggled to stand up onto the platform and walk along it.

Of particular interest was observing that healthy cows have slight variations in their gait and signal signatures daily. For this reason, a system that bases the decision solely on one trial and not on the cows past data would produce more false positives. For example, a stone may get wedged into the hoof of a healthy cow and produce variables that indicate lameness, but the next day the stone may fall out and the variables would be back to normal. For a practical system, the farmer wants as few false negatives and false positives as possible; therefore the system needs to keep track of current and past results of that particular cow to make the decision more robust. False negative results are worse than false positives as the farmer will lose faith in the system if they notice a lame cow that has not been identified. The system does not currently use past information about a cow in the logistic equation to determine the classification.

The performance of the calibration classification model is extremely dependent on the training data set supplied. The healthy cow data that was used was a stereotypical representation of how a normal cow naturally walks. The data collected on level 1 scored cows was not used in any models. It is unknown how adding level 1 cows to the data would affect the classification models. In a commercial system, level 1 cows would ideally be classified as healthy unless they are showing symptoms to suggest they are heading towards level 2, in which case treatment would be required.

The discriminant analysis model was found to correctly classify 96 % of all cows and 94 % of the lame cows in the control group. Comparatively, the GAITWISE system discriminant model averaged 84 % accuracy in correctly classifying lame cattle based on a case control study with two months of data from 80 dairy cows. The accuracy of the GAITWISE model is less than this study mainly due to classifying three levels of lameness (1, 2 and 3) which would consequently lower the average success rate. The StepMetrix system supposedly averages over 85 % accuracy in detecting lameness in individual cattle, although no scientific studies on the product were found.

The performance of the logistic regression model is excellent and is the best method of classification of this type of data. It would be very interesting to see how this model behaved when more data is available in future iterations. According to the set-up procedures of SPSS it is recommended that at least 400 samples/trial are used to build the calibration model. The more data that are available the more reliable and robust the model will become.

Reasons why this study has better results than similar studies could include:

- More load cells are used at a faster sampling rate, hence supplying more data to give a better representation of the actual signals.
- Novel mechanical arrangement of force plates.
- The data were captured naturally without intervention or separation gates which may reveal more information about the animal.
- Less data have been analysed – only compared a small sample group of healthy and lame cows.

Chapter 7: Conclusions and Future Improvements

The main objective of this study was to investigate whether differences between healthy and lame cattle could be identified by capturing ground reaction forces when the dairy cattle walked over the designed platform. Statistical techniques were used to build classification models based on calculated variables associated with lameness.

Although the developed WoP meets the specified requirements and functions as intended, there are still numerous areas for future enhancements. One key area is the optimisation of the mechanical design to make the platform more robust and use fewer parts. This can be achieved by using the optimal step length of 700 mm and fixing the platform sections in one place. This would remove the need for the four separate sub-frames and the load cells could be fixed straight to the main frame. The main framing structure could then be designed based on these measurements with box section or a similar material with a large second moment of area; this would increase the stiffness so that less twisting occurs. This twisting can have an effect on the weight being reported on the other sections which was seen when packers were not installed under the framing. The side rails and the base platform could then be folded from one continuous piece of sheet-metal, similar to the current Tru-Test walkover weigh platform.

Another possible hardware enhancement is to investigate using only one 24 bit 16 channel ADC in pseudo differential mode so only one electrical box with one microcontroller would be needed. The benefits of this design is the reduced complexity, no communication protocol is required, and fewer components would be needed which would make the system more reliable. The only disadvantage of this is that all 16 load cells would need to be routed to one electrical box meaning that longer cable lengths would be needed.

The algorithms developed to calculate average weight, stride lengths and hoof duration function as intended, however there are a couple of issues. These algorithms assume that only two peaks will occur on each section, therefore further improvement of these algorithms is required. The software can be improved by adding more exception handling code, so if invalid data were passed to the algorithm it does not crash. An algorithm for determining variables of level 3 cows also needs to be developed to classify the most obvious lame cows.

In future on-farm lameness scoring a minimum of three trained observers need to be present to score the herd, followed by averaging of their results. It would also be interesting to get the veterinarians to check the hooves of the lame cows above level 2 to say what disease or issue caused the lameness. It may be possible to teach the program to look for specific traits associated in the signals and determine what type of lameness it is.

To be certain of the BLR model more data are required to prove that it can classify level 1 cows and a range of cows from different farms. Using the same cows in the model over multiple days and assuming that they are independent is not as statistically strong as using 36 completely different cows.

The successful outcome from this project has been the development of a robust platform to be used in the milking shed. The WoP uses an array of load cells to measure the three main kinematic variables (force, position and time) which are related with lameness. The information from each platform segment is transmitted to the computer and recorded for post-processing algorithms to determine specific gait parameters. The WoP system was manufactured with four independent platform sections, with each section consisting of four ASB1000 shearbeam load cells (one in each corner), a 24 bit four-channel sigma-delta analogue-to-digital converter (ADC), and an ATmega328 microcontroller. The components were researched thoroughly before purchasing to ensure that the system used high quality components and would last numerous seasons in the harsh milking shed environment. The total cost to build the WoP and electronics was $1900, which is a reasonably low price considering retail prices of standard walkover weight scales are approximately $5000.

The analogue signals of the 16 load cells were digitized and the total weight and centre of pressure on each section was able to be calculated. The total weight on the tested platform segment was calculated with a maximum error of 0.4 %. The x and y coordinates were captured and tested to demonstrate the behaviour and accuracy when exposed to static and dynamic loads. It was found that the X-position mean error was 1.0 ± 2.2 mm and the Y-position mean error was 0.8 ± 1.8 mm. The sections were so sensitive that a finger could be placed lightly on the segments surface and moved around and the same pattern would be drawn on the computer monitor (the segment can be thought of as a large touchpad).

The laboratory testing of the step length algorithms found that the three methods produced very similar results, although the most accurate was the Peak method. The overall step length mean error and standard deviation is summarised below:

- Threshold Method: -2.66 ± 10.25 mm
- Peak Method: -2.40 ± 8.95 mm
- Radius Method: -2.57 ± 9.70 mm

The first field trial involving 10 dairy cows found that the calculated dynamic weight was on average 15 kg less than the cow's static weight. The mean error and standard deviation of combined platform segments is summarised below:

- Section AB = -20.14 ± 13.78 kg
- Section BC = -10.69 ± 10.57 kg
- Section CD = -10.15 ± 12.36 kg
- Combined Sections = -13.66 ± 7.52 kg

The second field trial involved 200 cows which were lameness scored by a trained observer. The captured data were analysed to compare variations in signals and variables between healthy and lame cows. The lame cow signal signatures had distinguishable differences compared to healthy cows, demonstrating that the original hypothesis was true. Weekly time series trends of variables between groups of level 0 and level 2 cows also showed noticeable differences indicating that measurable parameters change between groups. An important discovery was that 95 % of the time the hoof falls landed on one of the four segments, implying that the segment length and spacing's were correct.

The two sample T-tests found that there were 14 significant variables associated with determining lameness and they could be categorised into force, spatial and temporal parameters as shown below:

- *Force*:
  - Asymmetry in weight front limb
  - Asymmetry in weight rear limb
  - Asymmetry in diagonal weight
  - Asymmetry in side weight
- *Spatial*:
  - Average step overlap left-side
  - Average step overlap right-side
  - Asymmetry in step overlap L Vs R
  - Average step overlap
  - Average abduction left-side
  - Average abduction
- *Temporal*:
  - Asymmetry in stance time left-side
  - Asymmetry in stance time L vs. R
  - Asymmetry in stance time front hoof
  - Asymmetry in stance time hind hoof

Data from a control group of 25 cows were captured and analysed over a week period with the aim of classifying the cows using discriminant analysis and logistic regression. Only 22 out of the 25 cows were used in the models because the level 1 cows could not be defined as either healthy or lame. The models currently look at only one set of data for each cow and decide if it is lame or healthy. Future iterations of software should include at least the previous day of information collected about the particular cow to make a more informed decision.

The discriminant analysis models found that when less predictor variables were used the classification probabilities increased. A Quadratic discriminant model with prior probabilities specified was found to be the best DA model with a proportion correct of 96.5 %. The five predictor variables used in the model were:

- Asymmetry in weights front limb
- Asymmetry in weights rear limb
- Asymmetry in step overlap L vs. R
- Asymmetry in abduction L vs. R
- Walking velocity

Logistic regression was found to be the best method for classification with all 86 trials correctly classified as either healthy or lame. Unlike DA, logistic regression could use over 20 predictor variables, some with no significance at all, to build a model that had a 100 % success rate. The minimum amount of predictor variables that gave a perfect outcome was six, with these variables being:

- Asymmetry in front weights
- Asymmetry in rear weights
- Asymmetry in diagonal weights
- Asymmetry in stance L vs. R
- Average step overlap
- Average abduction

A number of recommendations were appointed for future improvements of the system. All the project aims were achieved, however more testing needs to be conducted over a longer period of time at more than one farm to validate the binary logistic regression model with more data. The logistic equation does not use the previous day's information of a particular cow, it solely determines lameness based on the one trial. The main advantages of this system is that a farm without an EID scanner could use the WoP to determine lameness, compared to the StepMetrix system which requires a scanner. A predictor variable of the previous day lameness score could be used in the model similar to the StepMetrix, although the results suggest that this is not necessary at this stage. Another benefit is that the natural flow of cows out of the milking shed was not disturbed with the WoP compared to the pressure sensitive GAITWISE system which required a stop gate. The WoP overall architecture may one day be used industrially to improve animal well-being and save farmers money in New Zealand and internationally.

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Appendices

Appendix 1: Critical Component Datasheets

AD7193 Datasheet

ANALOG DEVICES

4-Channel, 4.8 kHz, Ultralow Noise, 24-Bit Sigma-Delta ADC with PGA

Data Sheet **AD7193**

FEATURES

- Fast settling filter option
- 4 differential/8 pseudo differential input channels
- RMS noise: 11 nV @ 4.7 Hz (gain = 128)
- 15.5 noise-free bits @ 2.4 kHz (gain = 128)
- Up to 22 noise-free bits (gain = 1)
- Offset drift: ±5 nV/°C
- Gain drift: ±1 ppm/°C
- Specified drift over time
- Automatic channel sequencer
- Programmable gain (1 to 128)
- Output data rate: 4.7 Hz to 4.8 kHz
- Internal or external clock
- Simultaneous 50 Hz/60 Hz rejection
- 4 general-purpose digital outputs
- Power supply
  - AV_{DD}: 3 V to 5.25 V
  - DV_{DD}: 2.7 V to 5.25 V
- Current: 4.65 mA
- Temperature range: −40°C to +105°C
- 28-lead TSSOP and 32-lead LFCSP packages
- Interface
  - 3-wire serial
  - SPI, QSPI™, MICROWIRE™, and DSP compatible
  - Schmitt trigger on SCLK

APPLICATIONS

- PLC/DCS analog input modules
- Data acquisition
- Strain gage transducers
- Pressure measurement
- Temperature measurement
- Flow measurement
- Weigh scales
- Chromatography
- Medical and scientific instrumentation

GENERAL DESCRIPTION

The AD7193 is a low noise, complete analog front end for high precision measurement applications. It contains a low noise, 24-bit sigma-delta (Σ-Δ) analog-to-digital converter (ADC). The on-chip low noise gain stage means that signals of small amplitude can interface directly to the ADC.

The device can be configured to have four differential inputs or eight pseudo differential inputs. The on-chip channel sequencer allows several channels to be enabled simultaneously, and the AD7193 sequentially converts on each enabled channel, simplifying communication with the part. The on-chip 4.92 MHz clock can be used as the clock source to the ADC or, alternatively, an external clock or crystal can be used. The output data rate from the part can be varied from 4.7 Hz to 4.8 kHz.

The device has a very flexible digital filter, including a fast settling option. Variables such as output data rate and settling time are dependent on the option selected. The AD7193 also includes a zero latency option.

The part operates with a power supply from 3 V to 5.25 V. It consumes a current of 4.65 mA, and it is available in a 28-lead TSSOP package and a 32-lead LFCSP package.

FUNCTIONAL BLOCK DIAGRAM

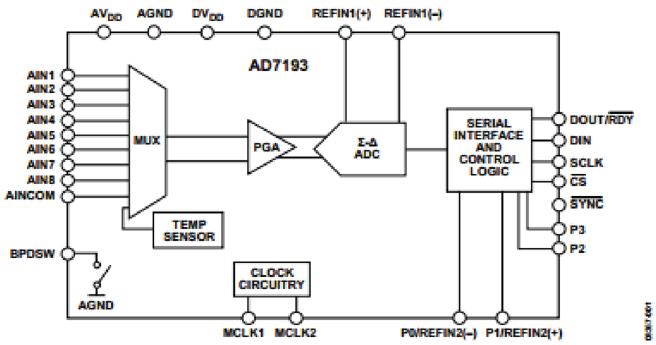


Figure 1.

The full datasheet for the AD7193 24-bit ADC can be found at:

http://www.analog.com/media/en/technical-documentation/data-sheets/AD7193.pdf accessed on 26 May 2015.

REF5040 Datasheet

TEXAS INSTRUMENTS

www.ti.com

REF5010, REF5020
REF5025, REF5030
REF5040, REF5045, REF5050

SBOS410F – JUNE 2007 – REVISED DECEMBER 2013

Low-Noise, Very Low Drift, Precision Voltage Reference

Check for Samples: REF5010, REF5020, REF5025, REF5030, REF5040, REF5045, REF5050

FEATURES

- LOW TEMPERATURE DRIFT:
  - High-Grade: 3ppm/°C (max)
  - Standard-Grade: 8ppm/°C (max)
- HIGH ACCURACY:
  - High-Grade: 0.05% (max)
  - Standard-Grade: 0.1% (max)
- LOW NOISE: $3\mu V_{PP}/V$
- EXCELLENT LONG-TERM STABILITY:
  - 45ppm/1000hr (typ) after 1000 hours
- HIGH OUTPUT CURRENT: ±10mA
- TEMPERATURE RANGE: –40°C to +125°C

APPLICATIONS

- 16-BIT DATA ACQUISITION SYSTEMS
- ATE EQUIPMENT
- INDUSTRIAL PROCESS CONTROL
- MEDICAL INSTRUMENTATION
- OPTICAL CONTROL SYSTEMS
- PRECISION INSTRUMENTATION

DESCRIPTION

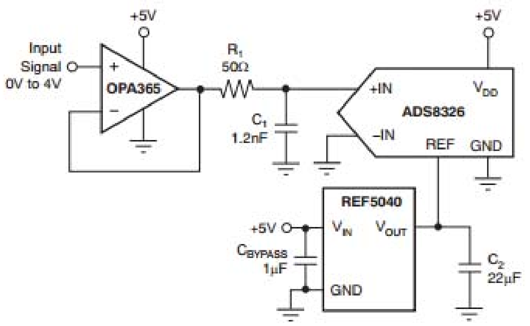
The REF50xx is a family of low-noise, low-drift, very high precision voltage references. These references are capable of both sinking and sourcing, and are very robust with regard to line and load changes.

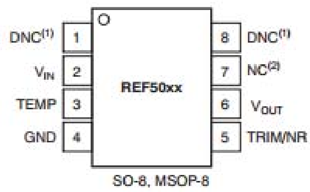
Excellent temperature drift (3ppm/°C) and high accuracy (0.05%) are achieved using proprietary design techniques. These features, combined with very low noise, make the REF50xx family ideal for use in high-precision data acquisition systems.

Each reference voltage is available in both standard- and high-grade versions. They are offered in MSOP-8 and SO-8 packages, and are specified from –40°C to +125°C.

REF50xx Family

MODEL	OUTPUT VOLTAGE
REF5020	2.048V
REF5025	2.5V
REF5030	3.0V
REF5040	4.096V
REF5045	4.5V
REF5050	5.0V
REF5010	10.0V





NOTES: (1) DNC = Do not connect.
(2) NC = No internal connection.

The full datasheet for the REF5040 voltage reference can be found at:
http://www.ti.com/lit/ds/sbos410f/sbos410f.pdf accessed on 18 June 2015.

AD8656 Datasheet

Low Noise, Precision CMOS Amplifier

Data Sheet **AD8655/AD8656**

FEATURES

Low noise: 2.7 nV/√Hz at f = 10 kHz
Low offset voltage: 250 μV max over V_{CM}
Offset voltage drift: 0.4 μV/°C typ and 2.3 μV/°C max
Bandwidth: 28 MHz
Rail-to-rail input/output
Unity gain stable
2.7 V to 5.5 V operation
−40°C to +125°C operation
Qualified for automotive applications

APPLICATIONS

ADC and DAC buffers
Audio
Industrial controls
Precision filters
Digital scales
Automotive collision avoidance
PLL filters

PIN CONFIGURATIONS

Figure 1. AD8655 8-Lead MSOP (RM-8) 8-Lead SOIC (R-8)

Figure 2. AD8656 8-Lead MSOP (RM-8) 8-Lead SOIC (R-8)

GENERAL DESCRIPTION

The AD8655/AD8656 are the industry's lowest noise, precision CMOS amplifiers. They leverage the Analog Devices DigiTrim® technology to achieve high dc accuracy.

The AD8655/AD8656 provide low noise (2.7 nV/√Hz at 10 kHz), low THD + N (0.0007%), and high precision performance (250 μV max over V_{CM}) to low voltage applications. The ability to swing rail-to-rail at the input and output enables designers to buffer analog-to-digital converters (ADCs) and other wide dynamic range devices in single-supply systems.

The high precision performance of the AD8655/AD8656 improves the resolution and dynamic range in low voltage applications. Audio applications, such as microphone pre-amps and audio mixing consoles, benefit from the low noise, low distortion, and high output current capability of the AD8655/AD8656 to reduce system level noise performance and maintain audio fidelity. The high precision and rail-to-rail input and output of the AD8655/AD8656 benefit data acquisition, process controls, and PLL filter applications.

The AD8655/AD8656 are fully specified over the −40°C to +125°C temperature range. The AD8655/AD8656 are available in Pb-free, 8-lead MSOP and SOIC packages. The AD8655/AD8656 are both available for automotive applications.

The full datasheet for the AD8656 amplifier can be found at:

http://www.analog.com/media/en/technical-documentation/data-sheets/AD8655_8656.pdf

accessed on 25 June 2015.

maxim integrated

MAX481/MAX483/MAX485/ MAX487–MAX491/MAX1487

Low-Power, Slew-Rate-Limited RS-485/RS-422 Transceivers

General Description

The MAX481, MAX483, MAX485, MAX487–MAX491, and MAX1487 are low-power transceivers for RS-485 and RS-422 communication. Each part contains one driver and one receiver. The MAX483, MAX487, MAX488, and MAX489 feature reduced slew-rate drivers that minimize EMI and reduce reflections caused by improperly terminated cables, thus allowing error-free data transmission up to 250kbps. The driver slew rates of the MAX481, MAX485, MAX490, MAX491, and MAX1487 are not limited, allowing them to transmit up to 2.5Mbps.

These transceivers draw between 120µA and 500µA of supply current when unloaded or fully loaded with disabled drivers. Additionally, the MAX481, MAX483, and MAX487 have a low-current shutdown mode in which they consume only 0.1µA. All parts operate from a single 5V supply.

Drivers are short-circuit current limited and are protected against excessive power dissipation by thermal shutdown circuitry that places the driver outputs into a high-impedance state. The receiver input has a fail-safe feature that guarantees a logic-high output if the input is open circuit.

The MAX487 and MAX1487 feature quarter-unit-load receiver input impedance, allowing up to 128 MAX487/ MAX1487 transceivers on the bus. Full-duplex communications are obtained using the MAX488–MAX491, while the MAX481, MAX483, MAX485, MAX487, and MAX1487 are designed for half-duplex applications.

Applications

Low-Power RS-485 Transceivers
Low-Power RS-422 Transceivers
Level Translators
Transceivers for EMI-Sensitive Applications
Industrial-Control Local Area Networks

Next Generation Device Features

- **For Fault-Tolerant Applications**
  MAX3430: ±80V Fault-Protected, Fail-Safe, 1/4 Unit Load, +3.3V, RS-485 Transceiver
  MAX3440E–MAX3444E: ±15kV ESD-Protected, ±60V Fault-Protected, 10Mbps, Fail-Safe, RS-485/J1708 Transceivers
- **For Space-Constrained Applications**
  MAX3460–MAX3464: +5V, Fail-Safe, 20Mbps, Profibus RS-485/RS-422 Transceivers
  MAX3362: +3.3V, High-Speed, RS-485/RS-422 Transceiver in a SOT23 Package
  MAX3280E–MAX3284E: ±15kV ESD-Protected, 52Mbps, +3V to +5.5V, SOT23, RS-485/RS-422, True Fail-Safe Receivers
  MAX3293/MAX3294/MAX3295: 20Mbps, +3.3V, SOT23, RS-485/RS-422 Transmitters
- **For Multiple Transceiver Applications**
  MAX3030E–MAX3033E: ±15kV ESD-Protected, +3.3V, Quad RS-422 Transmitters
- **For Fail-Safe Applications**
  MAX3080–MAX3089: Fail-Safe, High-Speed (10Mbps), Slew-Rate-Limited RS-485/RS-422 Transceivers
- **For Low-Voltage Applications**
  MAX3483E/MAX3485E/MAX3486E/MAX3488E/ MAX3490E/MAX3491E: +3.3V Powered, ±15kV ESD-Protected, 12Mbps, Slew-Rate-Limited, True RS-485/RS-422 Transceivers

Ordering Information appears at end of data sheet.

Selection Table

PART NUMBER	HALF/FULL DUPLEX	DATA RATE (Mbps)	SLEW-RATE LIMITED	LOW-POWER SHUTDOWN	RECEIVER/ DRIVER ENABLE	QUIESCENT CURRENT (µA)	NUMBER OF RECEIVERS ON BUS	PIN COUNT
MAX481	Half	2.5	No	Yes	Yes	300	32	8
MAX483	Half	0.25	Yes	Yes	Yes	120	32	8
MAX485	Half	2.5	No	No	Yes	300	32	8
MAX487	Half	0.25	Yes	Yes	Yes	120	128	8
MAX488	Full	0.25	Yes	No	No	120	32	8
MAX489	Full	0.25	Yes	No	Yes	120	32	14
MAX490	Full	2.5	No	No	No	300	32	8
MAX491	Full	2.5	No	No	Yes	300	32	14
MAX1487	Half	2.5	No	No	Yes	230	128	8

For pricing, delivery, and ordering information, please contact Maxim Direct at 1-888-629-4642, or visit Maxim Integrated's website at www.maximintegrated.com.

19-0122; Rev 10; 9/14

The full datasheet for the MAX487 RS-485 Transceiver can be found at: http://datasheets.maximintegrated.com/en/ds/MAX1487-MAX491.pdf accessed on 13 June 2015.

ATmega328 Datasheet

Atmel

ATmega48A/PA/88A/PA/168A/PA/328/P

ATMEL 8-BIT MICROCONTROLLER WITH 4/8/16/32KBYTES
IN-SYSTEM PROGRAMMABLE FLASH

DATASHEET

Features

- High Performance, Low Power Atmel®AVR® 8-Bit Microcontroller Family
- Advanced RISC Architecture
  - 131 Powerful Instructions – Most Single Clock Cycle Execution
  - 32 x 8 General Purpose Working Registers
  - Fully Static Operation
  - Up to 20 MIPS Throughput at 20MHz
  - On-chip 2-cycle Multiplier
- High Endurance Non-volatile Memory Segments
  - 4/8/16/32KBytes of In-System Self-Programmable Flash program memory
  - 256/512/512/1KBytes EEPROM
  - 512/1K/1K/2KBytes Internal SRAM
  - Write/Erase Cycles: 10,000 Flash/100,000 EEPROM
  - Data retention: 20 years at 85°C/100 years at 25°C[(1)]
  - Optional Boot Code Section with Independent Lock Bits
    - In-System Programming by On-chip Boot Program
    - True Read-While-Write Operation
  - Programming Lock for Software Security
- Atmel® QTouch® library support
  - Capacitive touch buttons, sliders and wheels
  - QTouch and QMatrix® acquisition
  - Up to 64 sense channels
- Peripheral Features
  - Two 8-bit Timer/Counters with Separate Prescaler and Compare Mode
  - One 16-bit Timer/Counter with Separate Prescaler, Compare Mode, and Capture Mode
  - Real Time Counter with Separate Oscillator
  - Six PWM Channels
  - 8-channel 10-bit ADC in TQFP and QFN/MLF package
    - Temperature Measurement
  - 6-channel 10-bit ADC in PDIP Package
    - Temperature Measurement
  - Programmable Serial USART
  - Master/Slave SPI Serial Interface
  - Byte-oriented 2-wire Serial Interface (Philips I^2C compatible)
  - Programmable Watchdog Timer with Separate On-chip Oscillator
  - On-chip Analog Comparator
  - Interrupt and Wake-up on Pin Change

The full datasheet for the ATmega328 microcontroller can be found at: http://www.atmel.com/images/Atmel-8271-8-bit-AVR-Microcontroller-ATmega48A-48PA-88A-88PA-168A-168PA-328-328P_datasheet_Complete.pdf accessed on 30 May 2015.

ASB1000 Datasheet

Model ASB

LOW COST SHEARBEAM LOAD CELL

A superb low cost weighing solution, yet surprisingly accurate with good long life features.

The ASB is a shearbeam load cell with M8 threads on the 125kg model and M12 threads on the balance of the range.

This is one of the most cost effective shearbeam cells available.

Robustly constructed in design with carefully selected high strength aircraft aluminium, it is an ideal selection for most weighing applications.

Used extensively in the agricultural industry it has proved to be a rugged long life load cell.

Marine grade anodised the ASB has an excellent protection rating of IP67 and is backed by a three-year warranty.

Many of the metric accessories throughout our accessory range can be used with this model.

APPLICATIONS

- Lower cost weighing applications
- Agricultural and harsh environments
- All general industrial weighing
- Both tension and compression

FEATURES

- Marine grade anodised
- Robust construction
- Most competively priced
- Wide capacity range 125kg ~ 1t
- Simple installation
- Suitable for most installation

Specifications

Note: All specifications are a maximum, as a % (±) of full load, unless otherwise stated.

Nominal Capacity	125kg ~ 1t	Safe Load	125% of Rated Capacity
Signal Output at Capacity	2mV/V ± 0.1%	Ultimate Load	300% of Rated Capacity
Linearity Error	< 0.025% FSO	Input Resistance	410Ω Nominal
Non-Repeatability	< 0.010% FSO	Output Resistance	352Ω Nominal
Combined Error	< 0.030% FSO	Insulation Resistance (bridge to ground)	> 5000 MΩ at 100V DC
Hysteresis	< 0.010% FSO	Excitation Voltage (Recommended)	5 ~ 12V AC/DC
Creep/Zero Return (30 mins)	< 0.035% / 0.025% FSO	Excitation Voltage (Maximum)	15V AC/DC
Zero Balance	< 3.000% Capacity	Storage Temperature Range	-50 ~ 70°C
Temperature Effect on Span/10°C	< 0.015% FSO	Cable Type	4mm, Screened, PVC Sheath 4 Core x 0.09mm² (28 AWG)
Temperature Effect on Zero/10°C	< 0.020% Capacity		
Compensated Temperature Range	-10 ~ 40°C	Cable Length	3 Metres
Operating Temperature Range	-30 ~ 70°C	Material	Aluminium
Service Load	100% of Rated Capacity	Finish	Marine Anodised

IP 67

Manufactured in New Zealand

PT Limited©

The full datasheet for the ASB1000 load cell can be found at: http://s3-ap-southeast-2.amazonaws.com/ptglobal-cdn/assets/54/WEB_ASB_804.pdf?AWSAccessKeyId=AKIAJEAX2FF3ZMX66G3Q&Expires=1433124212&Signature=HxAu84TZ7sm%2BB2r5Qg%2BaTX5byLY%3D accessed on 15 May 2015.

Appendix 2: Experimental Results

2.1. Load Cell Calibration Experiment

1.998mV	
Weight (kg)	ADC Reading
0	11
1	2100
2	4250
5	10650
10	21050
20	42400
30	63700
40	84600
50	105800
Scale Factor	**0.000472443**

1.999mV	
Weight (kg)	ADC Reading
0	11
1	2100
2	4200
5	10600
10	21200
20	42500
30	63800
40	85250
50	106500
Scale Factor	**0.000469303**

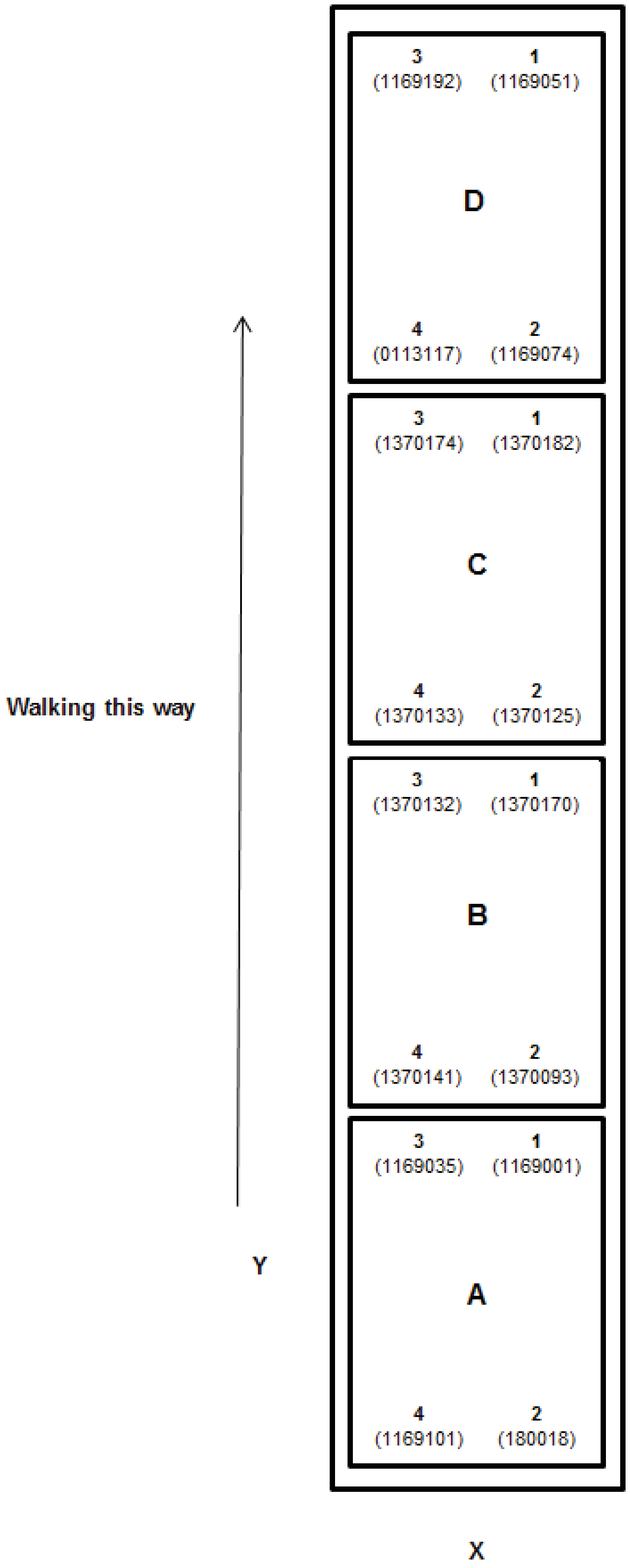
2.000mV	
Weight (kg)	ADC Reading
0	11
1	2100
2	4200
5	10600
10	21200
20	42750
30	64200
40	85700
50	106850
Scale Factor	**0.000467150**

2.001mV	
Weight (kg)	ADC Reading
0	11
1	2100
2	4200
5	10600
10	21200
20	42700
30	64200
40	85400
50	107000
Scale Factor	**0.000467308**

2.002mV	
Weight (kg)	**ADC Reading**
0	11.2705
1	2100
2	4200
5	10600
10	21400
20	43000
30	64500
40	85000
50	106500
Scale Factor	**0.000469060**

2.2. Load Cell Serial Numbers and Positions

Section	Loadcell	Serial Number	mV/V	Scaling Factor
A	1	1169001	1.998	0.0004724
	2	180018	2.001	0.0004673
	3	1169035	2.000	0.0004661
	4	1169101	1.998	0.0004724
B	1	1370170	2.000	0.0004661
	2	1370093	1.999	0.0004693
	3	1370132	2.001	0.0004673
	4	1370141	1.998	0.0004724
C	1	1370182	2.000	0.0004661
	2	1370125	2.000	0.0004661
	3	1370174	1.999	0.0004693
	4	1370133	1.999	0.0004693
D	1	1169051	2.002	0.0004691
	2	1169074	2.001	0.0004673
	3	1169192	2.000	0.0004661
	4	0113117	1.998	0.0004724



3
(1169192)
1
(1169051)
D
4
(0113117)
2
(1169074)
3
(1370174)
1
(1370182)
C
4
(1370133)
2
(1370125)
Walking this way
3
(1370132)
1
(1370170)
B
4
(1370141)
2
(1370093)
3
(1169035)
1
(1169001)
Y
A
4
(1169101)
2
(180018)
X

2.3. Test Results from First Human Walkover Dynamic Weighing

Running Average	**Section AB**	**Section BC**	**Section CD**
Run 1	60.99	61.06	60.50
Run 2	60.58	61.43	60.21
Run 3	61.27	60.64	60.50
Run 4	60.92	60.96	60.14
Run 5	61.20	60.73	61.05
Run 6	60.69	61.51	60.80
Run 7	61.33	61.33	60.80
Run 8	61.39	61.23	60.97
Run 9	59.58	60.93	59.78
Run 10	60.31	61.23	60.39
Average	**60.83**	**61.10**	**60.51**
Min	59.58	**60.64**	59.78
Max	61.39	**61.51**	61.05
Range	1.81	**0.87**	1.27
StDev	0.56	0.29	0.40
Error	-1.99	-1.08	-1.91

Weighted Average	**Section AB**	**Section BC**	**Section CD**
Run 1	61.59	61.77	61.19
Run 2	61.21	62.04	60.91
Run 3	61.82	61.46	61.46
Run 4	61.63	61.85	60.80
Run 5	61.99	61.50	61.99
Run 6	61.21	62.14	61.65
Run 7	61.80	61.80	61.35
Run 8	61.78	61.71	61.22
Run 9	60.64	61.71	60.66
Run 10	61.03	61.91	61.23
Average	**61.47**	**61.79**	**61.25**
Min	60.64	**61.46**	60.66
Max	61.99	**62.14**	61.99
Range	1.35	**0.68**	1.33
StDev	0.43	0.21	0.40
Error	-0.83	-0.51	-1.05

Appendix 3: Farm Trial Results

3.1. Test Results from Weight/Position Trial

Position (mm)		Actual Position (mm)		Weight (kg)	Measured Weight (kg)	Difference in Weight (Kg)	Difference in X Position (mm)	Difference in Y Position (mm)
X	Y	X	Y					
0	0	1.972	0.275	20	20.053	0.053	1.972	0.275
50	0	51.585	1.091	20	20.025	0.025	1.585	1.091
100	0	103.636	0.650	20	20.024	0.024	3.636	0.650
150	0	153.848	1.952	20	20.053	0.053	3.848	1.952
200	0	201.532	1.756	20	20.052	0.052	1.532	1.756
212.5	0	211.928	1.027	20	20.045	0.045	-0.572	1.027
250	0	251.429	1.107	20	20.083	0.083	1.429	1.107
300	0	301.392	0.266	20	20.124	0.124	1.392	0.266
350	0	350.581	0.845	20	20.109	0.109	0.581	0.845
400	0	401.170	0.255	20	20.095	0.095	1.170	0.255
425	0	422.549	0.122	20	20.131	0.131	-2.451	0.122
0	50	1.647	53.154	20	20.101	0.101	1.647	3.154
50	50	53.328	52.933	20	20.059	0.059	3.328	2.933
100	50	103.120	53.265	20	20.026	0.026	3.120	3.265
150	50	153.191	51.910	20	20.069	0.069	3.191	1.910
200	50	203.960	52.342	20	20.078	0.078	3.960	2.342
250	50	252.293	53.067	20	20.077	0.077	2.293	3.067
300	50	300.651	53.098	20	20.031	0.031	0.651	3.098
350	50	350.993	52.030	20	20.029	0.029	0.993	2.030
400	50	398.994	53.436	20	20.118	0.118	-1.006	3.436
425	50	420.721	52.466	20	20.126	0.126	-4.279	2.466
0	100	3.332	102.792	20	20.112	0.112	3.332	2.792
100	100	102.306	103.512	20	20.105	0.105	2.306	3.512
200	100	200.498	103.259	20	20.134	0.134	0.498	3.259
300	100	297.897	100.571	20	20.073	0.073	-2.103	0.571
400	100	397.131	102.153	20	20.110	0.110	-2.869	2.153
425	100	422.017	103.445	20	20.093	0.093	-2.983	3.445
0	200	2.025	201.039	20	20.068	0.067	2.025	1.039
100	200	102.132	199.461	20	20.062	0.062	2.132	-0.540
200	200	201.658	203.174	20	20.082	0.082	1.658	3.174
300	200	299.556	202.553	20	20.084	0.084	-0.444	2.553

400	200	398.813	201.912	20	20.080	0.080	-1.187	1.912
425	200	421.803	201.772	20	20.063	0.063	-3.197	1.772
0	300	1.439	301.916	20	20.062	0.062	1.439	1.916
100	300	103.648	301.386	20	20.065	0.065	3.648	1.386
200	300	202.660	298.810	20	20.032	0.032	2.660	-1.190
212.5	300	212.887	301.265	20	20.058	0.058	0.387	1.265
300	300	302.460	298.500	20	20.090	0.090	2.460	-1.500
400	300	401.482	298.051	20	20.103	0.103	1.482	-1.950
425	300	424.841	299.358	20	20.068	0.068	-0.159	-0.642
0	400	5.377	400.723	20	20.126	0.126	5.377	0.723
100	400	104.308	400.390	20	20.102	0.102	4.308	0.390
200	400	202.051	399.015	20	20.097	0.097	2.051	-0.986
300	400	303.057	397.921	20	20.090	0.090	3.057	-2.079
400	400	401.651	398.019	20	20.149	0.149	1.651	-1.981
425	400	425.072	397.563	20	20.093	0.093	0.072	-2.437
0	500	4.392	502.123	20	20.146	0.146	4.392	2.123
100	500	104.034	500.571	20	20.136	0.136	4.034	0.571
200	500	199.232	500.446	20	20.106	0.105	-0.768	0.446
300	500	300.265	498.478	20	20.067	0.067	0.265	-1.522
400	500	398.350	497.744	20	20.109	0.109	-1.650	-2.256
425	500	423.086	498.367	20	20.089	0.089	-1.914	-1.633
0	600	1.731	599.670	20	20.180	0.180	1.731	-0.330
100	600	100.962	601.556	20	20.119	0.119	0.962	1.556
200	600	200.114	598.454	20	20.119	0.119	0.114	-1.546
212.5	600	212.353	600.309	20	20.093	0.093	-0.147	0.309
300	600	298.996	598.805	20	20.104	0.104	-1.005	-1.195
400	600	399.980	597.615	20	20.091	0.091	-0.020	-2.385
425	600	422.682	598.298	20	20.069	0.069	-2.318	-1.702

3.2. Test Results from Stride Length Trial

600 mm Overall Results

Threshold Method (40kg)	Average	Range	StDev	Error
Run 1	599.66	19.52	7.84	-0.34
Run 2	597.68	17.93	6.58	-2.32
Run 3	595.90	27.93	9.28	-4.10
Run 4	595.90	18.18	7.25	-4.10
Run 5	597.47	32.22	13.09	-2.53
OVERALL	**597.32**	**23.16**	**8.81**	**-2.68**

Peak Method (3 Points)	Average	Range	StDev	Error
Run 1	599.47	17.22	5.73	-0.53
Run 2	599.72	16.63	6.26	-0.28
Run 3	596.48	28.67	9.96	-3.52
Run 4	595.78	22.25	8.15	-4.22
Run 5	596.04	26.51	9.48	-3.96
OVERALL	**597.50**	**22.26**	**7.92**	**-2.50**

Radius Method (10mm)	Average	Range	StDev	Error
Run 1	599.63	17.89	7.28	-0.37
Run 2	597.79	17.87	6.56	-2.21
Run 3	596.18	26.11	8.91	-3.82
Run 4	595.87	15.29	6.48	-4.13
Run 5	597.71	28.51	11.66	-2.29
OVERALL	**597.44**	**21.14**	**8.18**	**-2.56**

650 mm Overall Results

Threshold Method (40kg)	Average	Range	StDev	Error
Run 1	645.87	17.60	7.03	-4.13
Run 2	647.04	20.48	7.61	-2.96
Run 3	644.90	48.84	18.72	-5.10
Run 4	646.42	20.53	7.21	-3.58
Run 5	645.95	10.83	3.99	-4.05
OVERALL	**646.04**	**23.66**	**8.91**	**-3.96**

Peak Method (3 Points)	Average	Range	StDev	Error
Run 1	645.99	14.89	4.98	-4.01
Run 2	647.81	16.21	6.07	-2.19
Run 3	643.93	23.08	8.21	-6.07
Run 4	647.23	16.74	6.70	-2.77
Run 5	645.85	10.36	4.90	-4.15
OVERALL	**646.16**	**16.25**	**6.17**	**-3.84**

Radius Method (10mm)	Average	Range	StDev	Error
Run 1	645.82	15.65	6.26	-4.18
Run 2	647.40	23.47	8.40	-2.60
Run 3	645.25	26.97	11.49	-4.75
Run 4	646.49	21.65	7.58	-3.51
Run 5	646.23	11.66	4.05	-3.77
OVERALL	**646.24**	**19.88**	**7.55**	**-3.76**

670 mm Overall Results

Threshold Method (40kg)	Average	Range	StDev	Error
Run 1	668.56	20.16	6.70	-1.44
Run 2	667.92	26.59	9.54	-2.08
Run 3	665.14	63.38	22.06	-4.86
Run 4	667.14	28.67	9.58	-2.86
Run 5	673.80	40.92	17.31	3.80
OVERALL	**668.51**	**35.94**	**13.04**	**-1.49**

Peak Method (3 Points)	Average	Range	StDev	Error
Run 1	668.41	11.54	4.25	-1.59
Run 2	668.42	21.42	8.24	-1.58
Run 3	664.79	66.90	23.31	-5.21
Run 4	669.04	26.30	9.95	-0.96
Run 5	675.07	43.24	18.01	5.07
OVERALL	**669.15**	**33.88**	**12.75**	**-0.85**

Radius Method (10mm)	Average	Range	StDev	Error
Run 1	668.77	19.22	6.41	-1.23
Run 2	668.49	31.61	11.39	-1.51
Run 3	664.99	63.70	22.14	-5.01
Run 4	667.08	28.63	9.72	-2.92
Run 5	673.76	41.33	17.15	3.76
OVERALL	**668.62**	**36.90**	**13.36**	**-1.38**

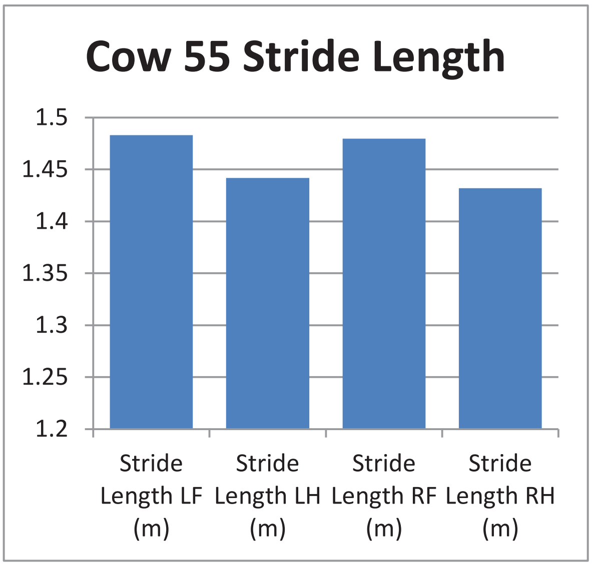
3.3. Trial 1 – Static and Dynamic Results

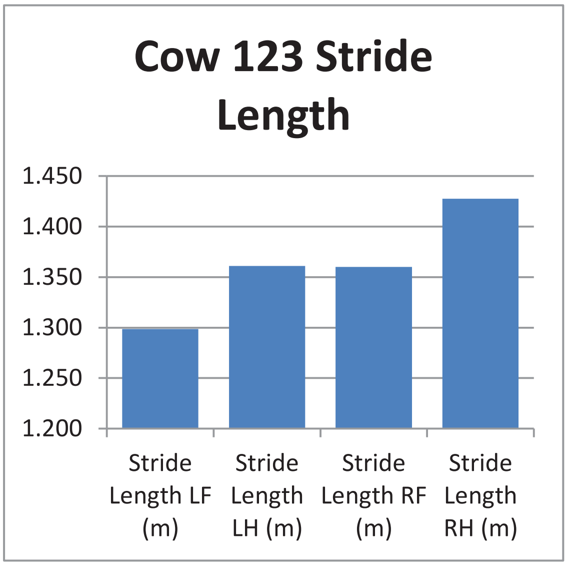
Cow EID	Static Weight (kg)	Average Dynamic Weight (kg)	Error (kg)
982 091001734424	550.00	534.70	-15.30
982 091001734362	552.10	536.20	-15.90
982 000124839853	562.00	549.60	-12.40
982 091001734048	500.70	491.30	-9.40
942 000015200296	455.10	440.50	-14.60
982 123464531778	387.60	376.20	-11.40
982 000091411599	550.20	535.60	-14.60
982 000091482234	594.60	580.70	-13.90
982 091001734420	522.10	512.80	-9.30
982 000091411587	616.00	596.20	-19.80

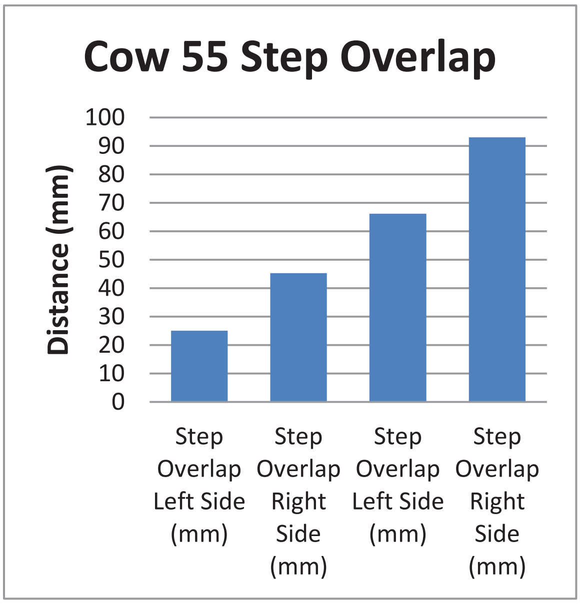
Averages of all 10 cow runs combined

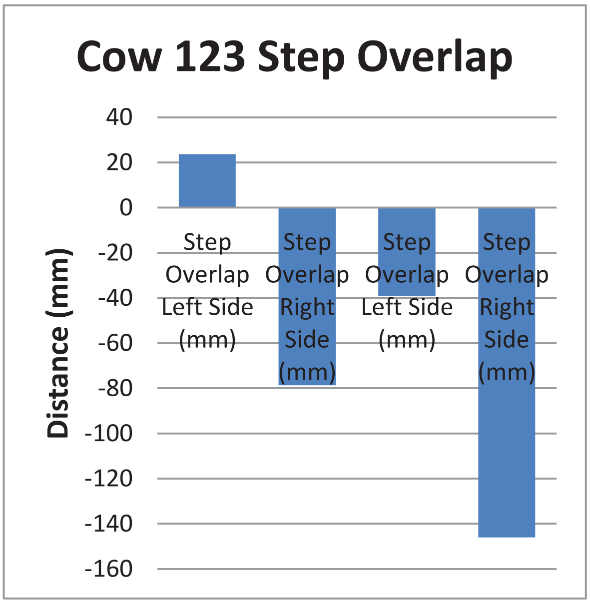
	Section AB	Section BC	Section CD	Combined
Min	533.40	553.77	551.13	551.49
Max	565.93	575.33	579.63	568.76
Range	32.53	21.57	28.50	17.27
StDev	13.78	10.57	12.36	7.52
Error	-20.14	-10.69	-10.15	-13.66

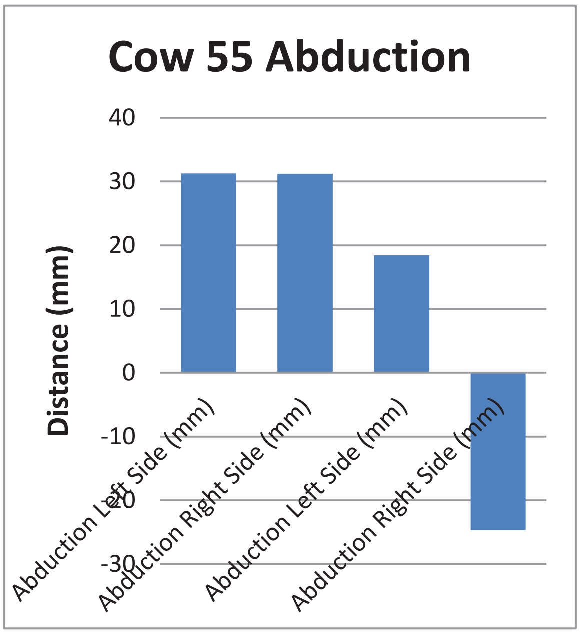
3.4. Trial 2 – Data Analysis

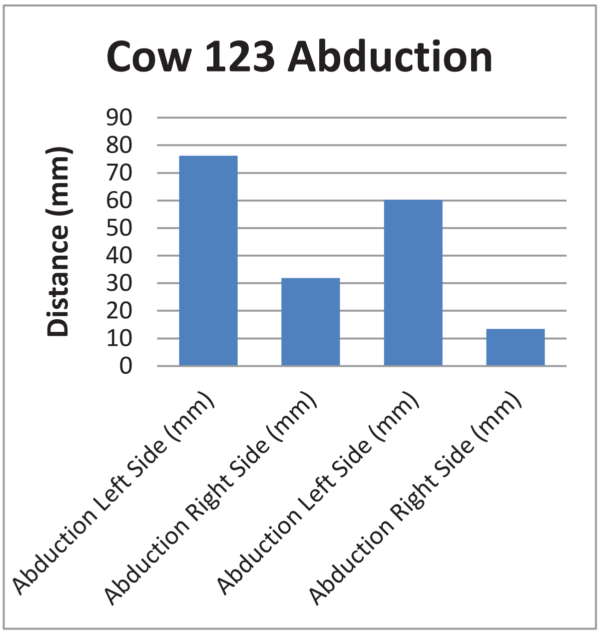


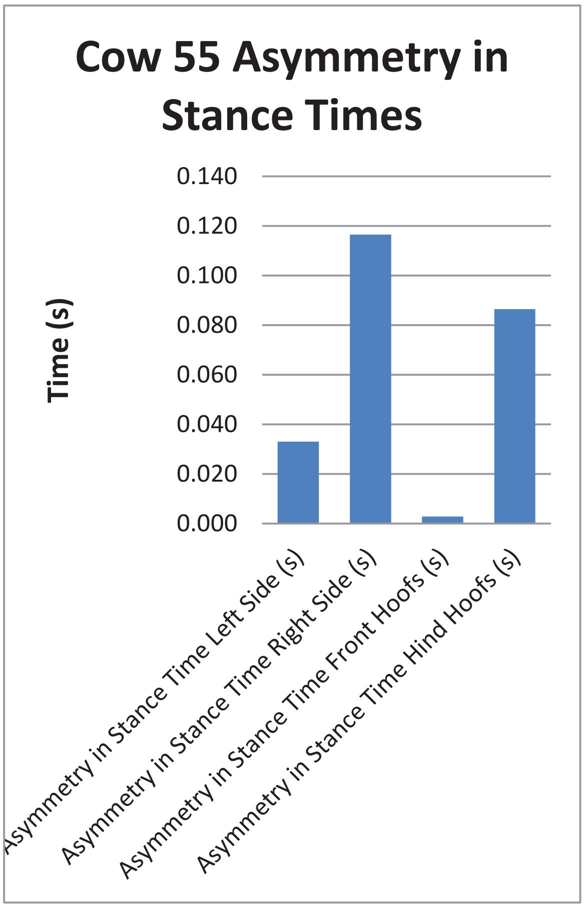


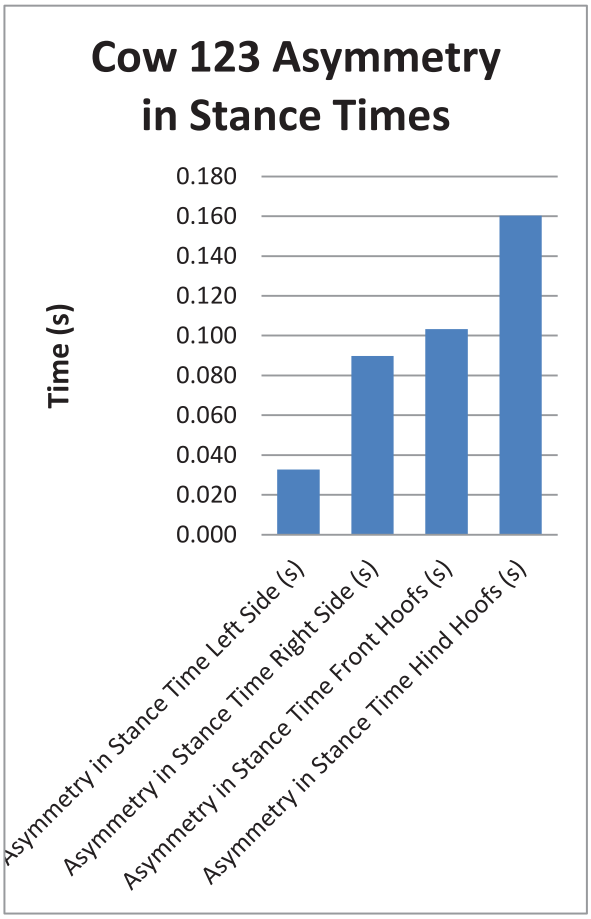





Cow 55 Abduction
Distance (mm)
40
30
20
10
0
-10
-20
-30
Abduction Left Side (mm)
Abduction Right Side (mm)
Abduction Left Side (mm)
Abduction Right Side (mm)


Cow 123 Abduction
Distance (mm)
90
80
70
60
50
40
30
20
10
0
Abduction Left Side (mm)
Abduction Right Side (mm)
Abduction Left Side (mm)
Abduction Right Side (mm)


Cow 55 Asymmetry in Stance Times
Time (s)
0.140
0.120
0.100
0.080
0.060
0.040
0.020
0.000
Asymmetry in Stance Time Left Side (s)
Asymmetry in Stance Time Right Side (s)
Asymmetry in Stance Time Front Hoofs (s)
Asymmetry in Stance Time Hind Hoofs (s)


Cow 123 Asymmetry in Stance Times
Time (s)
0.180
0.160
0.140
0.120
0.100
0.080
0.060
0.040
0.020
0.000
Asymmetry in Stance Time Left Side (s)
Asymmetry in Stance Time Right Side (s)
Asymmetry in Stance Time Front Hoofs (s)
Asymmetry in Stance Time Hind Hoofs (s)

3.5. Trial 3 – Two Sample T-test

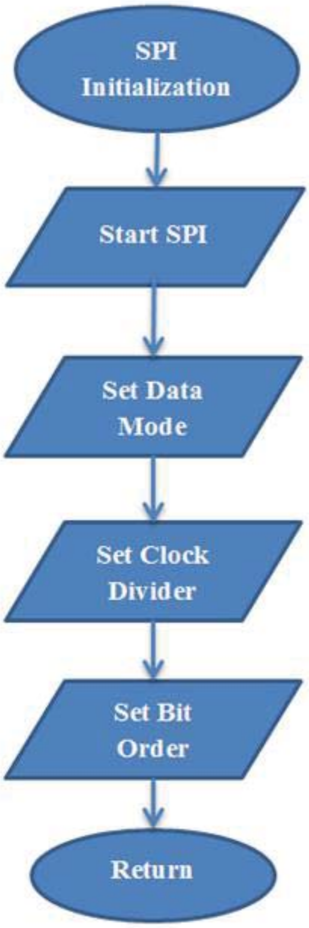
Lame LF

Variable	Healthy Cow (N = 10)		Lame Cow LF (N = 3)			
	Mean	*StDev*	*Mean*	*StDev*	*P-value*	*Significant*
NGRF LF	0.561	0.017	0.491	0.027	0.000	Yes
NGRF RF	0.557	0.015	0.548	0.030	0.215	NS
NGRF LH	0.442	0.017	0.484	0.033	0.000	Yes
NGRF RH	0.441	0.016	0.469	0.025	0.000	Yes
Asymmetry in Weight Front Limb (kg)	7.4	5.6	28.8	23.6	0.000	Yes
Asymmetry in Weight Rear Limb (kg)	7.8	6.0	20.9	12.9	0.000	Yes
Asymmetry in Diagonal Weights (kg)	10.9	7.2	36.5	18.4	0.000	Yes
Asymmetry in Side Weights (kg)	11.5	8.0	31.7	36.5	0.004	Yes
Average Front Step Length (m)	0.697	0.037	0.702	0.039	0.727	NS
Average Hind Step Length (m)	0.691	0.038	0.666	0.028	0.075	NS
Asymmetry in Front Step Length (m)	0.129	0.068	0.139	0.068	0.699	NS
Asymmetry in Hind Step Length (m)	0.140	0.065	0.260	0.101	0.000	Yes
Average Stride Left Side (m)	1.430	0.075	1.368	0.069	0.030	Yes
Average Stride Right Side (m)	1.403	0.085	1.460	0.078	0.077	NS
Asymmetry in Stride Length L Vs R (m)	0.068	0.050	0.110	0.053	0.031	Yes
Average Stride Length (m)	1.417	0.069	1.414	0.061	0.920	NS
Average Step Overlap Left Side (mm)	8	34	-52	61	0.000	Yes
Average Step Overlap Right Side (mm)	15	37	4	33	0.443	NS
Asymmetry in Step Overlap L Vs R (mm)	32	26	79	42	0.000	Yes
Average Step Overlap (mm)	12	29	-24	33	0.003	Yes
Average Abduction Left Side (mm)	2	24	55	39	0.000	Yes
Average Abduction Right Side (mm)	31	30	43	36	0.331	NS
Asymmetry in Abduction L Vs R (mm)	39	27	44	26	0.642	NS
Average Abduction (mm)	17	20	49	27	0.000	Yes
Average Stance Time Left Side (s)	0.994	0.133	1.161	0.089	0.001	Yes
Average Stance Time Right Side (s)	1.004	0.130	1.035	0.089	0.514	NS
Asymmetry in Stance Time Left Side (s)	0.054	0.043	0.190	0.141	0.000	Yes
Asymmetry in Stance Time Right Side (s)	0.073	0.058	0.087	0.024	0.481	NS
Asymmetry in Stance Time L Vs R (s)	0.034	0.033	0.129	0.084	0.000	Yes
Asymmetry in Stance Time Front (s)	0.046	0.035	0.180	0.147	0.000	Yes
Asymmetry in Stance Time Hind (s)	0.046	0.035	0.083	0.053	0.016	Yes
Number of runs	**50**		**9**			

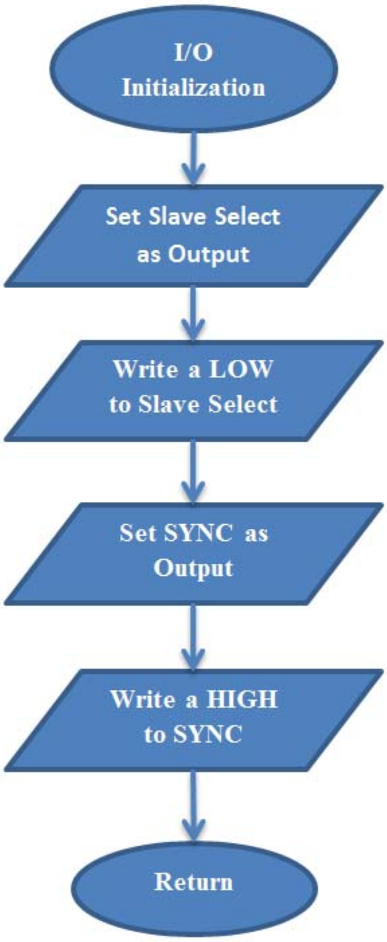
Lame RF

Variable	Healthy Cow (N = 10)		Lame Cow RF (N = 4)			
	Mean	*StDev*	*Mean*	*StDev*	*P-value*	*Significant*
NGRF LF	0.561	0.017	0.605	0.034	0.000	Yes
NGRF RF	0.557	0.015	0.508	0.024	0.000	Yes
NGRF LH	0.442	0.017	0.460	0.028	0.015	Yes
NGRF RH	0.441	0.016	0.437	0.025	0.601	NS
Asymmetry in Weight Front Limb (kg)	7.352	5.639	46.046	20.945	0.000	Yes
Asymmetry in Weight Rear Limb (kg)	7.842	6.048	10.665	10.695	0.264	NS
Asymmetry in Diagonal Weights (kg)	10.905	7.199	36.706	18.775	0.000	Yes
Asymmetry in Side Weights (kg)	11.491	8.031	56.231	26.622	0.000	Yes
Average Front Step Length (m)	0.697	0.037	0.687	0.018	0.403	NS
Average Hind Step Length (m)	0.691	0.038	0.673	0.021	0.124	NS
Asymmetry in Front Step Length (m)	0.129	0.068	0.190	0.093	0.019	Yes
Asymmetry in Hind Step Length (m)	0.140	0.065	0.202	0.047	0.004	Yes
Average Stride Left Side (m)	1.430	0.075	1.421	0.030	0.709	NS
Average Stride Right Side (m)	1.403	0.085	1.406	0.054	0.927	NS
Asymmetry in Stride Length L Vs R (m)	0.068	0.050	0.058	0.040	0.552	NS
Average Stride Length (m)	1.417	0.069	1.414	0.025	0.886	NS
Average Step Overlap Left Side (mm)	8.280	34.485	-28.653	51.349	0.007	Yes
Average Step Overlap Right Side (mm)	15.032	37.222	-27.046	52.488	0.004	Yes
Asymmetry in Step Overlap L Vs R (mm)	32.081	26.462	31.184	24.864	0.919	NS
Average Step Overlap (mm)	11.656	29.311	-27.850	47.716	0.001	Yes
Average Abduction Left Side (mm)	1.789	24.352	-0.309	24.738	0.799	NS
Average Abduction Right Side (mm)	31.326	29.789	64.952	50.416	0.008	Yes
Asymmetry in Abduction L Vs R (mm)	38.963	27.203	65.261	47.449	0.023	Yes
Average Abduction (mm)	16.557	19.724	32.322	31.843	0.049	Yes
Average Stance Time Left Side (s)	0.994	0.133	0.971	0.123	0.604	NS
Average Stance Time Right Side (s)	1.004	0.130	0.972	0.115	0.454	NS
Asymmetry in Stance Time Left Side (s)	0.054	0.043	0.045	0.041	0.495	NS
Asymmetry in Stance Time Right Side (s)	0.073	0.058	0.067	0.045	0.731	NS
Asymmetry in Stance Time L Vs R (s)	0.034	0.033	0.038	0.033	0.683	NS
Asymmetry in Stance Time Front (s)	0.046	0.035	0.058	0.063	0.402	NS
Asymmetry in Stance Time Hind (s)	0.046	0.035	0.049	0.032	0.821	NS
Walking Duration (s)	4.366	0.488	4.301	0.460	0.688	NS
Walking Velocity (m/s)	0.482	0.056	0.490	0.058	0.640	NS
Number of runs	**50**		**12**			

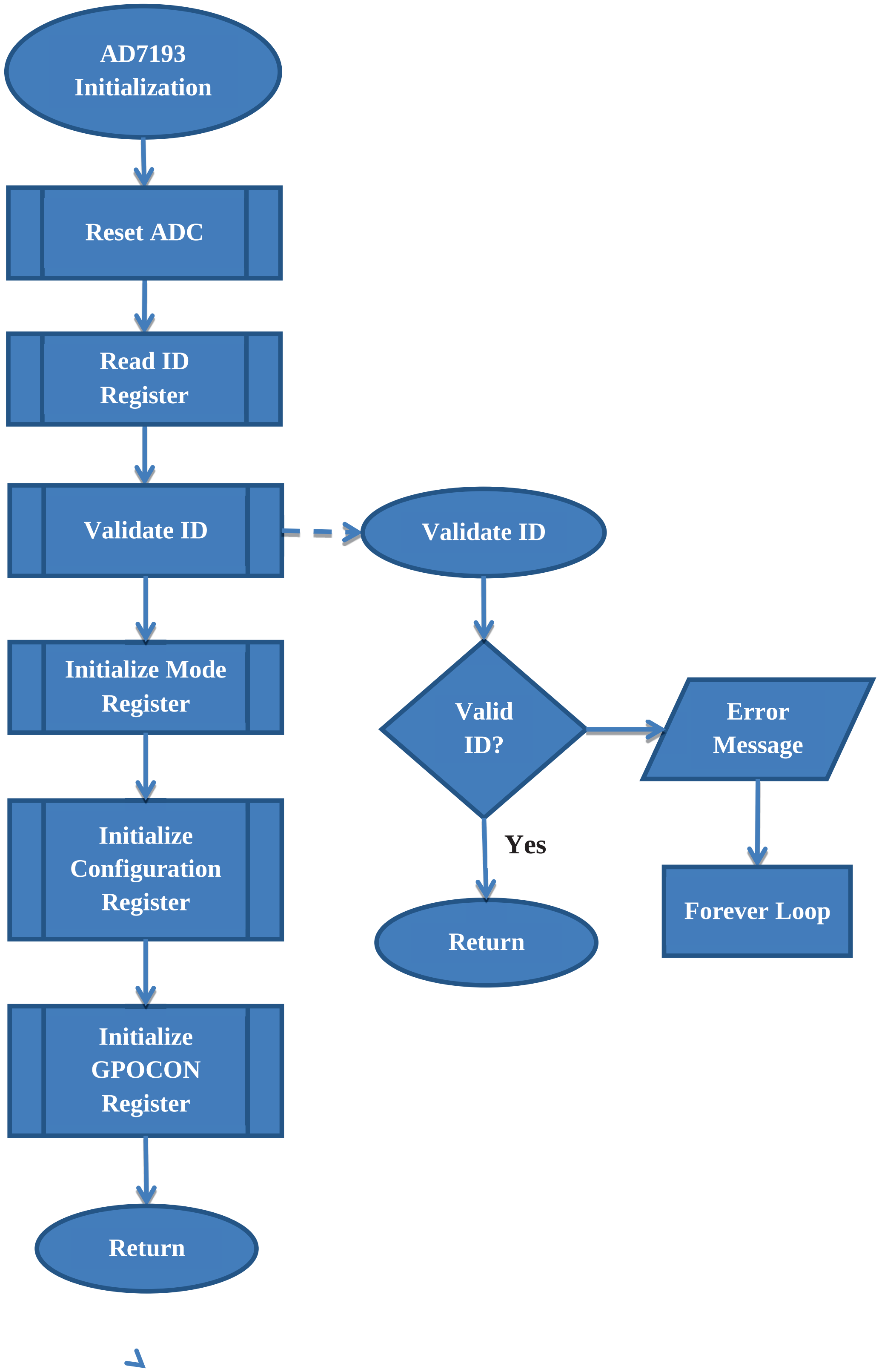
Appendix 4: AD7193 Programming Flow Diagrams



SPI initialization process



I/O initialization



AD7193 Initialization process

Read ADC and transmit to computer

Appendix 5: Load Cell Calibration

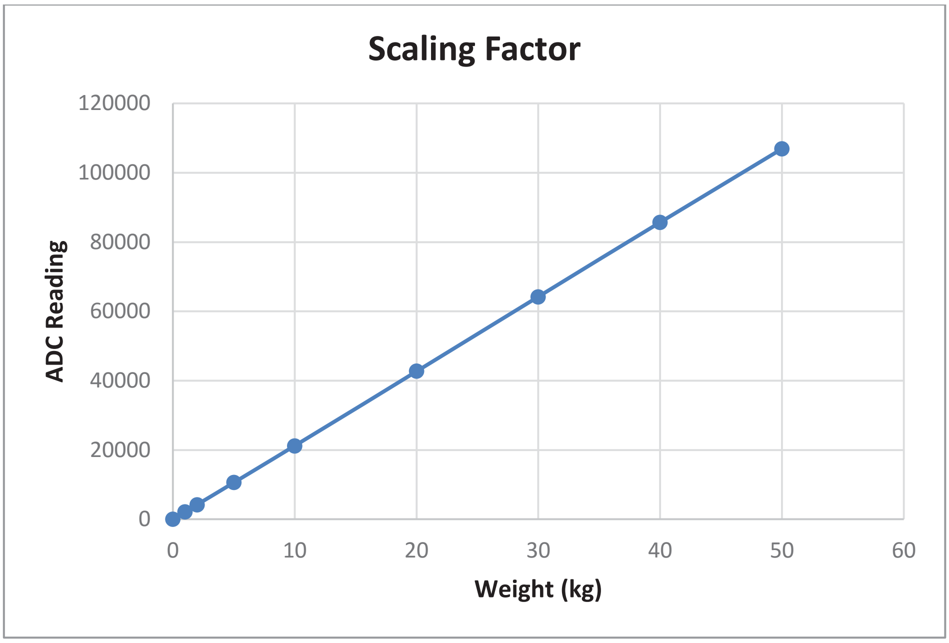
The five scaling factors were determined experimentally making use of a range of known weights varying from 1kg to 50kg. An aluminium plate to support the calibration weights (150mm x 150mm x 6mm) was made in the workshop which could bolt into the load cell.

50kg weight on load cell

MATLAB was used to capture and plot the ADC readings from each load cell when a calibration weight was placed on the load cell. The figure produced by MATLAB was then enlarged and analysed to find the average ADC reading for each calibration weight. The average was used as there is a small percentage of noise present due to the operation of the sigma-delta ADC. The average values obtained from the load cells with various full scale output characteristics at various calibration weights were entered into Excel and the slope of the line was calculated (Nel, 2015).

An example of the experimental results for load cells with a full scale output of 2.000mV/V is shown in Table 16. A linear slope is expected because of the strain gauge characteristics.

Table 16: Experimental calibration results for full scale output of 2.000mV/V



Full Scale Output of 2.000mV/V	
Calibration Weight (kg)	**ADC Reading**
0	11
1	2100
2	4200
5	10600
10	21200
20	42750
30	64200
40	85700
50	106850
Scaling Factor	0.00046715

S/N	: **1370133**
Model	: ASB
Capacity	: 1000 kg
mV/V	: 1.999
Type	: Aluminium Shear Beam

PT Limited
P.O. Box 102041 NSMC
Auckland, New Zealand
P.O. Box 7205 Baulkham Hills
BC, NSW 2153, Australia
sales@ptglobal.com

...better value by design!

CALIBRATION CERTIFICATE

Full Scale Output(mV/V)	: 1.999
Zero Load Output(%FS)	: 0.84
Non Repeatability(%FS)	:<0.010
Non Linearity (%FS)	:<0.025
Creep(%FS in 30min.)	:<0.035
Combined Error (%FS) (per VDI/VDE 2637)	:<0.030

Recommended Excitation(V)	: 5 to 12V
Operating Temperature(C)	: -30 to 70
Thermal Zero TC(%FS/C)	:<0.0020
Thermal Span TC(%FS/C)	:<0.0015
Input Resistance(ohms)	:411.9
Output Resistance(ohms)	:352
Insulation Res.(Mohm @50V)	: >5000
Year of manufacture	:Nil
IP Rating (IEC 529:1977)	: 67

WIRING CODE

RED	: + Excitation
BLACK	: - Excitation
GREEN	: + Signal
WHITE	: - Signal
BROWN	: +Sense
BLUE	:-Sense

CE

Caution: Altering the length of a 4 core cable will affect calibration.
Specifications are subject to change without notice.
www.ptglobal.com

QA Inspected.........
Passed.........

ASB-1000 Load cell calibration certificate

Appendix 6: Excel Spreadsheet Example

COW 8300 (629)				
Gait Variable	27/07/2015	28/07/2015	29/07/2015	30/07/2015
Visual Comment	Normal	Normal	Normal	Normal
Leading Leg	Right	Right	Left	Right
Location in Herd (fraction)	0.290	0.489	0.244	0.191
Weight LF (kg)	249.38	275.21	234.84	240.22
Weight RF (kg)	252.89	267.29	260.84	228.24
Weight LH (kg)	207.57	219.53	206.23	199.08
Weight RH (kg)	226.30	197.89	231.53	200.62
Section AB (kg)	467.19	492.81	475.49	445.31
Section BC (kg)	476.90	494.75	461.95	435.04
Section CD (kg)	468.95	467.12	457.95	438.85
Combined Sections (kg)	471.01	484.89	465.13	439.73
NGRF LF	0.529	0.568	0.505	0.546
NGRF RF	0.537	0.551	0.561	0.519
NGRF LH	0.441	0.453	0.443	0.453
NGRF RH	0.480	0.408	0.498	0.456
Asymmetry in Weight Front Limb (kg)	3.51	7.93	26.00	11.98
Asymmetry in Weight Rear Limb (kg)	18.74	21.64	25.30	1.53
Diagonal Weights RF & LH (kg)	460.46	486.82	467.07	427.32
Diagonal Weights LF & RH (kg)	475.69	473.10	466.37	440.84
Asymmetry in Diagonal Weights (kg)	15.23	13.72	0.69	13.51
Weight Left Side (kg)	456.95	494.75	441.07	439.30

Weight Right Side (kg)	479.20	465.18	492.37	428.86
Asymmetry in Side Weights (kg)	22.25	29.57	51.30	10.44
Front Step Length AB (m)	0.714	0.689	0.664	0.698
Front Step Length BC (m)	0.756	0.751	0.803	0.737
Front Step Length CD (m)	0.776	0.721	0.684	0.721
Average Front Step Length (m)	*0.748*	*0.721*	*0.717*	*0.719*
Hind Step Length AB (m)	0.684	0.662	0.604	0.628
Hind Step Length BC (m)	0.770	0.769	0.789	0.779
Hind Step Length CD (m)	0.779	0.762	0.736	0.698
Average Hind Step Length (m)	*0.744*	*0.731*	*0.710*	*0.702*
Asymmetry in Front Step Length (m)	0.042	0.062	0.139	0.039
Asymmetry in Hind Step Length (m)	0.087	0.106	0.185	0.150
Asymmetry in Average Step Length (m)	0.064	0.084	0.162	0.095
Stride Length LF (m)	1.531	1.472	1.468	1.458
Stride Length LH (m)	1.549	1.531	1.394	1.476
Stride Length RF (m)	1.469	1.440	1.487	1.435
Stride Length RH (m)	1.454	1.431	1.525	1.407
Average Stride Left Side (m)	1.540	1.501	1.431	1.467
Average Stride Right Side (m)	1.462	1.436	1.506	1.421
Asymmetry in Stride Length L Vs R (m)	0.079	0.066	0.075	0.046
Average Stride Length (m)	1.501	1.469	1.469	1.444
Front Step Width AB (m)	0.083	0.105	0.153	0.105
Front Step Width BC (m)	0.155	0.060	0.120	0.168
Front Step Width CD (m)	0.160	0.124	0.124	0.159

Average Front Step Width (m)	*0.133*	*0.096*	*0.132*	*0.144*
Hind Step Width AB (m)	0.175	0.198	0.266	0.157
Hind Step Width BC (m)	0.249	0.222	0.209	0.239
Hind Step Width CD (m)	0.253	0.237	0.185	0.259
Average Hind Step Width (m)	*0.226*	*0.219*	*0.220*	*0.218*
Asymmetry in Front Step Width (m)	0.072	0.063	0.033	0.063
Asymmetry in Hind Step Width (m)	0.074	0.024	0.057	0.083
Asymmetry in Average Step Width (m)	0.073	0.044	0.045	0.073
Step Overlap Left Side (mm)	31	22	-23	53
Step Overlap Right Side (mm)	1	-5	37	-16
Step Overlap Left Side (mm)	13	-36	51	35
Step Overlap Right Side (mm)	16	4	0	12
Average Step Overlap Left Side (mm)	22	-7	14	44
Average Step Overlap Right Side (mm)	8	0	18	-2
Asymmetry in Step Overlap L Vs R (mm)	13	7	4	46
Average Step Overlap (mm)	15	-4	16	21
Abduction Left Side (mm)	45	67	62	17
Abduction Right Side (mm)	47	26	50	34
Abduction Left Side (mm)	45	19	39	46
Abduction Right Side (mm)	49	95	23	54
Average Abduction Left Side (mm)	45	43	51	32
Average Abduction Right Side (mm)	48	60	37	44
Asymmetry in Abduction L Vs R (mm)	3	18	14	12
Average Abduction (mm)	46	52	44	38

Stance Time LF (s)	0.890	0.996	1.009	0.893
Stance Time RF (s)	0.926	0.924	0.975	0.921
Stance Time LH (s)	0.852	0.909	0.887	0.840
Stance Time RH (s)	0.933	0.985	0.884	0.932
Average Stance Time (s)	0.900	0.953	0.939	0.896
Average Stance Time Left Side (s)	0.871	0.952	0.948	0.866
Average Stance Time Right Side (s)	0.930	0.954	0.930	0.926
Asymmetry in Stance Time Left Side (s)	0.039	0.086	0.122	0.053
Asymmetry in Stance Time Right Side (s)	0.007	0.061	0.091	0.012
Asymmetry in Stance Time L Vs R (s)	0.059	0.002	0.019	0.060
Asymmetry in Stance Time Front Hoofs (s)	0.036	0.072	0.034	0.028
Asymmetry in Stance Time Hind Hoofs (s)	0.081	0.076	0.003	0.092
Walking Duration (s)	3.977	4.158	4.230	3.900
Walking Distance (m)	2.232	2.198	2.152	2.121
Walking Velocity (m/s)	0.561	0.529	0.509	0.544

Appendix 7: Altium Schematic

Final PCB Schematic