Automated Body Condition Scoring of Dairy Cattle

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Abstract

This research demonstrates the development and implementation of an automatic body condition scoring system for dairy cattle that can operate in a real-world environment. Body condition scoring is a subjective method used for measuring changes in energy reserves in many animals, including dairy cattle. These energy reserves can be measured by analysing specific regions on the cow to estimate the amount of fat the animal is carrying. This information allows for greater management of the herd by adjusting the feeding strategies to ensure that each cow is at an optimal condition score. Maintaining an optimal condition throughout the year has implications for milk yield, reproductive performance, animal welfare, and overall farm profits.

Current condition scoring methods are manual and are highly subjective, time consuming, expensive, and require a high level of training and competency. These limitations have created a demand for an accurate and objective scoring system. This research presents an automated system that utilises a single camera to be placed above the path of the cow at the entrance or exit to a milking platform or weigh scale. When the cow passes in view of the camera, the features are automatically extracted and converted to a conditions score. Tests have shown that the system successfully predicted the condition score within half a point of the true score for 83% of the 710 cows scored, and 96% within one point.

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Chapter 1

Introduction

Body condition scoring is a subjective method that reflects the changes in energy reserves; the energy reserves of dairy cattle have an impact on the milk yield, reproductive performance, herd health, animal welfare, and overall farm profits. An ideal condition score range based on the lactation cycle, has been identified based on research conducted over the past 20 years (DairyNZ, 2012). If the score for a given cow extends out of these recommended limits, it has the potential to cause issues relating to the overall milk yield, fertility and the general wellbeing of the cow (Schröder & Staufenbeil, 2006; Wildman et al., 1982).

The current method of condition scoring is a subjective technique as it is an individual's judgement of how they perceive the cow. Therefore, two observers independently scoring the same cow can achieve different results based on their experience, their interpretation of the features of the cow as well as the individual's state of mind at the time of scoring. Additionally, many farmers score the herd infrequently, or sometimes not all, due to the cost and time taken (Ferguson, Galligan, & Thomsen, 1994; Hady, Domecq, & Kaneene, 1994; Leroy et al., 2005; Pompe, DeGraaf, Semplonious, & Meuleman, 2005).

1.1 Research Objectives

Previous research has shown that image analysis has been used to obtain promising results in predicting the condition score for a given cow. Common limitations of these research projects are listed below:

- A small dataset was used to test the developed algorithm. This can give a false impression as the same results may not be achieved when given a larger sample size.
- Manual intervention is required to either verify the captured image before the analysis and/or select the points within the image to be analysed.
- Manual intervention is required to overcome issues associated with the variation in lighting conditions.

The primary objective of this research project is to develop a fully automated condition scoring system for dairy cattle. This can be broken down into smaller goals:

- The system must have a credible correlation to the manual body condition score.
- The system must be fully autonomous, that is it cannot have human interaction in order to function.
- The system cannot manipulate the flow of the cows

- The system cannot hinder the flow of the cow
- The system must be able to operate in a real-world environment, that is it should be able to operate in all lighting and weather conditions.

1.2 Significance of the Research

Findings of the research will add to the knowledge of computer vision techniques and farm management. This study will be significant in the sense that it will:

- Increase the wellbeing of the dairy cows by ensuring they are at an accurate condition score.
- Generate greater awareness among farmers on the importance of condition scoring.
- Assist in the education of those learning to condition score cows manually.

1.3 Thesis Structure

Chapter 2 highlights the need for an automated body condition scoring system and shows the impact it will have on animal welfare and economic benefits. Current methods and limitations of measuring energy reserves are discussed, followed by a summary of previous research into autonomous scoring systems.

Chapter 3 covers the hardware design. It explains the selection of components such as the embedded computer and imaging system. The development of the lighting system and power management circuitry is described, as well as the design of circuitry and housing.

Chapter 4 details the condition scoring algorithm. This section covers the settings used for image acquisition, the method of extracting the outline of the cow from the image, and then isolating and analysing the features. The full process of converting the image to a condition score is described, as well as the development process and other attempts methods.

Chapter 5 analyses the performance of the algorithm. This covers how credible the calculated score is when compared to several accredited veterinarians, the variation within the algorithm for subsequent milking sessions, and the robustness of the outline detection algorithm. Comparisons to the current manual method are also made.

Chapter 6 concludes this thesis and also proposes future research opportunities that could improve the detection accuracy,

Chapter 2

Body Condition Scoring

Condition scoring is a subjective method used for measuring changes in energy reserves in many animals, including dairy cattle. The management of body condition of dairy cows on dairy farms has implications for milk yield, reproductive performance, herd health, animal welfare, and overall farm profits. A condition score that is either too low or too high can indicate underlying nutritional deficiencies, health problems, or improper herd management (Wildman et al., 1982). Figure 2.1 two Friesian cows that have been scored on the New Zealand scoring system.

Figure 2.1 - Friesian Cows at two different condition scores (DairyNZ, 2012) (a) 3.0 (b) 6.0

Body condition scoring is achieved by a visual or tactile observation of the cow by a trained professional and is therefore a highly subjective method. There still remains a question as to how accurately condition scoring reflects actual changes in body fat given its subjective nature, despite the considerable amount of scientific literature on the subject (Leroy et al., 2005; Pompe et al., 2005)

2.1 Body Condition Scoring

The body condition score of a healthy cow will fluctuate throughout the year; key targets have been identified to optimise milk yield throughout the lactation period. These targets are based on research studies conducted over the past 20 years (DairyNZ, 2012). Figure 2.2 shows the fluctuation in the condition score, milk yield, and dry matter intake over a year.

The year can be divided into five phases; these are calving, early lactation, mid lactation, late lactation and dry. At calving it is recommended that the cow has a condition score between 5.0 and 5.5 depending on its age. During the early stages of lactation, the cow continues to increase the production of milk until a peak is reached. During this period there will be a loss in condition score as the energy required to produce the milk comes from the cows' body reserves. During mid-lactation the body condition gradually increases and a peak in the feed intake is reached. Late lactation is when the cows start to dry off and there is greater increase in condition. The dry phase is the final phase and there is no milk production.

The condition score should remain within certain limits throughout the year. Either over or under conditioning can cause issues relating to the overall milk yield, fertility and the general wellbeing of the cow (Schröder & Staufenbeil, 2006). Cows are generally expected to gain condition during the dry period before they calve again, however it is possible for a cow to have too much condition before calving. It has been found that if a cow in this situation was to lose too much condition it is more susceptible to certain diseases such as ketosis, mastitis, or retained placenta. Under-conditioning occurs when a cow has not received enough nutrition in their diet during middle to late lactation, if the cow is ill, or has an improper balance in the diet. Feeding the cow too much grass and not enough supplemented feed can cause an imbalance in proteins, to compensate the cow yields more milk causing a greater loss in condition. An under-conditioned cow at the time of calving produces less milk for the year and also a lower peak milk yield.

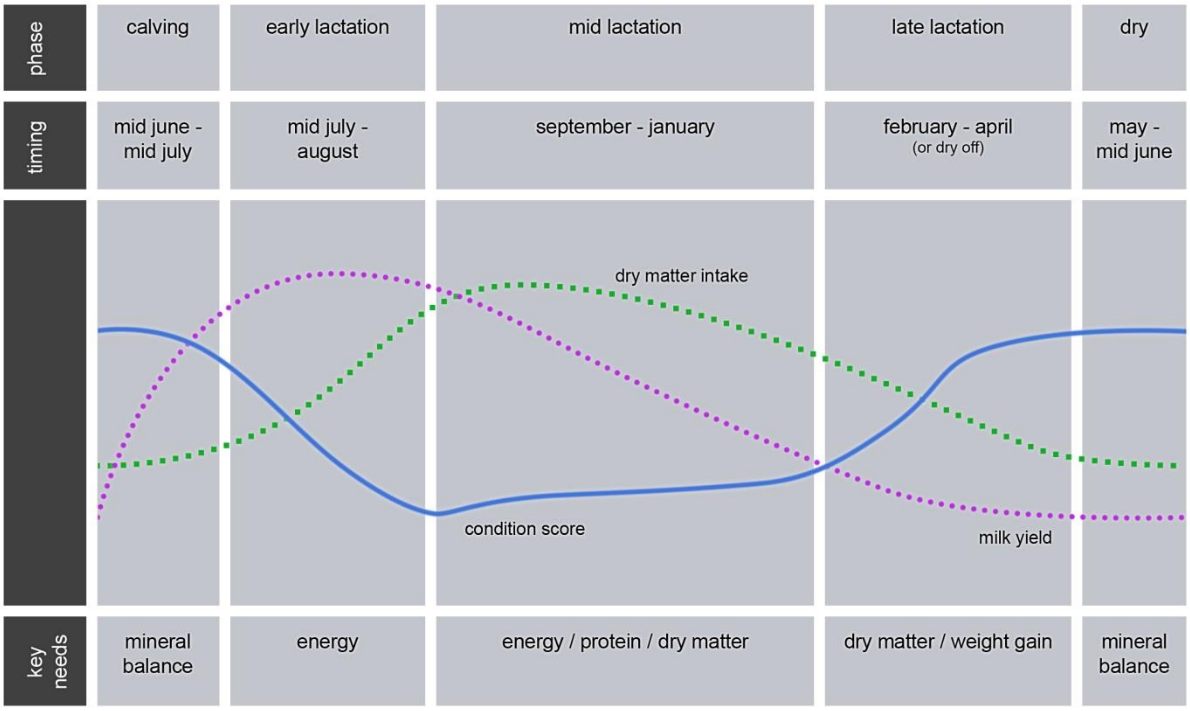


Figure 2.2 - Fluctuation of the body condition score, dry matter intake, and milk yield throughout the year (Seales Winslow, 2014; Stewart, 2005)

2.1.1 International Condition Scoring Systems

The first body condition scoring system was developed for sheep in the early 1960's (Jefferies, 1961). In the late 1970's the system was modified for beef cattle by (Lowman, Scott, &

Somervilee, 1976), it was then further modified to a 1 to 8 scale for dairy cattle by Earle (1976). Since this advancement, various other condition scoring systems have been developed around the world. All of these systems follow a similar numerical scale where the thin animals are assigned a low score while the obese animals are assigned a high score.

Table 2.1 shows a comparison between the primary body condition scoring systems that are currently being used around the world.

Table 2.1

Scale and inspection methods for international condition scoring systems for dairy cows

Country	Scale	Inspection	Source
New Zealand	1 to 10	Palpation and Visual	(K. A. Macdonald & Roche, 2004)
Australia	1 to 8	Visual	(Earle, 1976)
United Kingdom	0 to 5	Palpation	(Ferguson et al., 1994)
United States	1 to 5	Visual	(Ferguson et al., 1994)

The New Zealand and United Kingdom condition scoring systems involve palpating specific body parts, whereas the systems used in the United States and Australia are based entirely on visual assessment.

J.R. Roche, Dillon, Stockdale, Baumgard, and VanBaale (2004) conducted one of the first studies to examine the relationships between international scoring systems. The authors demonstrated that there was a relationship between the United States, Irish, New Zealand, and Australian condition scoring systems. This relationship is shown in Table 2.2.

Table 2.2

Relationship between international condition scoring systems (J. M. Bewley, Boyce, Roberts, Coffey, & Schutz, 2010; J.R. Roche et al., 2004)

New Zealand	**United States**	**Ireland**	**Australia**	**UK**
1.0	1.82	1.21	2.74	0.78
1.5	1.98	1.41	3.01	0.98
2.0	2.14	1.61	3.28	1.17
2.5	2.30	1.81	3.55	1.37
3.0	2.46	2.01	3.82	1.57
3.5	2.62	2.21	4.09	1.76
4.0	2.78	2.41	4.36	1.96
4.5	2.94	2.61	4.63	2.15
5.0	3.10	2.81	4.90	2.35
5.5	3.26	3.01	5.17	2.55
6.0	3.42	3.21	5.44	2.74
6.5	3.58	3.41	5.71	2.94
7.0	3.74	3.61	5.98	3.13
7.5	3.90	3.81	6.25	3.33
8.0	4.06	4.01	6.52	3.53
8.5	4.22	4.21	6.79	3.72
9.0	4.38	4.41	7.06	3.92
9.5	4.54	4.61	7.33	4.12
10.0	4.70	4.81	7.60	4.31

Note. Figures outside the range are extrapolated from the equations; United States = 1.5 + 0.32NZ, Ireland = 0.81 + 0.4NZ, Australia = 2.2 + 0.54NZ and UK = 1 + 0.39NZ

The climate in New Zealand is favourable for pasture growth for a greater period of time than other countries such as Australia and the United States. Therefore, these other countries must rely on using additional feed to maintain the energy requirements of the dairy cattle. This results in cows that are generally larger than those that are fed mainly pasture such as those in New Zealand. This results in a body condition scoring classification for New Zealand that is more sensitive to the changes at the lower end of the scale than the upper end. This is important to note as it shows that a simple numerical conversion from a pasture based system would likely exaggerate how thin the animals really are (Brougham, 1960; J.R. Roche et al., 2004).

2.1.2 Body Condition and Animal Welfare

Body condition score is often identified as an important indicator of the animals’ wellbeing. J. R. Roche (2005) stated that “allowing cows to lose excess condition post calving paints a poor picture of the dairy industry in the eyes of our customers”. Public perception is that thin cows with prominent hooks, pins and ribs are a welfare concern (Berry, Lee, et al., 2007). Extreme condition scores in either direction may be indicative of the state of animal welfare as well as poor management. Under-nutrition may occur when overall husbandry standards are low, when profits are low, or when there is a sudden change within the industry. Providing adequate nutrition is a fundamental requirement for the welfare of all livestock. The body condition score is only one indicator of under-nutrition and its use is limited by the subjective nature of the technique to measure it (Agenäs, Heath, Nixon, Wilkinson, & Phillips, 2006).

Improvements in animal health are one of the major benefits from managing cows for an optimal condition (Waltner, McNamara, & Hillers, 1993). Previous research has shown that obese cows experienced significantly more cases of disease than thin cows (Treacher, Reid, & Roberts, 1986). A major limitation with research designed to examine the effect of varying condition scores is the lack of animals in the extremes of the condition score ranges (Broster & Broster, 1998). Financial benefit is another reason for maintaining an ideal condition score throughout the year. Moran (2005) conducted a study which showed that having the cow at the recommended condition score at the start of the calving period resulted in a financial benefit. This benefit was based on the assumption that the condition score at calving had no effect on the reproductive performance for the first 63 days of the mating period.

Relationships have also been found between the condition of the cow at calving and various diseases. For example, metritis which is the inflammation of the wall of the uterus and is most prevalent during the early stages of lactation. Heuer, Schukken, and Dobbelaar (1999) observed that cows that had a condition score less than 3.0 had double the chance of contracting metritis. Markusfield, Galon, and Ezra (1997) reported that cows that lost more than 2.5 points of condition during the dry period were more likely to experience metritis.

Lameness is a major welfare problem for dairy cows and can lead to a reduction in condition as the cow spends less time feeding and more time lying down (Randall et al., 2015). Gearhart et al. (1990) proposed that higher conditioned cows may experience more lameness due to the increased mechanical stress placed on the joints due to the added weight. The authors noted that the cows that were over-conditioned at dry off were seven times more likely to experience foot problems in the subsequent lactation. It has also been found that cows with a low condition are more likely to be lame as it is linked to a reduced thickness in the cushion of the foot (Randall et al, 2015). The study also found a reduction in the number of cows that were lame as the condition score increased. Similarly, a German study found that under-conditioned cows at calving and early lactation were more likely to be lame (Hoedemaker, Prange, & Y, 2009). However, other studies have found no relationship between lameness and condition score (Heuer et al., 1999; Ruegg & Milton, 1995).

2.1.3 Body Condition and Milk Yield

It is difficult to find the true relationship between the condition score and milk yield as many of the studies include only a small number of animals at the extremes of the condition score scale (Suriyasathaporn et al., 1998). Frood and Croxton (1978) found the condition at calving was directly related to the cows ability to produce their potential milk yield. On a scale from zero to five, it was found that cows that were calved with a condition score less than 2.0 produced below their calculated potential milk yield, while those calved with a condition score above 2.5 produced above their potential milk yield. Grainger, Wilhelms, and McGowan (1982) noted that an increased condition score at calving resulted in a higher peak milk yield and a greater quantity of milk produced. This peak milk yield can be seen in the early lactation phase of Figure 2.2. This is in agreement with findings by Berry, Buckley, and Dillon (2007) who also concluded that the maximum milk production is associated with cows that are calved with a condition score of 6.0. Jacobs and Hargreaves (2002) stated that a cow that produced one extra litre per day at the peak may produce an additional 200 litres over the lactation period. K. A. Macdonald, Penno, Bryant, and Roche (2005) conducted a trial of 689 cows which show an increase in milk yield of up to seven percent in cows that maintained an optimal condition compared to those that lost condition. Similarly, Domecq, Skidmore, Lloyd, and Kaneene (1997) noted that a change in condition during the dry period affected the milk production in the subsequent lactation. The study showed that a one-point gain in condition between dry off and calving resulted in 545 litres more milk during the first 120 days of lactation. Each addition point after that resulted in a loss of 300 litres over the same time period. It was also indicated that cows that lost one point of condition during early lactation produced 242 litres more milk. Contreras, Ryan, and Overton (2004) reported that cows with a body condition score less than 5.5 at dry off tended to produce more milk than cows with a condition score greater than 6.0. Irish Holstein-Friesian cows had a greater milk yield if they were calved at a higher condition.

The average New Zealand dairy herd had 414 cows that produced 4,259 litres of milk between the start of the 2016 calving period through to the dry off in 2017. On average, each cow produced 381 kg of milk solids, comprised of 214 kg of milk fat, and 167 kg or protein (DairyNZ, 2017b). For the same time period, the price per kg of milk solids was $5.79 (DairyNZ, 2017a). Using these values and the results from the studies mentioned previously, the economic benefit of maintaining an ideal condition score can be calculated. Table 2.3 shows how the pay-out per cow can change based on how many litres of milk are produced. For example, Domecq et al. (1997) showed that a one point gain in condition between dry off and calving resulted in 545 litres more milk. This gives a total milk yield of 4,741 litres when added to the average; which equates to 420 kg of milk solids. This is an increase of 48 kg of milk solids and a pay-out increase of $277.92 per cow or $115,058 for the entire herd; assuming the average herd size of 414 cows (DairyNZ, 2017b).

Table 2.3

How the change in milk yield affects the pay-out per cow for the 2016/2017 New Zealand milking season

Milk (L)	**Milk Solids (kg)**	**Pay-out ($)**	**Change from Average**
4,196	371	2,148	0
4,741	430	2,489	+ 545L
4,439	393	2,275	+ 242L
3,896	345	1,997	- 300L
4,296	381	2,205	+ 100L

2.1.4 Body Condition and Nutrition

Condition scoring allows for the energy reserves of the cow to be estimated at any time during the lactation period. This estimate can be utilised as a management aid to determine if the nutritional requirements of the cow are being met. The nutritional requirements of the cow change throughout the lactation period and recognising the different needs for each phase through lactation is essential in ensuring the welfare of the cow and to optimise milk production. The nutrition requirements for protein, fibre, carbohydrate, calcium and phosphorous intake for early, mid, and late lactation are shown in Table 2.4. The consequences of a nutritional imbalance or deficit of these nutrients include a reduced milk fat percentage, reduced milk yield, and low body condition.

Table 2.4

Nutritional requirements based on the lactation phase (The National Academies, 2001).

	Lactation Phase		
Nutrient (Percentage Dry Matter)	**Early**	**Mid**	**Late**
Crude protein	17-19	15-16	13-15
Neutral detergent fibre	30-34	30-35	25
Acid detergent fibre	19-21	19-23	22-26
Non-fibre carbohydrate	30-42	30-44	30-45
Calcium	0.8-1.1	0.8-1.0	0.7-0.9
Phosphorous	0.5-0.9	0.4-0.8	0.4-0.7

Cows on pasture-based systems require a greater amount of energy than non-grazing cows due to the higher levels of activity (The National Academies, 2001). This additional energy requirement can be obtained by supplementing the diet with non-fibre carbohydrates (NFC). Pastures in spring tend to have a NFC content between 15 and 22 percent of dry matter due to the added water content. Feeding corn or a mixture of both starch and non-starch ingredients that have been finely ground will improve carbohydrate and protein utilisation which in turn, increases milk protein yield (Muller, 2003). Diets that contain high levels of grain may cause metabolic disturbances such as rumen acidosis which can decrease the milk fat content. To avoid this, the energy density can also be increased by supplementing fat. However, adding too much can impair rumen fermentation and fibre digestion (Kononoff, Grant, & Keown, 2006).

Protein intake is measured as crude protein which is a combination of both rumen degradable protein (RDP) and undegradable protein (UDP). The portion of feed that is digested in the rumen is known as rumen degradable protein. The ruminal microorganisms break down the RDP and form new amino acids and proteins known as microbial proteins. The portion of feed that passes through the rumen unchanged is known as undegradable protein or bypass protein. Some of the UDP is indigestible and passes through the digestive system without ever being broken down. The amino acids from both the RDP and UDP are synthesized into proteins that are required for growth, maintenance, milk production, and pregnancy (Knowlton & Nelson, 2003). When milk production is less than 12 litres per day, all protein in the diet can be RDP. The need for UDP increases as milk production increases and for milk production over 12 litres, at least some protein must be UDP (Jacobs & Hargreaves, 2002). During the early lactation phase the peak milk yield is reached which requires a high level of crude protein. The crude protein content that is required for high milk yields can exceed 16 percent of dry matter. Between 30 and 35 percent of this should be UDP to maximize protein utilisation. Common sources of bypass proteins include distiller’s grains, soybeans, fish meal, and processed soy protein (Kononoff et al., 2006). A high quality pasture will have a sufficient RDP but will require supplementation of UDP (Muller, 2003).

Carbohydrates are commonly divided into two categories, fibre and non-fibre carbohydrates (NFC). Fibrous carbohydrates are measured by the neutral detergent fibre (NDF) and the acid detergent fibre (ADF). The NDF content of the feed is indigestible and closely reflects its bulk and is often used to predict how much a cow will be able to eat of a diet without exceeding the capacity of the digestive tract. The ADF content is closely associated with the digestibility of the feed and is commonly used to predict the energy value of that feed. NFC are non-cell wall carbohydrates consisting of starch, sugar, pectin, and fermentation acids that serve as an energy source for the cow (Knowlton & Nelson, 2003). Diets that contain less than the recommended fibre levels can cause metabolic disturbances that result in acidosis or low fat levels (Kononoff et al., 2006). Adding buffers to the diet such as sodium bicarbonate can reduce the acidity in the rumen. Jacobs and Hargreaves (2002) recommends the use of buffers when the grain feed exceeds five kilograms per cow per day.

Vitamin and mineral supplements will only aid production if there is a deficiency in the diet. Vitamins can be divided into two categories: water-soluble and fat soluble. Water-soluble vitamins are not stored in the body tissue and therefore must be provided by the diet on a daily basis. Any excess vitamins will be excreted through the urine. Fat-soluble vitamins (A, D, E, and K) are stored in the cows' body and can cause poisoning. It is difficult to estimate the requirements of microminerals such as copper, cobalt, iron, or zinc as the requirement varies according to the absorption efficiency of the mineral, the lactation phase and age of the animal, the environment, and the interaction with other minerals. Mineral deficiencies are unlikely in grazing cows (Knowlton & Nelson, 2003; Kononoff et al., 2006), however this is dependant on the soil (Livestock Supplements, 2017); if the soil is either low or has an abundance in minerals, then supplementation may be required to ensure the nutritional requirements of the cow are met.

2.2 Management of Energy Reserves

Management of energy reserves in dairy cows is essential as changes in these reserves have a significant influence on milk yield, the overall welfare of the cow, and reproductive performance. An ideal management system is one which would quantify the amount of fat within the cow and measure how this changes over time. It is also important for this system to be able to monitor individual cows within the herd as well as the herd as a whole. The system should also be able to account for difference between breeds as it has been shown that cows deposit fat in different places based on their genetic makeup (Otto, Ferguson, Fox, & Sniffen, 1991; J.R. Roche, Macdonald, Burke, Lee, & Berry, 2007).

There are multiple methods for estimating the energy reserves of a cow including analysing the body composition post-slaughter and measuring metabolic and hormonal factors in the blood. More common methods include measuring the weight of the cow, taking ultrasound measurements, or estimating the body condition score. Each of these methods has its own limitations, for example, while analysing blood samples gives an accurate measurement of the energy reserves it is a difficult and expensive process to perform on a regular basis. Body weight is not an ideal measure of energy reserves as it is influenced by too many factors such as gastrointestinal content, milk production, pregnancy, and frame size. (Broster & Broster, 1998; Mulvany, 1981; Otto et al., 1991; Schröder & Staufenbeil, 2006).

2.2.1 Accurate Energy Reserve Measurements

The most accurate method for determining the amount of fat within an animal is post-slaughter with the contents of the digestive tracts removed (Otto et al., 1991); consequently this is not a viable method for continuous monitoring of energy reserves. There are a few highly accurate methods for measuring the energy reserves that can be done pre-slaughter. These are to measure the fat content of the ninth to eleventh rib as this has a high correlation with the fat content of the entire body (Otto et al., 1991), calculating the mean diameter of the fat cells, or using respiration calorimetry (Schröder & Staufenbeil, 2006). These methods are viable but can only be undertaken in a research setting where the focus is on accuracy and not on speed or cost.

Measuring metabolic and hormonal factors are an objective and accurate method for determining the body energy reserves for a cow. Such factors as NEFA, creatinine, albumin, BHBA, glucose, cholesterol, urea, insulin, IGF-1, and lactose can be measured (Schröder & Staufenbeil, 2006). These measurements have the advantage of providing an objective assessment; however they also require the collection of blood and analysis with expensive equipment. Therefore, these methods are considered to be too invasive, too expensive, and impossible to perform on a regular basis.

2.2.2 Energy Reserves and Body Weight

Estimating the body fat by measuring the live body weight is not accurate as changes in body weight are also associated with changes in internal protein, gastrointestinal content, organ weight, fetal growth, and frame size. (Broster & Broster, 1998; Mulvany, 1981; Otto et al., 1991; Schröder & Staufenbeil, 2006). As such, a change in body weight does not always indicate a change in the energy reserves. However, measuring live weight is one of the simpler methods as there are walk over weigh scales which are commercially available that can automatically measure the body weight of the cow. Research with these systems has indicated that the changes in body weight could be used for the early detection of some health problems (Maltz, 1997).

Body weight measurements allow for the general trend of the herd to monitored, however the individual weight is too variable to be used as a reliable measure of energy reserves. Maltz (1997) found that the body weight could vary up to three kg on a daily basis, and up to 11 kg over one week. This could be due to when the cow last ate as the rumen fill has a larger effect on body weight (Berry, Macdonald, Penno, & Roche, 2006). Bath et al (1966) noted that 11% of the live body weight could be associated to the rumen content.

2.2.3 Energy Reserves and Ultrasound

Fat depth is a good indicator of energy reserves as the proportion of subcutaneous fat is highly correlated to the total body fat (Butler-Hogg, Wood, & Bines, 1985). The use of ultrasound to measure the body fat has been demonstrated in multiple research studies.

Domecq, Skidmore, LLoyd, and Kaneene (1995) measured the subcutaneous fat of Holstein dairy cows at six different locations, the lumbar regions, hip joints, and tailheads for both the left and right sides. Each of the six locations had an R^2 value ranging from 0.36 to 0.65. Zulu et al. (2001) extended this research further and had R^2 values ranging from 0.62 to 0.67 with the highest correlation coefficient being for the lumbar measurement. As each area was strongly correlated, it was concluded that only one side or location was needed to determine the body fat levels.

K.A. Macdonald, Verkerk, and Penno (1999) compared ultrasound measurements taken at the 12th rib and between the hook and pin bones to the condition score. The R^2 values ranged from 0.26 to 0.37 in the late summer to 0.69 to 0.82 in the winter. The authors also indicated that the ultrasound measurements were of little value in measuring the fat deposits in cows at a lower condition scores.

Schröder and Staufenbeil (2006) demonstrated the effectiveness of measuring the subcutaneous fat on the back of the cow as a way of estimating the total body fat. This area of the cow has the largest deposit of adipose tissue and is therefore an optimal site to measure the subcutaneous fat. The authors proposed that measuring this area is preferred to calculating the body condition score because of its precision, speed, and ease of use.

These studies highlight the ideal locations to measure the subcutaneous fat. However, it is unlikely this method would ever be incorporated into an automated system as the equipment must come into direct contact with the animal.

2.3 Current Method of Condition Scoring

Although the various international body condition scoring systems vary slightly in their methods (Table 2.1), there is an anatomical correlation between the anatomical parts used to calculate the score. These include regions of the spine, long and short ribs, hip joint, pin bones, tailhead, depression between the hook and pin, and the thigh region (Earle, 1976; K. A. Macdonald & Roche, 2004; J.R. Roche et al., 2004; Wildman et al., 1982). These regions are shown in Figure 2.3.

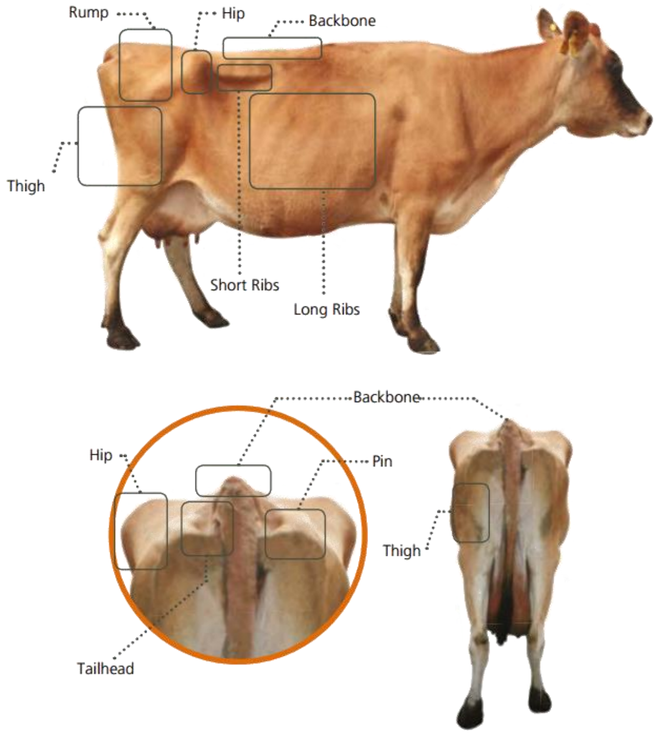


Figure 2.3 - Important body parts to consider when condition scoring cows (DairyNZ, 2012)

Figure 2.4 shows each of these regions in more detail; as the condition score decreases the bones will become more prominent as there is less fat around that region. Likewise as the condition score increases the bones will become less prominent and the region will appear more rounded. The images in Figure 2.3 are from a cow with a body condition score of 4.0.

a	b	c	d
e	f	g	h

Figure 2.4 - Recommended regions to analyse when condition scoring (DairyNZ, 2012)
(a) Backbone (b) Long Ribs (c) Short Rib (d) Hip
(e) Pin Bone (f) Tailhead (g) Rump (h) Thigh

2.3.1 Anatomical Correlation to Condition Score

Figure 2.5 shows how the features of the cow change over a range of condition scores from 3.0 to 6.0. From this it can be seen that at a lower condition score, the bones are more prominent and can be sharper to touch than at a higher condition score where they are more rounded in appearance or hidden altogether.

The importance of examining multiple regions on the cow to calculate the condition score was emphasized by Perkins, Smith, and Sniffen (1985) the authors believed that using one or two locations may be misleading. In contrast, Edmonson, Lean, Weaver, Farver, and Webster (1989) observed that the condition score was closely associated with the scores given in the pelvic and tailhead regions and therefore the condition score could be calculated by assessing only one of these regions.

Ferguson et al. (1994) used principal components analysis to determine which regions had the highest correlation to the condition score of the cow. The analysis showed that 83.6% of the variation within the body correlation matrix was explained by four principal component vectors; these were the hip joint, tailhead, pin bone and the depression between the hook and pins.

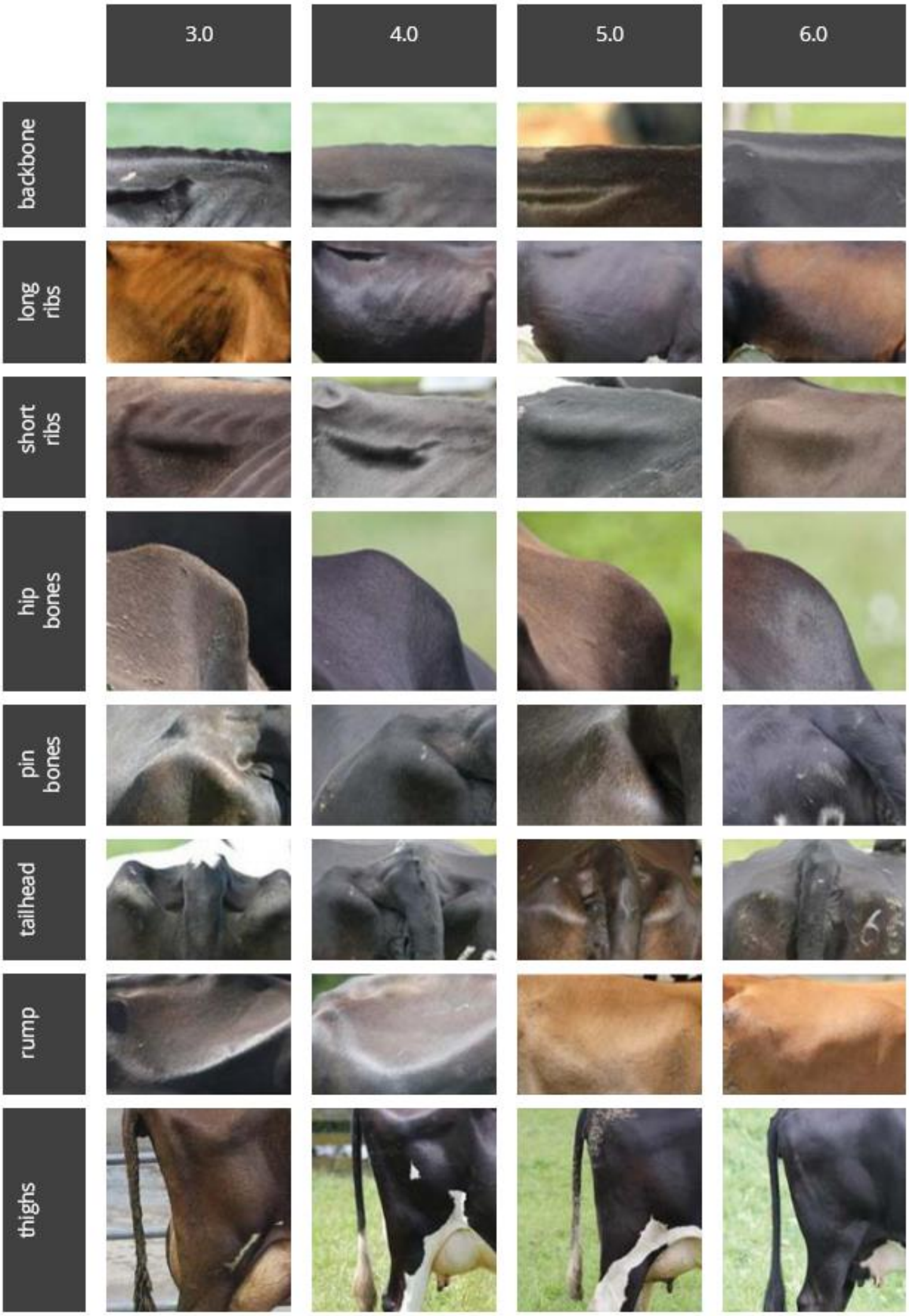


Figure 2.5 - How the features to analyse change with the condition score (DairyNZ, 2012)

2.4 Limitations of Current Scoring Systems

Relatively few dairy farms incorporate condition scoring as part of their dairy management strategy (Hady et al., 1994; Schwager-Suter, Stricker, Erdin, & Kunzi, 2000). Hady and Tinguely (1996) indicated that condition scoring was not adopted due to its subjectivity and concerns associated with the amount of data and time requirements. Ward (2003) suggested that condition scoring is not widely implemented “because it looks simple, does not produce a computerised report, and because it must be learned practically and revised frequently.”

2.4.1 Subjectivity

Condition scoring is a subjective technique as it is an individual’s judgement of how they perceive the cow. Therefore, two observers independently scoring the same cow can achieve different results based on their experience, their interpretation of the features of the cow as well as the individual’s state of mind at the time of scoring. Ferguson et al. (1994) demonstrated that 58% of the time, the body condition score calculated by four observers was agreed upon by other observers, and only varied by 0.25 points 33% of the time.

Kristensen et al. (2006) evaluated the reliability of body condition scoring by analysing the agreement in scores between practicing dairy veterinarians. A total of 2,230 scores were recorded by 51 practicing dairy veterinarians and 6 highly trained instructors. Each cow was assessed twice, with the second scoring approximately two and a half hours after the first. Within this time period, the instructors conducted a training session for the practicing veterinarians. To assess the agreement, a value was assigned where a zero represented no agreement, while a one represented perfect agreement. There was an agreement value of 0.86 for the repeated condition scores recorded for the same cows by the instructors. However, the agreement values for the veterinarians ranged from 0.22 to 0.75 for the first reading on the same cow, and 0.17 to 0.78 for the comparison of the two scores given two and a half hours apart. This shows how subjective the readings can be and the importance of training the assessors.

Assessors may incorrectly score the cows for various reasons, for example those with little experience tend to be more reluctant to score the cows near the end points of the body condition score scale (Kristensen et al., 2006). Additionally some expert assessors such as nutritionists or veterinarians may be hesitant to score cows in those ranges out of fear of offending their clientele (Ward, 2003). Overestimation of the condition score may occur in early lactation, young, or lean cows, and underestimation may occur in the dry, older, or fat cows (Schröder & Staufenbeil, 2006). Difficulties may also be encountered when scoring cows close to calving, or when scoring cows that are lying down or standing on a slope (Ward, 2003).

2.4.2 Differences between Breeds

In general, dual-purpose dairy breeds have more muscle than breeds selected primarily for milk production such as Holstein. Dual purpose dairy breeds deposit more of their fat within their abdomen than the beef breeds (Otto et al., 1991; J.R. Roche et al., 2007). Therefore, within dual-purpose breeds, the change in body condition may be indicative of changes in muscle mass instead of a change in fat content like with Holstein cows.

Schwager-Suter et al. (2000) concluded that the condition score of Holstein-Friesians were lower than that of Jerseys. Similarly, both Washburn, White, Green, and Benson (2002) and J.R. Roche et al. (2007) observed Holstein cows had lower body condition scores than Jerseys. However, Rastani, Andrew, Zinn, and Sniffen (2001) did not observe a difference in condition score between Holsteins and Jerseys. Heins et al. (2012) determined that pure Holstein cows has a lower condition score compared to Jersey crossed Holstein cows. Koenen et al. (2001) also confirms that as the percentage of Holstein genes increased, the condition score decreased.

2.4.3 Frequency of Scoring

The body condition score should be calculated at multiple points throughout the year. These are at dry-off, calving, and 30, 60, 90, 150, and 200 days in milk (Braun, Donovan, Tran, Mohammed, & Webb, 1987; Linn & Raeth-Knight, 2001). Many of those scores can be obtained at the same time as other events such as calving and reproductive exams. One of the most essential times to calculate the condition score is during mid to late lactation as it allows the farmer enough time to intervene and correct any problems (Braun et al., 1987; Ward, 2003). Hady et al. (1994) concluded that calculating the condition score every 30 days provides enough useful information to be a valuable management tool. This allows for enough time to monitor any changes that have been made and to allow for any further corrections.

The aim of the scoring frequently is to ensure the optimal condition score is met throughout the lactation period. Domecq, Skidmore, Lloyd, and Kaneene (1997) noted that a one-point gain in condition between dry off and calving resulted in an additional 545 litres of milk during the first 120 days of lactation. However, each additional point after that resulted in a loss of 300 litres over that same time frame. By scoring frequently, it can help to ensure that any changes made to alter the condition are effective and do not go beyond the target. Another benefit of frequently scoring the herd is to ensure the diseases such as metritis are less likely to occur as this is prevalent during the early stages of lactation. Markusfield, Galon, and Ezra (1997) noted that cows that lost more that 2.5 points of condition suring the dry period were more likely to experience metritis.

2.4.4 Conclusions

An automated system could overcome the limitations of the current method. An advantage of an automated body condition scoring system would be that a more objective, consistent measure of condition score would be provided than those recorded by human observers. For example, a human observer could score the same cow over consecutive days and record varying scores, while the cow actually experienced no change in body condition. An objective automated system would remove this source of error and detect changes in body condition rather than changes resulting from the ability of the human observer. An automated condition scoring system would also allow for more meaningful within-herd and across-herd comparisons of changes in condition scores.

An automated condition scoring system would also provide a more meaningful within-herd comparison of changes in condition scores when compared to a human scorer. This is due to the difficult nature of the task for a human scorer to provide consistent and unbiased scores over time.

Although condition scoring is a simple concept, it is a time consuming task (Ferguson et al., 1994; Hady et al., 1994; Leroy et al., 2005; Pompe et al., 2005). Upham (1990) recorded that it took 45 minutes for two people to calculate the condition score and enter the data for 220 cows, that is 24.5 seconds per cow. Perkins et al. (1985) estimated that an automated condition scoring system would take less than one minute per cow, in contrast. Drame, Hanzen, and Houtain (1999) indicated it could be accomplished in ten seconds per cow. Due to the advancements in technology since then, it is possible this could be done in seconds for each cow.

Automated condition scoring systems could be incorporated into animal health tracking system or within integrated monitoring system (Coffey, 2003). An automated system could also be used to predict at risk cows in advance of a problem, allowing for an adjustment to be made to prevent or minimise the consequences. In order for the system to be useful, the data would need to be incorporated with other management information systems and include decision support software to aid the producer towards appropriate action (Berry, Roche, & Coffey, 2008).

2.5 Automated Systems

The technology to collect the live body weight of dairy cows is commercially available and is used by a small percentage of dairy farms. As previously discussed, the changes in body weight do not accurately reflect the changes in energy reserves. Despite its limitations, many farmers measure the body weight as an indication to the body condition score. The relationship between body weight and the condition score has been investigated previously (Berry et al., 2006; Enevoldsen & Kristensen, 1997; Maltz, 1997; Otto et al., 1991) with varying outcomes. Otto et al. (1991) found that the body weight increased as the condition score increased in a linear fashion. While Maltz

(1997) found that the changes in body weight and condition score would sometimes contradict each other implying a lack of correlation. For example, in the early stages of lactation the body weight would increase while the condition score decreased. While (Berry et al., 2006) found that on average 1 point of condition would equate to 31kg. However, this varied from 17kg to 62kg depending on where the cow was within the lactation cycle.

The most comprehensive studies on using image processing techniques to estimate the live weight of animals has been performed on pigs. Brandl and Jorgensen (1996) calculated the live weights of pigs using image analysis. The authors suggested that calibration for individual herds would be required. Schofield, Marachant, White, Brandl, and Wilson (1999) used an automatic image analysis system to track the growth rates of pigs with a different algorithm used for each breed. Dirt and colour variation between the pigs presented challenges in the analysis of the data. However, the authors concluded that it would be more appropriate to capture large quantities of lower quality images and deleting those that failed a series of specified tests, than to increase the cost of the hardware. These tests involved detecting the pig based on the average grayscale value of the image, and calculating the approximate size of the pig based on the number of pixels. Wu et al. (2004) used a stereo image system to create three dimensional images of the pigs, it incorporated six high resolution cameras and three flash units. One major limitation to the system was that it required 90 minutes to construct a three dimensional model of the pig.

2.5.1 Related Work on Condition Scoring

Various studies have been undertaken on using image processing techniques to estimate the condition score of a cow. Pompe et al. (2005) used black and white photography and a line laser to collect a series of images from the rear of the cow. A three dimensional analysis of the images provided an outline of the left pin, left hook, and tailhead. There was no report of a statistical analysis comparing the analysis of the image to the condition score.

Leroy et al. (2005) used a digital camera positioned up to two meters from the rear of the cow to obtain a silhouette image from the tail to the legs. The contours of 19 predefined points which correspond to visual features were incorporated to determine the overall contour of each animal, from which a condition score was calculated. The authors concluded that it was possible to evaluate the body condition score automatically with an accuracy equivalent to a human.

Coffey (2003) used a remote controlled digital camera to capture the images as soon as the cows had been milked. A red laser light was used to create lines on the back of the cow. The camera was mounted to a rig allowing it to be adjusted for various cows, and positioned at 45° to the horizontal plane of the cows back. The laser lines were used in manual extractions of curvatures over the cow’s tailhead and buttocks. The curvature of these shapes was then modelled. The authors found that the correlation coefficient between tailhead curvature and condition score evaluated by experienced observers was 0.55, and the correlation coefficient of the curvature of the right buttock measured across the pin bone was 0.52. The images were often of poor quality, largely associated with problems with lighting. Another problem that was observed was that some cows that were receiving similar scores by human observers looked considerably different in images. This can indicate that either there were subtle difference that could not be detected in the images, or it shows how subjective the manual process is. Further, as with most body condition scoring research, there were few animals in the extreme ranges of the condition score scale, which had considerable impact on the results.

J.M. Bewley et al. (2008) expanded on the work of Coffey (2003). The authors analysed a single image captured of the dorsal view of the cow as it passed through the weigh scales by a standard digital camera. Twenty-three anatomical points were manually selected and used to define the shape of the cow. It was found that the hook angle, posterior hook angle, and tailhead depression were significant predictors of the condition score. 99.9% of the body condition scores were within 0.5 points of a human score, and 89.9% were within 0.25 points on a scale from 0 to 5. The observed scores were recorded on a weekly basis by two experienced employees on the farm. The authors noted multiple limitations of the study. Although the results showed a relationship between the calculated angles and the observed condition score, it was noted that this relationship could be with the body fat content and not the condition score. Also, the timeframe of the study was two months and is therefore too short to monitor significant changes that take place during the lactation period. It was also noted that the manual identification of points would not be feasible outside of research and that there was potential human error involved in identifying the points of interest. There were several limitations that were stated which related to the lighting and separation of the cow from the background of the image. Due to these limitations it was recommended that another imaging system be used to extract the information such as thermal imaging.

Halachmi, Polak, Roberts, and Klopcic (2008) tested the hypothesis that the body shape of a fatter cow is rounder than that of a thin cow and, therefore, may better fit a parabolic shape. Images were acquired by means of a thermal camera that allowed a very simple and straightforward shape extraction. The posterior part of the cow was considered and a parabolic fitting was performed. The absolute difference between the real body shape and the fitted parabola was used to estimate condition score for a cow. Halachmi, Klopcic, Polak, Roberts, and Bewley (2013) expanded on this and used a thermal camera to capture images that were automatically processed in MATLAB. One hundred and eighty-six cows were tested and there was a nonparametric Spearman’s rho correlation coefficient of 0.94 between the predicated and manual condition scores. It was noted that a larger study with more cows should be undertaken due to the lack of spread within the condition score range. On a five-point scale, the average score was 3 with a standard deviation of 0.4. That is that the majority of cows were between 2.5 and 3.5, so the model could be sufficiently tested by extreme cases.

Bercovich et al. (2012) were able to score 79.5% of the cows within 0.5 points of an estimated condition score given by a single qualified scorer. Six consecutive images of the cow were captured as the cow entered the milking shed. Each image was manually checked to determine if enough of the cow was within the frame in order for the algorithm to work. If the image passed the check it was automatically segmented and five key points around the tailhead region were identified. Based on these five points, the shape and angles of the region could be determined and correlated to a condition score. The authors noted that the use of a single human observer could limit the developed model, and also that the image capture method needed to be automated. The majority of captured images were not suitable to be analysed due to the orientation of the tail or the cow being out of frame.

Weber et al. (2014) measured the back fat thickness with a precision of 1mm allowing for recognition of slight changes in the subcutaneous fat using a time of flight camera. A Pearson correlation of 0.96 was found between the observed and calculated scores. The repeatability within each of the lactation stages was large and range from 0.80 to 0.89. There was no mention on the number of human scorers that were used to obtain the observed scores. It was noted that 96 Holstein-Friesian cows were used in the study and as such it was recommended that a larger dataset with other breeds would be worthwhile.

Tedín, J.A., and R.J. (2014) used images taken by a hand held camera of the rear of the cow to calculate the condition score. The authors used the rear of the cow as there is a high correlation between these features and the condition. They achieved promising results however several issues were noted with the use of the images obtained from the hand held device including position, illumination and changing backgrounds.

Hansen et al. (2015) utilised a three-dimensional camera mounted above the path of the cow. The authors noted difficulty with this setup and only had usable images of 115 of the 200 cows in the herd. Two reasons listed for preventing the analysis were that the cows tail was raised, and that the head of the following cow blocked the view of the cow of interest. The image processing algorithm worked by fitting a ball of a set radio and determining how well that fit to the detected surface. This was selected over the more common method of analysing features to remove any error introduced by identifying features incorrectly. It was noted that 14 of 15 cows were scored within 0.25 of the true condition score.

Spoliansky et al. (2016) also utilised a low-cost three-dimensional camera that was placed above the path of the cow. The authors were able to score all cows within one point, and 91% within half a point of the true score. However, one limitation of this study is that there were only 101 cows within the dataset, and 81 of those were used to train the machine learning algorithm. Therefore, only 20 cows were used within the test. The authors noted the system could function independent of the background can would require 10 cows with 120 seconds of video to train the system.

2.6 Conclusions from Previous Research

The demand for an accurate and frequent scoring of the body condition of dairy cows is increasing. Current condition scoring methods are highly subjective, time consuming, and expensive and as such there is a demand for an accurate and objective system. Ideally, this system would be an automated vision based system that could calculate the condition score at each milking session. Researchers have examined the possibility of condition scoring the animals using digital cameras. While the results have been positive, the methods used are not ready to be automated as they require the manual identification of reference points. This manual input is required as the silhouette of the cow changes between images due to the change in posture of the animal and the variations in lighting conditions. Additional research is needed to overcome these issues, which would potentially allow for a fully automated system to be developed.

An automated system could calculate the condition of a cow on a daily basis. This allows for the potential to predict at-risk cows in the early stages of various problems and allow for an adjustment to be made to prevent or minimise the consequences. As a daily calculation would produce vast amounts of data over time, the data would need to be used to generate the required information on condition score which could be incorporated with other management information systems and include decision support software to aid the users towards appropriate action.

Chapter 3

Hardware Design

In this chapter, the details of the hardware design of the system is presented. The first section identifies the requirements that the system must meet. A computer, camera, and lighting system are identified in the next three sections based on these system requirements. The fifth section covers the power regulation while the sixth covers the layout of the circuit board. The final section covers the enclosure and other external components.

3.1 System Requirements

There are several hardware design considerations that need to be met, these are:

1) The system must be able to calculate the condition score within two seconds to allow for possibility of drafting the cow if desired.
2) The system must be able to work in any lighting condition.
3) The system must be able to operate in a variety of environmental conditions such as sunshine, overcast, and rain.
4) The system must not hinder the flow of the cows.

Computer vision systems are primarily used in controlled static environments where factors such as illumination and the position of the subject can be controlled. The stated requirements indicate the system must operate in an uncontrolled environment and will require dynamic reactions to any changes.

The first requirement indicates the system must operate in real-time. In a general real-time computer vision system a response to an input is required within a predetermined time to ensure the system keeps up with an external event (Hennessy & Patterson, 2002). The external event in a computer vision system is the image acquisition and is equivalent to the frame rate. A higher frame rate results in a shorter time difference between consecutive images and therefore results in fewer differences between the two images. As the system is analysing cows walking beneath the camera, a frame rate of three frames per second is sufficient to ensure there is a difference between the images while still capturing enough data about the cow to determine the condition.

An external light source is necessary to meet the second requirement to guarantee a consistent illumination regardless of the ambient light. This external light source must be outside of the visible spectrum to ensure the cows are not startled in the early morning, as that would violate the fourth requirement.

The third requirement implies that all components must have a high ingress protection (IP) rating. The IP rating is used to define how effective an enclosure is from the intrusion of foreign bodies such as dirt or dust, as well as moisture. The enclosure that houses the electronic components should be dust tight; this requires a solid particle protection of six. It must also prevent water from entering from powerful water jets, which requires a liquid ingress protection of at least six. Therefore, the minimum IP rating of all external components is IP66.

The fourth requirement prevents the use of external structures such as tunnels to control the lighting, and gates to isolate the cows. It also highlights that the developed system must be an embedded image processing system where all components should be housed in a single enclosure to prevent multiple enclosures and wires spread around the environment

Embedded systems are computer systems that are designed to perform a single specific function. This function will generally have a specific time in which a response must be performed. In an embedded image processing application, this time period can include many algorithms such as those to reduce noise, segmentation of objects, feature identification, and decision making. Ensuring these algorithms can be performed within the allowed time, requires an adequate amount of processing power due to the large amount of data contained in the images.

3.2 Single Board Computer

A single board computer is the ideal platform for development of an embedded system. The computer contains all the required peripherals and allows any required modifications to be easily made to the system. A second option is to develop an application specific integrated circuit; this would be the most the most efficient solution in terms of power consumption and processing speed. However, these circuits are expensive and inefficient during development due to the difficulty of modifying the circuitry based on new conditions.

There are three main factors which have an influence on the computer selection; these are speed at which the processor can execute the algorithms, the amount of energy used for the execution, and the available communication protocols. The processor speed can be optimised to ensure as little energy is wasted as possible. This in turn improves the overall efficiency of the system; this is important as any heat produced will remain trapped in the sealed enclosure and as it is also wasted energy, it will reduce the battery life of the system.

At the time of purchasing the computer, the protocol that the electronic reader uses was unknown. Therefore it was required that the computer should have at least one SPI, I2C, UART, and USB port available; there should also be addition I/O ports to allow for expansion if required. There is a large range of single board computers available that meet the stated requirements. Table 3.1 shows an overview of four potential systems.

Table 3.1

Overview of four potential single board computers

Board	**Intel Galileo (Intel Corporation, 2014)**	**BeagleBone Black (BeagleBoard, 2014)**	**Odroid-U2 (Hardkernel, 2013)**	**Raspberry Pi (Raspberry Pi Foundation, 2014a)**
SoC	Intel Quark X1000	TI AM3358	Exynos 4412	Broadcom BCM2835
CPU	Intel X1000	ARM Cortex-A8	ARM Cortex-A9	ARM1176
Architecture	i586	ARM v7	ARM v7	ARM v6
Speed	400 MHz	1 GHz	1.7 GHz	700 MHz
RAM	256 MB	512 MB	2 GB	256 MB
Power Consumption	15W	10W	10W	2.5W
Voltage	5V	5V	5V	5V
Dimensions	107 x 71 mm	86 x 53 mm	48 x 52 mm	86 x 54 mm
PWM Output	6	8	6	1
UART	2	4	-	1
SPI	1	2	-	2
I2C	1	2	-	1
USB	1	1	2	1
Camera Input	-	-	-	1
Cost (NZD)	$150 (nicegear, 2014b)	$99 (nicegear, 2014a)	$89 (ameridroid, 2014)	$45 (nicegear, 2014c)
Advantage	CPU architecture	Small size	Small size Fast CPU Large RAM	Dedicated camera Small size Low power use
Disadvantage	Large size Slow CPU	High power use	Lack of GPIO	Slow CPU

Note. Prices were last updated on September 1, 2014.

The Raspberry Pi was selected as the development platform due to the low power consumption and the dedicated camera port. There are four models of the Raspberry Pi, Model A, Model B, Model A+, and the Model B+. Both the A+ and B+ models were in development at the time of the computer selection. The Model A has lower power consumption and fewer peripherals compared to the Model B. As these additional peripherals are not required the Model A was selected. An image of the Raspberry Pi is shown in Figure 3.1.

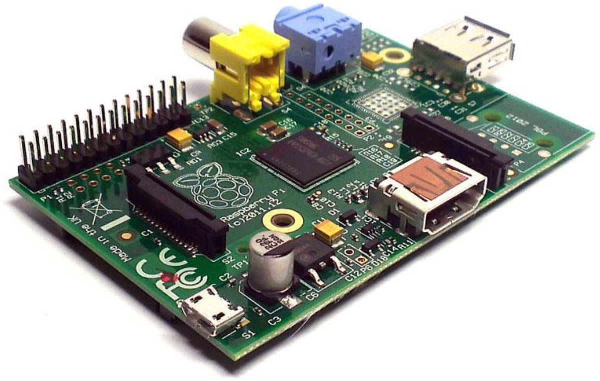


Figure 3.1 - Raspberry Pi Model A (Raspberry Pi Foundation, 2013)

The Raspberry Pi is a circuit board that is approximately the size of a credit card and offers the complete functionality of a computer. The Raspberry Pi contains a 32-bit ARM central processing unit (CPU) and a Video Core 4 graphic processing unit (GPU). Both of these are housed inside the Broadcom BCM2835 along with the memory.

3.3 Image Acquisition

The first step in any digital image processing system is to acquire an input image via the use of an image sensor. There are several requirements the sensor must meet; these are:

1) The resolution must be configurable
2) The sensor must have drivers available
3) The sensor must be able to record multiple images per second

The image resolution represents the quality of the image and is a measure of the number of pixels within an image. Having this field configurable ensures that an optimal balance can be found between the amount of data contained within the image, and the processing time.

The second requirement is essential in being able to communicate with the camera through the C++ code. Without the driver, more development time would be required on acquiring the image than on processing the image. Having an existing driver also allows for other properties of the camera to be set such as the shutter speed.

The frame rate is dependent on the selected resolution as the larger the image, the more data and more bandwidth is required.

3.3.1 Image Sensors

Charged Couple Device (CCD) and Complementary Metal Oxide Semiconductor (CMOS) are the two most common image sensors. These sensors are a two dimensional array of photoreceptors which convert the incoming light into an electrical charge at each location on the pixel grid. The main difference between the two sensors is that a CCD sensor converts charge to a voltage outside of the pixel array, while a CMOS sensor has the charge to voltage circuitry at each pixel. (Hain, Kahler, & Tropea, 2007; Magnan, 2003)

A less common image sensor is the microbolometer which allows the detection of wavelengths between 7.5µ and 14µm. This sensor has multiple microbolometer resistors that change their electrical resistance based on their temperature. These changes can be measured and used to produce a thermal image. (FLIR Commercial Vision Systems, 2008, 2012)

3.3.2 Testing

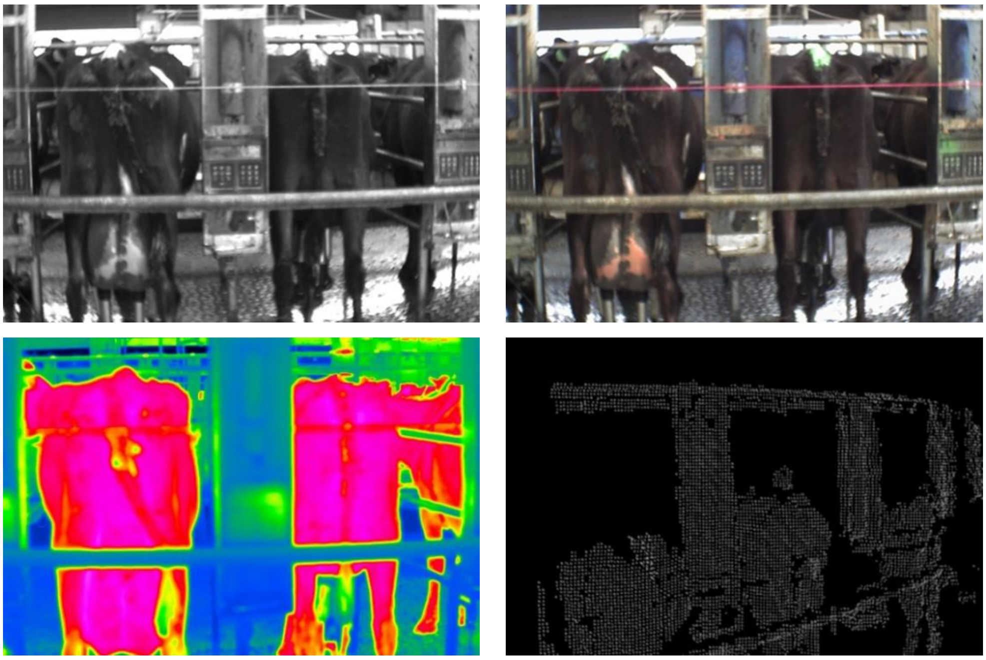
Four different camera systems have been tested using each of these image sensors; these are monochrome, full colour, thermal imaging, and three-dimensional imaging. Images from each of these cameras are shown in Figure 3.2.

The monochrome sensor was a CMOS Raspberry Pi NOIR camera that was modified to retrieve a single data channel. The main advantage of this sensor is that there is only one data channel and therefore the processing time is much lower than that of the other sensors. A disadvantage is the increased difficulty with isolating the cow within the image as this sensor contains the least amount of data compared to the others.

An Omni Vision OV9740 CMOS sensor was used to record images in full colour. The full colour allows objects to be identified by manipulating the colour channels. Doing this provided successful results on isolating the cows within small datasets. However, on larger datasets the variation in the ambient light throughout the day was too large to use this same extraction technique. Additionally, as both the colour of the background is unknown and the colour of the cow can vary based on breed, an extraction method based on colour cannot be done reliably.

The thermal imaging camera allows the cow to be easily isolated within the image as it is always warmer than the environment. However, the thermal camera tested does not many of the stated requirements; it is also a very expensive sensor when the thermal aspects of the image will not be analysed. Another disadvantage is distinguishing between multiple cows as they bunch up when they move.

There are different methods available to obtain a three-dimensional image of the environment. The sensor tested in this instance was the Microsoft Kinect, this works by using an infrared laser with a monochrome CMOS sensor. The depth information is obtained by passing the infrared laser through a diffraction grating that projects dots onto the environment. By analysing the distortion of these dots, the distance from the sensor can be calculated and used to produce a depth map (Popescu & Lungu, 2014). The main advantage of this sensor is being able to isolate a single cow within the image even when multiple cows are touching due to the differences in height. The disadvantage is that this sensor does not work in all environments and therefore does not meet all the stated requirements of the imaging sensor. When this sensor is used in an outdoor environment, the sunlight saturates the infrared sensor and prevents the depth from being calculated.



a	b
c	d

Figure 3.2 - Images from each camera system of the same scene (a) monochrome (b) full colour (c) thermal imaging (d) three-dimensional imaging

3.3.3 Algorithm Development

Each of the camera systems were used in the development of a detection algorithm. Several detection algorithms were developed as the hardware evolved over the course of the research project. Each new stage of the development was driven by the inability to isolate the cow within the majority of images from a large dataset.

The first iteration of the algorithm utilised a colour camera. This method required the image be segmented into four smaller regions and each of these regions were analysed individually to determine if the cow was present. If the cow was not present, a running average was calculated so there was a known background value for each pixel. The average was to taken account for variations in lighting conditions throughout the day. If the cow was present, then the background was subtracted leaving the cow in the foreground. These regions are shown in *Figure 3.3*.

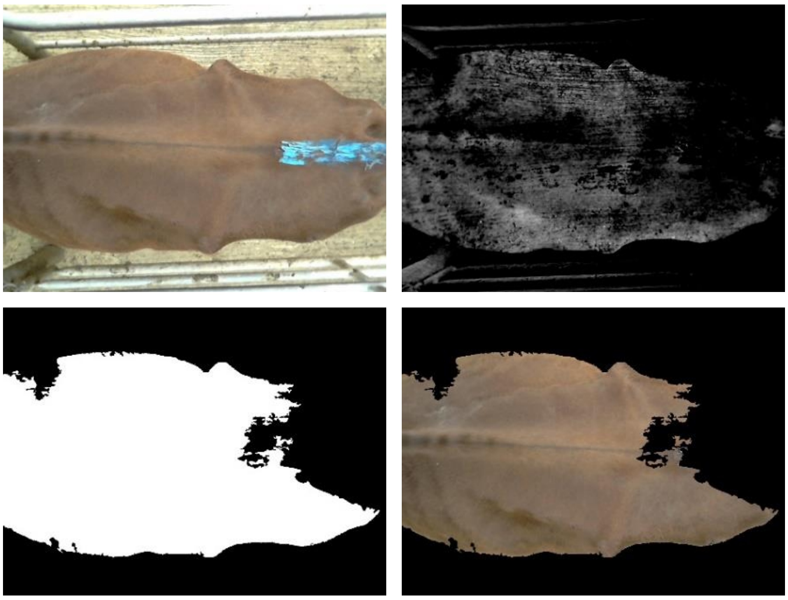
Figure 3.3 - Isolation method from a colour camera. Blue lines highlight each of the four regions used for the analysis.

There were two main issues that prevented the outline from being found in a reliable manner. The first was overcoming the variation in lighting; it was found that on a sunny day, the variation of light within a single image prevented the outline from being detected. An example of this is shown in Figure 3.4.

Figure 3.4 - Variation of light within a single image

In an attempt to overcome this variation, the image was converted from the RGB colour space to the HSV colour space. The HSV space has the advantage of separating the colour information from the luminosity, while this information is combined within each channel in the RGB colour space. While this sounds good in theory, in practice it was found to still fail at similar points to the previous attempt in the RGB space.

The second issue was with the methodology itself. The background subtraction was not reliable within these operating conditions as parts of the cow could also be removed. An example of this is shown in .



a	b
c	d

Figure 3.5 - Background subtraction method
(a) original image (b) background removed (c) mask (d) final image

Due to the difficulty of isolating the cow within the standard colour space, a thermal imaging camera was tested. While this provided useful information if a single cow was within the image, a similar isolation problem was still identified if there were multiple cows present within the frame. A second drawback of the thermal system is that the resolution of the sensor was inadequate for the analysis.

The use of three dimensional images was also tested. The primary advantage of using a 3D camera is that isolating the cow is almost a certainty as the depth information is present within the image allowing the known ground and environment values to be removed. It also allows for other features on the cow to be analysed, such as how prominent the spine, pins, and ribs are, assuming the camera has enough depth resolution. The addition of these features has the potential to increase the accuracy of the condition score calculation.

The main disadvantage of this camera system is that it could not be used in sunlight. The method of determining depth is to interlace IR light, however any sunlight can saturate the IR light rendering the depth information useless. Due to the restrictions of the project, a shield or tunnel could not be used to remove the sunlight; and as the system had to work in real world environments and remain unobtrusive, a solution could not be found that did not require the addition of external equipment.

This process lead to the development of the current and final system which uses Near Infrared (NIR) imaging. The lighting issues faced by both the colour and three dimensional imaging systems were overcome by implementing a dedicated light source within the system, and using a narrow bandwidth filter to eliminated unwanted wavelengths. Using NIR also has the benefit of being outside of the visible spectrum, so the light sources can be added without distracting workers or animals. Additionally, this sensor also meets the requirements, is low cost, and it was made to work with the Raspberry Pi. An image of this camera is shown in Figure 3.6.

Table 3.2

Overview of four potential imaging systems

	Monochrome	**Full Colour**	**Thermal Imaging**	**Three-dimensional**
Useable resolution	Yes	Yes	No	Yes
Driver available	Yes	Yes	No	No
All lighting conditions	Yes*	Yes*	Yes	Yes
All environmental conditions	Yes	Yes	Yes	No
Cost	Low	Low	Very High	Medium

*Requires an external light source.

Figure 3.6 - Raspberry Pi NOIR Camera (Raspberry Pi Foundation, 2014b)

3.4 Illumination

The ideal light source should be selected in a way that the output wavelength matches the sensitivity wavelength of the image sensor (Browne & Norton-Wayne, 1986). Gilblom and Yoo (2004) showed the efficiency of a CMOS sensor that had no ultraviolet or infrared filters, the efficiency of this sensor is shown in Figure 3.7. The selected wavelength needs to have the highest efficient possible and be outside of the visible spectrum for both humans and cattle; therefore the selected wavelength must be greater than 760nm. A wavelength of 850nm was selected as it is far enough into the near infrared (NIR) range that it is barely visible to humans and is a common frequency used in security systems (Axton Communications, 2014; SiOnyx, 2014).

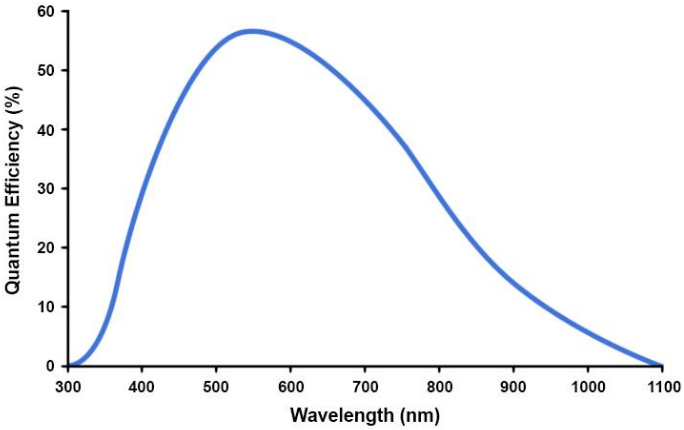


Figure 3.7 - Spectral response of a CMOS sensor (Gilblom & Yoo, 2004)

3.4.1 LED Selection

The selected LED was a SFH4350 High Power Infrared Emitter from Osram. The datasheet (OSRAM, 2011) states that this LED was specifically designed for infrared illumination for CMOS cameras in surveillance and machine vision systems. The SFH4350 has a centre of spectral emission of 850nm, and can be driven with a forward current up to 1A. The spectral emission for this LED is shown in Figure 3.8.

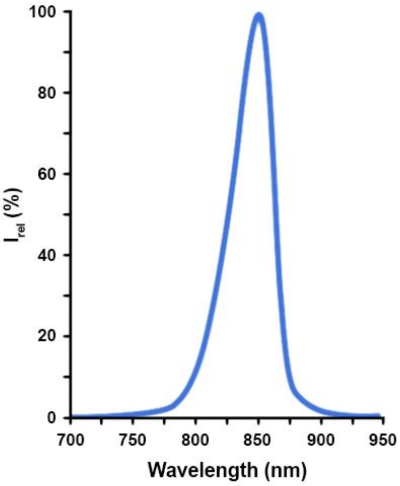


Figure 3.8 - Spectral emission of the Osram SFH4350 (OSRAM, 2011)

3.4.2 LED Driver Design

An LED driver will provide a consistent light source by ensuring the LEDs are driven with a constant current. The LM3401 was selected as the LED driver; there are three LED drivers in total with each driving two LEDs. A schematic of the driver is shown in Figure 3.9.

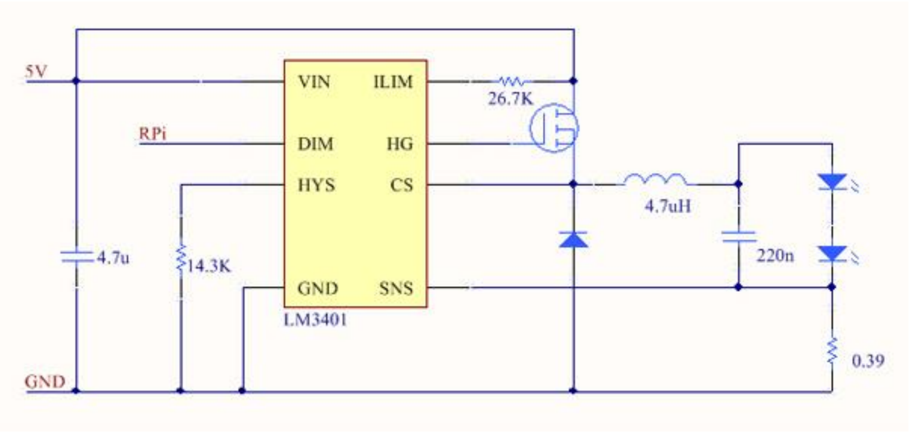


Figure 3.9 - Schematic of LED driver

The LM3401 is a switching controller designed to provide constant current to high power LEDs. The constant current is essential in ensuring a consistent light source. Figure 3.10 shows the LED current, the voltage at the SNS pin, and the voltage at the CS pin. This shows the current remains relatively constant even while the voltage is switching.

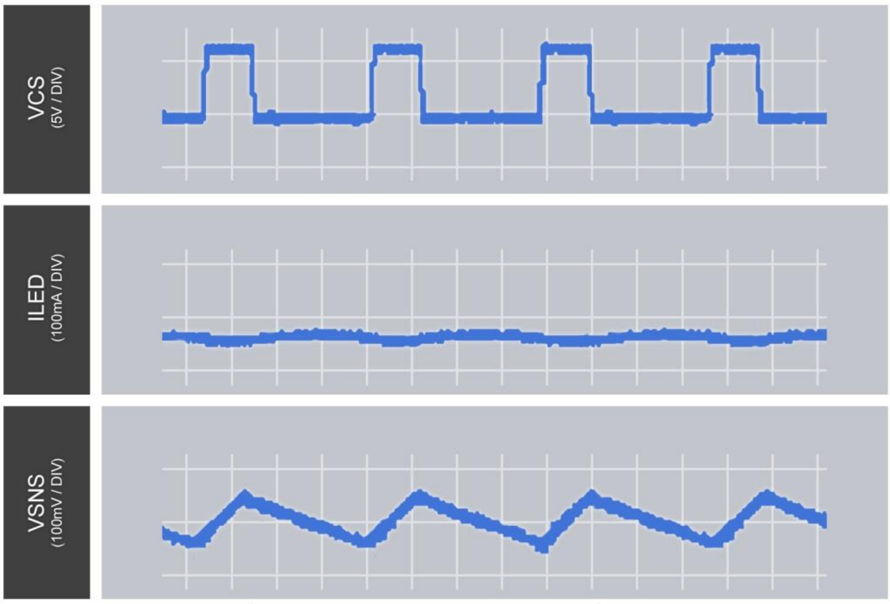


Figure 3.10 - Output waveforms to LED

3.4.3 Optical Filter

The ambient lighting conditions in which the system is operating has a significant influence on the outcome from the image processing. A narrow bandwidth filter was used to suppress the wavelengths that are both longer and shorter than 850nm to reduce the influence of the ambient light. Two filters with different bandwidths from Andover Corporation were tested; the spectral response of both these filters is shown in Figure 3.11.

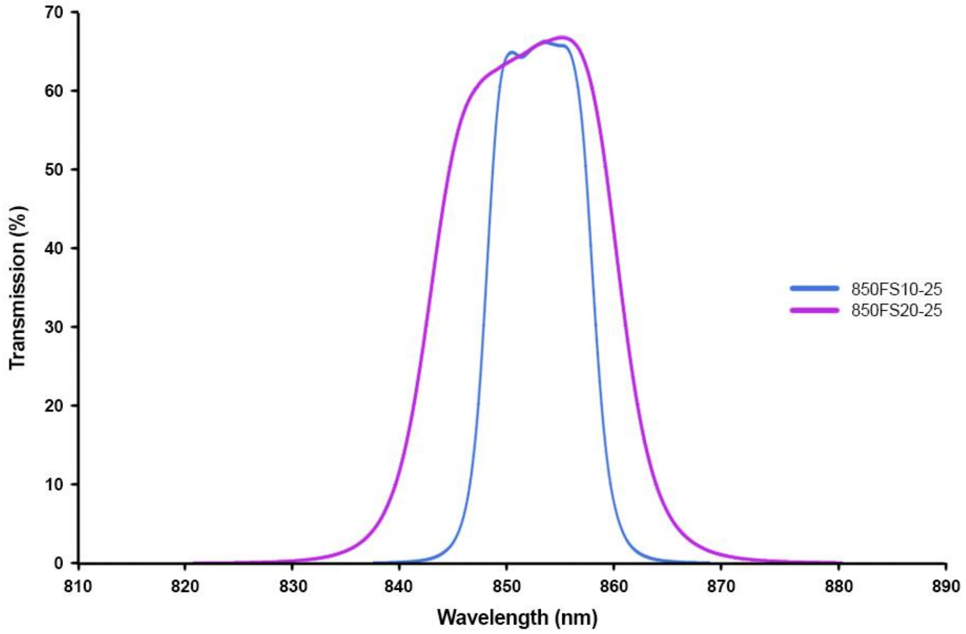
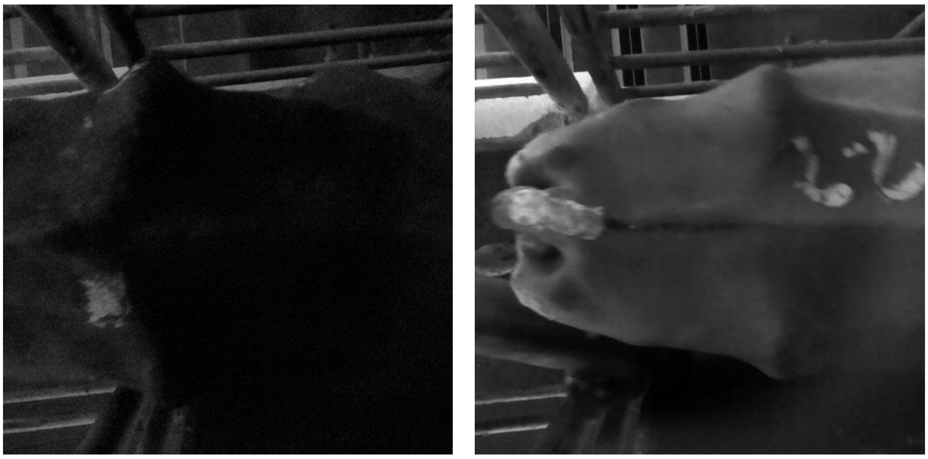


Figure 3.11 - Comparison of the spectral response of two narrow bandwidth filters

It can be seen that both filters have a peak transmission of 850nm. The 850FS10-25 has a bandwidth from 840nm to 860nm and a signal to noise ratio of seven. The 850FS20-25 has a bandwidth from 830nm to 870nm and a signal to noise ratio of 16. Andover Corporation tests each filter separately and sends the spectral response for that individual filter when it is ordered. Consequently, if two identical filters are ordered, there will likely be a slight difference in both the spectral response and signal to noise ratios. Images from both these filters are shown in Figure 3.12. The additional bandwidth provided by the 850FS20-25 and the higher signal to noise ratio results in a visibly clearer image. As a result, this filter was selected as the one to use in the system.

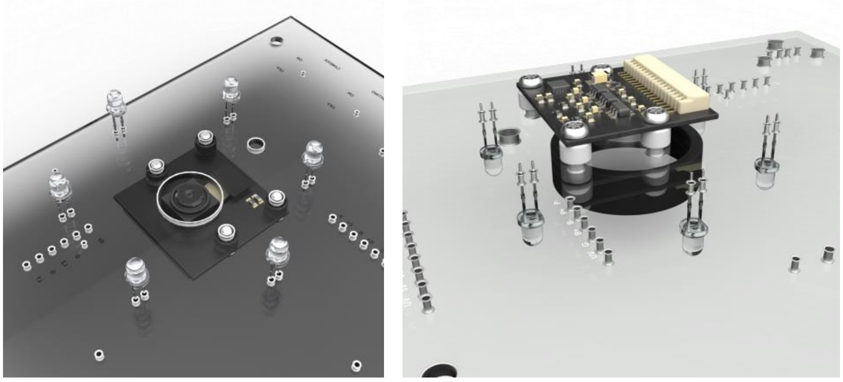


a	b

Figure 3.12 - Comparison of images from the (a) 850FS10-25 and (b) 850FS20-25

3.4.4 Imaging System Overview

A render of the imaging system is shown in Figure 3.13. This shows the layout of the LEDs in relation to the camera and the narrow bandwidth filter. These images show a transparent circuit board with no other components for clarity. The lens of the camera is placed over the centre of the filter and 4mm spacers are used to lift the camera board above the PCB. The LEDs are evenly spaced around the filter at a radius of 23mm.



a	b

Figure 3.13 - Overview of imaging system showing the location of LEDs in relation to the camera and filter. (a) bottom view (b) top view including filter

3.5 Power Regulation

The system requires both a 5V and 3.3V line; to achieve this, a single cell lithium ion battery is used. An overview of the power regulation circuitry is shown in Figure 3.14.

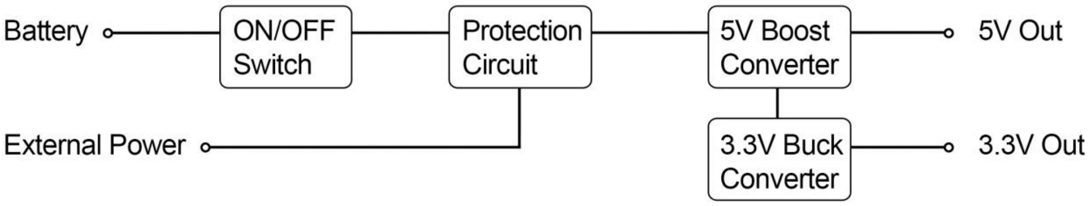


Figure 3.14 - Functional block diagram of the power regulation circuitry

3.5.1 Battery Protection

The system can be powered by an 18650-lithium ion battery or by an external power input, if both are connected the external input will also charge the battery. The external power input can be any voltage between 4V and 8V allowing the battery to be charged by USB. The battery protection circuit includes a TP4056 chip that monitors and charges the battery, and a DW01A chip that prevents both over-charging and over-discharging of the battery. The schematic for this circuit is shown in Figure 3.15. The MOSFET (8205A) switches the ground line, removing power to the system if required.

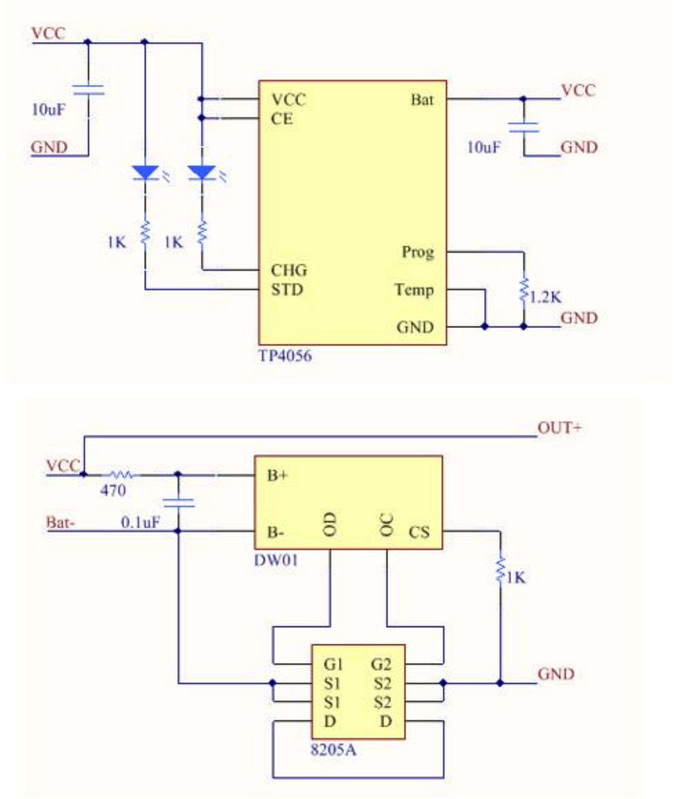


Figure 3.15 - Battery charging and protection circuit schematics

3.5.2 Voltage Regulation

All voltage regulation is done using DC/DC switch mode regulators due to the greater efficiency over linear regulators. Efficiency is important as the third and fourth requirements stated in section 3.1 indicate that the system must be in a sealed enclosure. A high efficiency will both increase the battery life and reduce the amount of heat produced by the components.

The output from the battery protection circuitry is an unregulated battery voltage that is connected to the 5V boost converter. This converter uses a TPS61230 IC and is a high efficiency step up converter optimised for products powered by a single cell lithium ion battery. The schematic is shown in Figure 3.16.

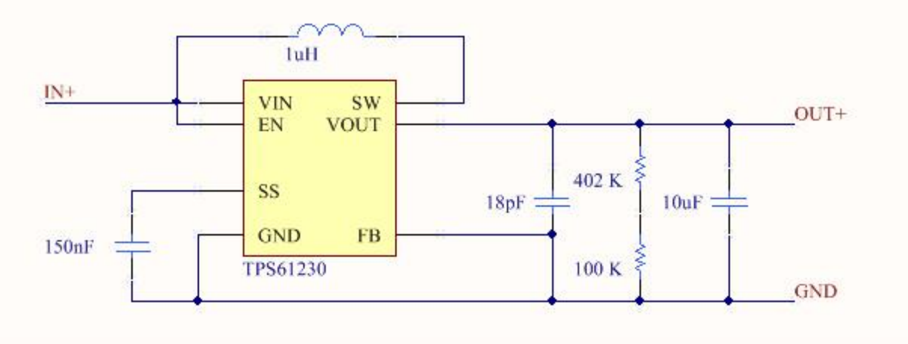


Figure 3.16 - 5V boost converter schematic

The Raspberry Pi has an on-board linear regulator that converts the 5V input to 3.3V. This regulator was replaced with a more efficient buck converter that uses the LM2596 IC. A trim pot is used on the feedback loop to adjust the output voltage, giving greater control to ensure that the output voltage is exactly 3.30V. The schematic for the buck converter is shown in Figure 3.17.

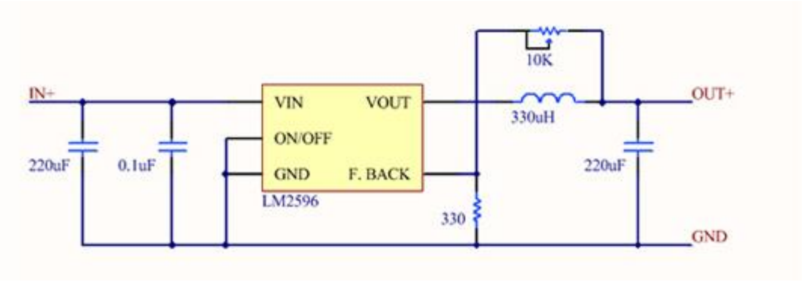


Figure 3.17 - 3.3V buck converter schematic

3.6 System Construction

As stated in section 3.2, the selected single board computer is the Raspberry Pi Model A. This will utilise the RPi NOIR camera for the image acquisition. The system is powered by a single cell 18650 battery that can easily be replaced or charged through an external power input. There is a narrow bandwidth filter and near infrared LEDs at 850nm to filter out the unwanted wavelengths.

3.6.1 System Overview

A functional block diagram showing how all the selected components are connected is shown in Figure 3.18.

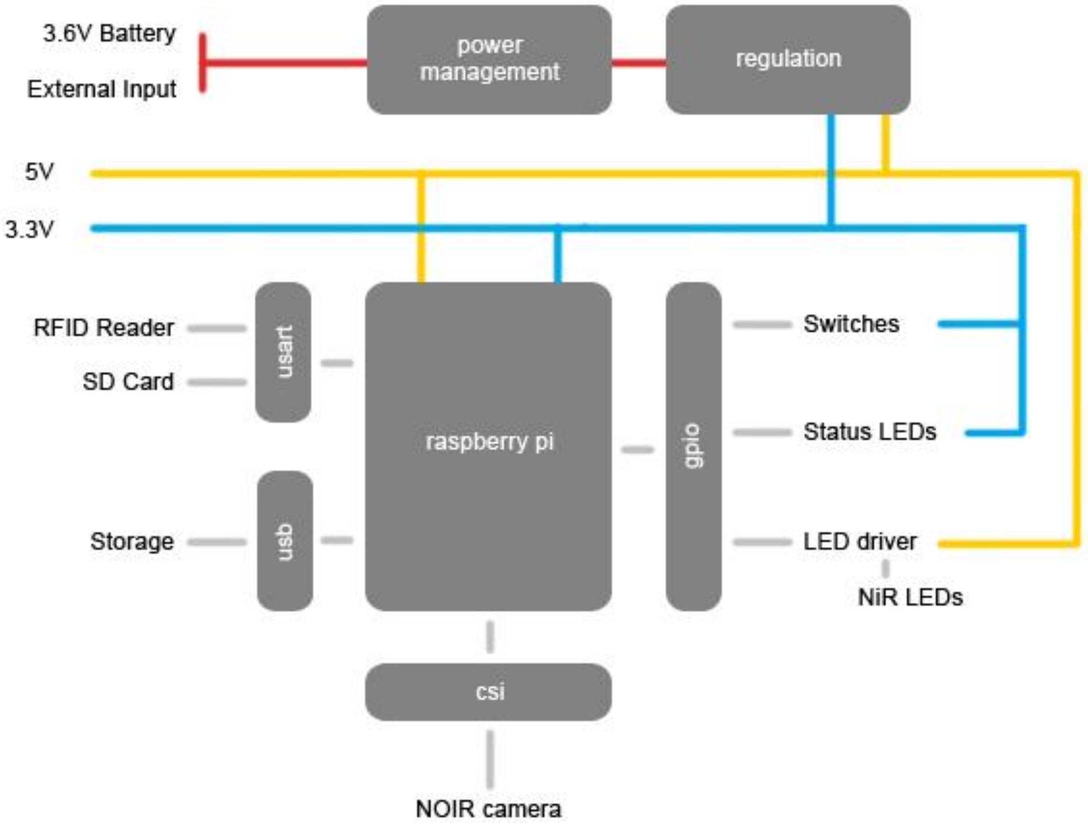
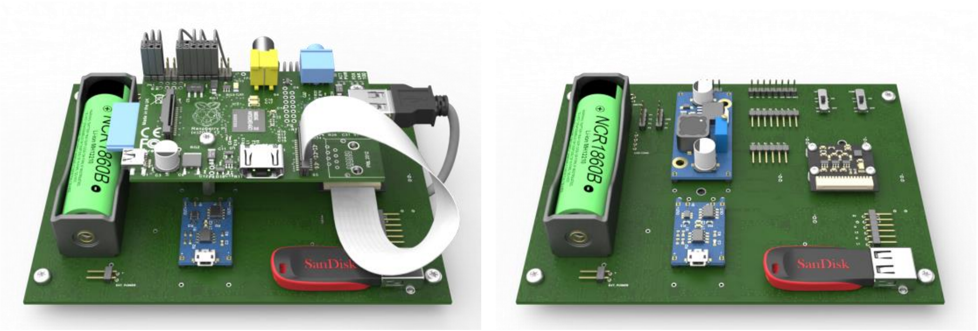


Figure 3.18 - Functional block diagram of the system

3.6.2 Circuit Board Layout

A printed circuit board (PCB) was manufactured to eliminate the need for wiring within the enclosure between components. The main requirement in designing the layout of the components was to ensure that the battery, USB drive, and switches could all be reached without the need to remove other components. As such, these components were placed around the edge of the board with all other components and connectors being placed under the Raspberry Pi. The voltage regulators and battery charging circuit are mounted on individual PCBs and connected to the main PCB through headers, allowing them to be easily replaced if required. Unused pins from the GPIO port on the Raspberry Pi were wired to various headers along with power and ground lines to simplify any future expansions. Two slide switches are present on the PCB that allows the user to select if the camera and/or lighting are enabled. Images of the PCB showing these features can be seen in Figure 3.19 both with and without the Raspberry Pi mounted. Further images of the system are shown in Appendix A.



a	b

Figure 3.19 - PCB layout

(a) including Raspberry Pi (b) main circuit board only

3.6.3 Enclosure

To ensure the third requirement stated in section 3.1 is met, the enclosure has a rating of Ingress protection (IP) rating of 67. This rating specifies the products resistance to both the ingress of solid foreign objects, and the ingress of water. In this instance, a rating of 67 specified that the enclosure will not allow any dust, and it can be immersed in water up to 1 meter deep before leaking. The selected enclosure used is a generic ABS enclosure.

Figure 3.20(c) shows the acrylic plate on the bottom of the enclosure. This protects the filter and LEDs from any damage and the o-ring helps to prevent moisture from entering the enclosure.

a	b
c	

Figure 3.20 - Enclosure (a) front view (b) rear view

(c) bottom view with acrylic plate

Chapter 4

Condition Scoring Algorithm

In this chapter the development of the condition scoring algorithm is described. The first section covers how the data was collected and the camera settings. The next section gives a brief overview of the image processing techniques that were used, and the process from image capture to condition score. Sections three and four cover these image processing techniques in more detail. The fifth section explains how the values obtained from the image analysis correlate to the condition score. The final section covers the development process of the algorithm.

4.1 Data Collection

4.1.1 System Placement

As discussed in the previous chapter, the system must be able to operate in a real-world environment and as such the data must be collected during normal farm operating hours, in an automated manner with no human intervention, and not interfere with any daily routines. In order to meet these requirements, three camera placements were investigated.

1) Top down view

This placement was utilised in several other studies including Leroy et al. (2005), J.M. Bewley et al. (2008), Halachmi, Polak, Roberts, and Klopcic (2008), Halachmi, Klopcic, Polak, Roberts, and Bewley (2013). There are several benefits to this placement, including:

- Low background noise. The background of the image is relatively static allowing the cow to be isolated using more traditional image processing techniques.
- Less movement. Having the camera above ensures there is only movement in the x and y planes as the cows are the same distance from the sensor. Where as a side facing camera would capture data of the cows' random movements both towards and away from the camera which could result in a lower accuracy with the analysis.
- The hardware can be concealed overhead making it less likely to frighten the cows.
- The hardware is less prone to damage by both the cows and farm workers.
- Easy to find locations to mount the system at different farms

2) Side on view

Placing the system to the side of the cow allows for the ribs to be analysed. However, there are four main obstacles with this placement:

- It is difficult to obtain an unobstructed view of the side of the cow for an automated system where the sensor would not be damaged by the cows or farm workers.
- The cows are at varying distances to the sensor
- The background is continually changing due to the environment or cows that are not of any interest passing in the background
- The sunlight can hit the sensor directly, or backlight the cow, both of which can significantly reduce the accuracy of the image processing.

3) Rear view

This placement was also utilised by other authors including Pompe et al. (2005), Leroy et al. (2005), and Tedín, J.A., and R.J. (2014). These authors noted a high correlation between the features at the rear of the cow and the condition score. However, this placement shares many of the same disadvantages as obtaining a side on view of the cow.

This led to the camera being placed above the path of the cow at the entry to the milking shed. The majority of the data collection done for the development of the algorithm was completed at Massey Farm 4, Palmerston North, New Zealand. The cows were primarily Friesian and were milked twice a day.

All cows had a visible identification tag that could be paired with an external RFID reader to log the ID of each cow as it passed under the camera. Alternatively, due to the location of the system at Massey Farm 4, a local RFID reader could also be utilised and paired to the data.

Figure 4.1 shows the location of the system at Massey Farm 4, this location was selected for multiple reasons:

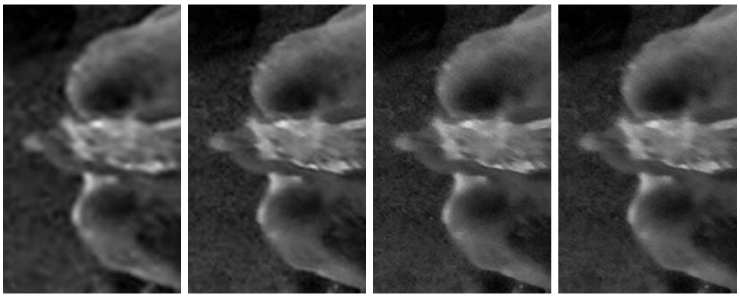
- The camera was two meters above the ground. At this height the full width of the race was within the image which also showed the full width of the cow would fit.
- The camera was able to mount to an existing structure. This meant there was nothing new to add that could potentially startle the cows which would hinder the flow.

a	
b	c

Figure 4.1 - System setup at Massey Farm 4
(a) proposed setup (b) side view showing camera above a cow
(c) front view showing the cows' perspective and the rotary platform

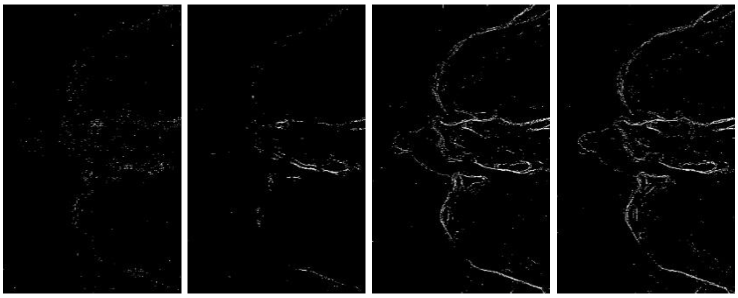
4.1.2 System Settings

The image resolution represents the quality of the image and is a measure of the number of pixels within that image. The selected hardware is highly configurable and allows for a range of resolutions to be used. A comparison of the same image taken at different resolutions is shown in Figure 4.2. Figure 4.3 shows the output from the edge detection algorithm before filtering. An ideal resolution of 640 x 640 was selected; using a square resolution allowed for a greater leniency with the camera placement compared to the standard resolution of 640 x 480. Compression artefacts are introduced at the lower resolutions; these reduce the accuracy of finding the true edge which is essential in the analysis. Using a higher resolution provides no benefit to the analysis and only results in an increased processing time, it also requires a higher bandwidth due to the additional data.



a	b	c	d

Figure 4.2 - Image resolution comparison
(a) 320 x 320 (b) 480 x 480 (c) 640 x 640 (d) 960 x 960



a	b	c	d

Figure 4.3 - Edge detection resolution comparison
(a) 320 x 320 (b) 480 x 480 (c) 640 x 640 (d) 960 x 960

The first requirement in section 3.1 indicates that the system must operate with a maximum latency of one second per cow, allowing for some overhead for processing the images. It was found that if a cow was moving quickly, it could cross the image frame in approximately one second. An ideal frame rate of three frames per second was selected as this ensures that multiple images of the cow can be captured, while allowing time to process each image. A lower frame rate could result in a loss of information if the cow was moving quickly as there would be fewer images to analyse. A higher frame rate would result in a longer processing time; in this case it would be possible from some images to be missed as the system would be busy processing. In both of these cases the accuracy could result in a loss of accuracy.

4.2 Algorithm Development

The image processing algorithm, and the hardware that was used, was in a process of continual development throughout the research project. The only constant was the location of the system which was always mounted above the cow where possible. An overview of the initial algorithms are shown below.

4.2.1 First Iteration: Colour Camera

The first iteration of the algorithm utilised a full colour camera and attempted to analyse the cow in a similar way to a trained human scorer as recommended by DairyNZ (2012). The way a human visually estimates the condition score requires estimating depth and to what extent the features are protruding. Estimating the depth using a two-dimensional is highly inaccurate particularly given the variation between different cows.

4.2.2 Second Iteration: 3D Camera

The problem of estimating depth was overcome by utilising a three-dimensional camera that could accurately return the depth measurement for a given x-y position. This was shown to be very promising with the analysis, however this sensor could not be used within the projects due to the limitations covered in Section 3.3.

4.2.3 Third Iteration: Thermal Camera

As the three-dimensional camera showed how the outline of the cow could be easily isolated from the background, a thermal camera was utilised to achieve the same result. The thermal camera would allow for the extension on previous studies carried out by Halachmi, Polak, Roberts, and Klopcic (2008) who also utilised a thermal camera to extract the outline. However, as also covered in Section 3.3, a thermal camera could not be used.

4.2.4 Fourth Iteration: NIR Camera

This led to the final iteration of utilising a near infrared camera. An overview of how the final algorithm works is illustrated in Figure 4.4. The input to the algorithm is a grayscale 640x640 image captured from the RPi NOIR sensor. This image is analysed to determine the following:

- Are the regions of interest within the image (tail and hips)?
- Is this the same cow as the previous image?

As a single cow can have multiple images associated to it, the algorithm will continue to average the values output from the analysis till that cow has left the frame. Once that cow has left the frame, the condition score can be calculated and associated to that ID.

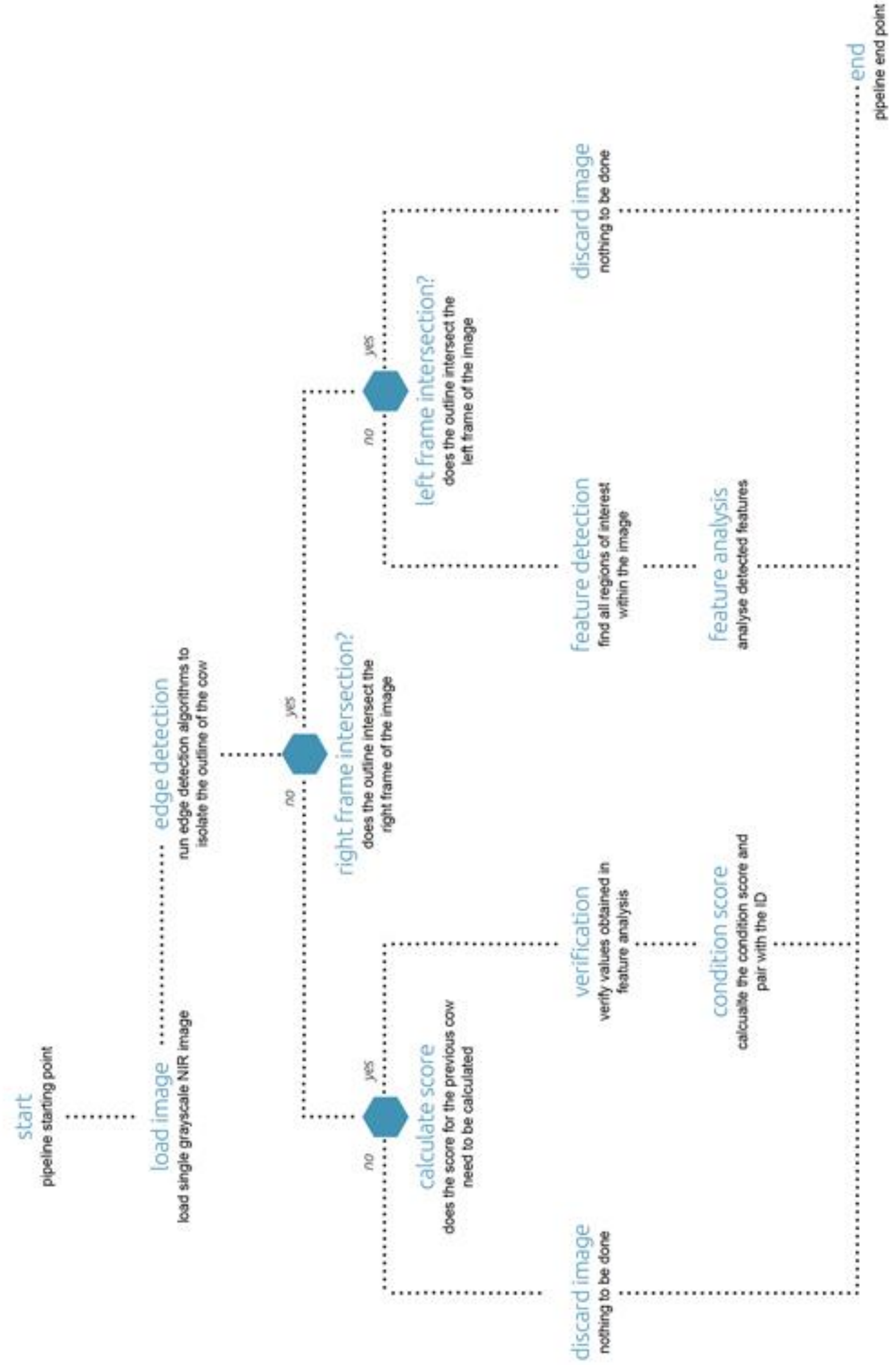


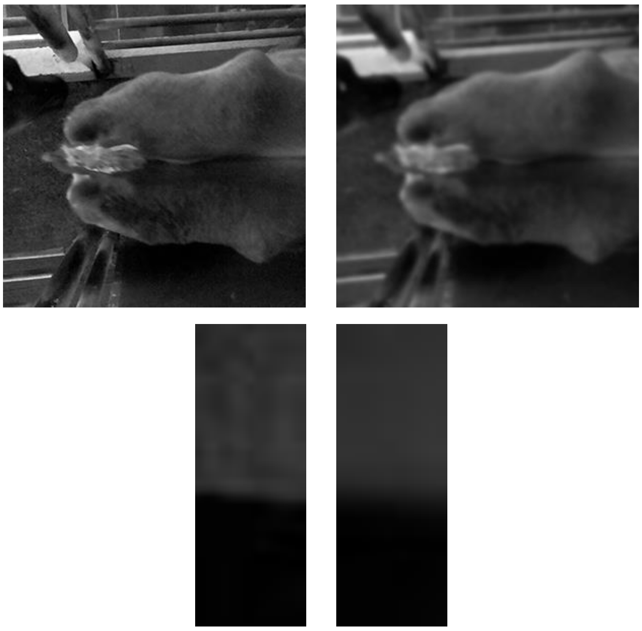
Figure 4.4 - Overview of the image processing pipeline for a single image

4.3 Edge Detection

In order to obtain the outline of the cow from within the image, an edge detection algorithm is required. An edge can be identified as a change in pixel intensity over a small range; an edge detection algorithm will scan each pixel within the image and identify the locations of these changes. It was found that using a single edge detection algorithm was insufficient in obtaining the outline of the cow in all images resulting in a number of images being incorrectly discarded. In an effort to reduce this error rate, two algorithms were applied to the original grayscale image and combined together to give a single outline. The failure to isolate the cow from a single algorithm can be attributed to the variety of environments the system must operate in, and the large number of differences between the cows themselves.

4.3.1 Gaussian Blur

The first stage in any edge detection process is to smooth the image to reduce any noise within the image. The smoothing helps to prevent any false detection caused by the noise by reducing high frequency content, whereas edge detection algorithms look for the high frequency content to identify the edge (Nixon et al. 2008). In this case, the smoothing of the image helps to remove the finer details such as the hair or details within the concrete on the ground. The output from the Gaussian Blur filter is shown in Figure 4.5. This shows that neighbouring pixels have smoothed to become an average intensity, removing many of the high frequency components throughout the image.



a	b
c	d

Figure 4.5 - Output from the Gaussian Blur filter

(a) cow before (b) cow after (c) edge before (d) edge after

4.3.2 Canny Edge Detection

The first edge detection algorithm is the Canny Edge Detector from the OpenCV library. This algorithm was selected over other common edge detection methods as it “is less likely than the other methods to be fooled by noise, and more likely to detect true weak edges” (MathWorks, 2015). This algorithm is run over the Gaussian Blurred image to give the result shown in Figure 4.6. This produces an initial outline that will be processed further in order to isolate the true outline of the cow.

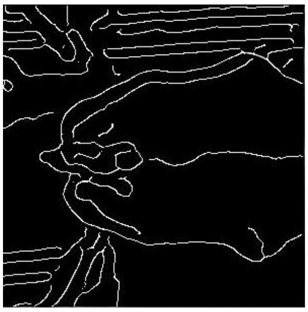


Figure 4.6 - Output of the Canny Edge Detection algorithm

The algorithm takes two inputs, a low threshold and a high threshold. Each pixel that the algorithm identifies as an edge has an associated gradient based on the difference between itself and the neighbouring pixel. If this gradient is higher than the high threshold, then the pixel is marked as a strong edge. If it is greater than the low threshold it is marked as a weak edge. If it is less than the weak edge, then it is discarded. A strong edge is extracted from a true edge within the image, while a weak edge may either be from a true edge or just a variation in colour within the image.

The Otsu threshold is a threshold utilised by the Otsu method which converts a grayscale image to a binary image. This method assumes that each pixel falls into one of two classes, a foreground or background class. The threshold is determined by finding the greatest variance between these two classes (Otsu, 1979). This threshold is calculated over the entire image and is set as the high threshold. The low threshold is set to half of the high threshold. This allows for the algorithm to be more adaptive to different environments and different breeds of cows.

4.3.3 Threshold Detection

A second edge detection algorithm was required to help ensure that a full outline of the cow could be obtained. The first step is to enhance the image by adjusting the contrast, this is achieved using histogram equalisation. The purpose of this step is to help distinguish the cow from the background. The next step is to calculate the average pixel intensity over three specific regions within the image, these are shown in Figure 4.7 and were specified as regions which would be filled by the cow if it was present within the image. Each pixel within the image is then checked to see where it lies in relation to the threshold, it is then coloured black or white depending on the outcome. The third step is to remove any small components in and around the cow before running the same Canny Edge Detection over the black and white image.

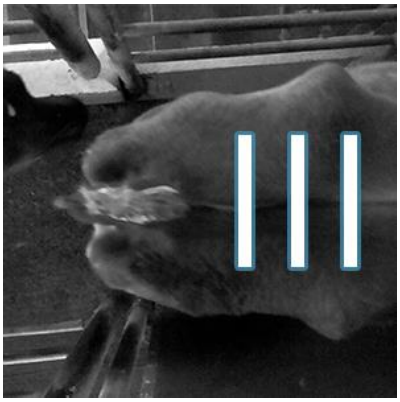


Figure 4.7 - Regions of interest to analyse to determine the intensity value of the cow

4.3.4 Outline Isolation

In order to obtain a single outline of the cow, both the Canny Edge Detection image and the Threshold Detection image are combined. Both of these images are binary images, and the output of this process is also a binary image. To achieve this, a new blank image is created with every pixel set to be black.

The first stage is to find where the outline lies within the image. The Canny Edge Detection image is analysed by starting at the centre right most pixel *(640, 320)* and moving along the x axis towards the centre checking for a white pixel. Up to 15 pixels are checked before the row is decremented and the process is repeated. If a white pixel is found, then the outline has been identified, otherwise the process of moving up one and towards the centre continues.

If no outline is identified, then the image is flipped horizontally and rechecked. This allows for the system to analyse cows walking in either direction. If there is still no outline identified, determined by the intersection with the right border of the image, then the image can be discarded. The head of the cow is of no interest to the analysis, as such there must be an intersection with the right side of the image in order for the tail region to be present within the frame.

At this point, there is a single pixel that has been identified as part of the outline at the top right of the image. The outline is then built up by searching for neighbouring white pixels in both images. This process is outlined in the flow chart shown in Figure 4.8.

A second pass is done to help remove the head of a second cow if it is present within the image. This check is only done if the outline intersects both the left frame of the image, and the right frame in the lower half of the image. In this case, the line of pixels that intersect the left frame up to the outline of the cow is removed. The outline of the cow is at a known intersection point where multiple outlines were found. If the outline only intersects the left frame, and not the lower half of the right frame, then the image is discarded as the tail region is not present in the image.

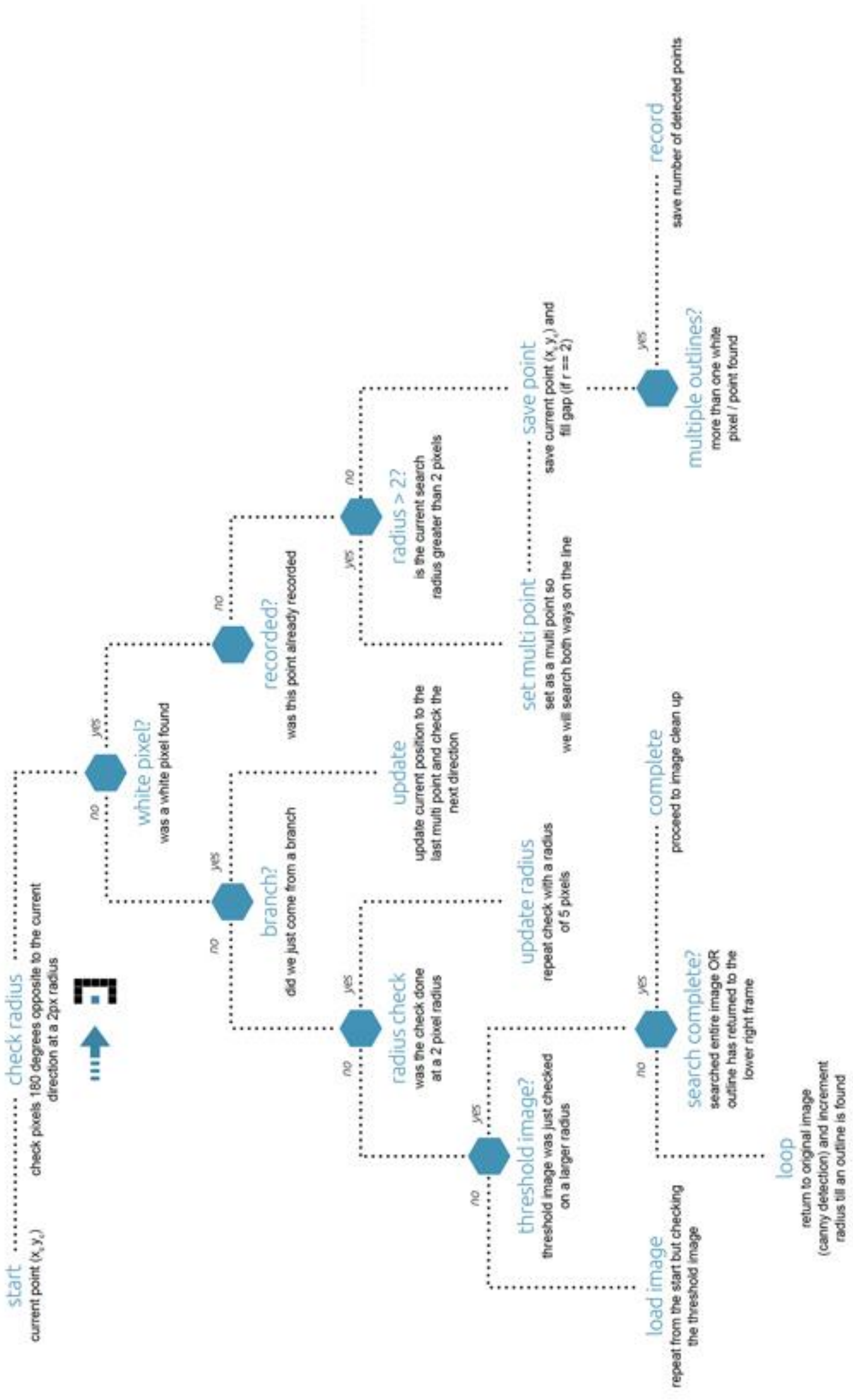


Figure 4.8 – Pipeline of the Outline Isolation process

4.3.5 Environment Removal

At this point it is possible to not have the full outline of the cow due locations of the outlines within the two images that were combined. The newly generated image is checked for any gaps by counting the number of connected components. If there is more than one connected component, then the image is dilated and eroded. The dilate procedure expands all the points allowing points that are close to each other to connect. The erode procedure works in reverse and will thin the newly expanded line back to the original width, but the newly connected lines will remain connected. If there are still multiple connected components then the distance between the two endpoints is checked, if this is less than ten pixels then a line is drawn between them otherwise it is left as a gap. Any connected components that have a small area are also removed. This process is shown in Figure 4.9.

Further steps are still required to remove unwanted parts from the newly created outline image. The first is to remove any connected components with a small area. These can be marks on the cow such as dirt, or background noise.

The second step is to identify the cow and remove any parts of the environment, this is achieved in multiple ways. Firstly, by finding the location of the cow based on the upper and lower detected edges. From there, connected components that connect at specific intersection points are copied to a newly created image. For example, if a line is drawn horizontally along the image from (0, 320) to (639, 320). Starting at the right side, the edge that intersects with this line will be the tail region and will be copied over.

Other parts of the environment can be eliminated based on specific conditions. For example, there cannot be vertical components to the right of the identified tail region, similarly there cannot be horizontal components to the left of the tail region. Utilising this information allows the majority of the environment, such as the bars on the race, to be removed from the outline.

4.3.6 Clean Up

At this point, the majority of the white pixels within the image is the true outline of the cow. It is possible that there are a few imperfections along the detected outline from the intersection points of the cow and where the parts of the environment were removed. The purpose of this step is to remove these imperfections to help improve the accuracy of the feature identification and analysis.

By traversing the outline, any identified points with multiple paths forward are analysed in more depth. The number of pixels from the intersection point till the end point is recorded and the short length is removed from the image.

A final sanity check is run over the outline to ensure that a head of a following cow has not been detected. To achieve this, the mid-point of the cow is identified and an imaginary line is drawn horizontally along what would be the spine. The vertical distances between this line and the detected outline both above and below this line are checked. Based on the ratios of these distances, the outline may be discarded. This check only needs to be done towards the tail.

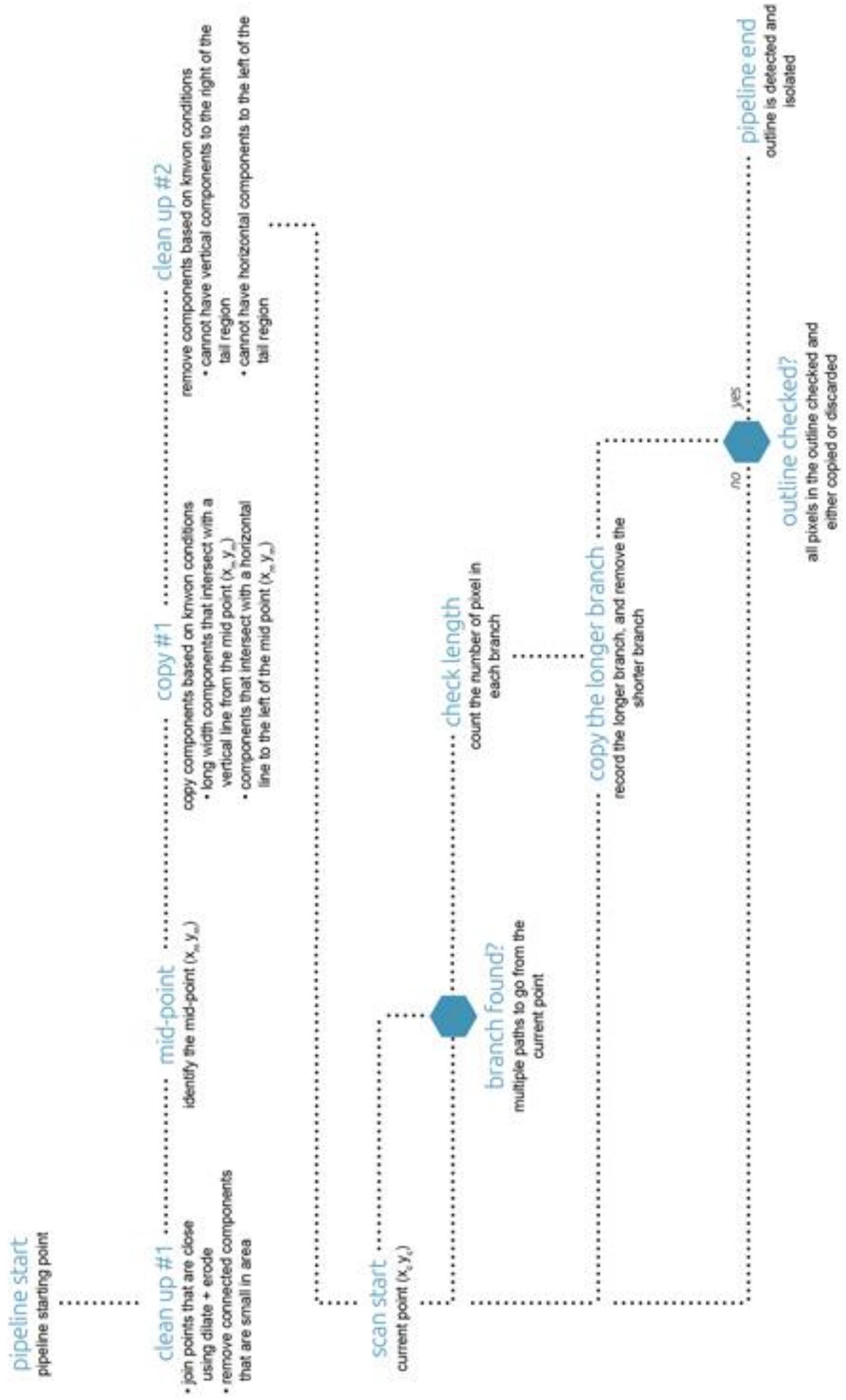


Figure 4.9 - Pipeline of the outline clean up and final isolation process

4.3.7 Known Issues

The proposed edge detection method is promising for isolating the cow, however there are still several issues that may arise. These issues can cause the outline to be falsely identified which has the possibility of interfering with the feature identification process and the condition score calculation. These include:

- If the tail is swaying side to side.
- If the leg is extended as the cow is walking.
- The tail region of the cow can be covered by the head of the cow following it.
- If the cow is positioned in such a way that the race is identified as part of the cow. This can occur if part of the hip lines up with a horizontal bar of the race.
- The spots on a cow can cause the outline to follow the wrong path. That is the identified outline will follow the into the cow due to the spot and not the true outline. This is because the contrast of the spot gives a stronger edge then that of the cow and the background, and is filtered out in the post processing.
- If the outline is invalid but passes all the checks. It is possible that incorrect features will be identified, and a parabola will be fitted to the detected outline and analysed.

Examples of these cases are shown in Appendix B.

4.4 Feature Identification and Analysis

Once the outline has been found, both hips and the tail region need to identified. Once the outline has been found, the two hips, and tail region need to be identified. These regions are then analysed and the output is associated to that cow. Each cow has four values associated to it, the hip, tail, a fitted parabola, and the final condition score. As each cow can have multiple images associated to it, these values are averaged and the condition score is only calculated once the cow has left the frame. A cow is deemed to have left the frame when there is no intersection with the right side of the image, or the location of the tail region is higher than 544 pixels in the x axis – this is 85% across the image.

These four values were selected to be analysed to extend on the research carried out by previous studies which showed a strong correlation to the estimated condition score. For example the work by Halachmi, Polak, Roberts, and Klopcic (2008) and Halachmi, Klopcic, Polak, Roberts, and Bewley (2013) showed a strong correlation between the condition score of the cow and the fit to a parabolic shape. Similarly J.M. Bewley et al. (2008), Coffey (2003), and Bercovich et al. (2012) all found a strong correlation between angles formed by specific anatomical points and the calculated condition score.

It is important to note that it is possible that both the hip and / or tail will not be identified and will therefore not be analysed. The only element of the image that is guaranteed to be analysed is the fitting of the parabola to the outline.

4.4.1 Hip Identification

The hips are found by analysing the positions of 11 points spaced 10 pixels apart on the x axis, as shown in Figure 4.10. These 11 points are shifted along the outline till the middle point is further from the centre than all other points. It is possible that this condition will not be met and no hip will be found; this is determined by the spread of the x and y values. Once the potential points begin to traverse vertically rather than horizontally, then the search for the his is abandoned and it is set as not being found within the image.

Once the mid-point of the hip has been identified, the remaining points that form the shape can be found. This is achieved by searching for a curve that is close to this mid-point. If no curve is found, then the outer points are set at this maximum distance. The mid-point and identified outer curve is shown in Figure 4.10.

This process is identical for both the top and bottom hips, and in both cases the search starts at the right frame of the image. This is done by starting at either the 0th index of the outline and progressing forwards, or the final index and progressing backwards through the data points.

Figure 4.10 - Location of the 11 points that specify the shape of the hip

4.4.2 Tail Identification

The two inner contours are found first. This is achieved by setting the starting index to be the left most point that is approximately at the mid-point of the height of the identified outline. From here the search for inner contours can be found by identifying the region where the outline will turn back on itself.

The outer contours are identified by looking for the region where the outline will turn back on itself after the inner contour. If the current location extends based the original starting index used to find the inner contour, then the search is stopped. This is generally due to the either a leg, tail, or part of another cow intersecting with the outline. An example of this is shown in Appendix C along with examples of other known issues.

Figure 4.11 - Location of the four angle used to analyse the tail region

4.4.3 Hip and Tail Analysis

Both the hip and tail are analysed in the same manner. This is to calculate the coefficients for the equation that fits a parabola to the three specified points. These coefficients are representative of how pronounced these features are. A higher condition score gives a less pronounced and more rounded feature, while a lower condition score gives a more pronounced feature. Figure 4.12 shows the three parabolas that are formed for the hip analysis.

Figure 4.12 - Location of the three parabolas analysed for a single hip

4.4.3 Parabola Fit

The final analysis is to fit a parabola to the outline and measure the distance between the fitted line and the identified outline given in section 4.3.4. The higher the variation, the lower the condition score. The lower the variation, the more the outline fitted to the parabola and therefore the higher the condition score. An example of a fitted parabola is shown in Figure 4.13.

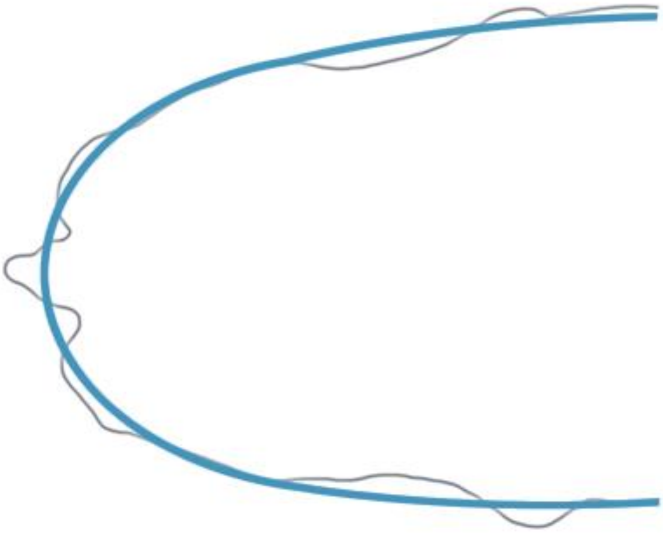


Figure 4.13 - Parabola fitted to the detected outline

To fit the parabola, the fitElipse OpenCV function was used. This “function calculates the ellipse that fits (in a least-squares sense) a set of 2D points” (OpenCV, 2015). The minimum distance between the identified outline and the fitted parabola is recorded for each point along the outline. The variance of the list of minimum distances is then recorded.

4.5 Condition Score Calculation

Each cow can have more than one image associated with it, meaning that each feature can be analysed more than once. A maximum limit was placed on the number of times a feature could be analysed, this was set to be ten. This was added as it was possible for a cow to remain under the camera for several minutes. Once the cow has left the frame, the results from each feature can be processed.

There are a total of 11 variables that are utilised, these are:

- Tail region x4
- Upper hip x3
- Lower hip x3
- Fitted parabola x1

The first step is to check each of these inputs before they are averaged for the potential of removing outliers. This check is only performed if the number of elements is greater than seven, if an outlier is found then it is discarded from the list. By only running this check if there are enough data points present increases the probability that an identified outlier is a true outlier that would have been caused by a failure in the outline detection. In order to check for outliers, the interquartile range (IQR) is calculated and any value that lies three times that value away from upper or lower quartile is classed as an outlier and removed.

The second step is to average some of the 11 variables so there are fewer inputs into the equation. This gives the following inputs:

- Tail outer (T_{OUTER}), average of two values
- Tail inner (T_{INNER}), average of two values
- Hip apex (H_{APEX}), average of two values
- Hip base (H_{BASE}), average of four values
- Fitted parabola (P)

Each of these values also has a weighting applied to it, as some factors have a greater effect on the output than others. This gives the final equation as:

$$CS = (\omega_{TO} \times T_{OUTER}) + (\omega_{TI} \times T_{INNER}) + (\omega_{HA} \times H_{APEX}) + (\omega_{HB} \times H_{BASE}) + (\omega_{P} \times P)$$

Chapter 5

Experimental Results

In this chapter, the hardware presented in chapter 3 and the software developed in chapter 4 are tested. Five tests were carried out to determine the accuracy and robustness of the condition scoring calculation. Each test is covered in its own section, followed by a section dedicated to the algorithm itself, and finally there is an overall discussion in the final section. It is important to note that there is no true condition score for the system to be compared to, and as such the system is being compared to the collective judgement of a group of individual scorers.

The system was installed on three separate farms giving a range of cows and operating environments; an overview of these farms is shown in Table 5.1.

Table 5.1

Overview of the farms where the system was installed for testing

Farm	# cows	Friesian	Jersey	Cross Breed	System Location
Farm 1	242	103	1	138	Entrance to rotary
Farm 2	230	230	0	0	Weight scale
Farm 3	281	10	271	0	Exit of rotary

A total of 710 cows were manually condition scored by a group of either two, three, or five accredited Diary NZ condition scorers. The credibility of the system output can then be compared to individuals who are trained in condition scoring cattle. Figure 5.1 shows the distribution of scores for both the average manual condition score and the calculated system score. The scores are rounded to the nearest 0.25 as that was the minimum resolution used. It is important to note that some human scorers rounded to 0.5 and not 0.25 like others. From this it can be seen that 75% of the scores fall between 3.5 and 4.75, with the most common score being 4.0. This highlights an important issue that the system has not been tested or calibrated at the extremes of the condition scoring scale.

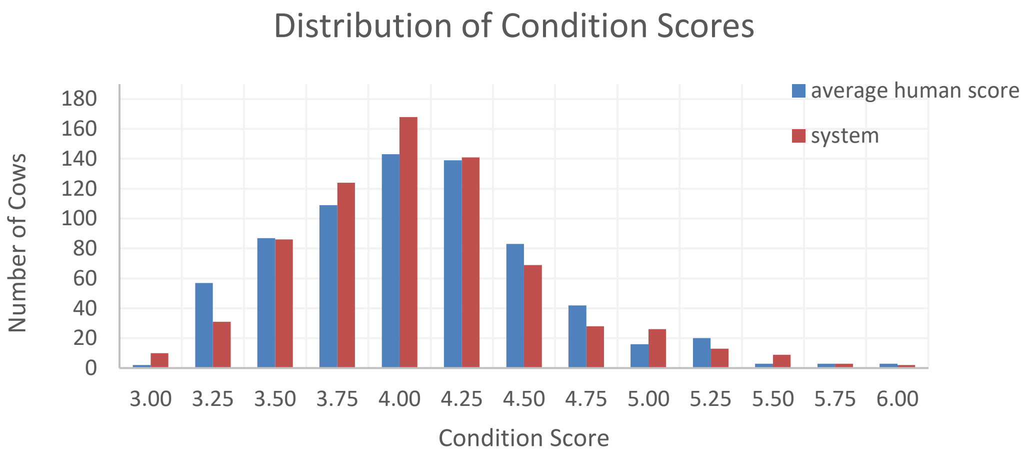


Figure 5.1 - Distribution of condition scores for both the average human score and system score

5.1 System Accuracy

In this section, the accuracy of the systems calculated condition score is determined.

5.1.1 Methodology

In order to determine the credibility of the calculated score, between two and five DairyNZ accredited condition scorers were sent to each farm to manually calculate the body condition score of the herd. An average condition score for each cow could then be calculated and compared to the calculated system output for the same cow. Table 5.2 shows the number of cows, images captured, and the number of accredited scorers for each farm. The number of images is the total number within that dataset, this includes images that are discarded automatically by the detection algorithm such as those that only contain the background. The number of images used to calculate the condition score can range from one to ten per cow.

Table 5.2
Number of cows, images, and accredited scorers for each farm

Farm	**# Cows**	**# Images**	**# Scorers**
Farm 1	199	6,593	3
Farm 2	230	14,243	5
Farm 3	281	8,118	2
Total	710	28,954	10

Note. Not all cows on Farm 1 were manually condition scored which accounts for the difference in the number shown in Table 5.1.

5.1.2 Results

The condition score must be approximated by making the assumption that the true score of a cow is the average of all the human scores for that cow. In doing this, the bias of both the system and each individual scorer can be calculated. To calculate the bias of the system, the difference between the calculated score and the average human score is determined.

$$\overline{x_{sb}} = \frac{1}{N}\sum_{i=1}^{N}(xt_i - xs_i) = 0.0107$$

where $xt = average\ human\ score$ and $xs = system\ calcualted\ score$

The standard deviation of this bias is given by:

$$\sigma_{sb} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \overline{x_{sb}})}{N}} = 0.3786$$

This was also repeated for each of the scorers and the results are given in Table 5.3.

Table 5.3

Scorer bias - comparing the average human score to the individual

Scorer	Bias	Std. Dev	Scorer	Bias	Std. Dev
A	-0.139	0.28	E	0.088	0.41
B	0.142	0.34	F	0.229	0.46
C	0.198	0.43	G	0.024	0.60
D	0.168	0.36	H	-0.006	0.69

To calculate the probability that the system will fall within range of a specified score, the following equation can be used:

$$P_{SCORE} = P\left(\left(\left(-\frac{1}{2}\times SCORE\right) - CCF - \overline{x_{sb}}\right)\Big/\sigma_{sb} < Z < \left(\left(\frac{1}{2}\times SCORE\right) + CCF - \overline{x_{sb}}\right)\Big/\sigma_{sb}\right)$$

where $SCORE$ is how close the system should be to the average human score.

The probability that the system score will fall with 0.5 of the average human score is:

$$P_{0.5} = P\left(\frac{-0.3857}{0.3786} < Z < \frac{0.3643}{0.3786}\right) = 0.68$$

The probability that the system score will fall with 1.0 of the average human score is:

$$P_{1.0} = P\left(\frac{-0.6357}{0.3786} < Z < \frac{0.6143}{0.3786}\right) = 0.90$$

The calculated condition scores that the system output did not match the theoretical probabilities shown above. The system scores given in the testing were shown to have a higher accuracy, this can be seen in Table 5.4. This shows the system scored 83% within half a point, and 98% within one point. While the theoretical probabilities are 68% within half a point, and 90% within one point. This is also shown in Figure 5.2 which shows a scatterplot of the System Score vs. The Average Human Score.

Table 5.4

Percentage of scores that fall within the given range - measured for the system

Error	**Count**	**Total**	**Percentage**
0.5	591	591	83%
1.0	104	695	98%
1.5	15	710	100%

Figure 5.2 shows how the system score compares to the average human score. The Pearson Correlation Coefficient for the 710 cows was calculated to be 0.73.

An analysis of the system score and the average score is given in Table 5.5. From this it can be seen that both the system calculated score and average human scores are very similar.

Table 5.5

Analysis of the system score and average score

Statistic	**System Score**	**Average Score**
Average	4.2	4.1
Median	4.0	4.0
Std Dev	0.52	0.53

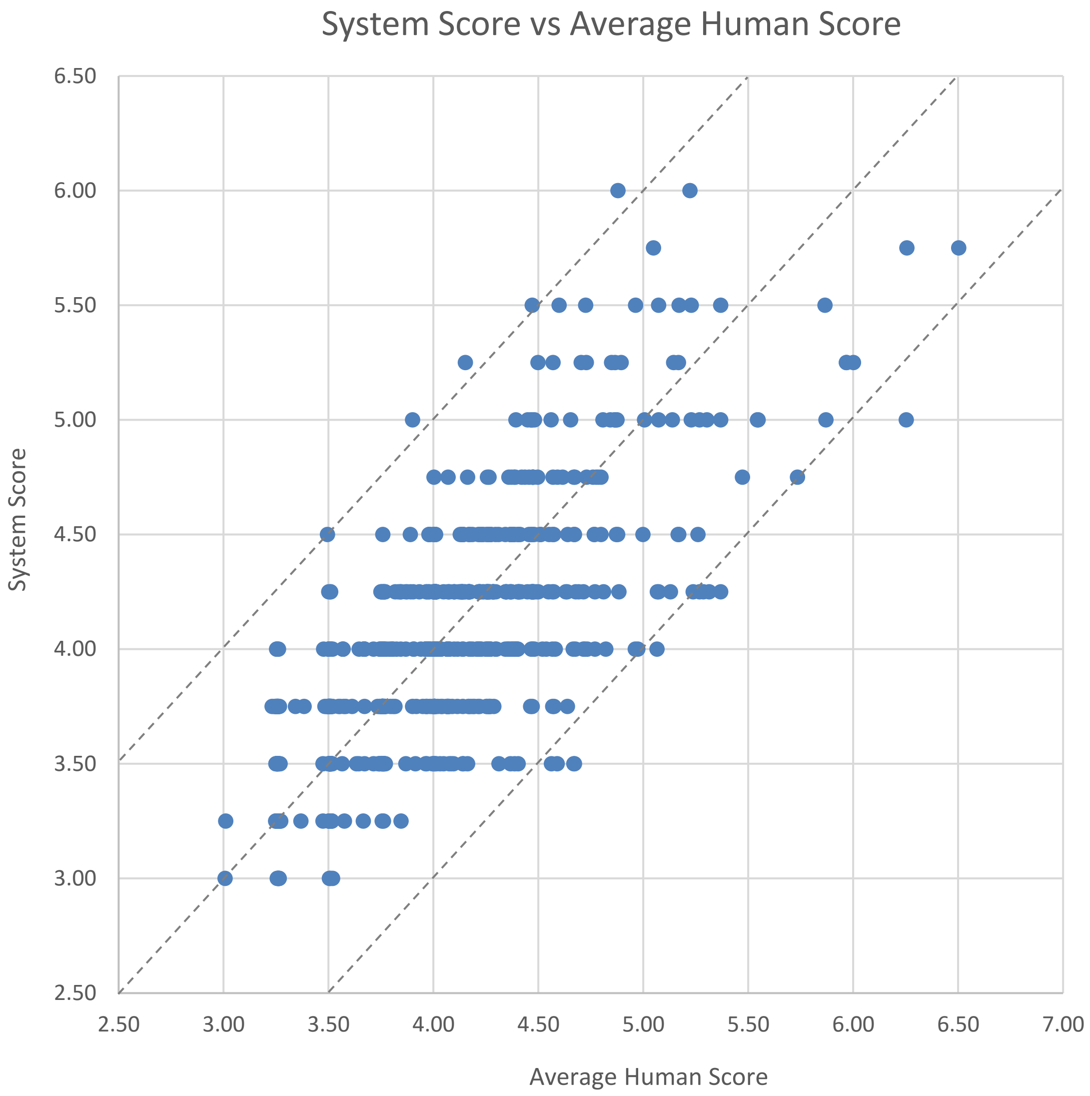


Figure 5.2 - System Score vs Average Human Score

To compare this to the accuracy of the current manual scoring methods, the frequency at which the manual scores matched, or fell within 0.5, or 1.0 of the average human score were calculated using the same methodology. Table 5.6 shows the percentage of how often the manual score fell within the given range of the average human score. Comparing these results to those given in Table 5.4, it can be seen that the system performed better than scorers B, C and H in both categories, and performed better than all but two scorers in one category.

Table 5.6

Percentage of scores that fall within the given range

Person	**Within 'x' Points of the Average Human Score**	
	$x = 0.5$	$x = 1.0$
A	83	98
B	70	93
C	54	89
D	85	97
E	90	99
F	83	95
G	89	96
H	78	95

5.2 System vs. Time

The second test was to monitor how accurately the system could track a single cow over an extended period of time.

5.2.1 Methodology

The system was setup at Farm 1 to capture images of the same herd on a weekly basis from September 18, 2014 through to March 17, 2015. During this time period, the herd was also manually scored by a single DairyNZ accredited condition scorer on a monthly basis.

It was possible that some cows were drafted and were therefore not present at every milking session. If a cow was missing from one dataset but was present in the next, then it was kept in the analysis. However, if the cow was also missed from the second dataset, it was removed from the analysis. In total, there were 202 cows present from the September 18, 2014 through to March 17, 2015.

5.2.2 Results

Figure 5.3 shows the average system calculated condition score for the herd over a six month period along with the ideal condition score range (Seales Winslow, 2014; Stewart, 2005; DairyNZ, 2012). From this it can be seen how well the system tracks the performance of the herd over an extended period of time. It is worth noting that the system score that is shown is only form one milking session per week. As such, the analysis that is shown is not necessarily a true representation of the herd as it may contain outliers that would otherwise be removed by taking the average of the full week of data. However, this does show the potential of the system being used to track the performance of the herd from a farm management perspective.

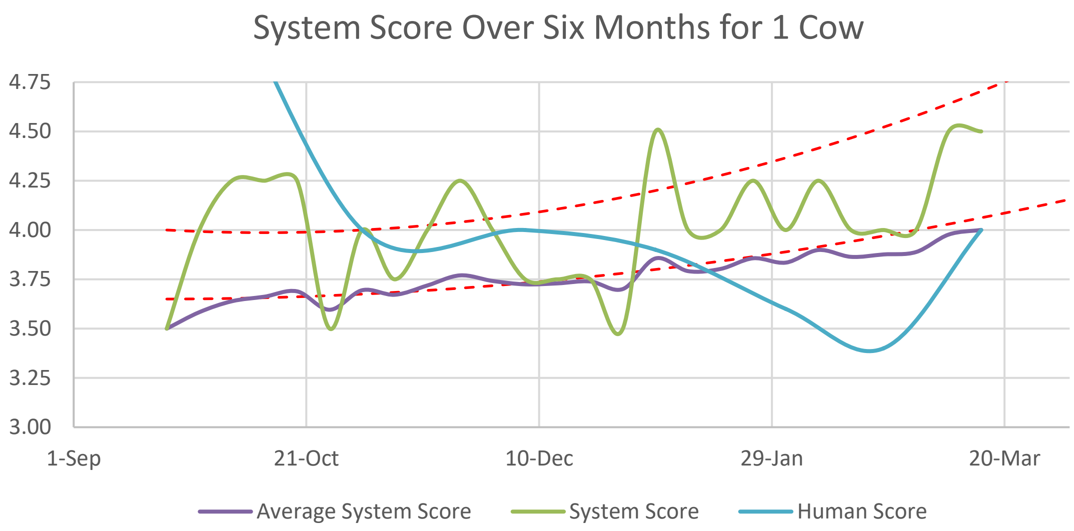


Figure 5.4 shows a running average of the scores for the cow from Figure 5.3. From this it can be seen that the average contains much less variance as expected and tracks along the lower recommended condition score. There are two things that should be noted, first is that this average is taken over six weeks with one reading per week; and not multiple consecutive readings per week as done in section 5.3. Second, is that the human score is on a monthly basis and as such contains fewer data points when compared to the system calculated score.

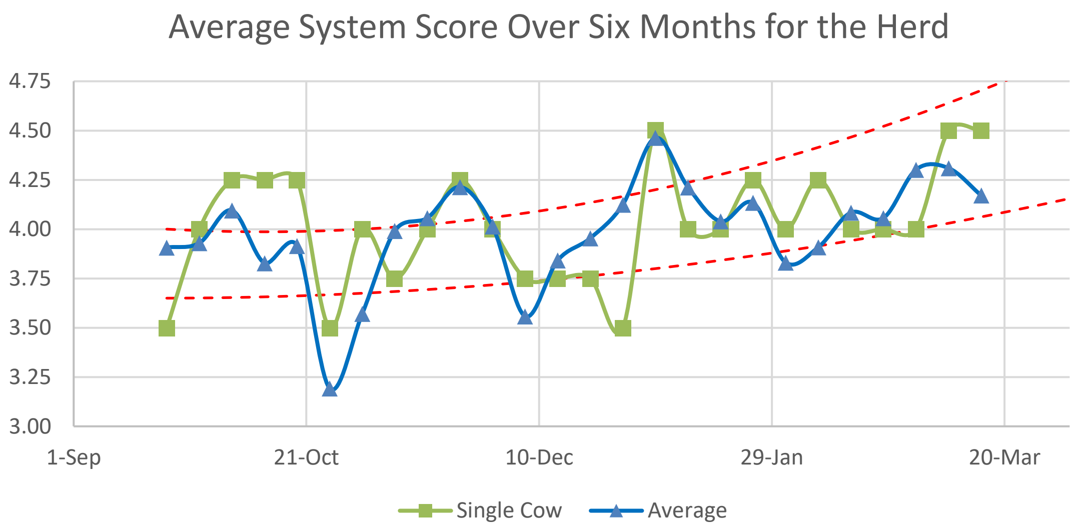


Figure 5.3 - Average condition score of the herd, and the score of a single cow, over a six-month period along with the ideal score range.

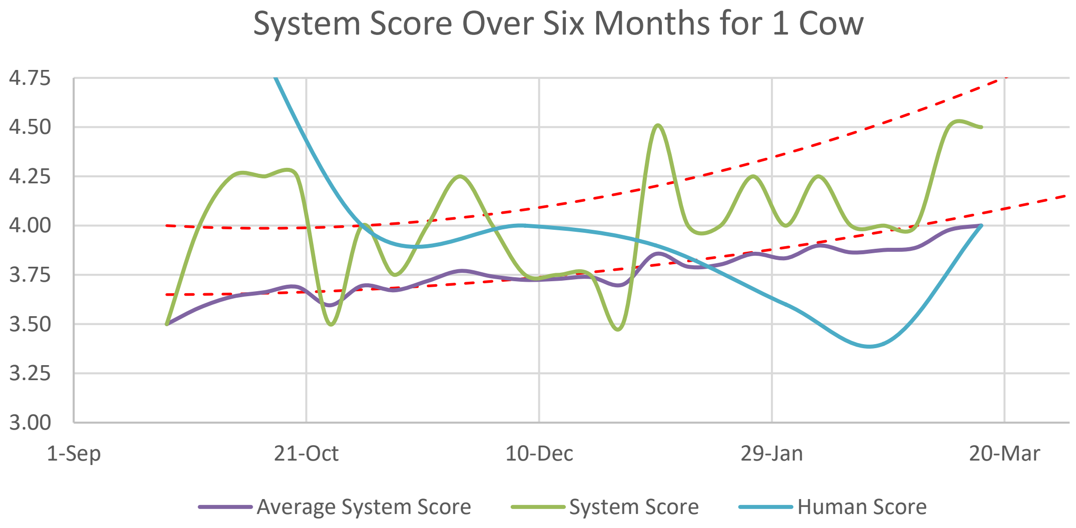


Figure 5.4 – System calculated score (raw and running average) and the Human given score over a six-month period

5.3 System Variation vs. Human Variation

The third test was to determine if the amount of variation that is inherent with the system is less than the variation present between human scorers. This test is essential in determining the validity of the system.

5.3.1 Methodology

To measure the variation between human scorers, groups of accredited condition scorers manually calculated the score of each herd either at the same milking session or at two consecutive milking sessions. Each person was isolated from the others to prevent communication while scoring; this was done to ensure that one scorer could not influence another. Each cow was scored once by each individual.

In order to quantify the variation present within the system, it was installed on Farm 1 for nine days, Farm 2 for ten days, and Farm 3 for five days. Over this period of time the system would calculate a condition score for each cow twice a day as both the morning and afternoon milking sessions were analysed. The variation in the calculated condition score could then be monitored over time for a given cow, highlighting the amount of noise inherent within the system.

5.3.2 Results

The variation present between scorers can be clearly seen in Figure 5.5 which shows the distribution of scores given to each cow for each of the three farms. An analysis of each scorer per farm is shown in Table 5.7, from this it can be seen that

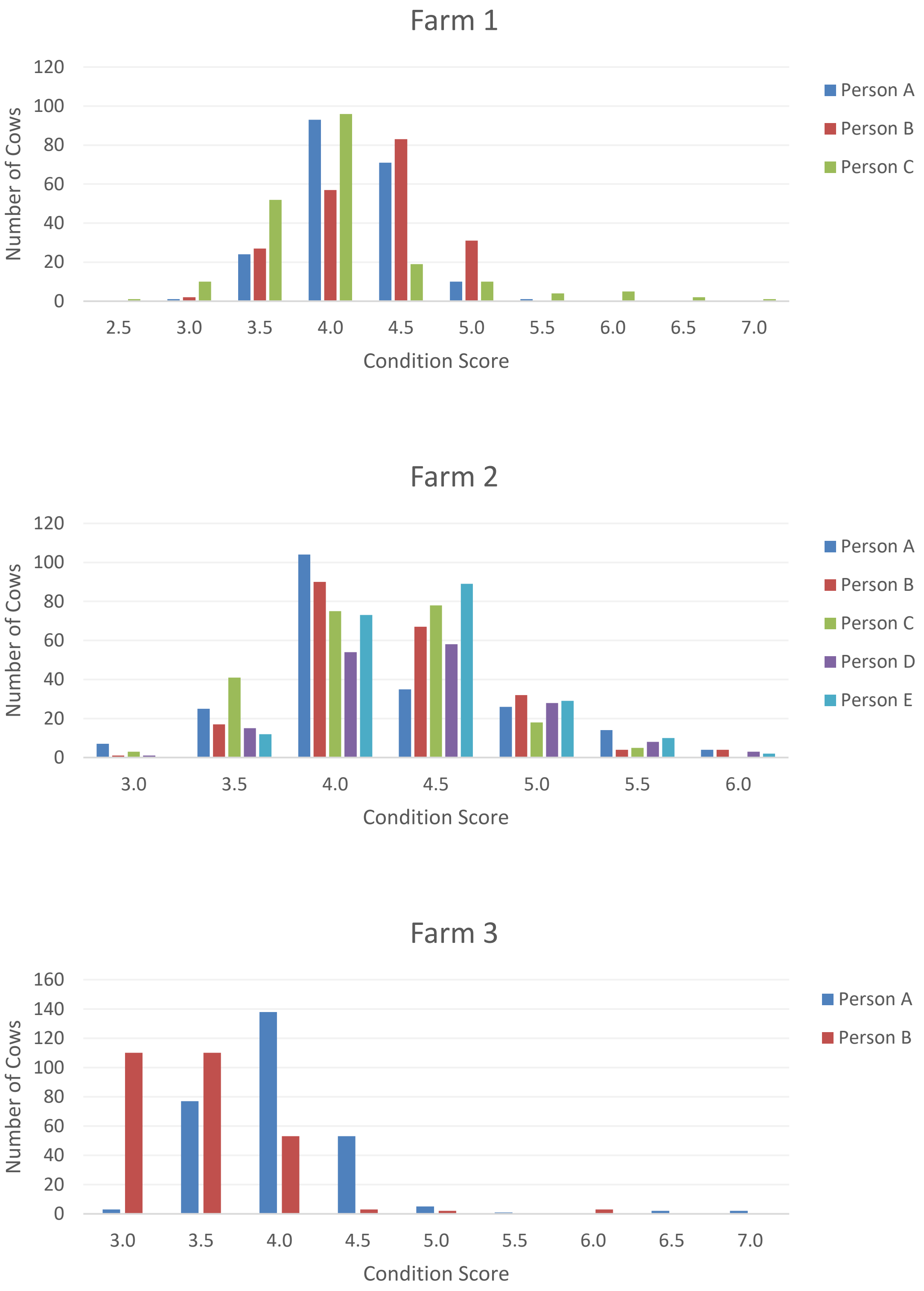


Figure 5.5 - Manual condition scores for each of the three farms

Table 5.7

Analysis of each scorer at each farm

Scorer	Farm	Mean	Median	Std Dev
A	1	4.2	4.0	0.4
B	1	4.3	4.5	0.4
C	1	4.0	4.0	0.7
D	2	4.2	4.0	0.6
E	2	4.3	4.0	0.5
F	2	4.2	4.0	0.5
G	2	4.4	4.5	0.6
H	2	4.4	4.5	0.5
I	3	4.0	4.0	0.5
J	3	3.4	3.5	0.5

While the manual condition scoring was being performed at Farm 1, eight cows were scored twice as they remained on the rotary platform after the first pass. Table 5.8 shows the difference in scores between the first and second pass. Although this only occurred for eight cows, this still shows that there can be a significant difference in the manual score given by the same scorer to the same cow only a few minutes apart.

Table 5.8

Manual condition scores for cows that were scored twice within the same session

Cow	Person A		Person B	
	Pass 1	Pass 2	Pass 1	Pass 2
1	5.5	5.0	5.0	5.0
2	4.0	4.5	4.0	5.0
3	4.5	4.0	4.5	4.0
4	4.0	4.0	3.5	4.5
5	4.5	3.0	3.5	4.5
6	4.5	3.5	4.0	4.5
7	3.5	4.0	3.5	3.5
8	4.5	3.5	4.0	4.0

All five scorers scored 132 of the cows from Farm 2. Table *5.9* shows how often these scorers are in agreement, and also how often the score differs by 0.5 points, 1 point, or 1.5 points. On average, it was found that the five scorers from Farm 2 had a person to person variance of 0.55. This was found by:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N}(\max(\alpha_{1:5}) - \min(\alpha_{1:5})) = 0.552$$

where $\alpha_{1:5}$ = score given to cow α by scorer $1:5$

Table 5.9

Range of condition scores for Farm 2 across all five scorers

Score Range	# Cows	Percentage
0	12	9.1%
0.5	74	56.1%
1	43	32.6%
1.5	3	2.3%

Table 5.10 shows the scores for a specific selection of cows at Farm 2. These cows were selected as it shows how all five scorers can be in agreement and give the same score to the same cow, as seen in the last three rows. While at the same time, the same five scorers can vary the scorers given by up to 1.5 points, as shown in the top three rows.

Table 5.10

Variation in condition scores for Farm 2 across five accredited scorers

Cow #	Person A	Person B	Person C	Person D	Person E	Average
260	3.5	4.0	3.5	4.0	4.5	3.90
3	5.0	4.5	5.0	5.5	4.0	4.80
10	5.0	4.5	3.5	4.5	4.5	4.40
42	4.0	4.5	4.5	4.5	4.5	4.40
267	4.5	4.5	4.5	4.5	4.5	4.50
39	3.5	3.5	3.5	3.5	3.5	3.50

To quantify the variation within the system, the cows at Farm 1 were scored for 13 milking sessions over nine days. The maximum difference of the system calculated condition score between consecutive milking sessions was recorded, Table 5.11 shows this variation for the herd.

Two cows were randomly selected from this dataset, the calculated scores for these two cows over these milking sessions is shown in Figure 5.6. Over the entire period Cow 1 varied from 3.5 to 5.0 and Cow 2 varied from 3.75 to 4.5. Between consecutive milking sessions the scores varied by up to 1.0, and 0.5 points for Cow 1 and Cow 2 respectively.

Table 5.11
Maximum variation from system calculated score over 13 milking sessions at Farm 1

Variation	# Cows
0	0
0.25	36
0.5	111
0.75	39
1.0	12
1.25	1

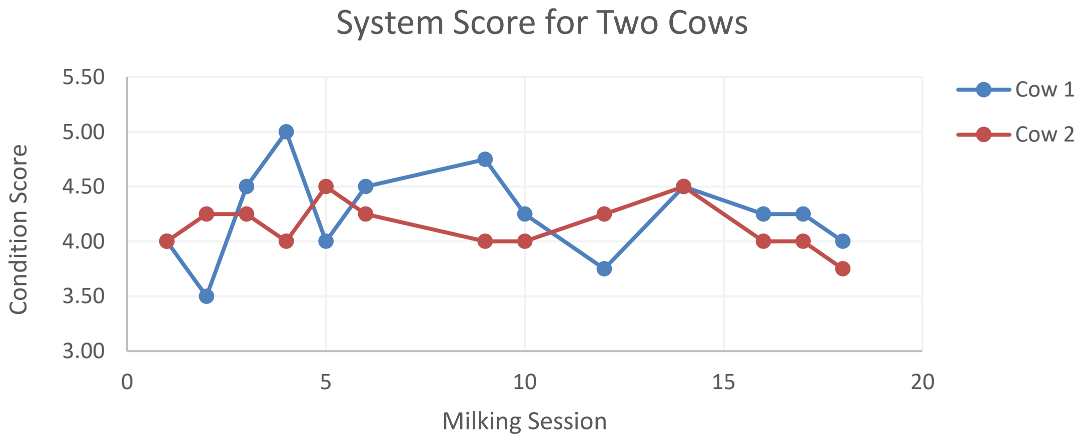
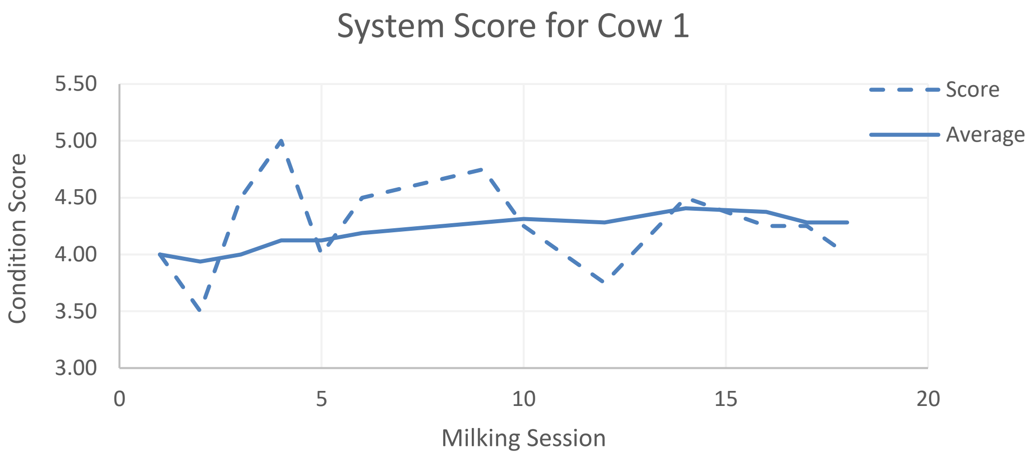


Figure 5.6 - Inherent variation shown by the system calculated condition score for two cows for 13 milking sessions of 9 days.

However, as this system has a real word application, an automated system would utilise a running average of the previous data to assist in removing some of this variation that is inherent within the system. Figure 5.7 shows the original scores for both cows 1 and 2, along with a running average of the past four days or eight milking sessions. This time frame was selected as a shorter time frame allows for a greater influence from the noise, potentially giving an invalid condition score. While a larger time frame would increase the delay between the change occurring and the system reporting the new condition. This allows for any true shifts in the condition score to be picked up on a weekly basis. It should be noted that the human estimated score is not present on these figures as there was only a single scorer so it may not represent the true score of the cow.



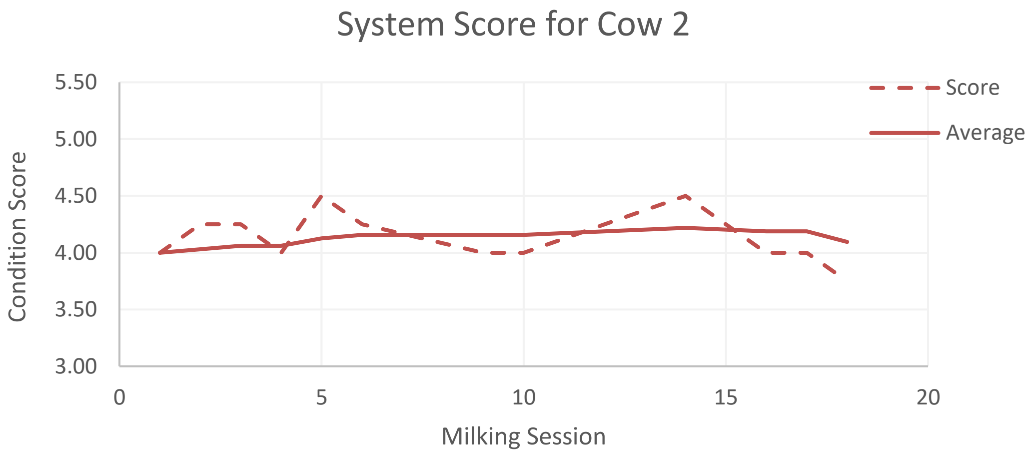


Figure 5.7 – System scores for two cows showing the raw calculated score and a running average

5.4 Algorithm Robustness

The fourth test was to verify the algorithms performance in a fully autonomous operating mode.

5.4.1 Methodology

The primary purpose of this test was to determine how well the outline detection functioned as the requirements state that the system must be able to operate without any human intervention. In order to do this, each detected outline was visually inspected where a pass or fail given based on how well the detected outline represented the cow within the image. Those images that passed would proceed onto the feature analysis allowing a condition score to be calculated for that cow and compared to the average human score, allowing for a comparison to the results obtained in section 5.2.

5.4.2 Results

In total 604 out of 710 cows were analysed, that is 106 cows that passed the outline detection check failed a visual inspection. These failures were due to the either the environment, or a following cow, altering the shape of the detected outline. The analysis was re-run over these 604 cows and the results are shown in Table 5.12 which gives a comparison between the original fully automated method, and the second method containing an intermediate manual visual inspection.

Table 5.12

Comparison of the fully automated system and a visually inspected system

	Automatic	**Inspected**
$\overline{x_{sb}}$	0.0107	-0.0330
σ_{sb}	0.3786	0.2926
$P_{0.5}$	68%	80%
$P_{1.0}$	90%	97%

Out of the 604 cows, 279 had a small change in score while the majority remained unchanged. This was expected due to the small number of images that make up the analysis for a given cow. Of those that did change, 87% were by 0.25, and 15% by 0.5.

Figure 5.8 shows the distribution of condition scores both before and after the visual inspection removed these cows from the analysis. From this it can be seen that the distribution remains largely unchanged, meaning that it was not a specific range of condition scores that the outline detection algorithm struggled with.

The probability of the system scoring within specific ranges of the average human score is shown in Table 5.13 along with the accredited scorers. This is sorted by the probability of giving the exact average human score.

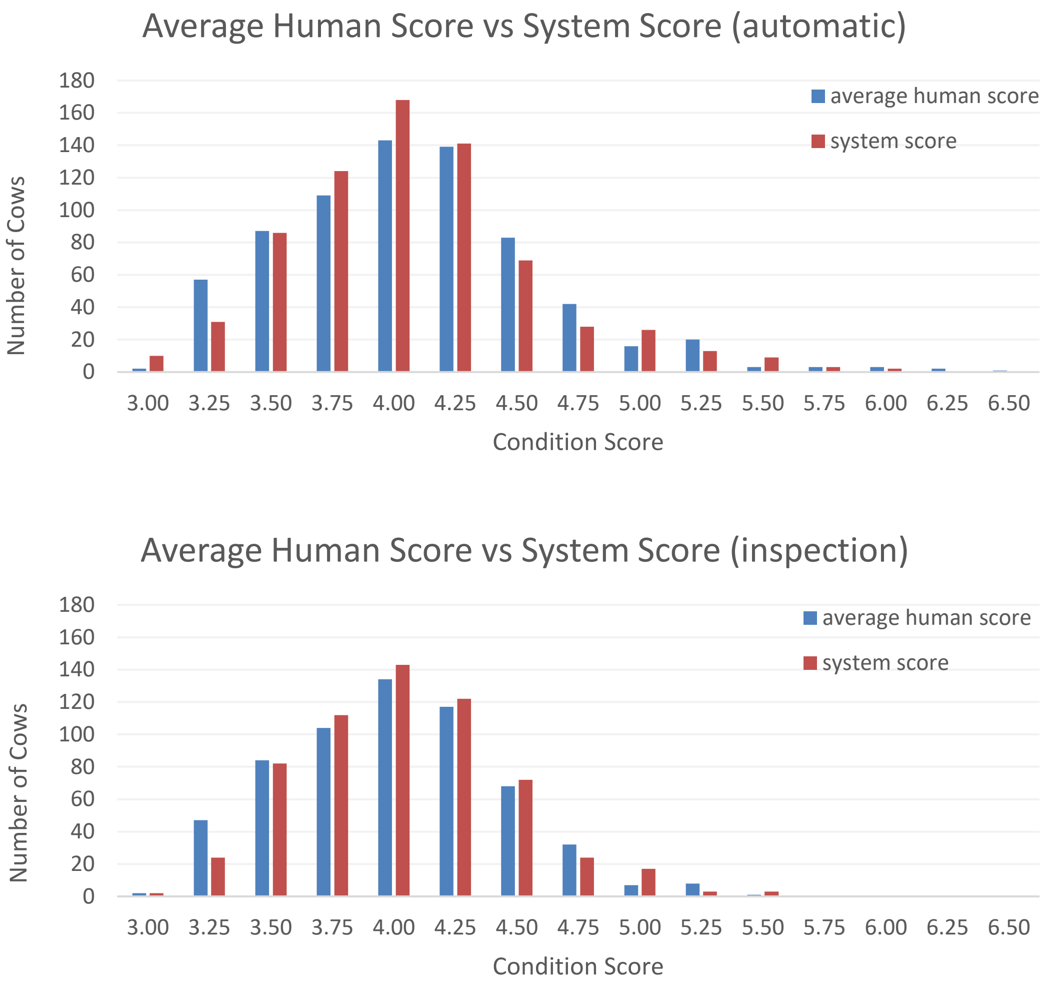


Figure 5.8 - Comparison of the condition score distribution between the average human and system scores

Figure 5.9 shows how the system score after the visual inspection compares to the average human score. Comparing this directly to Figure 5.2 shows a reduction in the spread of scores at the higher range. The Pearson Correlation Coefficient for the 604 cows was calculated to be 0.77. This is slightly higher than the original calculation.

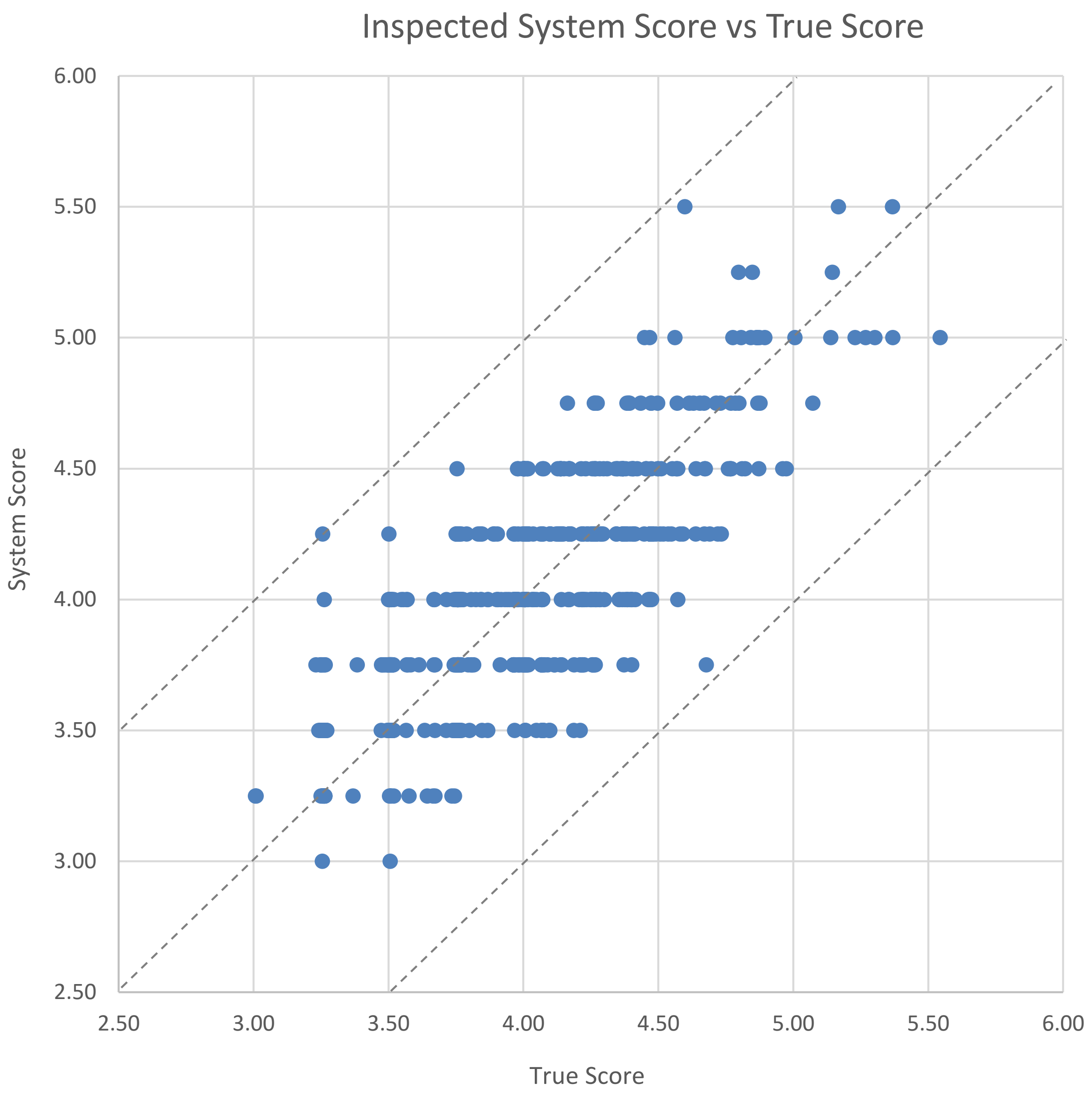


Figure 5.9 – Inspected System Score vs True Score

Table 5.13

Percentage of scores that fall within the given range for both accredited scorers and the system. Sorted by the probability of giving the exact average human score

Scorer	**Within 'x' Points of the Average Human Score**		
	$x = 0.0$	$x = 0.5$	$x = 1.0$
Person A	43	83	98
Person B	34	70	93
System: Inspected Outline	33	85	97
Person G	32	89	96
Person E	28	90	99
System: Automated Outline	26	68	90
Person H	25	78	95
Person D	24	85	97
Person F	24	83	95
Person C	23	54	89

5.5 Condition Score vs. Breed

The fifth and final test was to determine what affect the breed of the cow had on the condition score.

5.5.1 Methodology

In order for the breed to have an effect, the average difference between the average human score and given score must be large enough for the score to change. That is, the difference must be larger than 0.5 as this is the resolution of the scoring system in New Zealand. This gives the hypothesis as:

$$H_0 \colon \mu \geq 0.5 \text{ and } H_A \colon \mu < 0.5$$

For this test, all scores were rounded to the nearest 0.5. The absolute difference between the average human score and given score were then calculated for all accredited scorers and the system. From this the probability of the score exceeding 0.5 for each of the three breeds was then calculated.

5.5.2 Results

The breed of cow has no effect on the calculated condition score. Table 5.14 shows the calculated probabilities for each scorer and breed of cow, which shows that the P value in each instance is less than 0.05 and therefore the null hypothesis stated in section 5.6.1 can be rejected.

Table 5.14

Probability of each scorer exceeding 0.5 of the average human score based on the breed

	Scorer	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**System**
Fresian	Std. Dev (σ)	0.19	0.20	0.25	0.16	0.14	0.19	0.16	0.18	0.24
	Average ($\overline{x}$)	0.20	0.27	0.32	0.25	0.20	0.25	0.20	0.25	0.32
	Sample Size (N)	113	113	103	215	215	220	167	168	344
	P Score (P)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed	Std. Dev (σ)	0.19	0.20	0.25						0.16
	Average ($\overline{x}$)	0.20	0.28	0.36						0.32
	Sample Size (N)	96	96	96						96
	P Score (P)	0.00	0.00	0.00						0.00
Jersey	Std. Dev (σ)	0.19	0.20							0.25
	Average ($\overline{x}$)	0.29	0.30							0.24
	Sample Size (N)	270	270							270
	P Score (P)	0.00	0.00							0.00

5.6 Experimental Discussion

In this section the results obtained in the previous sections are discussed. There are three main aspects of the system to analyse, these are the determining how credible the calculated condition score is, how much variation is inherent within the system, and how robust the developed algorithm is.

5.6.1 Credible Condition Score

The systems calculated condition score has been calibrated using trained veterinarians that have been certified using the DairyNZ Body Condition Score Assessor Certification Program. This program was developed by DairyNZ to help standardise condition scoring across the country. (DairyNZ, 2015).

When directly comparing the systems calculated condition score with the average human score, it can be seen that there is a correlation coefficient of 0.73. Ideally, this relationship would be stronger, but it does show that there is some strength in the ability of the system to be a predictor for the condition score.

It can be seen in Table 5.3 that the bias within the system calculated score is lower than seven of the accredited scorers. This table also shows that the spread of differences between the system calculated score and average human score is one of the smallest. The combination of these two parameters proves the system is precise in the calculation of the condition score when compared to the average human score.

The system successfully predicted the condition score of 83% of the 710 cows within half a point of the average human score. This shows that the score was calculated with a greater accuracy than what the probabilities suggested which was that the system should only score 68% within half a point. The discrepancy in accuracies will come from the use of the correlation coefficient factor in the probability calculation. Both of these accuracies highlight two important facts.

First, the system calculated condition score is the same accuracy as two accredited scorers for being within half a point of the average human score. This can be seen in Table 5.6 which gives the percentage of how often the manual score fell within the given range of the average human score. Similarly, it performed as accurate as one other scorer for predicting the score within one point at 98%.

Second, with an accuracy of 68% the system would not be sufficient in providing useful data to a farm management system. However, Table 5.6 shows that two accredited scorers had accuracies similar to this with 54% within half a point, and 70% within half a point respectively. This highlights a main issue with the current manual scoring method as this accuracy is not sufficient for an automated system.

These points demonstrate that the system is able to calculate the condition score with an accuracy that is at least equivalent to that of an accredited scorer. However, it also shows that the accuracy of the fully automated system does not exceed that of all the human scorers.

Table 5.13 shows how the performance of the system increases when a visual inspection is applied to the images. If each scoring method is ranked based on the accuracy, the original fully automated system scores ninth for both scoring within half a point, and within one point of the average human score. This increases to third for both categories when the visual inspection is applied to the processing. This highlights the potential of the system if the errors can be removed from the analysis.

Table 5.15 shows how the system accuracy compares to previous studies that have been undertaken. All studies are on the same scale ranging from 0 to 5; the system scores from this study were converted using the equations given in Table 2.2. It can be seen that the system performs very well and shows some promise for developing the system further.

Table 5.15

Comparison to previous studies

Score Range	**Within 0.25**	**Within 0.5**
J.M. Bewley et al. (2008)	90%	100%
System (Inspected)	92%	99%
System (Automated)	83%	97%
Spoliansky et al. (2016)	-	91%
Bercovich et al. (2012)	50%	79.5%

5.6.2 System Variation

From the results in Section 5.4 it can be seen that there can be a significant amount of variation between people performing manual condition scoring. Table *5.9* shows the range of scores from five trained scorers. From this it can be seen that all five scorers were in complete agreement only 9.1% of the time, and therefore there are discrepancies with the scores 90.9% of the time. Table 5.10 shows how the scores from these same five accredited scorers can vary by up to 1.5 points for the same cow.

This variation is also evident when looking at Table 5.8 which shows the difference in scores for cows that were scored twice by the same person. It can be seen that both scorers scored the cows differently the second time more times than the same score was given. In one instance, a significant difference of 1.5 points was given between the first and second pass, even though only minutes had passed between the two scorings.

There is also a significant amount of variation within the system. Figure 5.6 shows how the calculated score for one cow varied by 1.5 points and the score for the second varied by 0.75, over a nine-day period. This shows that the variation present within the systems calculated score is similar to that of a single trained human scorer. In both instances the scores varied by as much as 1.5

As this research is focused on developing an automated system as part of a real-world application, a running average of previous calculated conditions would be used to assist in removed some of this variation that is inherent within the system. As any true change in condition score is slow, there would not be a significant difference between consecutive milking sessions. This allows time for the system to take multiple measurement and calculate a running average to base any decisions or future calculations on. A time frame of four days, or eight milking sessions, was selected to average over as a shorter time frame allows for a greater influence from the noise, potentially giving an invalid condition score. While a larger time frame would increase the delay between the change occurring and the system reporting the new condition. This allows for any true shifts in the condition score to be picked up on a weekly basis. From Figure 5.7 it can be clearly seen that there is a significant reduction in the apparent variation. The calculated score varied by 0.47, while previously it was 1.5 points; and similarly the score for the second cow varied by 0.22, while previously it was 0.75 points.

5.6.3 Algorithm Robustness

Discarding images from the feature analysis that had a poor result from the outline detection algorithm has resulted in a significant improvement in the accuracy of the system. This is shown in both Table 5.12 and Table 5.13

From Table 5.12 it can be seen that while the average error was slightly greater once the images were removed from the analysis, the spread of the errors was less. *Figure 5.8* shows the distribution of the scores remained unchanged, implying that a specific range on condition scores was not responsible for the lower accuracy.

Table 5.13 quantifies the improvement in accuracy when compared to the accredited scorers. The fully automated system was only greater than one scorer in the probability of scoring within half a point of the average human score. While after visually inspecting the outlines, the probability of the system giving the exact average human score increased from 26% to 33% which is greater than all but two of the accredited scorers.

This adjustment to the outline selection highlights the importance this section plays on calculating the overall accuracy of the system. The predicted condition score had a 68% probability of being within 0.5 points of the average human score. After manually inspecting each of the detected outlines, and discarding those images that were subjectively deemed to be invalid, the probability increased to 80%.

The algorithm developed within this research study was designed to extend the research carried out by previous studies which showed a strong correlation to the estimated condition score. For example the work by Halachmi, Polak, Roberts, and Klopcic (2008) and Halachmi, Klopcic, Polak, Roberts, and Bewley (2013) showed a strong correlation between the condition score of the cow and the fit to a parabolic shape. By adding the angles formed by specific anatomical points and the calculated condition score, similar to the work done by J.M. Bewley et al. (2008), Coffey (2003), and Bercovich et al. (2012), a more robust algorithm can be developed that can still give a calculated condition even if features are missing from the analysis.

Table 5.15 shows that with further improvements to the outline detection algorithm, the system within the research study can outperform those developed in previous studies by achieving the highest accuracy within 0.25 points of the true score.

Chapter 6

General Discussion, Conclusions and Recommendations

This research project presented the development and implementation of an automatic condition scoring system for dairy cattle that can run in a real-world environment. A significant portion of time was dedicated to the development process of the hardware to ensure there was a stable platform for the software to run on.

The developed system successfully predicted the condition score within half a point of the average human score for 83% of the 710 cows scored, and 96% within one point. This accuracy is very similar to several of the accredited veterinarians; however, the results also showed that there was significant variation with the predicted score between consecutive sessions. This variation was found to be equivalent to that of one of the scorers.

The initial goals for the research project have been met. As stated in Chapter 1, these were:

- **The system must have a credible correlation to the manual body condition score**. The developed system has shown to have an accuracy equivalent to that of trained scorer, and also a similar variation in the scores given. Therefore, while the score may be credible it would also be considered low for an automated system as it should outperform accredited scorers.
- **The system must be fully autonomous**. It is possible for the developed system to run autonomously. However, it was found that by visually inspecting the detected outlines, the probability that the system would score within half a point of the average human score increased from 68% to 80%.
- **The system cannot manipulate the flow of the cows**. This was achieved by mounting the system above an existing entrance or exit where the cows were already forced to be single file.
- **The system cannot hinder the flow of the cow**. This was achieved by mounting the system above the path so it was not in the way or in view of the cow.
- **The system must be able to operate in a real-world environment**. The developed system can operate in all lighting conditions due to the use of lighting and a filter. It can also sustain wet weather conditions and being sprayed by workers with a hose cleaning the path.

6.1 Challenges

Several challenges have been identified that have the potential to lower the accuracy of the system.

6.1.1 Outline Detection

The outline detection is arguably the most critical part of the software. If the detected outline is incorrect, it has the potential to proceed to the feature detection and analysis. There are three possible outcomes of the outline detection algorithm, these are:

- The outline is detected as intended
- The detected outline follows the colouring of spots or parts of the environment
- The back of the cow is blocked by the cow following, preventing the analysis

Attempts were made to automatically correct any mistakes that pass through the edge detection algorithm, however this is not a guarantee. The improvement to the accuracy made by removing images from the detection shows both that these automated checks can be improved, and that the outline detection itself needs to be improved.

6.1.2 ID Reading and Association

While the identification of the cow has not been the focus of the project, it is still an integral part of tracking cows. There were two issues that were identified:

First, it was found that a cow could trigger the EID reader and not be seen by the camera. That cow would back away and a second cow would come in. This would offset all the IDs by one as the second cow would now have the ID of the first, the third cow would have the ID of the second etc. To overcome this, the images were manually checked and ensured the correct ID was assigned, and the id’s of the cows were also written by down as they passed under the camera.

The second issue was with the manual condition scoring. The IDs that were recorded had to be checked to ensure they were all the same number as it was possible for the scorer to misread the ID tag. This could be corrected as the cows were in an approximate order and the IDs were recorded by several other sources such as other scorers and the EID system.

6.1.3 Manual Scoring

An unavoidable challenge faced in the development of any automated system is the reliance on a manual score to calibrate the system. There is the possibility for the manual scoring to introduce the scorers own subjectivity into the system calibration. This will be more evident if the number of scorers used to calibrate the system is low.

6.2 Future Work

Firstly, the ideas related to overcoming the challenges are presented first. Some challenges will always be present such as the position of the cow under the camera. However, some of the challenges mentioned above can be potentially solved with the following solutions.

6.2.1 Imaging System

The imaging system should be upgraded to utilise a three-dimensional camera. The primary benefits of doing this are:

- The outline detection will become more accurate and robust across a range of environments. This has the potential to run a continuous calibration to ensure the ground level is always updated, based on the change in depth for each pixel. This will allow the system to be more aware of its operating environment allowing the cow to be extracted more reliably compared to a blanket value of ignoring everything beyond a specified distance.
- The analysis of the current features can remain the same.
- Analysis of new features can be added to increase the accuracy of the calculation. These features could include the long and short ribs as shown in Figure 6.1. These are clearly visible in the two-dimensional camera but cannot be isolated and analysed in a reliable method. Other methods such as fitting a sphere to the shape of the cow are also a possibility (Hansen et al., 2015).
- Hansen et al. (2015) and Spoliansky (2016) noted positive results with utilising a three-dimensional sensor.

The limitations of upgrading to a three-dimensional camera are:

- The camera and target may need to be shielded from direct sunlight
- Hansel et al. (2015) noted similar difficulties with isolating the cow, however these issues can be overcome based on adjusting the physical setup and the imaging processing algorithm that is used.
- The camera is significantly more expensive than the current setup if it is to work in an outdoor environment. A low-cost camera could be utilised the camera can be housed in a way to block the sunlight.
- The camera would require a larger power supply than the current setup.

Figure 6.1 - Image of the cow from above showing the detail of the ribs

6.2.2 Cow Flow Manipulation

Manipulating the flow of cows to ensure that only one cow is beneath the system at a given time will potentially improve the overall accuracy of the system given the current imaging sensor. A three-dimensional sensor will not benefit from this as much as the current setup as a second cow can be filtered out by tracking the changes and the corresponding directions in height.

Ensuring only one cow near the system will be beneficial to the current system for multiple reasons:

- Force the cows to slow down which would ensure better image analysis
- The following cow will be unable to obstruct the view of the current cow under the camera
- The ID will be linked to the correct cow

6.2.3 Machine Learning

The use of a machine learning system is a different approach to the image analysis. This approach combines the typical computer vision system with a subset of artificial intelligence, meaning the system can learn.

The primary benefits of doing this are:

- The system can continue to learn over time improving the reliability of the calculations
- It is likely that the variation from within the system would reduce as it learns from more datasets over time
- Very accurate and fast method of analysis. Although the accuracy is dependent on the images used to train the system.
- It may only take one or two milking sessions to train the system to work on a new farm. Spoliansky et al. (2016) noted it required 10 cows with 120 seconds of video each. This

information could then be shared with other systems allowing for more accurate calibrations.

The limitations of implementing a machine learning system are:

- A significant amount of data is required to initially train the system. This will take a considerable amount of time to collect, and the imaging system would need to be finalised first.
- How the system gives the results is not known. That is, the system takes the input image and gives an output with no justification or ability for the user to check the logic involved in the decision making. This black box approach can be undesirable in some cases.

6.2.4 Detection Algorithm

Sections 5.4 and 5.6.3 show that discarding images from the feature analysis based on the results from the outline detection algorithm can significantly improve the accuracy of the system. Based on these results it can be seen that further work is required to improve the current algorithm in order to fully automate the process. An alternative is to update the imaging system as mentioned in section 6.2.1 as this would require a new isolation algorithm as the input would be different.

6.2.5 Additional Testing

Additional data collection and analysis is required to improve the algorithm, quantify the system performance, and quantify the performance of the current manual method. These tests would include:

- Test with more trained professionals. Using the scores from ten individuals is not a good representation of the current scoring method. Increasing this number will reduce the subjectivity within the system calibration and also give a more accurate comparison between the current scoring method and an automated system.
- Test that the same cow will give the same score if analysed again straight away. This was unintentionally tested with the manual scoring for a few cows and is covered in section 5.3. However, this should be expanded to a larger test with both the system and manual scoring. As discussed in section 5.6.3, the variation within the system is currently too great so this test would provide a useful platform in order to verify if any changes to the algorithm have improved this.
- Test other breeds of cows. It was shown in section 5.5 that the breed had no effect, however images of all breeds of cows have not been analysed and therefore this may not hold true for all breeds.
- Test how well the system can track the performance of the herd. As mentioned in section 5.2, further testing should be done to analyse each milking session of an extended period of time. The results of this would help to determine how well the system can be used in a farm management role.

- Test other condition scores. As identified earlier, a major limitation with this research is the lack of animals at the extremes of the condition score ranges. It will be extremely difficult to find a large number of cows with these extreme scores as no farmer would willingly reduce the milk output and endanger the health of the animal. One possibility would be to go overseas to capture images of cattle during a drought as the cows are more likely to be low end of the condition scoring scale.

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Appendix A

The following shows the hardware construction

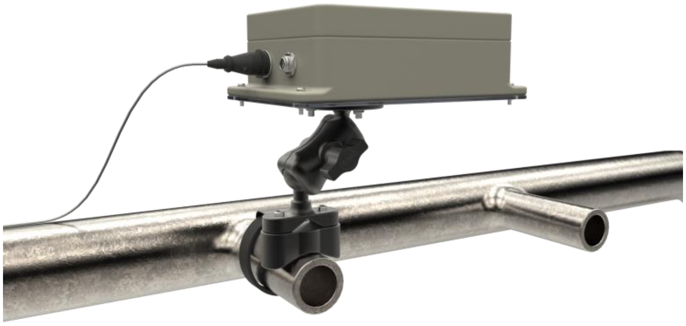
Narrow bandwidth filter and NIR LEDs can be seen on the bottom level.

PCB acts as a mounting platform for all other components. This shows all the power circuitry – battery, regulator, and charging circuit.

All other components have been added. This includes the USB drive, power switch, status LEDs, and the camera

The Raspberry Pi sits above everything else.

View of the system from the front showing the RAM mount

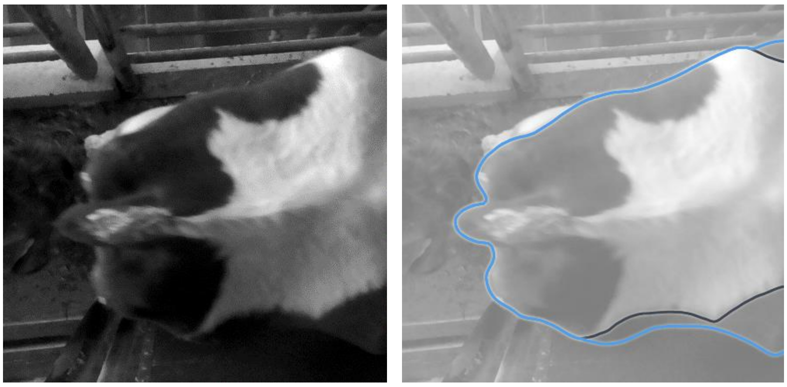


View of the system from the rear with the EID connector plugged in.

Appendix B

The following shows examples of the known challenges faces with the outline detection process.

The detected outline follows the wrong path based on the colouring of the cow.



The cow following can block the view of the tail regoins with its head. This is likely to occur if the cow under the camera cannot move forward and the cows behind bunch up. In this instance it is likely that there is already a captured image of the tail region before the view was blocked.

The position of the tail can give a false outline. This tends to only occur if the cow has remained stationary for a period of time beneath the camera and as such there is likely to be a good image of that cow before this occurred.