

Non-intrusive automated measurement of dairy cow body condition using 3D video

Mark Hansen¹
mark.hansen@uwe.ac.uk

Melvyn Smith¹

Lyndon Smith¹

Ian Hales¹

Duncan Forbes²

¹ The Centre for Machine Vision
Bristol Robotics Laboratory
University of the West of England, Bristol, UK

² Kingshay Farming and Conservation Ltd.
West Bradley
Somerset, UK

Abstract

Regular scoring of a dairy herd in terms of various physical metrics such as **Body Condition Score (BCS)**, mobility and weight are essential for maintaining high animal welfare. This paper presents preliminary results of an automated system capable of non-intrusively measuring **BCS** automatically as the cow walks uninhibited beneath a 3D camera. The system uses a 'rolling ball' algorithm on the depth map which simulates how well a ball of a set radius fits the surface. In this way a measure of angularity is generated which is shown to be inversely related to **BCS** on 95 cows. The measurements are shown to be highly repeatable with 14 out of 15 cows being scored within one quarter **BCS** score repeatedly and seven of those being scored within an eighth of a **BCS** score.

1 Introduction

Regular monitoring of a dairy herd helps a herdsman identify problems early and find solutions where possible to maintain the herd's welfare. Typical measures for this include **BCS**, mobility scoring and weighing the animals. For the most part, these are performed manually, are time consuming and in the case of **BCS** and mobility, are subjective. They can also cause discomfort to the animal (*e.g.* weighing or palpating the cow in a crush). Failure to ensure high animal welfare can lead to detrimental effects on cow productivity and longevity. To be able to obtain the information, on a daily basis, without the need of intervention allows the farmer to precisely manage the herd as a whole as well as being able to target specific cows that have shown specific problems. In this paper, we introduce such a system that estimates the **BCS** of each animal that passes beneath the camera, non-intrusively and in real time, without the need for the animal to break her stride. Fig. 1 shows the set up of the camera in relation to the cow.

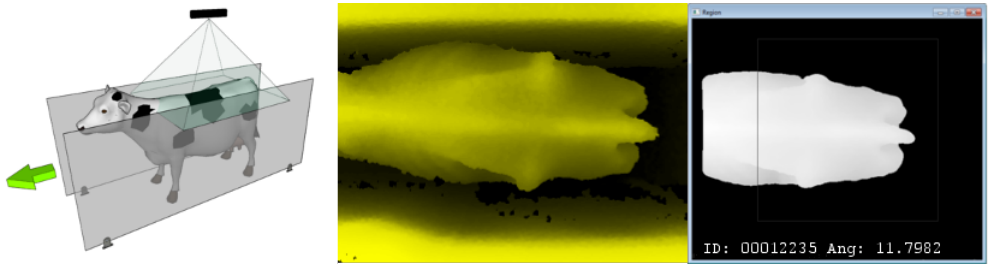


Figure 1: System apparatus (left) showing the position of the depth camera above the cow which passes unconstrained beneath. The narrow race permits only one cow through at a time. The camera's approximate field of view is also shown. Raw depth image of a cow is shown in the middle, and a screen shot of a processed cow is shown on the right.

The system we introduce is based on the variables which human experts use to estimate the **BCS** (Penn. State University 5 point method). In the past systems have been developed to measure the angles of a projected 2D boundary around the cow [11, 12] and more recently the use of 3D imaging has led to more shape based analysis [13]. However, none use the overall curvature of the surface of the cow's back to provide this information even though this is what is effectively being proxied by manual **BCS** measurement. Our system uses a 'rolling ball' algorithm on a depth-map from a commercially available 3D camera to estimate the angularity of the surface of the cow which is inversely proportional to the **BCS** (e.g. a skinny cow will be more angular than a fat cow).

2 Method

This section outlines algorithms and hardware used for the automated estimation of angularity. The preprocessing steps (shown in Fig. 2) are required to produce depth data suitable for use by the algorithms which actually perform the measurement.

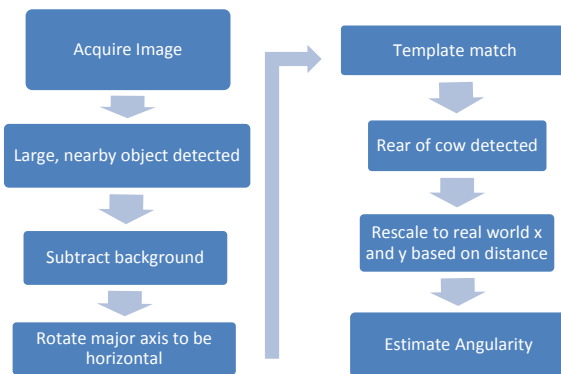


Figure 2: Pipeline of the image pre-processing steps used for automated assessment of angularity

2.1 Algorithm for angularity estimation

BCS is an essential indicator for monitoring cow condition, and in turn herd welfare. It focusses largely on the region of the hook and pin bones. A fatter cow has a higher score, and a leaner cow a lower score on the typically used 1-5 scale (Pennsylvania State University's Scoring Method). 3D imaging therefore lends itself very well to automating this analysis.

The approach we have adopted uses the rolling ball algorithm. This is a morphological operation which is analogous to attempting to fit a ball at every point across a surface. A small ball will be able to fit into all the nooks and crannies of the 3D surface, while a larger one will not. This allows us to estimate the angularity of the surface which correlates well with the fatness of the cow. A fat cow will be more rounded, whereas a lean cow is more angular through concavities at the pin bone regions and sharper areas around the hook. By comparing the results of the operation with the original depth image, it is possible to score the cow.

We have chosen the rolling ball algorithm because of the robustness that is provided by using a global image rather than relying on finding/tracking certain points (*e.g.* hooks and pins) which could lead to errant points being selected for analysis.

The use of the rolling ball algorithm as a measure of angularity for aggregate inspection on laser acquired range images is discussed in detail in [5] but this is the first time it has been applied to livestock. The rolling ball is simulated by the opening morphological operation (an erosion followed by a dilation) applied directly to the depth image (Eqn. 1).

$$A \circ B = (A \ominus B) \oplus B \quad (1)$$

A rolling ball with a diameter of 70px was found experimentally to provide the most discriminating results on a range of cows from **BCS** 2.25 to 4. It would also be possible to implement a scheme using different sized balls to see which fits best, or select the ball size as a function of the size of the cow.

2.2 Implementation

The automated BCS measuring device consists of any suitable depth camera (in this case an Asus Xtion Pro) and a computer (Intel i7 CPU) with 8GB RAM and a graphics card (GTX970). The camera is positioned 1.5-2m above the cow in a shaded area, over a narrow race which forces cows to walk in single file beneath it. The equipment is enclosed in an IP66 rated housing to ensure that the components do not get damaged either by dust or water. The housing is capable of withstanding a high pressure jet for cleaning purposes.

Cows are identified using an off the shelf EID reader capable of reading HDX ear tags present on the cow. The antenna is positioned just upstream of the camera's **Field Of View (FOV)** so that the ID is read



Figure 3: The device is shown at the top of the image with the cows passing beneath.

while the cow's body is in view of the camera.

The capture and analysis software is coded in C++ using computer vision algorithms developed as part of the OpenCV 2.4.10 and OpenNI libraries. The code is optimised to perform heavy image processing operations on the GPU. This delivers close to real-time (10-15fps) processing for angularity estimation. The frames are also recorded in order to allow for offline re-processing if required.

3 Method

In order to test the efficacy of this novel imaging approach to **BCS** estimation, two sets of data were recorded from a herd of ~200 Holstein-Friesians in terms of *accuracy* and *repeatability*. Accuracy refers to the agreement between ground truth (manually taken) **BCS** scores and the angularity scores measured by the device. Repeatability refers to the how closely the device scores the same cow on repeated viewings.

Accuracy was assessed by comparing the consensus of manual **BCS** scores taken by three trained staff with those obtained by the system on the following day for cows from each **BCS** score present in the herd. Ideally the scores would be compared on the same day, but logistical problems prevented this. Future work will address this. However it is unlikely the cows will change drastically in a day.

In order to test the repeatability, 15 cows were selected from the herd and passed under the system five times on the same day. All readings were taken in under an hour. Not all cows were read five times due to a cow sometimes having her tail out (which affects the reading due to high curvature around the entire tail head region and is automatically rejected by heuristically detecting whether the last pixel of the spine/tailhead falls too far behind the rest of the cow) or a following cow obscuring the view of the current cow's rear with her head. Manual **BCS** scores were not available for this test, so the repeatability is measured as the range of scores that were obtained for each cow across appearances.

4 Results

4.1 Accuracy

From the total herd of about 200 cows, the system automatically scored 115. There are three main reasons why the whole herd is not scored: a) a cow has her tail out, b) a following cow is obscuring the rear of the current cow with her head, and c) the RFID system has not successfully detected a tag. There is no obvious way of solving the first two, but future work will look at addressing the third.

Of the 115 scored, 95 had also been manually scored. Fig.4 shows the average angularity score for each **BCS** group. This indicates an inverse relationship meaning that as a cow lays down fat, her angularity decreases while her **BCS** increases. A one-way single factor ANOVA (analysis of variance) shows that the difference between **BCS** groups is significant. Those that do not follow the trend (2.25, and 3.75) only had a small number of measurements taken and are therefore probably not truly representative values.

The differences between adjacent groups at smaller **BCS** values are less than at the higher end. Interestingly similar findings for cows outside a **BCS** range of 2.5-4 is also seen in

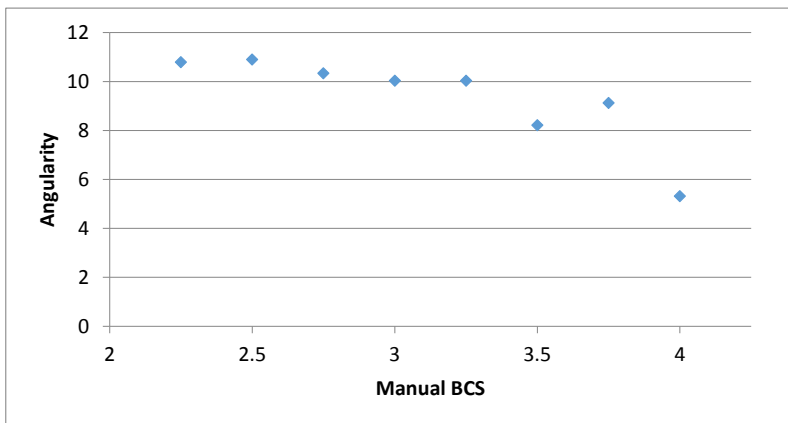


Figure 4: Average angularity scores which have been automatically determined for 95 cows plotted against manually scored **BCS**. There is an inverse relationship *i.e.* the fatter the cow the lower her angularity.

human observers [4]. We aim to increase the difference between adjacent scores with further tuning (perhaps by weighting areas differently, or adapting the radius of the rolling ball).

Even if this is not possible, it may be sufficient to be able to detect trends over time. Assuming the device is sensitive to small changes of an individual animal, the absolute **BCS** score is less important than a relative change in the angularity. Future work will look to assess the sensitivity of the system in this regard.

Fig.5 shows examples of the images that were acquired by the device to estimate the angularity of the cow, along with the manual **BCS** and the angularity score. Note the greater greyscale range in the tailhead and pin bone regions between lower and higher scoring **BCS** animals.

4.2 Repeatability

Figure 6 shows the median angularity scores along with the minimum and maximum recorded for each cow across all the appearances. Although each cow passed underneath the system five times, the system was not able to pick up each cow every time due to the presence of another cow, or because the tail was out (which means that the frame is automatically discarded as this results in a large increase of angularity around the tail head).

We now use the previous results to give an indication of what the angularity scores relate to. The range from the previous experiment was 11.61 (2.25 **BCS**) – 5.32 (4 **BCS**). This represents seven discrete levels of **BCS**, and 6.29 angularity points. Each quarter **BCS** can therefore be represented by 0.89 angularity points. A range in angularity score of 1.88 therefore represents ± 0.25 .

As reported by Ferguson *et al.* ([4]), experienced observers are unable to detect changes of ± 0.25 over one time period, and hence the system presented here operates at or above this rate. Cow 9 is the exception which is just outside this range with one anomalous reading out of the five, when there was a great deal of crowding under the camera. Apart from this instance, these figures show that the system works very reliably over numerous sessions to

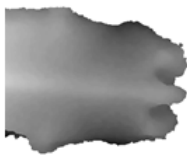

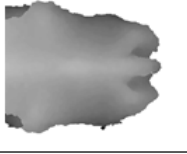
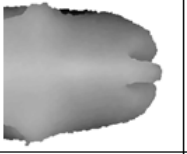
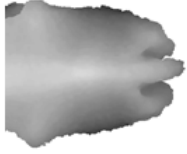



Depth Map	BCS	Angularity	Depth Map	BCS	Angularity
	2.25	11.61		3.25	9.84
	2.5	11.27		3.5	8.8
	2.75	11.14		3.75	8.52
	3	10.34		4	5.32

Figure 5: Example cow from each **BCS** score available from the herd showing the segmented depth map which is used to generate the angularity score.

provide the same score for each animal.

5 Conclusion

We present preliminary results of an automated system that uses a novel morphological approach on 3D data to measure angularity of a dairy cow's body shape which is believed to be a proxy to the animal's body condition score. The results show a high repeatability of the device when scoring an individual cow (across 15 cows), and an inverse relationship between angularity and **BCS** (across 95 cows).

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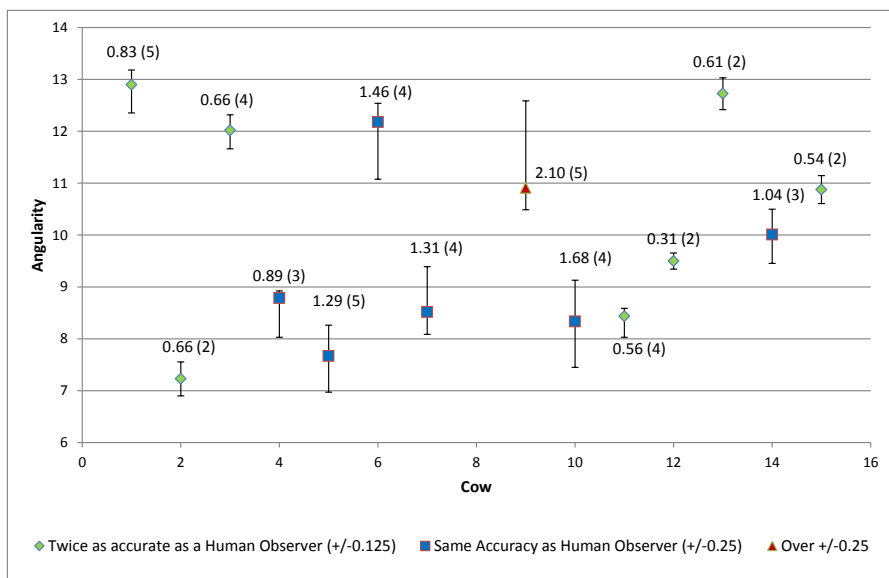


Figure 6: Median angularity for each cow across appearances. Error bars represent the range of scores which is shown in the data label accompanied by the number of appearances in brackets. Green data points indicate that repeated angularity scores fall within twice the repeatability score typically shown by humans, blue show those in line with human repeatability and red show worse repeatability.

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