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Automatic assessment of dairy cattle body condition score using thermal imaging

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ABSTRACT

Automatic and objective dairy cow body condition scoring has the potential to be used as a feed, reproduction, health and longevity management tool. The feasibility of including a body shape measurement in automatic monitoring of body condition was evaluated. The hypothesis tested was that the body shape of a fatter cow is more round than that of a thin cow and, therefore, may better fit a parabolic shape. The more prominent hooks and the tailhead depressions of a thin cow tended to diverge from the parabolic shape. An image-processing model appraised body shape. The novelties in this study compared to the previous ones (Halachmi et al., 2008; Bewley et al., 2008) were: (1) completing the full-automation of the system and (2) more accurate reference, not ultrasound. The model was implemented and its outputs were validated against manual body condition scoring (BCS) of 186 Holstein-Friesian cows. Pearson correlation between the thermally sensed BCS and the manual BCS was 0.94.

1. Introduction

Body condition scoring (BCS) estimates mobilization of energy reserves of cattle or the degree of fatness or thinness using a 5-point scale (Edmondson et al., 1989). The BCS is used as a feed management tool (Gillund et al., 2001). BCS influences productivity, reproduction (Dechow et al., 2002; Pryce et al., 2006), health and longevity (Heinrichs and Ishler, 1989). However, the current method of measuring BCS is manual and subjective; thus, the scores depend on the person scoring, familiarity with the cows, and consistency between scoring periods (Laven, 2002). Manual estimation of BCS is time consuming and requires trained labor. Therefore, the development of a device for automatic, objective monitoring of body condition scoring may be of economic interest.

Several attempts to automate BCS are reported in the literature. Coffey et al. (2003) captured digital images of the rear view of cows, and extracted curves manually by using image editing software and a mouse to isolate the lines. Sharony (2003) patented the automatic use of a three-dimensional representation of a region of interest and the use of an array of spatially separated light components, a light detector assembly, and a control unit for calculating the curvature of regions of a cow. Kriesel and McQuilkin (2005) patented a configuration of a light source, structural means for defining a target area for positioning a target animal, and a single camera. Ferguson et al. (2006) recorded multiple images from the rear of the cow at an angle of 0–20° relative to the tailhead, and three nutritional advisors independently assessed BCS from the images. Peacock et al. (2006) patented the use of 2D imaging for automated BCS recording, including the use of thermal imaging Bewley et al. (2008) used a digital camera to identify 23 points, corresponding to anatomical features, for potential predictions of BCS. These points were used to calculate 15 angles around the hooks, pins and tailhead. Keren and Olson (2007) used thermal imaging in assessing energy requirements for cattle on pasture. Halachmi et al. (2008) (1) reported a relatively low R-square statistic between thermal camera measurements and fat and muscle thickness, his R^2 was 0.47 and (2) did not reach full-automation since right frames from the video stream were selected manually. Recently, a 'Kernel PCA-Based Shape descriptor' was develop by Azzaro et al. (2011) representing an important step forward, because the researchers used visible-spectrum rather than thermal imaging. A visible spectrum has great potential because these cameras are relatively inexpensive. However, (1) Azzaro et al. (2011) compared the parabola- based algorithm (Halachmi et al., 2008) without its core feature – thermal imaging, and (2) Azzaro et al. (2011) reported only a semi-automation. A visible-spectrum combined with the Kernel PCA has great potential although Azzaro et al. (2011) did not reach full automation.

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None of these studies effectively achieved full BCS automation.

Therefore, the aim of the present study was to develop an apparatus and method for automatic and objective monitoring of BCS. The hypothesis tested was that the body shape of a fatter cow is more likely to be round than that of a thin cow and easily fit to a parabolic shape. The more prominent hooks and tailhead nadirs of a thin cow diverge from the rounded shape defined by the parabola.

2. Materials and methods

Nomenclature. Body condition scoring, BCS; Thermally sensed body condition scoring, TBCS; STD stands for Standard Deviation, and MAE stands for Mean Absolute Error (MAE). Radio frequency identification, RFID.

Data. Data for this study were collected at the SAC, Crichton Royal Farm in Dumfries, Scotland, UK, in December 2008. The study involved 186 Holstein cows. The BCSs in this farm ranged from 2 to 5 on 1 to 5 scale. The thermal images were collected 3 times per day, morning, noon. evening for 2 weeks (14 days) at the exit of the milking parlor.

Anatomical terms. The anatomical points of interest used in this study were (1) the hook bone (the most lateral point of the ilium), (2) the tailhead (the dorsal aspect of the root of the tail) and (3) the pins (the tuber ischium, the caudal point on the floor of the pubis, and the tuber ischium or pin bone).

Model validation, reference number ('the gold standard'), and statistics. The validation test was performed by comparing the model results with human observations of BCS. "Reference numbers" refers to the human BCS observations. The model was developed from images collected on days 1 and 2, and was validated on the subsequent days. The reference values were the average manual BCS assessments, monitored 7 times during 7 successive days (December 12–18, 2008) by one single expert who used the 5-point scale described by Ferguson et al. (1994). The average STD of the 7 reference scores across the week was 0.08 points. The BCS assessment and the thermal camera measurements were performed in the same week. The reference BCS was the average across all the data and no data were filtered out.

SPSS software was used to calculate nonparametric Spearman's rho correlation coefficient and analysis of variance (ANOVA). A regression line of the thermally sensed BCS (*Y*-axis) over the human observed BCS (*X*-axis) was fitted. Ideally, a perfect model ($R^2 = 1$) would be 45° degree line crossing the axis's origins.

Thermal camera. Halachmi et al. (2008) used InfraCAM SD thermal camera (FLIR Systems INC., Wilsonville, Oregon, USA) equipped with a focal plane array detector with a resolution of 120 × 120 pixels and a spectral range of 7.5–13 μm. In the current experiment, the camera was a L3-Thermal-Eye, model number TSC4500, S/N ZB595 DSP version 4.10.03 FPGA version 6.04 (L-3 Communications, 13532 N. Central Expressway, MS37 | Dallas, TX 75243 | USA) 320 × 240 pixel array and a spectral range of 7–14 μm.

Cow identification. The thermal camera was attached to the barn ceiling, 310 cm above ground level, above a weigh station at the exit of the milking parlor. The cows were identified electronically by the weigh station's radio frequency identification (RFID).

Image pre-processing and selecting a frame from a video. The image pre-processing was implemented by Matlab software. Halachmi et al. (2008) reported that the frames were manually examined in order to select the best frame from each cow. In the current experiment, the frames were selected automatically; The object extraction phases were: (I) converting RGB (red green blue) to BW (black–white) format, (II) measure properties of image regions (Regionprops Matlab function) and then label connected components in 2-D binary image (bwlabel Matlab function). At this point, (III) the largest object was the cow object. The frame with the highest intensity of the largest object (the cow object) was selected. Selecting the frame (video slicing, software 3, listed below) was simultaneously running with the cow identification (software 2 described below) and video acquisition (software 3 described below).

Pseudocode and flowchart (Fig. 1) *of the imaging algorithms*. Four software tasks were running in parallel in real time while the animal is on the weighing scale:

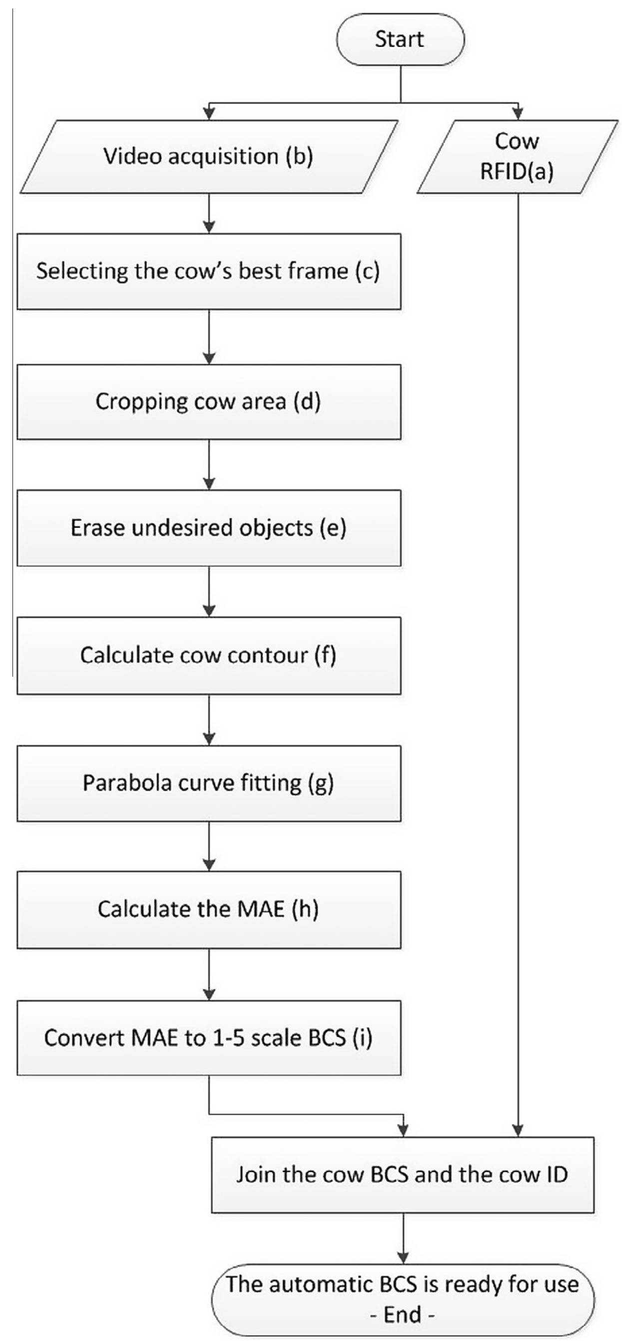

Fig. 1. Flowchart of the image processing steps of one single cow. The RGB (red green blow) file is converted to BW (black white) format. MAE stands for Mean Absolute Error between the cow contour and the fitted parabola curves. Cow identification (RFID) system is an off-the-shelf existing in the farm. Eventually the output is the automatically extracted body condition score (BCS). No human is involved in the entire process.