

Advances in automatic detection of body condition score of cows: a mini review

Abstract

BCS is a method to estimate body fat stores and accumulated energy balance of cows. This value influences productivity, reproduction, and health of cows. Therefore, it is important to monitor BCS to achieve a better animal response. In practice, this task is performed by expert scorers mainly visually, and could vary between scorers and be time-consuming. For this reason, several studies have tried to automate BCS by applying image analysis and machine learning techniques. An overview of selected studies is provided in this mini review.

Keywords: precision livestock, body condition score, automatic detection, image analysis

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Abbreviations: BCS, body condition score; ICT, information and communication technology; 3D, three-dimensional

Introduction

The BCS system is a means of accurately determining body condition of cows, independent of body weight and frame size,¹ using a 5-point scale with 0.25point increments (with 1 representing emaciated cows and 5 representing obese cows).^{2,3} Extreme values of BCS are related with health risk, low productivity level and impaired pregnancy rate.⁴⁻⁷ The subjectivity in the judgment of raters can lead to different scores for the same cow under consideration, or inconsistent scores of the same expert, which requires regular repeatability assessments.⁸ As a result of the increasing availability of wide range of information and communication technology (ICT), more and higher-quality information to be available is expected in support of daily decision-making.⁹ Consequently, there are multiple opportunities for automation and digitalization of livestock farming tasks, and different studies have particularly focused on automation of BCS. This brief review selects the most relevant and recent studies on the topic.

Discussion

Different authors have studied the feasibility of utilizing digital images to determine BCS. In this mini review relevant works later than 2007 and based on cow images from a top view were considered. In the Table 1 main characteristics and results from the selected papers are shown.

Developed methods have two stages:

- Image analysis techniques to extract relevant characteristics (such as angles, distances and areas between anatomical points; intensity/depth pixels values; cow contour or a representation of

it) to differentiate fat reserves levels of cows; Usage of collected characteristics to implement a BCS estimation model.

- Mostly, there are two types of models used: regression analysis models (as in)¹⁰⁻¹⁶ and algorithms that measure cow's body angularity (as in)¹⁷⁻¹⁹ according to the hypothesis that the body shape of a fatter cow is rounder than that of a thin cow. Moreover, three automation levels are described. In the lowest level are,^{10,12,15} which require to manually identify anatomical points in the images to extract characteristics to develop the estimation models. In the medium level are,^{11,13,20} where the input images used are manually selected, but the rest of the process is automatic. Finally, in the highest level are,^{14,16-19} where the process is completely automated. Among the latter studies, only^{17,18} carry out real time estimations (i.e. estimation result is showed to the user few seconds after the cow goes under the camera) because image preprocessing techniques (segmentation, normalization, features extraction) used in the other studies are time-consuming. In more recent studies the use of 3D cameras is more frequent. The use of thermal cameras,^{17,21} although allows an easy segmentation of the entire body of the cow (the warm cow shape highlight above its cold surroundings), are less common probably associated to their higher costs. In Marilyn Krukowski¹¹ and Dorota Anglart²⁰ they used red breed dairy cows because the camera used to acquire the images has operational problems with black pigment cows. The selected studies applied different statistical metrics to estimate BCS visually observed by experts, and the most frequently used indicator was the accuracy of the automatic estimated scores to be within ± 0.25 and within ± 0.50 increment score of the manual BCS. However, more efficient computing processing methods based on powerful machine learning technique fated to improve BCS accuracy are under testing.²²

Table 1 General characteristics and results of BCS estimation systems

Work	Camera	Cow breed	Dataset size (# of images)	Automation level	Real time	Results
Bewley et al. ¹⁰	2D Digital	Holstein-Friesian	834 (US-BCS), 767 (UK-BCS)	Low	NO	92.79% within 0.25, 100% within 0.5
Krukowski ¹¹	3D, ToF	SRB	351 (training), 120 (test)	Medium	NO	Test Set: 20% within 0.25, 46% within 0.5
Anglart ²⁰	3D, ToF	SRB	1329 (10% training, 90% test)	Medium	N/A	R=0.84. 69% within 0.25, 95% within 0.50
Azzaro et al. ¹²	2D Digital	Holstein-Friesian	286	Low	NO	Err _{r, LOOCV} =0.31
Halachmi et al. ¹⁷	Thermal	Holstein	172	High	YES	R=0.94
Bercovich et al. ¹³	2D Digital	Holstein	87 (training), 64 (test)	Medium	NO	Test set: R ² =0.64. Around 50% within 0.25, around 100% within 0.75
Salau et al. ¹⁴	3D, ToF	Fleckvieh	540 (for GLM with all features). 514 (for correlation analysis on individual features)	High	NO	R _{GLM} ² =0.7
Hansen et al. ¹⁸	3D, Light Coding (RGB + depth sensor)	Holstein-Friesian	95	High	YES	N/D. Inverse relationship between angularity and BCS. High repeatability scoring an individual cow (14/15). Test Set 1: R=0.89 y RMSE=0.31.
Fischer et al. ¹⁵	3D, Light Coding (RGB + depth)	Holstein	57 (training), 25 (test cows), 25 (test stage)	Low	NO	Test Set 2: R=0.96 y RMSE=0.32
Shelley ¹⁹	3D, Light Coding (RGB + depth sensor)	Holstein	18517	High	NO	71.35% within 0.25, 93.91% within 0.5 R ² =0.75.
Spoliansky et al. ¹⁶	3D, Light Coding (RGB + depth sensor)	N/A	11824	High	NO	74% within 0.25, 91% within 0.5

2D, two dimensional; 3D, three-dimensional; ToF, time-of-flight; SRB, swedish red breed; GLM, generalized linear model; US-BCS, united state body condition score; UK-BCS, united kingdom body condition score; R, correlation coefficient; R², coefficient of determination; LOOCV, leave one out cross validation; RMSE, root mean square error

Conclusion

The literature attempts to automate BCS assessment look promising as a tool for supporting cattle decision-making, in a context where ICT technology is becoming more efficient, productive, and cheaper. Acceptable accuracy within the range of human error has been reported, with room for improvement as more effective computing processing methods became available.

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Conflict of interest

Author declares that there is no conflict of interest.

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