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A 3D CAMERA APPROACH TO EVALUATING BODY CONDITION SCORE IN WALKING DAIRY COWS

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Abstract. *Body Condition Score (BCS) is an important index for assessing body fat accumulation in cattle and plays a crucial role in managing cattle productivity, feeding efficiency, and overall health. Currently, BCS evaluations predominantly rely on visual assessment and palpation by specialized personnel, which is time-consuming and labor-intensive. Consequently, many farms refrain from utilizing BCS for cattle management. Previous studies have focused on BCS evaluation of stationary dairy cows in rotary parlors, but this approach is not feasible for small and medium-sized livestock producers lacking such facilities. To enable BCS management for dairy cows on any farm, we propose a system utilizing image processing technology for evaluating cows while walking. In this system, 3D cameras are employed to capture images, and an evaluation model is constructed using feature extraction and multiple regression analysis. This model allowed the evaluation of cows with large BCS within an error margin of 0.25.*
Keywords: Body Condition Score (BCS), Dairy cows, Multiple regression analysis, 3D camera, Visual evaluation, Feature extraction

1. **Introduction.** In recent years, in the Japanese livestock industry, while the number of dairy cattle farms has been decreasing year by year due to the aging of the population and lack of workers, the number of cattle per farm has been increasing year by year [1]. This means that forms of livestock farming are becoming larger than in the past. As a result, there is a growing demand to reduce the labor burden on livestock farmers and to improve management efficiency. In response, development, and research on technologies to automate various farm tasks has been active in recent years, and many of these technologies, such as automatic milking robots and manure disposal machines, have already been introduced to the public [2]. However, there are still many technologies that are not widely used, one of which is the Body Condition Score (BCS) evaluation, which indicates the degree of body fat accumulation in livestock, and is a widely used method proposed by Ferguson et al., which is based on visual and palpatory evaluation called the UV method [3]. The Body Condition Score (BCS) of a dairy cow is typically assessed on a scale of 1 to 5, with increments of 0.25. A higher BCS indicates a greater accumulation of fat in the cow. BCS is closely associated with feeding rate, milk production, and feed efficiency, making it valuable not only for monitoring health status but also for efficient farm management. Cows with a high BCS are said to have a higher likelihood of leading to birthing accidents such as difficult deliveries. On the other hand, cows with low BCS require immediate improvements to address issues such as reduced milk production and poor reproductive performance [4]. The decline in milk volume is particularly significant

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as it directly impacts farm profits. Additionally, in recent years, the prices of formula feed have been rising due to various factors, including the international price of corn, a key ingredient, influenced by the situation in Ukraine and other variables such as raw materials and exchange rates. Figure 1 illustrates the trend of formula feed mill delivery prices [5]. As it is not feasible to reduce the amount of feed given to livestock, this price increase poses significant challenges for livestock farmers, emphasizing the importance of minimizing excess costs.

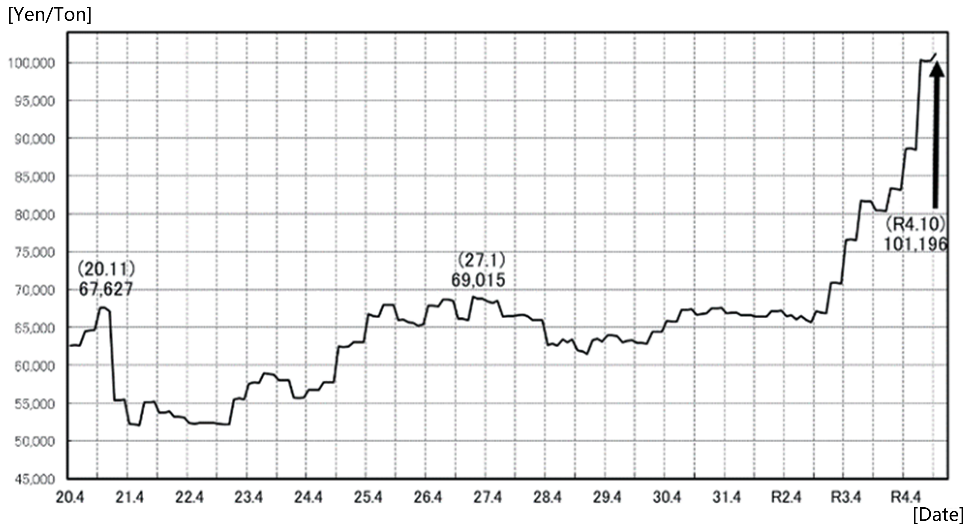

Figure 1. Trends in formula feed mill delivery prices [5]

The general BCS evaluation method is to evaluate each cow by visual inspection and palpation by an expert, but it requires a lot of time and effort to determine the BCS of all individuals on the farm. Therefore, it is necessary to evaluate all cows by the same person as much as possible when evaluating BCS. Therefore, while this is feasible for small to medium farms with a few dozen cows, it is extremely difficult for large dairy producers with more than several thousand cows to monitor BCS of all cows every few weeks. For the above reasons, although BCS is a very important indicator, many livestock farmers do not conduct regular BCS diagnoses of all their animals. Furthermore, it is not easy to pass on the technology of an ambiguous indicator whose evaluation is subjective to the observer to young farmers. Therefore, quantitative and fully automated daily BCS evaluation is required.

The purpose of this study was to develop a system to automate the currently manual BCS measurement from image acquisition to BCS estimation using ICT. The system was developed to estimate BCS for stationary dairy cows riding in a rotary parlor, which is only used on large farms. However, a larger percentage of livestock farms are small or medium-sized. In order to incorporate BCS measurement in small and medium-sized farms, this study aims to construct an environment in which any size farm can manage dairy cows by BCS by building an automated system from image acquisition to BCS estimation, targeting dairy cows in walking condition. We developed a system that automatically and objectively evaluates BCS by acquiring 3D images of livestock using a 3D camera and analyzing them using image processing technology and confirmed its effectiveness through demonstration experiment.

In past research on BCS evaluation, many studies have utilized classifiers to assess their accuracy. Alvarez et al. used the lightweight SqueezeNet network to learn features directly from a specific image data consisting of the depth image of dairy cow and achieved a classification accuracy of 78% with an error of 0.25 or less in BCS assessment [6]. Liu et al. defined 3D shape features from the selected six regions within the defined ROI formed with the landmarks on the cow's back and achieved a classification accuracy of 76% with an error of 0.25 or less in BCS assessment [7]. Shi et al. created a feature extraction network and achieved a classification accuracy of 80% with an error of 0.25 or less in BCS assessment [8]. Additionally, Zhao et al. developed a training method based on efficient net and achieved a classification accuracy of 91.21% with an error of 0.25 or less [9]. Given that BCS is assessed by experts only in increments of 0.25, this study also aims for an error of 0.25 or less.

This paper is structured as follows. Chapter 2 presents the pre-processing method for the acquired 3D images and the feature extraction method for BCS evaluation. Chapter 3 shows the experimental setup and the results of the multiple regression analysis. Chapter 4 provides the experimental results and discussions. These chapters clearly demonstrate the development of an automated BCS measurement system and its effectiveness. Finally, Chapter 5 concludes the paper.

2. Proposed Method.

2.1. Pretreatment. First, we will discuss the processing method for extracting only the area of the target object, the cow, from the distance image and the pre-processing for extracting features from the captured data. To acquire information on the back of a dairy cow, this study uses a 3D camera to capture a distance image of the target by shooting a walking dairy cow from directly above. The specifications of the 3D camera are resolution, 176×132 pixels; viewing angle, $60^\circ \times 40^\circ$ (horizontal $\times$ vertical); frame rate, 25 fps; measurement distance, $300 \sim 8000$ [mm]; maximum measurement range, 30 [m].

Figure 2 shows the algorithm for cow region extraction. 3D cameras record the linear distance from the camera to the object, so the further away from the center of the image, the larger the value of each pixel. Therefore, it is necessary to normalize the distance data to uniformly perform thresholding for the entire image [10].

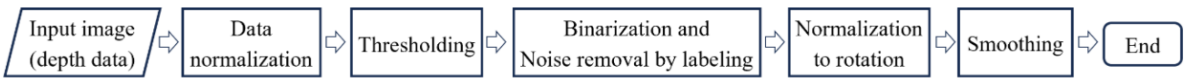

Figure 2. Algorithm for cow region extraction

Next, background removal by thresholding is performed. By setting a threshold value for distance data and eliminating data that does not meet that threshold value, background can be removed even from a single distance image.

Also, in this study, 8-connected labeling is used to count the number of pixels per region after labeling, and continuous regions with less than a certain number of pixels are considered as noise and removed. This process makes it possible to extract cows with a large number of connected pixels that are directly under the image, even when two or more cows are in the image.

Next, walking cows are often not photographed straight to the camera. To obtain the feature values under the same conditions in such cases, it is necessary to rotate the image and align the cow's body orientation. First, we connect the coordinate with the largest value in the top row of the distance image with the coordinate with the largest value in the area near the cow's waist. Basically, the point of maximum height on the cow's body surface is on the line of the spine, so the line connecting these two points will follow the line of the spine [10].

Finally, smoothing is performed on the distance image from which only the cow region is extracted. Noise outside the cow region can be removed by the process described above, but the fine noise on the cow region still exists, so it is removed by the smoothing process.

There are various types of smoothing filters, such as averaging filters, median filters, and Gaussian filters. Considering the results of feature quantities obtained and compared using these filters and the fact that the cattle being photographed are walking, an averaging filter with a kernel size of 5×5 is used in this study. Figure 3(a) shows an example image of a cow's back before the smoothing process and Figure 3(b) shows an example image of a cow's back after the smoothing process.

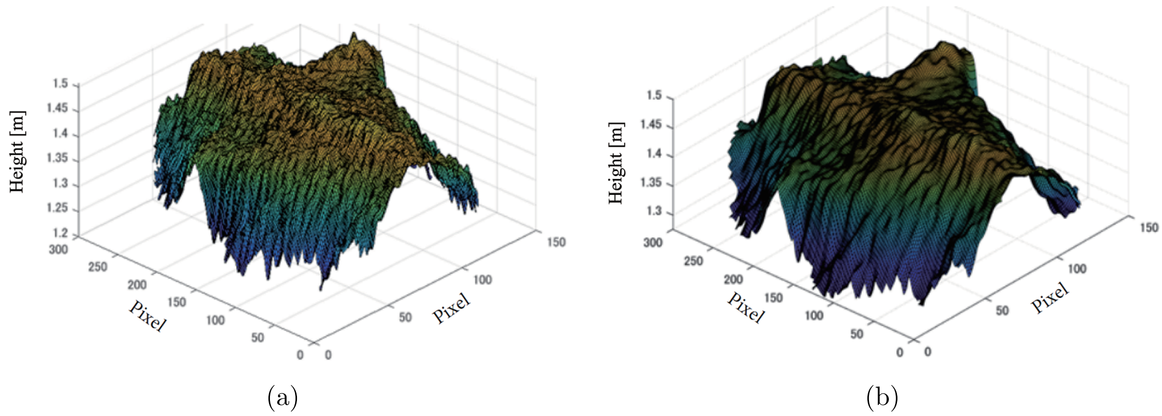

FIGURE 3. (a) Before smoothing, (b) after smoothing

2.2. **Feature extraction for BCS estimation.** This section describes the extraction of features for estimating BCS from the cattle distance data obtained in the previous processes.

The actual BCS evaluation by visual and palpation is mainly based on the degree of fatness around the cow's rump; cows with low BCS have more irregularities on the body surface due to the pelvic skeleton and ligaments being exposed, while cows with high BCS have less irregularities on the body surface due to fat between the skeleton and ligaments being hidden. In other words, the degree of unevenness can be quantified from all angles and used as a characteristic for BCS evaluation. In this section, we describe a proposed method for quantifying unevenness.

As a method for quantifying the uneven shape of the body surface, a method using the Root Mean Square Deviation (RMSD) is employed as a feature value. This is the main feature used in the previous methods of this study [10]. Unlike previous studies, in this study, the mean square deviation is not calculated for all cow regions, but only for the region near the hips, which is particularly uneven. The RMSD is calculated only for the bottom 50% of each image, and the average of these calculations is defined as the feature F_{RMSD}. Figure 4 shows an example of curve approximation using the least-squares method for a single row of data.

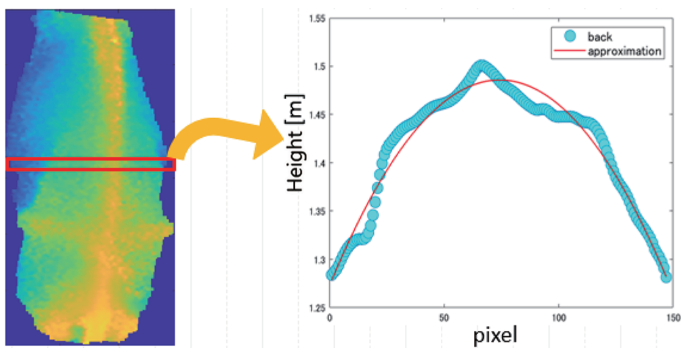

FIGURE 4. Curve approximation by the least-squares method

First, we create a 3D convex hull, which is the smallest convexity that can cover the distance image of a cow when it is considered as 3D shape data. In this study, the function convex hull in the programming language MATLAB was used to create the 3D convex hull. Since many skeletons protrude from the body surface in the hip region of cattle, there is little difference in the volume of the convex hull between fat cows and lean cows. However, fat cows accumulate more fat between skeletal points and their actual volume is closer to the volume of the convex hull. This is used as a feature to predict the BCS of cattle.

Figure 5 shows an example of a 3D convex hull obtained from a smoothed image. In the proposed method, the ratio of the volumes of these two volumes is defined as the feature value F_{conv} using Equation (1); it is expected that this feature value will be closer to 1 for cows with higher BCS.

$$F_{conv} = V/V_{conv} \tag{1}$$

where V_{conv} is the volume of the convex hull and V is the volume of the original 3D data.

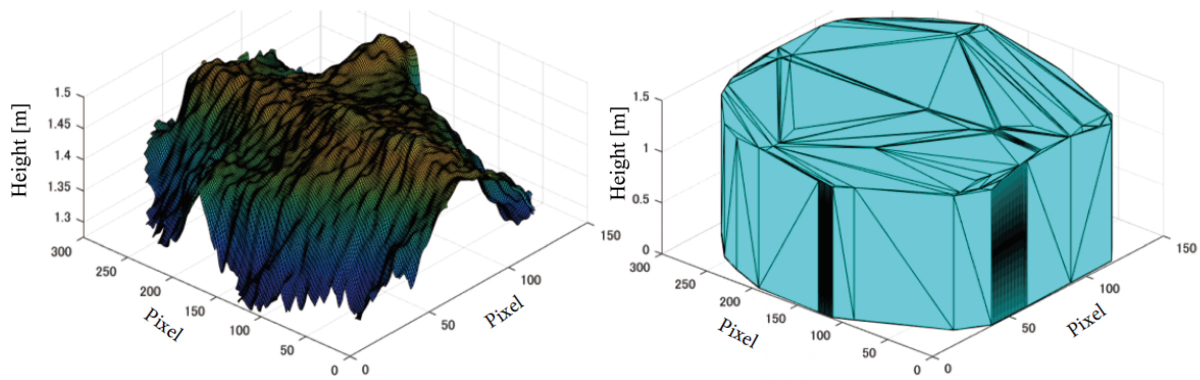

Figure 5. An example of a 3D convex hull

Not all dairy cows to be managed for BCS are adult cows. In other words, it is necessary to consider whether the above characteristic values are appropriate for the size of each individual cow. For this reason, the individual size of the target cows is taken into account as a feature value. First, the highest point is extracted from the smoothed height data, and a row of height data including that point is extracted. As used in the rotation process, basically, the point of maximum height on the body surface of a cow is on the line of the spine, so by taking the average of these data, we define the feature value H_{mean} as the individual size of each cow.

When we look at the cow from the rump side, we can see that there is a valley from the spine to the sit bones, and since BCS evaluates the accumulation of body fat, we thought that the larger this valley is, the more lean the cow can be judged to be. Therefore, a region of interest was set for the ridge, and the difference between the maximum and minimum values within the region of interest was defined as the feature value H_{val}. Since the ridges are usually in the same position when the rotation process is performed, we specified the coordinates of the region of interest and defined it as the region of interest. Figure 6 shows an example of the extracted region of interest.

3. **Experiment.**

The experiments in this study were conducted at the Sumiyoshi Field, a farm owned by the Faculty of Agriculture, University of Miyazaki. An ifm efector O3D303 was installed in the passageway where cows return from the milking parlor to the free stall barn after milking, and data for the experiment was captured. The development environment and language used to implement the proposed method was MATLAB 2022b.

To construct the BCS estimation model, we asked experts to measure the BCS of 24 cows kept at Sumiyoshi Field and obtained distance images of each cow. From these

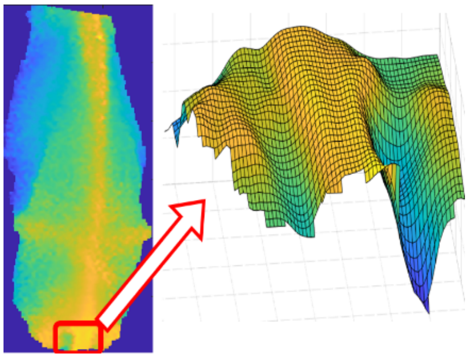

Figure 6. Area of interest in the ridge

data, we extracted the features described in Chapter 2 and constructed a BCS estimation model. In this study, multiple regression analysis is used to create the BCS estimation model [11]. BCS and features for a total of 700 frames of data taken from January 16 to January 18, 2023 were used as training data. The estimated model equation for BCS obtained by multiple regression analysis is shown in Equation (2).

$$BCS = (-3.3563) * F_{RMSD} + (-0.4642) * F_{conv} + 0.9474 * H_{mean} + (-2.6232) * H_{val} + 3.3302 \quad (2)$$

Using the above equation, accuracy verification was performed on data taken from January 16 to January 18, 2023. Calculations were performed for each frame of measured data. In addition, we manually selected the frame when the cow passed directly under the

Table 1. BCS and measured data for each cow

Individual number	BCS	1/16 morning	1/16 evening	1/17 morning	1/17 evening	1/18 morning	1/18 evening
M46	3.25			2.84		2.88	2.96
M50	3.25					3.23	3.26
M56	2.75				2.8	2.57	2.73
M60	2.5						2.74
M61	3	2.99	3.03	3.01	2.98	3.01	3.07
M62	2.25						2.74
M63	2.5						2.94
M65	3	2.97	2.99				3.03
M66	3.25		3.18			2.87	2.84
M68	3	2.97		2.89	3.09	2.79	3.03
M69	3.5				3.13	2.95	2.96
M70	2.75	2.93	2.96	2.87	2.95	2.94	3.03
M71	3.25				3.03		3.09
M72	2.75	2.75		2.74	2.77	2.69	
M74	2.75				2.76	2.8	2.95
M75	2.75		2.79		3.14		3.24
M76	3.25		2.93		2.97	2.86	2.65
M77	3.5	3.03	3.09		3.13		3.06
M78	2.75	2.73		2.79			2.9
M79	2.25			2.72	2.18	2.53	2.55
M80	2.75				2.82		3.08
J11	3.75	3.67			3.72	3.67	3.67
J18	3.75		3.68	3.74	3.74	3.71	3.73

camera, took the average of the 10 frames before and after, and summarized the cow's score, expressed as three significant digits. The BCS and measured data for each cow are summarized in Table 1.

4. **Results and Discussion.** Table 2 summarizes the relative errors of these BCS and measurement data. As can be seen in the table below, the average relative error of the measured data was completely different for each cow, with some having an average relative error of 0.01 (1%) or less and others having an average relative error of 0.1 (10%) or more. Here, we focused on the data with a mean relative error of 0.1 (10%) or more, which we considered to be particularly outlier values, and observed the data. There were 18 data with a mean relative error greater than 0.1 for which the relative error was greater than 0.1.

TABLE 2. Average relative error between BCS and measurements

Individual number	BCS	Mean relative error
M46	3.25	0.110
M50	3.25	0.005
M56	2.75	0.030
M60	2.5	0.096
M61	3	0.008
M62	2.25	0.218
M63	2.5	0.176
M65	3	0.008
M66	3.25	0.088
M68	3	0.031
M69	3.5	0.139
M70	2.75	0.072
M71	3.25	0.058
M72	2.75	0.008
M74	2.75	0.032
M75	2.75	0.112
M76	3.25	0.122
M77	3.5	0.121
M78	2.75	0.025
M79	2.25	0.124
M80	2.75	0.073
J11	3.75	0.018
J18	3.75	0.008

Two features were observed in these data: one was missing data in the distance images. Figure 7 shows an example of a binary image with no missing data and a binary image with missing data. Each pixel in the white area of the image contains height data from the ground, while the black area contains no data. Therefore, it is possible that the calculation of each feature was not performed accurately and that wrong results were obtained as the result of the calculation. The next possibility is that the cows were photographed while they were standing still directly under the camera. In this case, since the subject was a walking cow, all training data were taken from frames of the cow in walking motion. The undulations of the body surface of a stationary cow are smaller than those of a cow in walking motion. This may have prevented accurate calculations, as there would have been no difference in each score for each feature. The average relative error including these

Figure 7. Normal and missing distance images

Table 3. Example of BCS follow-up of cows (M61)

Date	1/16 (M)	1/16 (E)	1/17 (M)	1/17 (E)	1/18 (M)	1/18 (E)	1/25 (M)	1/31 (E)
BCS	2.99	3.03	3.01	2.98	3.01	3.07	3.12	2.89

M: Morning, E: Evening

outliers was 0.062 (6.2%), which means that the calculation could be performed within an error of 0.25 even for the data with a large BCS of 3.75.

Essentially, BCS is tracked throughout the year to ensure that each cow is at the right score at the right time, such as managing cows from late lactation to dry off to prevent them from becoming overfed [12]. Therefore, BCS was measured for the data taken from January 16 to January 18, 2023, and January 25 and January 31, 2023, used in this experiment. Table 3 shows an example of the follow-up for one cow. As shown in Table 3, many cows do not show large fluctuations in BCS over a day or two. However, by opening a certain period, such as one week, changes were observed, albeit gradually.

5. **Conclusion.** In the model of the previous study, the results of k-fraction cross-validation on the overall data were evaluated using the Mean Absolute Error (MAE) [10,13], but since the results performed in this study had large outliers and were likely to be pulled by those outliers, the relative error of each cow was used as an indicator of the relative error of each cow. The large relative error between the expert's score and the BCS estimation model can be attributed to the same reasons mentioned in Chapter 4. In addition, the fact that the BCS values manually calculated by the experts were evaluated only in increments of 0.25 and that differences of less than 0.5 were considered by different evaluators suggests that these values are reasonable, and that the validity of the proposed method has been confirmed. In the future, we would like to conduct long-term BCS management based on the proposed method and the model obtained in this study, and to monitor the progress. In addition, some parts of the BCS estimation are done manually, and we need to devise a method to fully automate the process. In addition, we have searched for a method to supplement missing data but have yet to find an effective method. We would like to improve the above problems and to develop long-term BCS management to build an environment in which dairy cows can be managed by BCS on any size dairy farm.

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