Potential for Estimation of Body Condition Scores in Dairy Cattle from Digital Images

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ABSTRACT

Body condition scoring, an indirect measure of the level of subcutaneous fat in dairy cattle, has been widely adopted for research and field assessment or for management purposes on farms. The feasibility of utilizing digital images to determine body condition score (BCS) was assessed for lactating dairy cows at the Scottish Agricultural College Crichton Royal Farm. Two measures of BCS were obtained by using the primary systems utilized in the United Kingdom (UK-BCS) and the United States (USBCS). Means were 2.12 (± 0.35) and 2.89 (± 0.40), modes were 2.25 and 2.75, and ranges were 1.0 to 3.5 and 1.5 to 4.5 for the UKBCS ($n = 2,346$) and USBCS ($n = 2,571$), respectively. Up to 23 anatomical points were manually identified on images captured automatically as cows passed through a weigh station. Points around the hooks were easier to identify on images than points around pins and the tailhead. All identifiable points were used to define and formulate measures describing the cow's contour. For both BCS systems, hook angle, posterior hook angle, and tailhead depression were significant predictors of BCS. When the full data set testing only the angles around the hooks was used, 100% of predicted BCS were within 0.50 points of actual USBCS and 92.79% were within 0.25 points; and 99.87% of predicted BCS were within 0.50 points of actual UKBCS and 89.95% were within 0.25 points. In a reduced data set considering only observations in which the tailhead depression angle was available, adding the tailhead depression to models did not improve model predictions. The relationships of the calculated angles with USBCS were stronger than those with UKBCS. This research demonstrates the potential for using digital images for assessing BCS. Future efforts should explore ways

to automate this process by using a larger number of animals to predict scores accurately for cows across all levels of body condition.

Key words: body condition scoring, digital image, image analysis, intervention technology

INTRODUCTION

The primary method of assessing body energy reserves of dairy cows is a subjective analysis of energy reserves, termed body condition scoring. Body condition scoring is accomplished by visual or tactile assessment of a cow by a trained evaluator. The usefulness and relative precision of body condition scoring is well-documented (Wright and Russel, 1984; Ferguson et al., 1994; Hady et al., 1994; Schwager-Suter et al., 2000; Kristensen et al., 2006). Largely because of a variety of health effects in early lactation, interest in body condition scoring has increased in recent years (Gearhart et al., 1990; Coffey, 2003; Kristensen et al., 2006).

Although the benefits of regular body condition scoring are intuitive to most dairy producers, nutritionists, and consultants, relatively few dairy farms have incorporated it as part of their dairy management strategy (Hady et al., 1994). Jim Ferguson (University of Pennsylvania, Kennett Square; personal communication, 2006) estimated that less than 5% of US dairy herd managers regularly assign BCS to their cows. There are many reasons for the lack of adoption of this system, mostly related to its subjectivity and the time commitment required. Ward (2003) postulated that body condition scoring is not widely adopted "because it looks simple and does not produce a computerized report, and because it must be learned practically and revised frequently." These concerns have led to a search for alternative means of assessing body energy reserves in cattle. Ferrell and Cornelius (1984) described the ideal system for determination of body composition as one that is "accurate, easy to perform, inexpensive, applicable to a wide range of ages and compositions,

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and suitable for applications on the live animal with minimal perturbation of subsequent performance.”

De Campeneere et al. (2000) proposed the use of video image analysis to measure the conformation and body size traits of cattle in an objective manner. Ferguson et al. (2006) recommended the use of digital images, which could be provided remotely to farm advisors, for assessment of BCS in nutritional management. These researchers concluded that the differences observed with these digital photographs were similar to what would be observed within and between scorers in a typical live scoring scenario. Coffey et al. (2003) proposed that automatic recording of BCS would increase its usefulness for dairy herd managers. The accuracy of an estimate of body composition obtained from image analysis depends on both the correlation between the image and the body part and the correlation between the body part and body composition. Coffey (2003) conjectured that BCS obtained from images could be at least as good as, if not better than, traditional BCS at assessing body lipid content.

Indeed, this method has been tested successfully in other farmed species. Digital imaging has been applied for assessing body shape, weight, and fatness in live pigs (Brandl and Jørgensen, 1996; Schofield et al., 1999; Doeschl et al., 2004). Arias et al. (2004) used digital image processing and neural networks to extract information from images of Zebu cattle, with correlations between 0.89 to 0.99 between BW and area, perimeter, length, hip width, abdomen width, and scapula width. Recently, Negretti et al. (2008) demonstrated the usefulness of computerized image analysis for predicting BW and BCS in lactating Mediterranean buffalo. Using images taken from behind the animal while calculating angles from the spine to hooks and the surface area of the hindquarters, these researchers developed regression equations, with R^2 ranging from 0.77 to 0.96 for these 2 parameters. Despite the success with other species, few research groups have approached the idea of automatic body condition scoring in dairy cattle (Coffey et al., 2003; Leroy et al., 2005; Pompe et al., 2005). Pompe et al. (2005) used black-and-white photography and a line laser to collect a series of images from the rear of a cow. A 3-dimensional analysis of the images provided an outline of the left pin, left hook, and tailhead. No statistical analysis comparing image analysis with BCS was reported. Leroy et al. (2005) used a digital camera, positioned 1.5 to 2.0 m from the rear of the cow, to obtain a silhouette image of the cow from the tail to the legs. The contours of 19 predefined points, corresponding to visual features, were incorporated to determine the overall contour of each animal, from which a BCS was calculated.

The most extensive work on automated body condition scoring for dairy cattle was conducted by Coffey (2003) at the Scottish Agricultural College, working with collaborators from the Silsoe Institute. Observational BCS (Lowman et al., 1976; Mulvany, 1977) were obtained from 3 scorers. Light lines were created on the back of the cow by using a red laser light shone through a prism. The camera was mounted to a rig, with sliding rails for cows of varying sizes, and was positioned at a 45° angle to the horizontal plane of the cow's back. The laser lines were used in manual extractions of curvatures over the cow's tailhead and buttocks. The curvatures of these shapes were then modeled. As with most body condition scoring research, there were few animals in the extreme ranges of the BCS scale, which had a considerable impact on the results. The correlation coefficient between tailhead curvature and subjective BCS evaluated by experienced observers was 0.55, whereas the correlation coefficient of the curvature of the right buttock as measured across the pin bone was 0.52. Coffey et al. (2003) warned that a limitation of any system that uses shape to assess body condition is the fact that the protrusion of bones on a cow may not necessarily mean she is thin.

An automated body condition scoring system would be preferred to observational scoring because it would require less time, be less stressful on the animal, be more objective and consistent, and possibly be more cost effective (Leroy et al., 2005). The objective of this work was to explore the potential for automation of body condition scoring by using digital images taken from above the cow.

MATERIALS AND METHODS

Data for this study were collected at the Scottish Agricultural College Crichton Royal Farm in Dumfries, Scotland, from September to November 2006. The Holstein-Friesian cows in this herd are part of the Langhill pedigree herd, which has been selected since 1970 as a high genetic merit line and a control line. Furthermore, the management systems used mean that equal numbers of control and select animals are managed together as one group on a high- or low-concentrate feeding regimen. The genetic selection strategy of this herd is described in more detail by Pryce et al. (2001). One-half of the herd is housed year round, whereas the other half of the herd is housed during the winter and grazed during the summer with as much homegrown feed as possible. Cows are milked 3 times per day.

The BCS were collected for 13 wk (September 5 to November 28, 2006). Scores were obtained weekly by using 2 different BCS systems, which are the primary

systems used within the United Kingdom (Lowman et al., 1976; Mulvany, 1977) and the United States (Edmonson et al., 1989; Ferguson et al., 1994). The Lowman/Mulvany (**UKBCS**) system involves palpation of specific body parts, using a 0 to 5 scale with 0.25 intervals. The Edmonson/Ferguson (**USBCS**) system is based entirely on visual assessment, using a 1 to 5 scale with 0.25 intervals. The UKBCS were assessed by 2 experienced employees of the farm in a permanent weigh station as cows left the milking parlor after the a.m. milking. These scores are continually collected as part of the genetic studies of the Langhill herd. The USBCS were assessed by a visiting scientist from the United States trained in BCS, using the flowcharts developed by Ferguson et al. (1994). The USBCS were collected while cows were loose in free stalls (cubicles), in holding pens, or in the field in the p.m. For most weeks, UKBCS were collected on Tuesday and USBCS were collected on Friday. The exceptions to this rule were that UKBCS were collected on Thursday, October 26, 2006, and USBCS were collected on Thursday, September 7, Thursday, November 16, and Wednesday, November 22, 2006. Admittedly, the number of evaluators in this study is a limitation. However, financial and logistical constraints of bringing multiple scorers trained in multiple systems into 1 location were impractical. General cow demographic information was obtained from a database of Langhill records.

Within-cow outliers were removed for both systems by comparing BCS obtained during successive weeks. When a given BCS differed from preceding and subsequent scores by more than ± 0.25 , the score was removed from the data set. For example, with 3 successive scores of 3.00, 3.75, and 3.00, the 3.75 was removed. For the first and last week of the study with each system, scores were removed if the scores differed by more than ± 0.25 from the adjacent score. The objective of this editing technique was to remove individual BCS that were clearly inconsistent with scores for an individual cow over a short time frame. This edit removed 129 and 59 scores from the UKBCS and USBCS data sets, respectively. When BCS was missing, either because it was not recorded or because of this editing technique, the score of the 2 adjacent (week before and week after) scores was used to represent BCS for that week if the adjacent scores were identical. After these edits, means were 2.12 (± 0.35) and 2.89 (± 0.40), modes were 2.25 and 2.75, and ranges were 1.0 to 3.5 and 1.5 to 4.5 for the UKBCS ($n = 2346$) and USBCS ($n = 2571$), respectively.

Black-and-white images were collected with a digital camera placed above the permanent weigh station. The camera pointed downward toward and approximately 60 to 70 cm above the cows' backs. The camera was

stationary and remained at the same height throughout the duration of the project. The weigh station was located in an exit alley from the parlor within an enclosed barn with minimal artificial lighting. When the rear gates of the weigh station closed after cow entry, the camera was triggered to capture an image from the cow in the station. Relative to collection of subjective BCS on the day of the week when scores were collected, image collection occurred simultaneously with UKBCS and before USBCS. Images were identified with a time stamp and stored for subsequent analysis. Image time stamps were matched with weigh-station time stamps to identify the cows being photographed. Ten cows with distinctive markings were selected to verify this matching process. Among images with a visible cow, this verification demonstrated that these 10 cows were identified consistently throughout the data set, with only 1 exception. In that case, there was no image for the cow on that particular day, indicating the cow either ran through the weigh station without stopping or did not pass through the weigh station. Although the herd was milked 3 times per day, images were generally available only for the early p.m. milking because of lighting limitations at the a.m. and late p.m. milkings. Images were collected from September 29, 2006, to November 29, 2006.

Twenty-three anatomical points, corresponding to identifiable features, were classified for potential influence on BCS (Figures 1 and 2). A computer program was created to identify these points on the collected images. With this program, image files are loaded and points are identified manually and visually with the click of a computer mouse. When the point has been identified, an x/y coordinate corresponding to this point is recorded in a separate text file. If a point is not discernible on a particular image, that point is set to missing. Any image in which both hooks were not clearly visible was considered to be of insufficient quality and no points were recorded. Points were selected moving clockwise around the cow, starting with the left forerib (facing the cow) and ending with the right forerib. An edit was performed on the data to remove any points that did not follow this pattern. When all 23 points were identified, the x/y coordinates created an outline of the cow (Figure 2). Distances between points on opposite sides of the cow were calculated (e.g., right hook to left hook) as measures of width at various points. These points were also used to calculate angles reflecting the shape of the contour of the cow. Fifteen angles, around the hooks, pins, and tailhead, were calculated in this manner when points were available (Figure 3).

For each image, 7 composite anatomical angles were calculated by using the mean of opposing angles from the cow's left and right sides. For example, a composite

Figure 1. Twenty-three key anatomical points identified (where possible) for each image.

hook angle was calculated as the average of the left and right hook angles. Similarly, a coefficient of variation was calculated corresponding to each of the composite angles for each image. Cutoff values for outlier removal of these composite angles were created by using the mean $\pm$ 3 standard deviations of these coefficients of variation across the entire data. When the coefficient of variation corresponding to an individual image composite angle was greater than or less than these cutoff values, the respective composite angle was removed. The objective of this edit was to remove angles where the left and right angles were considerably different, likely indicative of the cow standing diagonally within the weigh station, a poor-quality image, or gross errors in point identification.

A weekly average of each composite angle, along with the tailhead angle, was calculated for each cow-week combination. Weeks were defined relative to the date of scoring for the respective BCS systems, with the date of scoring in the middle of the week. For example, when cows were scored on Friday with the USBCS, information from images taken on the Tuesday, Wednesday, and Thursday before scoring, the Friday of scoring, and the Saturday, Sunday, and Monday after scoring were included in the weekly averages. Because cows were scored on different days when using the 2 BCS systems, the week and, consequently, images included in analysis were different for the 2 systems. Weekly averages with less than 2 composite hook angles were removed from the data set before model creation.

The MIXED procedure of SAS (SAS Institute Inc., Cary, NC) was used to analyze models for prediction of BCS by using the angles obtained from the images. These models were performed as a repeated measures

Figure 2. Sample cow outline using 23 key anatomical points: 1) left forerib, 2) left short rib start, 3) left hook start, 4) left hook anterior midpoint, 5) left hook, 6) left hook posterior midpoint, 7) left hook end, 8) left thurl, 9) left pin, 10) left tailhead nadir, 11) left tailhead junction, 12) tail, 13) right tailhead junction, 14) right tailhead nadir, 15) right pin, 16) right thurl, 17) right hook end, 18) right hook posterior midpoint, 19) right hook, 20) right hook anterior midpoint, 21) right hook start, 22) right short rib start, 23) right forerib.

analysis with variables repeated by week, with cow as the random subject. First-order autoregressive [AR(1)] was chosen as the covariance because this structure fit the nature of the data well across models using Schwarz's Bayesian information criterion (**BIC**) to assess the fit of alternative models. All composite angles were considered in preliminary models, but only effects significant at $P \leq 0.05$ are included in the models reported here. Two models were developed for each BCS system. The first model included only the better defined angles in the hook region (**AHR**) as predictors of BCS for each system. Because angles in the rump region (**ARR**) were available for only a small portion of the total images, we created models with (reduced) and without (full) ARR, attempting to fit these angles as fixed effects. The full data set included 834 and 767 observations for USBCS and UKBCS, respectively, whereas the reduced data set included 303 and 278 observations for USBCS and UKBCS, respectively. Because the full data set contained nearly 3 times more observations, these data likely described the relationship between BCS and angles obtained from images more effectively.

Mixed model 1 was defined as

$$y_{ij} = \mu + \text{Cow}_i + \beta_1 \text{HA}_{ij} + \beta_2 \text{PHA}_{ij} + \beta_3 (\text{HA} \times \text{PHA})_{ij} + e_{ij}, \quad [1]$$

where y_{ij} is the j th USBCS or UKBCS of cow i ; μ is the intercept; Cow_i is the i th cow; β_1 , β_2 , and β_3 are re-

gression coefficients corresponding to the covariables average hook angle (HA_{ij}), average posterior hook angle (PHA_{ij}), and the interaction of hook angle and posterior hook angle ($HA \times PHA_{ij}$), respectively; and e_{ij} is residual error. Because the AHR were available for a large proportion of images, this model was fit by using the full data set.

Model 2 tested the less clearly discernable ARR in addition to AHR as predictors of BCS for each system. Mixed model 2 was defined as

$$y_{ij} = \mu + Cow_i + \beta_1 HA_{ij} + \beta_2 PHA_{ij} + \beta_3 (HA \times PHA)_{ij} + \beta_4 TD_{ij} + \beta_5 (PHA \times TD)_{ij} + e_{ij}, \quad [2]$$

where β_4 and β_5 are regression coefficients corresponding to the covariables average hook angle, average tailhead depression (TD_{ij}), and the interaction of average posterior hook angle and average tailhead depression ($PHA \times TD_{ij}$), respectively, and other terms are as defined for model 1. Because ARR were available for a smaller proportion of images, model 2 used the reduced data set. To evaluate the additional value of information from ARR, model 1 was used for the reduced data. Variables were selected for the models, using a 0.05 significance level.

During the last week of the study, anatomical measurements of live cows were collected. Hip height was measured by using a wooden stick with a perpendicular attachment placed on the cow's hooks. Hook width was measured by using the distance between the outside edge of the left and right hooks.

RESULTS AND DISCUSSION

Among cows assessed for both UKBCS and USBCS during the observation period, mean milk production was 25.10 kg (± 8.12), with a range of 1.30 to 52.60; mean parity was 2.46 (± 1.39), with a range of 1 to 6; and mean DIM was 190.98 (± 104.65). For subjective BCS, means were 2.12 (± 0.35) and 2.89 (± 0.40), modes were 2.25 and 2.75, and ranges were 1.0 to 3.5 and 1.5 to 4.5 for the UKBCS ($n = 2346$) and USBCS ($n = 2571$), respectively. When this same data set was used, scores between the 2 systems were highly correlated ($r = 0.77$); this relationship is explored in more depth by Bewley and colleagues (J. M. Bewley, R. E. Boyce, D. J. Roberts, M. P. Coffey, and M. M. Schutz; unpublished data).

Description of Data and Angles

Because of problems with lighting or setup limitations with the experimental equipment, usable images

Figure 3. Angles calculated using the key anatomical points: 1) left hook anterior angle, 2) left hook anterior curvature, 3) left hook angle, 4) left hook posterior angle, 5) left hook posterior curvature, 6) left thurl to pin angle, 7) left tailhead depression, 8) tailhead angle, 9) right tailhead depression, 10) right thurl to pin angle, 11) right hook posterior angle, 12) right hook posterior curvature, 13) right hook angle, 14) right hook anterior curvature, 15) right hook anterior angle.

were available only for 46 of 61 possible days. The authors originally hoped to get 2 or 3 usable images per week, so installing lighting to enable the capture of images at the morning and evening milking sessions was considered unnecessary. In retrospect, the additional images that could have been captured would have helped improve the robustness of the system by providing more examples of each cow, from which the clearest images could have been selected. An autoexposure would also have been helpful to avoid image saturation and overexposure. The average number of usable images per day was 72.44, with a standard deviation of 42.91 and a range of 6 to 149. Usable images were available for 242 different cows. On average, there were 13.77 images per cow, with a standard deviation of 8.59 and a range of 1 to 38. The primary reason for deeming an image nonusable was lighting, because there was simply not enough contrast between the background and the cow's body to identify anatomical landmarks. This issue was more prominent for cows that were predominantly black; predominantly white cows were much easier to identify. There were also issues with regard to cow position beneath the camera. In some cases, an image was taken of either the front or rear quarter of the cow, preventing assessment of the anatomical points of interest. Cows standing at an angle within the weigh station were also a problem. Tails moving within images and dirt also prevented some images from being used.

Table 1. Discernible points from valid images

Point	Points discernible, n	Percentage of images
Left forerib	2,052	61.58
Left short rib start	3,111	93.37
Left hook start	3,332	100.00
Left hook anterior midpoint	3,332	100.00
Left hook	3,332	100.00
Left hook posterior midpoint	3,332	100.00
Left hook end	3,332	100.00
Left thurl	3,214	96.46
Left pin	1,952	58.58
Left tailhead nadir	790	23.71
Left tailhead junction	763	22.90
Tail	994	29.83
Right tailhead junction	472	14.17
Right tailhead nadir	484	14.53
Right pin	1,999	59.99
Right thurl	3,210	96.34
Right hook end	3,209	96.31
Right hook posterior midpoint	3,209	96.31
Right hook	3,209	96.31
Right hook anterior midpoint	3,209	96.31
Right hook start	3,208	96.28
Right short rib start	3,053	91.63
Right forerib	1,973	59.21

Because the definition of a usable image was that the hooks were identifiable, it is not surprising that of the 3,332 usable images in the data set, nearly 100% of the points around the left and right hooks were identified (Table 1). Similarly, the approximate location of the thurls was identified in more than 96% of images. The foreribs and start of the short ribs were identified in fewer images. Last, the points around the tailhead and pins were the most difficult to identify. A portion of this difficulty can be attributed to the position of the tail at the time the image was taken. On some images, this area was outside the picture frame. The impact of poor lighting was magnified in this region. Finally, identification of points around the pins and tailhead is challenging because of the lack of a clear anatomical feature, particularly on cows with more fat deposited in this region.

Correlations were calculated between USBCS (Table 2) and UKBCS (Table 3) and weekly composite angles. All correlations of composite angles with USBCS were significantly different from zero ($P < 0.01$). Correlations with UKBCS were significantly different from zero ($P < 0.02$) for all composite angles except tail angle. The hook posterior angle ($r = 0.5239$), hook angle ($r = 0.4834$), and tailhead depression ($r = 0.3104$) had the strongest correlations with USBCS. The hook posterior angle ($r = 0.4601$), hook angle ($r = 0.3301$), hook anterior curvature ($r = 0.1984$), and tailhead depression ($r = 0.1856$) had the strongest correlations with UKBCS. The correlations for the 2 hook angles were similar to those found by Coffey (2003), whereas the correlations for all

other angles were considerably lower, possibly owing to different methods by which images were obtained in that study. These correlations are considerably lower than those reported by Arias et al. (2004) in Zebu cattle, with correlations between 0.89 and 0.99 between BW and area, perimeter, length, hip width, abdomen width, and scapula width. These higher correlations, although based on a smaller number of images, likely reflect the advantages of automated image extraction (which allowed for calculation of additional anatomical features) and the use of an objective dependent variable (BW). Edmonson et al. (1989) also found that overall BCS was most closely associated with scores given in the pelvic and tailhead regions. Although the correlations of USBCS and UKBCS with the hook anterior angle were moderate ($r = 0.2459$, 0.1416 , respectively), they were not nearly as strong as with the hook posterior angle. This demonstrates that the cow is more likely to deposit fat in the area between the hooks and thurls than around the short ribs.

Correlations among angles were highly variable and not always significant. These correlations were generally lower than those of Ferguson et al. (1994), who used visual scores of similar regions. Correlations of the anterior or posterior hook curvature with other angles were generally low. This inconsistency likely indicates that these angles were not describing the contour of the cow as consistently as other measures and were therefore probably not necessary for evaluation of BCS. Similarly, the tail angle did not correlate well with other angles, although it was based on fewer

Table 2. Correlations among US BCS (USBCS) and average of angles from the left and right sides of cows¹

Item	USBCS	Hook anterior angle	Hook posterior angle	Hook angle	Tailhead depression	Hook anterior curvature	Hook posterior curvature	Thurl to pin angle	Tail angle
USBCS	1	0.2459***	0.5239***	0.4834***	0.3104***	0.2083***	0.1171***	-0.1960***	0.1942**
Hook anterior angle		1	0.2181***	0.7801***	0.2125***	0.1583***	-0.0220	-0.1088*	0.0270
Hook posterior angle			1	0.5574***	0.1304*	0.1714***	0.0882*	-0.1678***	0.0946
Hook angle				1	0.2552	0.1425	0.0213	-0.1662***	0.0768
Tailhead depression					1	0.0579	0.0158	-0.2879***	0.6398***
Hook anterior curvature						1	0.0919**	-0.1236*	-0.0115
Hook posterior curvature							1	-0.0044	-0.0102
Thurl to pin angle								1	-0.2411***
Tail angle									1

¹USBCS = BCS using the Ferguson et al. (1994) system.
 *** $P < 0.001$; ** $P < 0.01$; * $P < 0.05$; $P > |r|$ under H_0 : $r = 0$.

Table 3. Correlations among United Kingdom BCS (UKBCS) and average of angles from the left and right sides of cows¹

Item	UKBCS	Hook anterior angle	Hook posterior angle	Hook angle	Tailhead depression	Hook anterior curvature	Hook posterior curvature	Thurl to pin angle	Tail angle
UKBCS	1	0.1416***	0.4601***	0.3301***	0.1856**	0.1984***	0.0868*	-0.1501**	0.0922
Hook anterior angle		1	0.2312***	0.7631***	0.1463*	0.1668***	-0.0403	-0.1174*	-0.0249
Hook posterior angle			1	0.5823***	0.1482*	0.1795***	0.0296	-0.1745***	0.0923
Hook angle				1	0.2120***	0.1418***	-0.0105	-0.1543**	0.0486
Tailhead depression					1	-0.0380	-0.0283	-0.2359***	0.5882***
Hook anterior curvature						1	0.0571	-0.1101*	0.0235
Hook posterior curvature							1	-0.0227	-0.0373
Thurl to pin angle								1	-0.0458
Tail angle									1

¹UKBCS = BCS using the Mulvany (1977) system.
 *** $P < 0.001$; ** $P < 0.01$; * $P < 0.05$; $P > |r|$ under H_0 : $r = 0$.

Table 4. Mean, standard deviation, and number of observations for selected angles by the US BCS (USBCS) and the United Kingdom BCS (UKBCS)¹

Item	Hook angle			Hook posterior angle			Tailhead depression		
	Mean	SD	n	Mean	SD	n	Mean	SD	n
USBCS									
2.00	125.29	4.51	5	154.47	2.84	5	108.69	0.00	1
2.25	126.27	6.29	45	155.91	3.75	45	105.23	12.07	13
2.50	128.96	7.80	171	156.32	4.27	168	105.00	9.80	56
2.75	131.99	6.83	230	157.06	4.14	230	108.26	9.26	96
3.00	133.73	7.16	137	158.53	4.14	137	108.03	6.71	57
3.25	137.86	7.56	174	161.08	4.03	174	109.90	9.68	54
3.50	136.54	11.07	45	163.01	4.34	44	112.58	8.68	15
3.75	143.84	8.10	19	167.24	3.43	19	118.46	6.58	7
4.00	153.79	5.52	4	170.05	3.02	4	128.24	7.89	3
4.25	153.21	0.00	1	166.27	0.00	1	—		0
4.50	151.93	2.87	3	167.52	0.70	3	131.85	0.00	1
UKBCS									
1.00	130.63	9.47	2	154.28	2.49	2	—		0
1.25	128.94	6.45	13	156.22	2.60	13	109.02	6.60	5
1.50	128.90	6.31	42	156.51	3.66	42	104.84	11.54	12
1.75	130.31	7.71	118	156.64	4.50	117	108.96	8.72	38
2.00	132.90	7.34	257	157.88	4.43	257	108.48	10.57	95
2.25	134.46	8.32	213	159.29	4.54	212	108.36	8.84	85
2.50	136.44	10.75	81	162.24	4.04	80	109.63	8.79	27
2.75	136.20	9.07	23	165.90	3.91	23	112.48	4.23	9
3.00	145.02	6.59	14	165.44	2.93	23	126.06	7.94	4
3.25	148.98	10.59	7	168.56	3.96	7	123.84	9.98	3

¹UKBCS = BCS using the Mulvany (1977) system; USBCS = BCS using the Ferguson et al. (1994) system.

images. This may reflect some error in identification of the tail point (point 12; Figure 2) because of variation in the tail position at the time of image capture.

The means for the 3 composite angles with the highest correlations with USBCS and UKBCS are summarized by assigned BCS (Table 4). For each angle, a trend of increasing angle size with increasing BCS was observed for both systems. In other words, as BCS increased, the angle flattened toward a straight line (180°). This linear relationship is also demonstrated in Figures 4, 5, and 6. From these graphs, it is also clear that the relationship between USBCS and each of the 3 angles was stronger than with UKBCS. When this same data set was used, scores between the 2 systems were highly correlated ($r = 0.77$), but differences between the 2 systems likely still exist (J. M. Bewley, R. E. Boyce, D. J. Roberts, M. P. Coffey, and M. M. Schutz; unpublished data). For the hook angle and hook posterior angle, this indicates that the hooks were less sharp or prominent with increasing BCS. In fact, this was similar to the descriptions that Ferguson et al. (1994) used within their flowchart distinguishing between round or angular hooks. The hook posterior angle also likely corresponds to the depression between hooks and pins, which was negatively correlated with BCS ($r = -0.44$) when measured manually in recent research at the University of Wisconsin-Madison (Daehnert et al., 2007).

For the tailhead depression, this indicates that the angle reflecting the depression around the tailhead changed as this region filled with body reserves. This corresponds to the use of the coccygeal (tailhead) ligament within the flowchart of Ferguson et al. (1994). Another way of describing these changes is that the degree of “boniness” changed as the level of fat varied (Coffey et al., 2003). These results support our hypothesis that BCS is reflected in angles around the hooks and rump as measured by using digital images. The changes between BCS scores were not perfectly linear in this data set, however. For example, the average hook posterior angle was 170.05 for cows with a BCS of 4.0 on the US scale, but decreased to 166.27 and 167.52 for cows with a score of 4.25 and 4.50, respectively. This result is most likely a factor of having such a small number of animals with scores of 4.25 (1) and 4.50 (3). The standard deviations for these categories were also relatively high. This result may also suggest that the changes in anatomical features after a cow reached a certain level of condition in either direction were too small to detect.

The correlations between USBCS and angles obtained from images (Table 2) were generally higher than those between the UKBCS and the angles obtained from images. This difference likely reflects slight differences in the way that cows were scored when using these 2 systems. Because the USBCS system is entirely visual,

Figure 4. Average hook angle versus A) the US BCS (USBCS) and B) the United Kingdom BCS (UKBCS).

whereas the UKBCS system is visual and tactile, it seems intuitive that angles obtained from images would more closely reflect the USBCS than the UKBCS. The question of which method more accurately predicted body reserves remains. This difference also suggests that a more direct measure of body reserves, such as ultrasound, may be a more appropriate measure for an automated BCS system than visual BCS. Additionally, the USBCS data set included 43 cows that were not included in the UKBCS. These cows were older cows that were no longer a part of the genetic studies of the Langhill herd. Older cows may have more distinctive anatomical features, making prediction of BCS using images easier than for younger cows.

Model Development

The primary objective of this work was to develop models to describe BCS by using the information ob-

Figure 5. Average posterior hook angle versus A) the US BCS (USBCS) and B) the United Kingdom BCS (UKBCS).

tained from the collected digital images. Results from the 6 mixed models (model 1 for the full data set, models 1 and 2 for the data subset with tail head information and 2 scoring systems) developed are shown in Table 5. Akaike's information criterion (AIC) and Schwarz's BIC are the 2 metrics used to assess the goodness of fit of the model. With both criteria, lower values indicate a better fit. Generally, the AIC and BIC should not be compared across models. However, because the 2 sets of models using the reduced data set contained the same observations and a base set of fixed effects, comparisons within these pairs could be made.

For each system, we developed models by using only the observations with ARH available, with (model 2) and without (model 1) the ARR. In this manner, a comparison could be made to determine the benefit of this additional information. For both BCS systems, the models without the ARR effects (model 1) actually had a lower AIC and BIC, indicating that these models fit

the data better. Thus, in this data set, there was no additional value of including information about the angles around the tailhead and points. Nevertheless, given the small number of images for which ARR angles were discernible and its significance in the reduced models, future work should consider the potential for adding information from the rump region to improve on the predictive abilities of the models developed here. The rump region represents a major area of fat deposition in dairy cattle and most visual BCS systems incorporate some assessment of this area.

Because the tailhead depression did not improve the models, all remaining discussion of models focuses on model 1 using the full data set. The residuals for these 2 models for both BCS systems were normally distributed. For the USBCS model, 100% of predicted BCS were within 0.50 points of the actual BCS and 92.79% were within 0.25 points. For the UKBCS model,

99.87% of predicted BCS were within 0.50 points of the actual BCS and 89.95% were within 0.25 points. These results are similar to those of Leroy et al. (2005), who found, on a series of 32 test images, that the deviation between the calculated score and a BCS assessed by an expert was 0.27. In lactating buffalo, Negretti et al. (2008) reported differences of 0.26 and 0.27 units when using a 1 to 9 BCS scale. However, the range of scores of animals in this study was fairly narrow (5 to 8). Ferguson et al. (1994) found that human observers agreed with a modal BCS of 4 observers 58.1% of the time and varied by only 0.25 units 32.6% of the time. Thus, BCS changes of 0.25 cannot realistically be detected, even with trained observers. In our data set, the agreement between subjective BCS and BCS as predicted by image analysis was similar to the expected difference between 2 different subjective BCS observers.

Figure 6. Average tailhead depression versus A) the US BCS (USBCS) and B) the United Kingdom BCS (UKBCS).

Figure 7. Predicted versus actual A) US BCS (USBCS) and B) United Kingdom BCS (UKBCS).

Table 5. Model parameters and *P*-values for fixed effects in 6 models describing BCS^{1,2,3}

Item	USBCS model 1, full data	USBCS model 1, reduced data	USBCS model 2, reduced data	UKBCS model 1, full data	UKBCS model 1, reduced data	UKBCS model 2, reduced data
Observations, n	834	303	303	767	278	278
Akaike's information criterion	-230.8	28.6	36.5	-96.7	53.7	75.3
Bayesian information criterion	-220.7	37.4	45.3	-87.1	62.3	83.9
Fixed effects						
Intercept	0.011	0.007	<0.001	0.004	0.039	0.007
Average hook angle	0.043	0.008	0.028	0.005	0.020	0.051
Average posterior hook angle	0.055	0.013	0.001	0.014	0.064	0.011
Average posterior hook angle × average hook angle	0.025	0.004	0.0178	0.005	0.018	0.048
Average tailhead depression			0.009			0.074
Average posterior hook angle × average tailhead depression			0.007			0.075

¹Only angles around the hooks were tested as covariates for model 1.

²Angles both around the hooks and around the tailhead were tested as covariates for model 2.

³The full data set included all images with valid hook angles, whereas the reduced data set included only images with valid hook and tailhead angles.

Predicted scores from these models against actual scores for both systems are depicted in Figure 7. Examples of images from a thin and a fat cow (Figure 8) visually demonstrate the difference in the contours of animals of varying BCS. The hooks of the thin cow were much more prominent and pronounced than those of the fat cow, and this was reflected in the difference in the angles measured from these images. Further, the depression around the tailhead was more pronounced. A potential concern and limitation of the ability to predict BCS by using images is highlighted by Figure 9. In models predicting both USBCS and UKBCS, the residuals increase in magnitude with increasing BCS. In effect, these models overpredict the BCS of thin cows and underpredict the BCS of fat cows. This result should not be surprising, given that in a well-managed herd, such as the one used in this study, few cows score at either extreme of the BCS scale. Thus, this result is likely reflective of inadequate data from cows with particularly low or high BCS to predict their BCS properly by using images. Moreover, Ferguson et al. (1994) concluded that BCS could be separated by 0.25 units between 2.5 and 4.0, but by only 0.5 units below 2.5 or above 4.0. Using the New Zealand body condition scoring system, Gregory et al. (1998) found that the actual amount of body fat did not change much at lower BCS.

Future efforts in this area should strive to work in large herds where, even in a normal distribution, there will be more cows in extreme categories or in herds with an unusual number of thin and fat cows. The ability to identify thin and fat cows is imperative for successful on-farm adoption of automated BCS because this is where the real value of BCS lies. The largest benefits in body condition scoring result from using information about why cows are outside the optimal BCS range for

their respective parity and stage of lactation to improve herd nutritional management strategies.

To check for the robustness of these models, residuals from the mixed model for USBCS were compared against 4 cow descriptors: height, width, DIM, and parity (Figure 10). Cow height and width did not appear to have an impact on the residuals, with equal dispersion of residuals across cow heights and widths. However, there was some influence of DIM and parity. Residuals appear to decrease as parity increases, indicating that predicted scores for older cows were closer to the actual score. It is possible that anatomical features, especially skeletal structures, become more prominent as cows mature. Further, the variation in BCS is likely less for cows in earlier parities within a herd, because they would have experienced the dynamic changes in BCS associated with calving fewer times. Younger cows tend to score higher than older cows (Otto et al., 1991; Schwager-Suter et al., 2000). In turn, this may make it more difficult to distinguish between changes in BCS when using anatomical features in this small data set. In theory, BCS should be independent of the age of the cow; however, this result may indicate a need for a series of models by parity. The subjectivity of BCS may also be a limiting factor because overestimation of BCS may occur in early-lactation, young, or lean cows, whereas underestimation may occur in dry, older, or fat cows (Schröder and Staufenbiel, 2006). This should be explored in future work examining automated BCS with a larger number of animals in each parity.

The trend for increasing residuals as lactation progressed probably indicates that cows in later lactation had higher BCS. As mentioned earlier, our models were lacking in their ability to predict BCS of extremely fat or thin cows. Thus, this relationship is likely reflective

Figure 8. Examples of predicted US BCS (USBSCS) of a thin cow (top) and a fat cow (bottom). Top: USBSCS = 2.50; predicted USBSCS = 2.63; average posterior hook angle = 149.99°; average hook angle = 116.62°. Bottom: USBSCS = 3.50; predicted USBSCS = 3.62; average posterior hook angle = 172.14°; average hook angle = 153.47°.

of the overall lack of dispersion of BCS in this data set. Brandl and Jørgensen (1996) demonstrated varying residuals among swine breeds for prediction of BW. Although only one dairy cattle breed was examined in this study, the difference in residuals between swine breeds is analogous to the differences observed for parity and DIM in our work, indicating that multiple predictive equations may need to be developed for various animal descriptive categories. Precision for estimating BW in swine has generally been greater than observed in our research. For example, Schofield et al. (1999) estimated swine weights within 5% of actual weights by using image analysis. Perhaps one explanation for earlier success with digital imaging in the swine industry is that there is less variability between individual animals in

Figure 9. Model residuals for A) the US BCS (USBSCS) and B) the United Kingdom BCS (UKBCS).

swine than in cattle. Furthermore, the swine work has generally been conducted with solid-colored animals; in automated image analysis, multicolored (e.g., black and white Holstein) animals represent a potential obstacle. Because most image analysis techniques rely on variations in color, ignoring differences in hair-coat patterns, which are clearly not related to either BW or BCS, can prove challenging.

Model Limitations and Future Considerations

If images were consistently available on a daily basis for all cows, models could be improved through the use of more stringent outlier removal strategies. With 7 images in a week, an image with angles that clearly deviated from the other images during that week could be removed before assignment of a predicted BCS. Un-

Figure 10. Full US mixed model residuals versus A) cow height, B) cow width, C) parity, and D) lactation stage.

fortunately, using such strict rules in this small data set would have removed too many images, resulting in only a small pool of images for model development. Future research efforts should focus on ways of obtaining images more frequently by using a larger number of animals across a wider range of scores to improve on the relationships demonstrated here. Because of the short duration of this project, we were unable to determine whether the measured angles changed within cows, reflecting the changes expected in a cow's BCS during a lactation. Before technology adoption, it is essential to establish that this important pattern is reflected by using images from cows followed through complete lactations.

Another limitation to consider is potential error in identifying the anatomical points of interest. The human eye and hand are subject to some degree of error. Furthermore, the anatomical points chosen do not necessarily all correspond to an obvious visual clue.

Similarly, the USBCS were provided by one evaluator and the UKBCS by 2 evaluators. Consequently, subjectivity and human error limit the value of collected BCS as predictors in the developed models.

An automated method of point extraction may prove superior to this manual extraction technique. Whereas previous work has focused primarily on images of the rear of the cow (Coffey, 2003; Leroy et al., 2005; Pompe et al., 2005), this research focused on a top-down view of the cow. To gain a better perspective of the cow's anatomy, it may be necessary to combine these 2 approaches, possibly aiming for a 3-dimensional view of the animal.

In the models presented here, the number of angles used in prediction equations (2 to 3) was relatively limited. Edmonson et al. (1989) stated that a score from a single area is a good indication of overall BCS. However, observational BCS involves assimilation of information about multiple visual cues of the cow by

the human brain. Whether 2 to 3 points will provide a sufficient representation of overall energy reserves remains to be determined. Perhaps more accurate algorithms could be developed by compiling information from additional geometrical calculations. Although not possible with the images in this data set, it would be beneficial if adjustment could be made for differences in cow size and posture (Leroy et al., 2005).

Although the results of this study demonstrate a clear relationship between angles calculated by using digital images and BCS, this relationship may or may not imply a relationship with actual body fat content. Estimates of the degree to which BCS represent actual body fat have varied considerably, with correlation coefficients of 0.57 to 0.90 (Wright and Russel, 1984; Otto et al., 1991; Waltner et al., 1994). Although BCS is used as the "gold standard" for assessing body energy reserves, it is not a perfect measure of energy reserves and is limited by its subjectivity. Future efforts should attempt to define how BCS obtained from image analysis, in addition to subjective BCS, reflect actual body fat. Initially, this may be accomplished by using a more objective measurement of energy reserves, such as ultrasound. However, with a goal of determining the amount of fat within an animal's body, the greatest degree of accuracy can be obtained only in a postslaughter chemical analysis of the entire body, with contents of the digestive and urinary tracts removed (Otto, 1990). It may also be useful to measure the angles around the hooks and pins used in this study on live animals to compare with angles calculated by using image analysis.

Analysis of Other Traits

The correlation between hip width, as measured cowside, and the distance between the hooks in images (Figure 11) was high ($r = 0.8553$, $P < 0.001$). This result is promising, particularly considering that hip width was measured only one time and that the images were not adjusted for cow height. This correlation validates that the analyzed images were reflective of actual cow dimensions. Further, if this type of technology were used for automated body condition scoring, measurements such as hip width and pin width could be incorporated into genetic evaluations.

CONCLUSIONS

The potential applications for automated body condition scoring are immense. This research builds on the work of Coffey (2003), who demonstrated the potential of using digital images in assessing BCS of dairy cattle. In our work, there appeared to be a strong relationship

Figure 11. Mean distance between hooks from images versus cowside measured hip width.

between the angles measured and BCS as determined by trained evaluators. Clearly, the manual identification of points is not feasible beyond labor-intensive research studies. Although the tailhead information did not add much value to predictive models in this study, the potential for using this information to supplement hook descriptions should be explored further in future work. Finally, future studies should place strong emphasis on selecting herds with an ample number of cows with low and high BCS to ensure that automated scoring systems accurately detect these critically important animals.

Because of limitations related to lighting and separation of the cow image from the background of the image, standard digital photography may not function well in an automated system. Rather, other technologies, such as thermal imaging, should be explored to facilitate extraction of information from images automatically. Arias et al. (2004) successfully demonstrated how digital image processing and neural networks could be used for automatic extraction of morphological descriptions of a cow's body by using differences in color within an image. As these imaging technologies are applied in other industries, the costs of these technologies will continue to decrease. Similarly, computer storage limitations are no longer a major concern. Once the aforementioned technical difficulties are overcome, automated body condition scoring may become an integral part of decision making on modern dairy farms.

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