AUTOMATIC COW'S BODY CONDITION SCORING

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Abstract

This study presents a computer vision tool to automatically estimate body condition scoring (BCS). BCS indicates energy reserves of dairy cows for estimating their fatness or thinness according to a 5-point scale. Digital Images of eighty seven cows were collected in an Israeli research dairy farm using a Nikon DSLR camera located at the entrance of the milking parlor. The cows were manually scored by an expert. Images were manually selected. Cow's tail head area and its contour were segmented and extracted automatically. Two types of features of the tail head contour were extracted for BCS prediction: (1) shape measurements: five anatomical points that were automatically detected by analyzing the sequence of the peaks and valleys of the tail head contour. The angles and distances between these five points were computed. (2) A one dimensional vector of the distances from each point in the contour to the object center. The BCS prediction models using the five anatomical point's feature and by one dimensional contour vector resulted with R^2 of 0.61 indicating that it is possible to automatically extract and analyze BCS.

Key words: Dairy cow, energy reserves, body condition scoring (BCS), image processing, segmentation, feature extraction.

1. Introduction

Body condition scoring (BCS) estimates energy reserves of cows and their fatness or thinness according to a 5-point manual scale (Hady et al., 1994). Evaluation of BCS is an important management tool for analyzing health problems, feed intake and optimal insemination time (Rodenburg, 2004). Currently, BCS is measured manually (Roche et al., 2009): this is a time consuming process, it requires training, and its scores are subjective and may be influenced by the previous cow examined (Halachmi et al., 2008). Despite several attempts to automate BCS of dairy cows (Coeffy et al., 2003, Fergusson et al., 2006, Bewley et al., 2008 Halachmi et al., 2008, Azzaro et al., 2011) -it is still handled manually with no commercial applications. Halachmi et al. (2008) extracted the cow contour from thermal images and predicted BCS by calculating the mean absolute error between a fitted polynomial and the cow contour. Bewley et al. (2008) and Azzaro et al. (2011) marked manually 23 anatomical points on the cow contour and used them as features for a BCS prediction model.

This research advances the work of Halachmi et al., 2008 assuming that the curvature of the tail head contour reflects BCS and presents a prediction model that uses automatic computer vision tools.

2. Objective

The present study aims to develop an automatic computer vision tool to evaluate the cow's BCS.

3. Methods

The images were collected in a research farm located at ARO, Bet Dagan, , Israel between October 2011 and February, 2012. The data set contained eighty seven images of seventy one different Holstein cows. All cows were manually scored by an expert using the BCS 1-5 scale based on Ferguson et al. (1994) evaluation chart. A Nikon D7000 DSLR camera was located at the entrance of the milking parlor at 2.5 meter height. The images were taken before noon milking. The camera was activated from a PC by Camera Control pro 2 software. Each time a cow entered through the parlor gate the camera was activated, and six consecutive images with a resolution of 1632X2464 were acquired. All images were downloaded to the PC. Images for off-line processing were selected manually using the following criteria: (1) the entire tail head area was in the camera view frame. (2) The tail head area was not connected to forging objects including other cows. (3) The cow tail was straightened. Figure 1 demonstrates two selected images (on the top) and two deselected images (bottom).
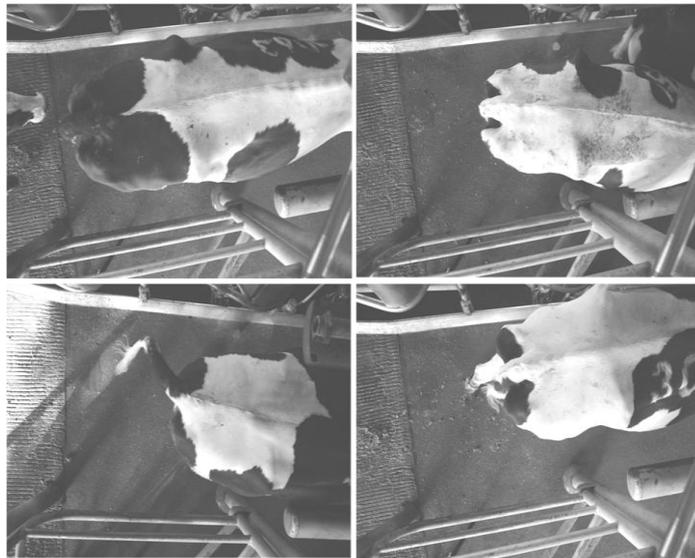

Figure 1- Cows entering the milking parlor. Two selected images (top) and two not-selected images (bottom)

Image processing and segmentation were performed with suitable color masks, automatic threshold and morphological operations as detailed in the following section. Two prediction models were developed: linear regression using backward selection method and partial least square regression (PLSR). The models were validated with *'Leave-One-Out'* method.

4. Algorithms

4.1 Image segmentation

Several Edge detection operators (such as Sobel, Prewitt, Canny) were tested, none of them were able to distinguish between the cow contour and lines created by black and white stains. Therefore, the preferred segmentation method used color transformation of both the acquired image and a background image. The selected color transform was the difference between the red space (R) and the green space (G). This transform emphasizes the difference between the floor and the other objects in the image. Following the transformation, each image was converted to its gray-level values. This procedure allows computing an automatic threshold by Otsu method (Otsu, 1979) conducted by Matlab's Gray thresh function. For final segmentation both images (cow and background image) were transformed to binary images and then, the background image (after erosion operation for small objects removal) reduced from the cow image. The outcome of the process was a binary image containing the cow and noise objects. At this stage, a noise can appear due to many reasons such as secondary objects in the image caused by parts of another cow entered the frame, or by another object in the background such

as mud, cow manure, "connected" to the cow object. The cow object in the binary image was determined assuming it was the largest object in the image. The object was then rotated to a horizontal orientation so the edge of the tail head could be founded by the minimal index of the object in the horizontal axis. Only the upper third part of the object was saved in order to eliminate artificial cuts created in the segmentation by the background objects. The last stage involved ninety degrees rotation of the object and filling small "holes" (by labeling them by Matlab 'bwboundaries' function) in the cow's body that may occur from the segmentation procedure and previous operations. The result of this process was a binary image of the tail head area of the cow. The segmentation procedure is illustrated in Figure 2.
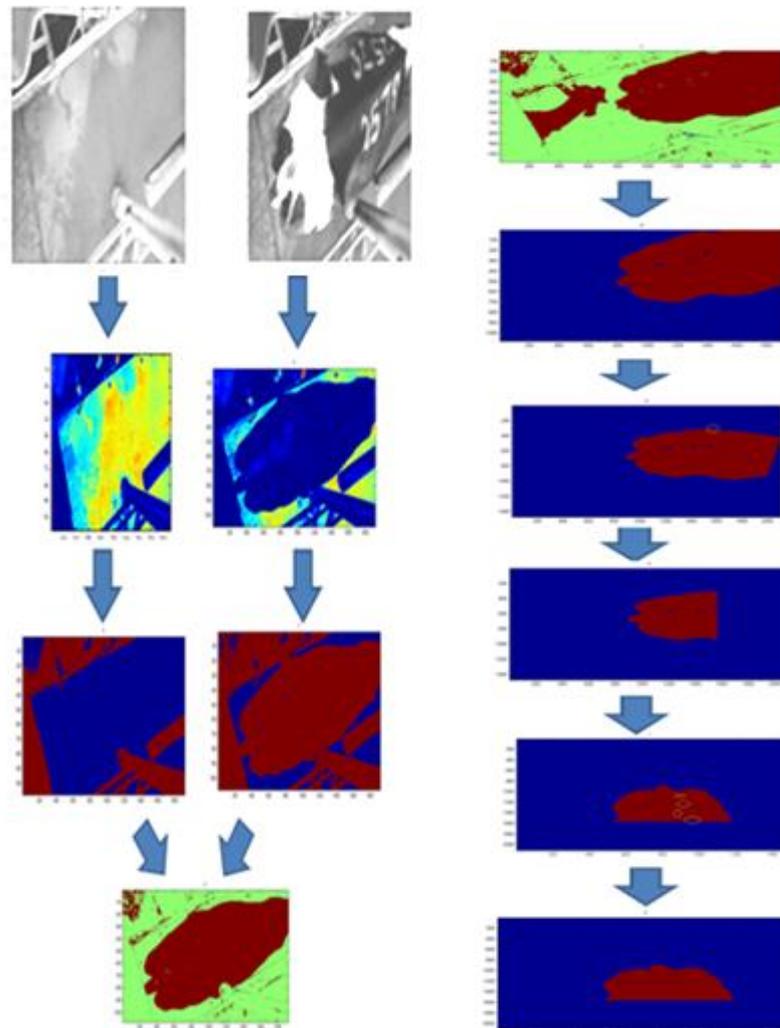

Figure 2- Segmentation procedure: On the left side, the background and the cow image transformed to the R-G space, followed by automatic threshold and reducing the background from cow image. On the right side, first, small objects are removed followed by rotation, saving the upper part of object, 90 degree rotation and holes filling. The result of the process is the binary tail head area (bottom).

4.2 Feature extraction

In order to eliminate the influence of the cow size on image features the tail head contour was extracted after normalizing it to a given number of points and scaling it to a 0:1 range that will represent the new cow curve. The features extracted (Figure 3) were the angles and distances between five anatomical points that were automatically detected by analyzing the sequence of the peaks and valleys of the tail head contour. The most important features were selected using

Stepwise Regression. The cow contour was also presented as a one dimensional vector of the radial distance from each point in the contour to the object center.
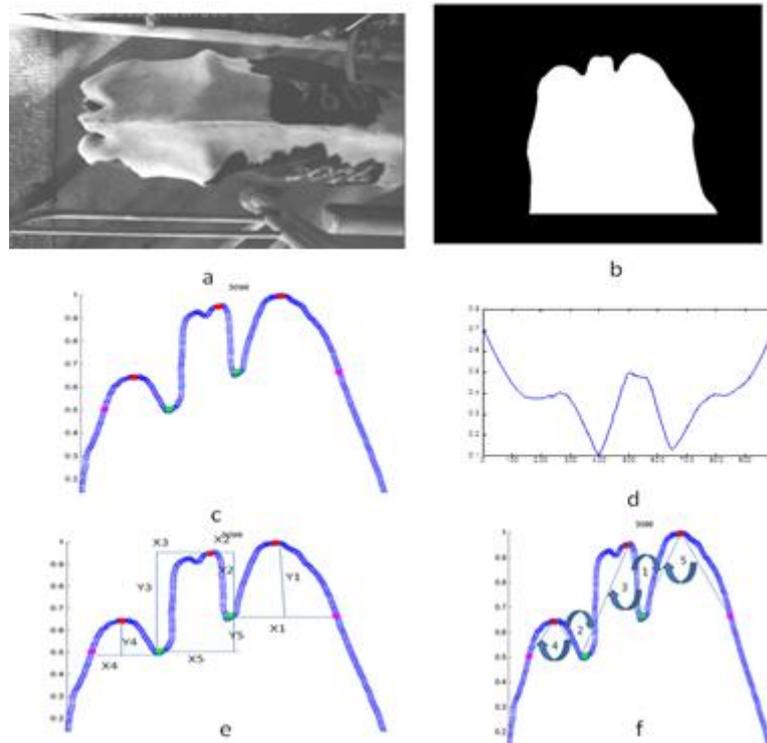

Figure 3- Feature extraction: Original image (a), the segmentation outcome (b), the cows normalized contour (c), one dimensional cow curve (d), vertical and horizontal distances (e), and angles between peaks and valleys points (f)

4.3 Prediction models

Two prediction models were developed: the first model was developed using linear regression, where the distances and angles features were used as prediction variables. Due to the asymmetries of the shape measures extracted automatically, a model that uses the average distance and angles from both sides of the tail head was developed. The regression model was developed with a backward elimination regression using SPSS software. All angles and distances were considered in the primal model. In the modified final model, only significant (P<0.05) variables were incorporated:

$$\text{BCS} = \beta_1 \text{Avg}(\text{angle1,2}) + \beta_2 \text{Avg}(\text{angle4,5}) \beta_1 \text{Avg}(\text{Y1,4}) \quad [1]$$

Where BCS is the computed score of the cow, $\text{Avg}(\text{angle1,2})$ is the average value of angle 1 and angle 2, $\text{Avg}(\text{angle4,5})$ is the average value of angle 4 and angle 5, and $\text{Avg}(\text{Y1,4})$ is the average value of the Y1 and Y4. β_i are the regression coefficients. All horizontal measurements (X), Y2, Y3, Y5 and angle 3 were excluded from the model.

The second model used the cow contour as the prediction variable. The contour vector size is 1X1000 for each cow. Partial least square regression (PLS toolbox, Eigenvectors Inc.) was used to calculate a small number of latent variables that describe the majority of the variance data in the contour. The number of the latent variables was selected as the number that provides minimum value for the root mean square error (RMSE) in the '*Leave-One-Out*' method in order to avoid over fitting of the variables selected to the data.

5. Results

5.1 Shape feature

The R^2 obtained by the shape features was 0.61 and 0.56 using the 'Leave-One-Out' method. The linear correlation between the five anatomical points features (five distances and angles, Figure 3 e-f) and the BCS are shown in Table 1. The Y1, Y4, and Angle1-5 features were correlated with BCS (correlation higher than 0.5 are marked in red). These results confirm the research assumption: **the higher the distance between the peaks and valleys the thinner the cow is** (negative correlation) and **wide angles indicates a rounder cow** (positive correlation). On the other hand, the X1-X5, Y1-Y5, and Angle1-5 features were interrelated, correlated among themselves, because the angles are based on the distances between the peaks and valleys and vice versa. This fact may limit the model results.

Table 1- Correlation of shape measurements with BCS

X1	X2	X3	X4	X5
-0.42	-0.20	0.01	-0.38	-0.15
Y1	**Y2**	**Y3**	**Y4**	**Y5**
-0.52	-0.49	-0.44	-0.53	-0.19
Angle1	**Angle2**	**Angle3**	**Angle4**	**Angle5**
0.70	0.63	0.75	0.72	0.69

5.2 One dimensional cow curve feature

Figure 4 shows that while selecting more variables, the error on the calibration set (calculated by RMSE) reduces monotonically (green line). On the other hand, the error of the validation (the '*leave one-out*' method, blue line) reaches a minimum value (around 0.5) with three variables and then the error increases dramatically. Therefore, the number of variables selected for the model building was three. The results achieved by this model did not indicate improvement in predicting BCS. The R^2 obtained by latent variables on the calibration set was 0.6.
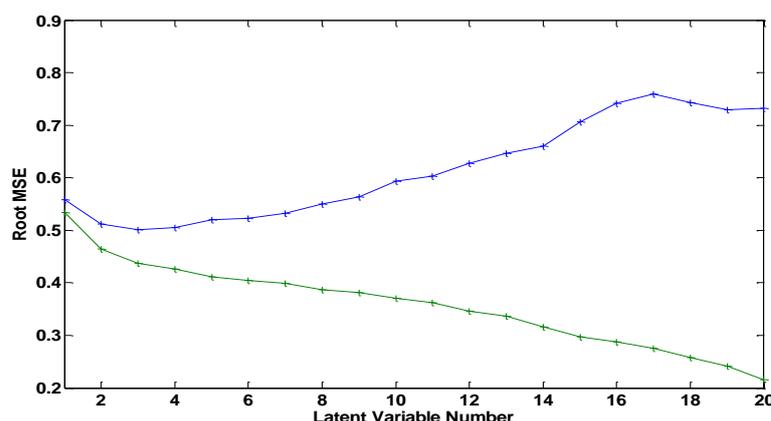

Figure 4-Variable selection by Root MSE on calibration (green line) and Leave one out method (blue line). In three variables the RMSE reach minimum value.

6. Discussion and conclusions

A computer vision tool aiming at automatic evaluation of the dairy cow's BCS was developed. Using shape features a R^2 of 0.6 was obtained using shape features and by using three latent variables of the cow contour. By using the five anatomical point features: fifty percent of the observation errors were smaller than 0.25; 79.5% of the observation errors were smaller than

0.5; 92.3% of the observation errors were smaller than 0.75 and only 5% of the observation errors were higher than 1. These results indicate that it is possible to automatically extract features for BCS prediction from digital images.

The average error rate was 0.33 – slightly weaker than results presented by Azzaro et al., (2011) -0.31. The results are also weaker than results presented by Bewley et al. (2008). Potential reasons are: (1) in addition to the tail head Bewley et al. (2008) and Azzaro et al., (2011) used the hook area which was impossible to extract automatically under our research conditions. (2) Bewley et al. (2008) and Azzaro et al., (2011) applied their methods manually, not automatically. It seems that additional training of the model may improve it results. Furthermore, the manually BCS was provided by only one expert, due to its natural error and subjectivity may limit the model statistical results. For complete process automation it is necessary to automate the frame selection procedure, while capturing the image stream. The majority of images are not suitable for processing due to many reasons (e.g., the cow is out of frame or bad orientation of the tail). Ongoing research (Bercovich, 2012) aims to improve results.

8. Acknowledgments

9. Reference

1. Azzaro, G., Caccamo, M. ,Ferguson J.D, Battiato S., Farinella M., Guarnera C., Puglisi G., Petrigiliero R., Licitra G. 2011. Objective estimation of body condition score by modeling. *Journal of Dairy Science 94: 2126-2137.*
2. Bercovich, A. THEISIS Automatic cow body condtion scoring. Unpublished MSc thesis. Dept. of Industrial Engineering and Management, Ben-Gurion Univesity of the Negev, Beer Sheva, Israel. (September 2012).
3. Bewley, J.M., A.M. Peacock, O. Lewis, R.E. Boyce, D.J. Roberts, M.P. Coffey, S.J. Kenyon, and M.M. Schutz. 2008. Potential for estimation of body condition scores in dairy cattle from digital images. *Journal of Dairy Science 91: 3439-3453.*
4. Coffey, M. P., T. B. Motram, and N. McFarlance. 2003. A feasibility study on the automatic recording of condition score in dairy cows. *British Association Animal Science: 131.*
5. Ferguson, J. D.,Galigan, D.T., Thomsen, N. 1994. Principal disriptors of body condition score in Holstien cows. *Journal of Dairy Science 77:2695–2703.*
6. Ferguson, J. D., G. Azzaro, and G. Licitra. 2006. Body condition assessment using digital images. *Journal of Dairy Science 89:3833–3841.*
7. Hady P,J , Domecq J. J., Kaneene J. B. 1994. Frequency and precision of body condition scoring in dairy cattle. *Journal of Dairy Science 77: 1543-1547.*
8. Halachmi I, P.Polak, D.Roberts, M.Klopcic . 2008. Cow body shape and automation of scoring BCS. *Journal of Dairy Science 91:4444–4451.*
9. Roche, J.R., Friggens, N.C., Kay, J.K., Fisher, M.W., Stafford, K.J., Berry, D.P. 2009. invited review: Body condition score and its association with dairy cow productivity, health, and welfare. *Journal of Dairy Science 92, 5769−5801*
10. Rodenburg, J. 2000. Body Condition Scoring of Dairy Cattle. *Retrieved on October 24, 2010, from www.omafra.gov.on.ca.*