Assessment of Cow's Body Condition Score Through Statistical Shape Analysis and Regression Machines

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Abstract

This study explores the feasibility of estimating the Body Condition Score (BCS) of cows from digital images by employing statistical shape analysis and regression machines. The shapes of body cows are described through a number of variations from a unique average shape. Specifically, Kernel Principal Component Analysis is used to determine the components describing the many ways in which the body shape of different cows tend to deform from the average shape. This description is used for automatic estimation of BCS through regression approach. The proposed method has been tested on a new benchmark dataset available through the Internet. Experimental results confirm the effectiveness of the proposed technique that outperforms the state-of-the-art approaches proposed in the context of dairy cattle research.

1. Introduction and Motivations

The energy reserves in cows in terms of body fat stores and mobilization during the different lactation stages have important implications for milk production, animal well-being, reproductive performance, and, more generally, farm productivity. Body Condition Score (BCS) is widely considered an important tool for management of dairy cattle because it is a simple and repeatable system used to evaluate body fat stores and estimate cumulative energy balance through visual or tactile inspection (Ferguson et al., 1994). The score range used by most dairy management advisors applies a scale from 1 to 5, with 1 representing emaciated cows and 5 representing obese cows.

Despite the general consensus on the benefits of the BCS evaluation in farms, less than 5% of US dairy farms have adopted this practice in the production chain. The main reasons that discourage the use of the traditional BCS evaluation techniques are the lack of computerized reports (Ward, 2003), the subjectivity in the judgment that can lead to different scores for the same cow under consideration, and the complex, not immediate, and time consuming on-farm training of technicians. Furthermore, the measurements must be revised frequently on each cow augmenting hence the costs for the farms.

The feasibility of estimating the BCS from digital images has been demonstrated in recent works. Ferguson et al. (2006) assessed the ability to assign a BCS to a dairy cow directly from digital photographs. In that study, BCS could be assessed by human observers from digital photographs or a video taken from the rear of a cow at a 0 to 20 degree angle relative to the tail head. Bewley et al. (2008) assessed the feasibility of using digital images to determine BCS employing a semi-automatic estimation technique from digital images. They considered a single image of the dorsal view of the cow captured automatically as cows passed through a weigh station and used 23 anatomical points to define the shape of the body of the cow. These points, selected in a manual way, were used to compute 15 angles around the hooks, pins, and tailhead, in order to describe the cow's contour. A regression machine was employed to infer the BCS from the computed angles. Halachmi et al. (2008) tested the hypothesis that the body shape of a fatter cow is rounder than that of a thin cow and, therefore, may better fit a parabolic shape. The posterior part of the cow was considered in performing the parabolic fitting. The BCS estimation was achieved by considering the absolute differences between the real body shape and the fitted parabola.

The main objective of this study is to propose a technique able to describe the shape of body cows in a reconstructive way. Shapes of cows were reconstructed by using a linear combination of basis shapes obtained through Kernel Principal Component Analysis (KPCA). KPCA is used to model the variability of the shapes of cows within a set of examples. In this manner cows' body shapes were described through the different variability from the average shape considered into the kernel space. The method produced a compact description of the shape to be used for automatic estimation of BCS through regression approach. A benchmark dataset useful for dairy cattle research purposes, available through the Internet[1], was also built as reference for researchers and/or technicians. The dataset was used to test and compare the proposed method with respect to the other state-of-the-art approaches cited above. The experimental results confirm the effectiveness of the proposed approach that achieves the best performances in terms of BCS estimation accuracy.

The remainder of the paper is organized as follows: Sections 2, 3, and 4 describe the proposed system for BCS assessment. Section 5 details the experimental settings and reports the obtained results. Finally, conclusions and avenues for further research are given in Section 6.

2. Cows' Body Shapes and Their Alignment

Among the visual cues used by human visual system, the shape provides important information that allows humans to distinguish between objects of different categories (Belongie et al., 2002) as well as information that are relevant to understand the differences in the appearance of an object within a specific class (Cootes et al., 1992). Shapes are typically represented by locating a finite number of landmarks on the outline of an object. The mathematical representation for n landmarks located into the shape of an object is a $2n$-dimensional column vector:

$$\mathbf{s} \quad = \quad [x_1, x_2, \ldots, x_n, y_1, y_2, \ldots, y_n]^T = [s_1, s_2, \ldots, s_n, s_{n+1}, s_{n+2}, \ldots, s_{2n}]^T \tag{1}$$

In this paper we have used the 23 anatomical points indicated by Bewley et al. (2008) as landmarks useful to represent the outline of cows' body shapes (Figure $1(a)$). We started by considering the following shape definition (Dryden and Mardia, 1998): "*Shape is all the*

1. The BCS Database is available at: http://iplab.dmi.unict.it/bcs/

geometrical information that remains when location, scale and rotational effects are filtered out from an object". According to this definition, to obtain a consistent shape representation, location, scale and rotational effects were filtered out by aligning the corresponding anatomical landmarks of the different involved shapes. The alignment of cows' body shapes was carried out by establishing a coordinate reference system (position, scale and rotation, commonly known as pose) to which all shapes referred. The reference anatomical landmarks we used for this task were the landmarks corresponding to foreribs, tail and hooks, as highlighted in Figure 1(a). First, shapes were translated to the origin (Figure 1(b)). Shapes

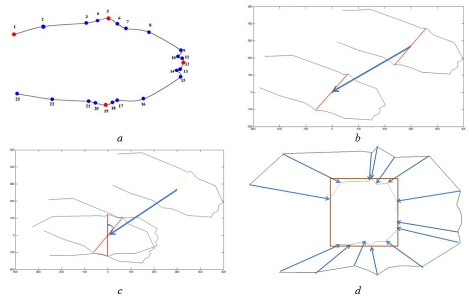


Figure 1: Anatomical landmarks in a cow body shape (a), shape translation (b), shape rotation (c), and shape scaling (d).

were then rotated such that the left hook and the right hook had the same horizontal coordinate (Figure 1(c)). To perform translation and rotation of shapes, the middle point between the left hook bone and the right hook bone was taken into account. Finally, shapes were scaled to fit in a unit square (Figure 1(d)). After alignment, all the shapes referred to the same coordinates system centered into the origin. Shapes were hence modeled by using the statistics on the 23 anatomical landmarks.

3. Kernel PCA Based Shape Analysis

In computer vision literature, several shape descriptors have been proposed (Cootes et al., 1992; Belongie et al., 2002; Xu et al., 2009). Shape descriptors based on Kernel Principal Component Analysis (KPCA) has been successfully used for statistical shape analysis and recognition (Samuel et al., 2006; Sahbi, 2007). Kernel PCA is the extension of PCA to deal with non-linear cases using the technique of kernel methods. The basic idea beyond kernel methods is to map the data in the input space into a high dimensional feature space via some non-linear function Φ and then apply a linear method in the augmented space to do further analysis.

Let $\mathbf{S} = \{\mathbf{s}_1, \ldots, \mathbf{s}_m\}$ a set of cows' body shapes and $\mathbf{S}^{'} = \{\mathbf{s}_1^{'}, \ldots, \mathbf{s}_m^{'}\}$ the set of shapes obtained through the alignment procedure (see Section 2). Let $\Phi : R^{2n} \rightarrow R^{n_\Phi}$ be a mapping function acting on the input space $\mathbf{S}^{'}$. The mean shape of $\mathbf{S}_\Phi^{'}$ can be simply computed as follows:

$$\overline{\mathbf{s}_\Phi^{'}} = \frac{1}{m}\sum_{i=1}^{m}\Phi(\mathbf{s}_i^{'}) \tag{2}$$

The sample mean is the vector that minimizes the sum of the squared error criterion function:

$$\overline{\mathbf{s}_\Phi^{'}} = \underset{\mathbf{v}_\Phi}{\operatorname{argmin}}\sum_{i=1}^{m}||\mathbf{v}_\Phi - \Phi(\mathbf{s}_i^{'})|| \tag{3}$$

The sample mean $\overline{\mathbf{s}'_\Phi}$ is the zero-dimensional descriptor of the dataset $\mathbf{S}'_\Phi$ and can be considered as a "prototype" of the data (i.e., it is the most similar to all the sample into the dataset), but it does not reveal any of the variability in the data. The modes of variations, the ways in which the points of the shape into the Kernel space tend to move with respect to the average shape, can be found by applying principal component analysis (PCA) to the deviations from the mean $\overline{\mathbf{s}'_\Phi}$. In this way a shape into the kernel space can be considered as a linear combination of basis shape into the kernel space, and the basis components can be used as descriptor of the shape. Kernel PCA finds the principal axes by diagonalizing the following matrix:

$$\mathbf{C}_\Phi = \frac{1}{m}\sum_{i=1}^{m}\left[\left(\Phi(\mathbf{s}'_i) - \overline{\mathbf{s}'_\Phi}\right)\left(\Phi(\mathbf{s}'_i) - \overline{\mathbf{s}'_\Phi}\right)^T\right] \tag{4}$$

Specifically, taking into account the $n_\phi \times n_\phi$ covariance matrix above, the modes of variation are described by the unit eigenvectors of $\mathbf{C}_\Phi$ such that

$$\mathbf{C}_\Phi \mathbf{e}^\Phi_j = \lambda^\Phi_j \mathbf{e}^\Phi_j \qquad j = 1, \ldots, n_\Phi \tag{5}$$

$$\mathbf{e}^{\Phi\,T}_j \mathbf{e}^\Phi_j = 1 \qquad j = 1, \ldots, n_\Phi \tag{6}$$

where λ^Φ_j is the j^{th} eigenvalue of $\mathbf{C}_\Phi$. The eigenvectors of the covariance matrix corresponding to the largest eigenvalues describe the most significant modes of variations in the variables used to derive the covariance matrix $\mathbf{C}_\Phi$. Taking into account the considerations made by Halachmi et al. (2008), where the BCS is estimated using a parabolic fitting of the cows' body shapes, in our experiments we have tested a polynomial mapping function to model the shape of cows.

4. Cows' Body Shape Descriptor and BCS Estimation

The eigenvectors $\{\mathbf{e}^\Phi_j\}_{j=1}^{n_\Phi}$ useful to describe the shapes in a reconstructive way were computed using Kernel PCA (see Section 3). Any shape in the training set mapped into the kernel space through Φ can therefore be generated by using the following equation:

$$\Phi(\mathbf{s}'_i) = \overline{\mathbf{s}'_\Phi} + \sum_{j=1}^{n_\Phi} a^\Phi_{i,j}\mathbf{e}^\Phi_j \tag{7}$$

where

$$a^\Phi_{i,j} = \mathbf{e}^{\Phi\,T}_j\left(\Phi(\mathbf{s}'_i) - \overline{\mathbf{s}'_\Phi}\right) \tag{8}$$

The eigenvectors $\{\mathbf{e}^\Phi_j\}_{j=1}^{n_\Phi}$ are the set of basis of the shapes into the kernel space $\mathbf{S}'_\Phi$ useful to generate new samples. Unseen shapes in the kernel space can be generated by varying the values of each $a^\Phi_{i,j}$ taking into account that its variance is represented by λ^Φ_j. Since most of the samples lie within three standard deviations of the mean, the suitable range for $a^\Phi_{i,j}$ is $[-3\sqrt{\lambda^\Phi_j}, 3\sqrt{\lambda^\Phi_j}]$. This range is also used to detect outlier (probably due to error in manual labeling). Given a training set of cows' body shapes, Kernel Principal Component Analysis can be applied after alignment and hence each shape $\mathbf{s}'_i$ can be described into the Kernel space by using the vector $\mathbf{a}^\Phi_i = [a^\Phi_{i,1}, ..., a^\Phi_{i,n_\Phi}]$. The shape descriptors of the training set can be used together with a regression machine to build a system for BCS estimation:

$$BCS_i = a^\Phi_{i,n_\Phi} w_{n_\Phi} + a^\Phi_{i,n_\Phi - 1} w_{n_\Phi - 1} + ... + a^\Phi_{i,1} w_1 + w_0 \tag{9}$$

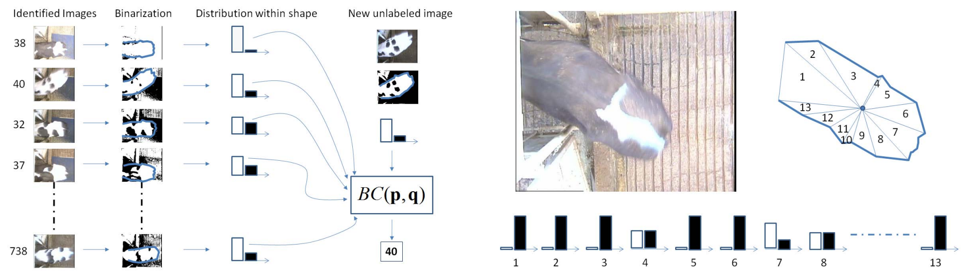
Given the descriptors of the shape in the training set, the regression model can be fitted by using a simple least squares method. The learned parameters $[w_0, w_1, ..., w_{n_\Phi}]$ are then used to infer the BCS of new shape samples describing them through the basis $[\mathbf{e}_1^\Phi, ..., \mathbf{e}_{n_\Phi}^\Phi]$ previously learned on the training set, the sample mean $\overline{\mathbf{s}'_\Phi}$, and the formula (8).

5. Experimental Settings and Results

Images of cows in a dairy farm were acquired by means of a standard network digital camera. The camera was positioned at the exit gate from the couple of milking robots at 3 m from the floor to allow capturing images of the dorsal area of cows (top-left in Figure 2(b)). The image acquisition system gathered a huge amount of data (approximately 172800 images for each acquisition interval of four hours) to be analyzed. The useful information (i.e., the cow is in the scene) was contained in a very small subset (about 40). To overcome this problem, the selection of the frames to be analyzed has been done through a series of image processing algorithms (see Battiato et al. (2010) for all details). The filtering process led to a final set with 286 images, corresponding to 29 different cows. An ad-hoc software application was implemented to allow technicians to label each acquired image with the 23 anatomical points useful for BCS estimation according to Bewley et al. (2008).

At the beginning of the acquisition time, 2 technicians were employed to identify the cows at the exit alley of the milking robot. The clocks of both the image acquisition system and the technicians were synchronized. Technicians filled a report with one record for each cow involved in the experiment. The report contained the cow identification (ID) marked in the collar, the BCS, estimated according to Ferguson et al. (1994), and a timestamp. Once the report was completed, the assigned BCSs were properly associated to acquired cows' images by using the timestamp. This procedure produced a dataset of 29 images (one for each cow involved in the experiment) labeled with the mean of BCSs estimated by the two technicians.

A semi-automatic procedure was adopted to assign ID label and BCS score (i.e., the ground truth) to all the other acquired images selected by the filtering pipeline. To establish similarity between images labeled by the technicians and unlabeled images obtained with the filtering process, each image was first binarized by considering the average color within the shape region, and then represented as a binary distribution taking into account the black and white pixels within the shape region (Figure 2(a)). Similarity between the distributions related to different images was measured by using the coefficient of Bhattacharyya (1943). Since the binarized texture of cows can be similar in their distribution if the shape is considered as whole, in the final solution we adopted a more robust representation of the content of images based on a binary distribution for each subregion of the shape obtained considering anatomical landmarks and the center of mass of the anatomical points (Figure 2(b)). The similarity between two images, represented by using binary distributions of subregions within the shape is obtained by averaging the similarity of distributions of corresponding subregions measured with the Bhattacharyya coefficient. The developed software took as input an image from the labeled dataset and retrieved the first K (K=10 in our experiment) similar unlabeled images. A technician was employed to associate the retrieved unlabeled images to the target labeled image through visual inspection. The ID and BCS of the target image were automatically associated by the software to the images selected by the technician. This software was useful to speed up the labeling phase.



(a) Similarity between cows' images. (b) Binary distribution of subregions.

Figure 2: Ground truth propagation.

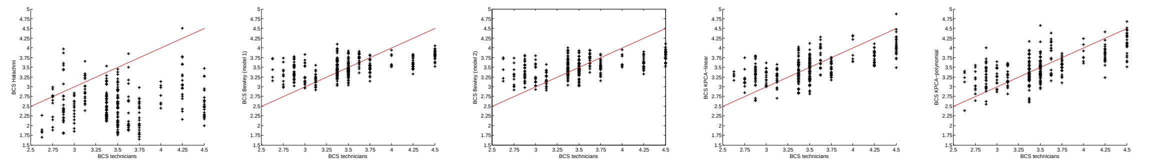
Method	Mean BCS error
Modified Halachmi	0.9837
Bewley (model 1)	0.3295
Bewley (model 2)	0.3289
KPCA - Linear Kernel	0.3218
KPCA - Polynomial Kernel	0.3059

Table 1: Mean BCS error comparison.

All the labeled images together with the related ground truth (anatomical points and BCS) and the labeling SW are available at http://iplab.dmi.unict.it/bcs/.

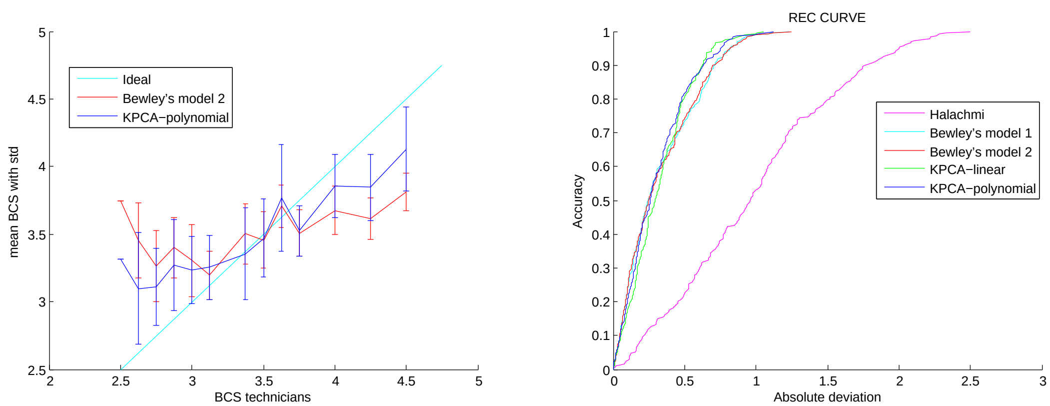
In order to assess the effectiveness of the methods, the Leave One Out Cross Validation (LOOCV) procedure and the Regression Error Characteristic Curves (REC) (Bi and Bennett, 2003) were used. Each run of LOOCV involved a single observation of the dataset as test, and the remaining samples as training data. This was repeated to guarantee that each sample was used once as the test data. The average error rate was computed taking into account all runs. The REC curve is essentially the cumulative distribution function of the error. The area over the curve is a biased estimation of the expected error of an employed regression model.

Results of errors obtained from estimation of BCS using the different models are reported in Table 1. The Halachmi approach was not able to provide satisfactory results (Figure 3(a)). The parabolic fitting might be not accurate enough when is performed considering only the 23 labeled points. Bewley's models obtained similar results (model 2 was slightly better than model 1) (Figure 3(b) and Figure 3(c)). Their performances are better for the central BCS values (around 3.5) and worst in the extreme cases (2.5 and 4.5) corresponding to thin or fat cows. Our approach, in particular the one using polynomial kernel, outperformed the other techniques, obtaining satisfactory results even in the extreme cases. Predicted BCS versus true BCS (estimated by technicians) results are reported in Figure 3(d) and Figure 3(e). As shown in Figure 4(a), the KPCA with polynomial kernel is able to follow the ideal line better than Bewley's approach. In Figure 4(b) the comparison through REC curves confirms that the proposed method outperforms state-of-the-art techniques for BCS assessment.



(a) (b) (c) (d) (e)

Figure 3: Predicted BCS versus true BCS (estimated by technicians). (a) Halachmi approach. (b) Bewley's model 1. (c) Bewley's model 2. (d) Proposed approach KPCA-Linear. (e) Proposed approach KPCA-Polynomial.



(a) KPCA-Polynomial vs Bewley's model 2.

(b) REC Curves comparison.

Figure 4: (a) Proposed kernel approach with polynomial kernel (blue line) versus Bewley's model 2 (red line). As shown in (a) the proposed approach follows the ideal line better than Bewley's model. In (b) the REC Curves of the different models involved in the comparison confirm the effectiveness of the proposed approach.

6. Conclusion and Future Works

BCS estimation systems are desired to cut down time and costs of the traditional BCS estimation techniques. These systems can produce an objective evaluation of BCS in a way that is less invasive for the cows. In this paper a new method for BCS estimation is discussed. The cow body shape is described considering the deviation from the average shape in the kernel space. The method produced a description of the shape to be used for automatic estimation of BCS through a regression machine. Experimental results confirm the effectiveness of the proposed approach that outperforms the previous state-of-the-art methods in the field. A second contribute of this study is the new benchmark dataset useful for research purposes. The new BCS dataset is publicly available through the Internet. Future works will be devoted in building a fully automatic system for BCS evaluation in which the shape of a cow will be automatically extracted through segmentation procedure from digital images acquired with a low cost camera. Additional side views will be included and combined with the dorsal view to better estimate the BCS. Moreover, the benchmark database will be extended to include more samples and extreme cases (cows with BCS<2.5 and 4.5<BCS).

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