ESTIMATION OF COW'S BODY CONDITION SCORE FROM IMAGES

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ABSTRACT

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. This study explores the possibility to efficiently semi-automate the process of body condition scoring using images acquired by commercial low-cost digital cameras. The proposed method has been compared with respect to state-of-the-art approaches obtaining the best performances for Body Condition Score evaluation.

1. INTRODUCTION

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 [1]. 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 [2].

Despite the general consensus of dairy producers, nutritionists, consultants, and herd managers, 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 [3], 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.

Recent studies have addressed the problem of BCS estimation directly from digital images. Ferguson et al. [4] assessed the ability to assign a BCS to a dairy cow 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. [5] 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. Halachmi et al. [6] 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 and a parabolic fitting was performed. The absolute differences between the real body shape and the fitted parabola were used to estimate BCS.

Despite the progress in this research area, such studies have not addressed the problem of modeling the shape of body cows to build a robust descriptor for automatic BCS estimation. Among the visual cues used by human visual system, the shape provides important information that allows humans to distinguish between objects of different categories [7] as well as information that are relevant to understand the differences in the appearance of an object within a specific class [8]. In computer vision literature, several shape descriptors have been proposed [7, 8, 9]. More specifically, shape descriptors based on Principal Component Analysis (PCA) [8] are used to consider the different variability of anatomical landmarks with respect to the average shape.

The aim of the present study is to model the shape of the body of cows by capturing variability with respect to a "prototype" shape properly derived by a set of examples and then exploiting these variabilities to describe the cows' body shape in a reconstructive way. The BCS estimation is performed after learning a regressor on the kernel PCA space of cow's shapes. A further objective was to build a benchmark dataset useful for dairy cattle research purposes, available through the Internet [1]. The experimental results confirm the effectiveness of the proposed approach that outperforms all previous approaches in terms of BCS evaluation accuracy.

The remainder of the paper is organized as follows: Section 2 describes the employed model. Section 3 details the experimental settings, and reports the obtained results. Finally, conclusions and avenues for further research are given in Section 4.

2. PROPOSED METHOD

A general scheme of a system for semi-automatic evaluation of the BCS from digital images is shown in Figure 1. The system consists of two different blocks: *Training* and *Employing*. The *Training block* is used to learn the parameters of the model employed to infer the BCS from features extracted on digital images. The parameters are learned by using a set of labeled examples. Once the training is completed the learned parameters are exploited in the model to infer the BCS of new samples during employing phase.

Each block is composed by different modules organized in a sequential pipeline. The *Training Block* is composed

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

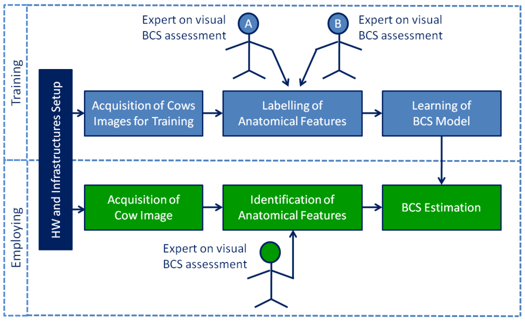

Fig. 1. Scheme of the proposed approach.

by three modules used for acquisition of training examples, for labeling of anatomical features, and for learning the BCS model parameters. The *Acquisition module* is used to acquire images to be used as examples in the learning of the model parameters. During the acquisition, the experts on visual BCS assessment should evaluate on site the BCS of the involved cows in order to build a consistent labeled dataset containing images with the corresponding BCS. The *Labeling module* is devoted to the labeling of anatomical features on the acquired digital images by making use of a user-friendly interface that allows the experts to mark the anatomical features. The *Learning module* is devoted to properly learn the set of parameters involved in the BCS model (e.g., regressor on anatomical points) making use of the labeled dataset.

The *Employing Block* is composed by three sequential modules dedicated respectively to acquire a new unlabeled sample, to identify the anatomical features through user intervention and to automatically estimate the BCS of the sample under consideration by using the model parameters obtained in the learning phase. Both *Training* and *Employing* share the same Hardware and Infrastructures Setup.

2.1. PCA Based Shape Analysis

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:

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

Let $\mathbf{S} = \{\mathbf{s}_1, \ldots, \mathbf{s}_m\}$ a set of shapes and $\mathbf{S}^{'} = \{\mathbf{s}_1^{'}, \ldots, \mathbf{s}_m^{'}\}$ the set of shapes obtained through the alignment procedure (see section 2.3). The mean shape of $\mathbf{S}^{'}$ can be simply computed as follows:

$$\overline{\mathbf{s}^{'}} = \frac{1}{m}\sum_{j=1}^{m}\mathbf{s}_j^{'} \quad (2)$$

The sample mean $\overline{\mathbf{s}^{'}}$ is the zero-dimensional descriptor of the dataset $\mathbf{S}^{'}$ and can be considered as a "prototype" of the data, in the sense that 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 tend to move with respect to the average shape, can be found by applying principal component analysis (PCA) to the deviations from the mean $\overline{\mathbf{s}^{'}}$. In this way a shape can be considered as a linear combination of basis shape, and the basis components can be used as descriptor of the shape [8].

2.2. Kernel PCA Based Shape Analysis

Kernel PCA has been successfully used for statistical shape analysis [10]. 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 ($\mathbf{S}^{'}$ in our case) 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 $\Phi : R^{2n} \rightarrow R^{n_\Phi}$ be a mapping function acting on the input space $\mathbf{S}^{'}$. Kernel PCA finds the principal axes by diagonalizing the following matrix:

$$\mathbf{C}_\Phi = \frac{1}{m}\sum_{j=1}^{m}\left[\left(\Phi(\mathbf{s}_j^{'}) - \frac{1}{m}\sum_{i=1}^{m}\Phi(\mathbf{s}_i^{'})\right)\left(\Phi(\mathbf{s}_j^{'}) - \frac{1}{m}\sum_{i=1}^{m}\Phi(\mathbf{s}_i^{'})\right)^T\right] \quad (3)$$

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

$$\mathbf{C}_\Phi \mathbf{e}_k^\Phi = \lambda_k^\Phi \mathbf{e}_k^\Phi \qquad i = 1, \ldots, n_\Phi \quad (4)$$

$$\mathbf{e}_k^{\Phi\,T}\mathbf{e}_k^\Phi = 1 \qquad k = 1, \ldots, n_\Phi \quad (5)$$

where λ_k^Φ is the k^{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 $\mathbf{C}_\Phi$. Note that the original linear method PCA is a particular instance of the kernelized method (e.g., Kernel PCA) since the a possible mapping function is $\Phi(\mathbf{x}) = \mathbf{x}$. Taking into account the considerations in [6], where the BCS is estimated using a parabolic fitting of the cows' shape, in our experiments we have used Kernel PCA to model the shape of cows. Specifically we used the Linear and Polynomial mapping function to produce the results in Section 3.

2.3. Shape Alignment

To obtain a consistent shape representation, location, scale and rotational effects need to be filtered out. This can be done by aligning the corresponding anatomical landmarks of the different involved shapes. The alignment of shapes was carried out by establishing a coordinate reference (position, scale and rotation, commonly known as pose) to which all shapes must be referred. The reference anatomical landmarks we used for this task are the landmarks corresponding to foreribs, tail and hooks, as highlighted in Figure 2(a).

First, shapes are translated to the origin (Figure 2(b)). Shapes are then rotated such that the left hook and the right hook have the same horizontal coordinate (Figure 2(c)). To perform translation and rotation of shapes, the middle point

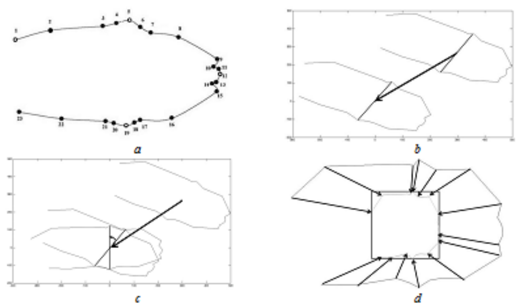

Fig. 2. Anatomical landmarks in a cow body shape (a), shape translation (b), shape rotation (c), and shape scaling (d).

between the left hook and the right hook was taken into account. Finally, shapes are scaled to fit in a unit square (Figure 2(d)). After alignment, all the shapes referred to the same coordinate system centered into the origin.

2.4. Cows' Body Shape descriptor and BCS Estimation

The eigenvectors $\{\mathbf{e}_k^{\Phi}\}_{k=1}^{n_\Phi}$ useful to describe the shapes were computed using Kernel PCA (see Section 2.2). Any shape in the training set mapped into the kernel space through Φ can therefore be generated by using the following equation:

$$\Phi(\mathbf{s}_j^{'}) = \frac{1}{m}\sum_{i=1}^{m}\Phi(\mathbf{s}_i^{'}) + \sum_{k=1}^{n_\Phi} a_{j,k}^{\Phi}\mathbf{e}_k^{\Phi} \tag{6}$$

where

$$a_{j,k}^{\Phi} = \mathbf{e}_k^{\Phi T}\left(\Phi(\mathbf{s}_j^{'}) - \frac{1}{m}\sum_{i=1}^{m}\Phi(\mathbf{s}_i^{'})\right) \tag{7}$$

The eigenvectors $\{\mathbf{e}_k^{\Phi}\}_{k=1}^{n_\Phi}$ are the set of basis of the shapes into the kernel space $\Phi(\mathbf{S}^{'})$ useful to generate new samples. Unseen shapes in the kernel space can be generated by changing the values of each $a_{j,k}^{\Phi}$ taking into account that its variance is represented by λ_k^{Φ}. Since most of the sample of the training set lies within three standard deviations of the mean, the suitable range for $a_{j,k}^{\Phi}$ is $[-3\sqrt{\lambda_k^{\Phi}}, 3\sqrt{\lambda_k^{\Phi}}]$. The range of each $a_{j,k}^{\Phi}$ can be used to detect outlier that in our case are probably due to error in manual labeling. Given a training set of cow shapes, kernel principal component analysis can be applied after alignment and hence each shape $\mathbf{s}_j^{'}$ can be described by using the vector $\mathbf{a}_j^{\Phi} = [a_{j,1}^{\Phi}, ..., a_{j,n_\Phi}^{\Phi}]$. The shape descriptors of the training set can be used together with a linear regressor to build a system for BCS estimation:

$$BCS_j = a_{j,n_\Phi}^{\Phi}w_{n_\Phi} + a_{j,n_\Phi-1}^{\Phi}w_{n_\Phi-1} + ... + a_{j,1}^{\Phi}w_1 + w_0 \tag{8}$$

Given the descriptors of the shape in the training set, the regression model can be fitted by using 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 by using the basis $[\mathbf{e}_1^{\Phi}, ..., \mathbf{e}_{n_\Phi}^{\Phi}]$ learned on the training set.

3. 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.

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, we developed a series of ad-hoc image processing algorithms. First, a filtering was performed through the analysis of the absolute interframe error between adjacent frames. When a cow passes through the gate the absolute interframe error typically has higher values with respect to that obtained by the difference of two images without cow (background). Considering an acquisition interval of four hours, a peaks and valleys plot is obtained. Each peak represents an image containing a cow whereas the valleys are only related to the background. The filtering software identifies the highest peaks and then a fixed number of images (200 in our implementation) was selected automatically around them. Considering the reduced subset, the mean absolute interframe error was then used as starting point for local variance analysis (i.e., the variance was computed considering a sliding window of 20 elements). Plateau was strongly related to consecutive background frames and a background frame *Bg* was selected from this uniform region. Afterward, the differences between all the selected frames and *Bg* were computed. The peak indicated the frame that differed more with respect to *Bg*: the corresponding frame therefore contained the whole cow. In order to cope with motion blur, out of focus, and other acquisition problems, five frames around the identified frame were selected. Finally the best frame was manually identified among the five frames. The aforementioned filtering process led to a final set with 286 images, corresponding to 29 different cows. An ad-hoc application was implemented to allow technicians to label each acquired image with the 23 anatomical points useful for BCS estimation according to [5]. 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) 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 [2] was not able to provide satisfactory results. The parabolic fitting, performed considering only the

[2]The experiment in which the Halachmi approach is used exploit only the 23 anatomical points of the cows' shape.

Method	Mean BCS error
Modified Halachmi	0.9837
Bewley (model 1)	0.3295
Bewley (model 2)	0.3289
Proposed Model 1: Linear Kernel PCA	0.3218
Proposed Model 2: Polynomial Kernel PCA	0.3059

Table 1. Mean BCS error comparison.

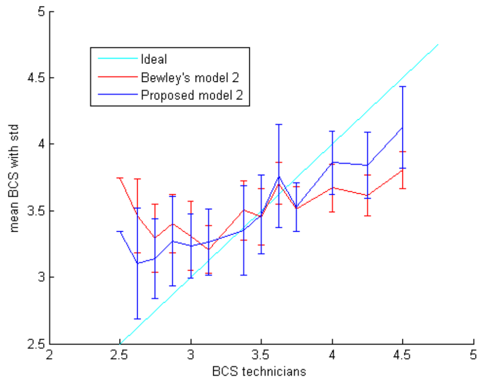

Fig. 3. Proposed kernel approach with polynomial kernel (blue line) versus Bewley's model 2 (red line). Our approach follows the ideal line better than Bewley's model.

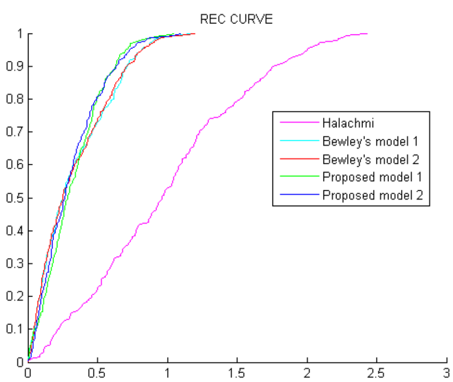

Fig. 4. REC Curves of the different models involved in the comparison.

labeled points, may be not accurate enough. Bewley's models obtained similar results (model 2 was slightly better than model 1). 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 approaches[3], in particular the one using polynomial kernel, outperforms the other techniques, obtaining satisfactory results even in the extreme cases. As shown in Figure 3, the method employing polynomial kernel is able to follow the ideal line better than Bewley's approach. In Figure 4 the comparison through REC curve confirms that the proposed approach outperforms state-of-the-art methods in estimating BCS.

[3]We call *Proposed Model 1* the approach in which Linear Kernel is used, whereas *Proposed Model 2* the ones exploiting Polynomial Kernel.

4. 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 introduced. 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 which outperforms the previous state-of-the-art methods in the field. A second contribute of the paper is related the benchmark dataset built for dairy cattle research purpose. 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 considered to better estimate the BCS. Moreover, the benchmark database will be extended to include more samples and extremal cases (cows with BCS<2.5 and 4.5<BCS).

5. REFERENCES

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