Computers and Electronics in Agriculture 100 (2014) 139–147

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Comparison of a three-dimensional and two-dimensional camera system for automated measurement of back posture in dairy cows

S. Viazzi [a], C. Bahr [a], T. Van Hertem [b], A. Schlageter-Tello [c], C.E.B. Romanini [a], I. Halachmi [b], C. Lokhorst [c], D. Berckmans [a,*]

[a] Division of Measure, Model and Manage Bioresponses (M3-BIORES), KU Leuven, Kasteelpark Arenberg 30, B-3001 Leuven, Belgium
[b] Institute of Agricultural Engineering, Agricultural Research Organization (ARO), Volcani Center, P.O. Box 6, IL-50250 Bet-Dagan, Israel
[c] Wageningen UR Livestock Research, P.O. Box 65, NL-8200 AB Lelystad, The Netherlands

ARTICLE INFO

Article history:
Received 26 February 2013
Received in revised form 5 November 2013
Accepted 14 November 2013

Keywords:
Dairy cow
Lameness detection
Back posture
Image processing
Three-dimensional camera

ABSTRACT

In this study, two different computer vision techniques to automatically measure the back posture in dairy cows were tested and evaluated. A two-dimensional and a three-dimensional camera system were used to extract the back posture from walking cows, which is one measurement used by experts to discriminate between lame and not lame cows. So far, two-dimensional cameras positioned in side view are used to measure back posture. This method, however, is not always applicable in farm conditions since it can be difficult to be installed. Shadows and continuous changes in the background also render image segmentation difficult and often erroneous.

In order to overcome these problems, a new method to extract the back posture by using a three-dimensional camera from top view perspective is presented in this paper. The experiment was conducted in a commercial Israeli dairy farm and a dataset of 273 cows was recorded by both the three-dimensional and two-dimensional cameras.

The classifications of both the two-dimensional and the three-dimensional algorithms were evaluated against the visual locomotion scores given by an expert veterinary.

The two-dimensional algorithm had an accuracy of 91%, while the three-dimensional algorithm had an accuracy of 90% on the evaluation dataset.

These results show that the application of a three-dimensional camera leads to an accuracy comparable to the side view approach and that the top view approach can overcome limitations in terms of automation and processing time.

1. Introduction

Lameness, which can be defined as a deviation in gait as a way to reduce pain (Scott, 1989), is a major problem regarding animal welfare (Bruijnis et al., 2012), herd management and productivity in dairy farms (Booth et al., 2004). Economic losses due to lameness not only consist in the treatment of the animal, but also in decreased milk yield (Green et al., 2002; Archer et al., 2010), reduced reproductive performance (Sprecher et al., 1997; Garbarino et al., 2004), increased culling risk (Barkema et al., 1994; Booth et al., 2004) and increased production costs (Cha et al., 2010).

The most common method to detect lameness is visual locomotion scoring (Flower and Weary, 2009), in which the scores are based on the visual observation by a trained expert. An expert's evaluation relies on various parameters such as gait asymmetry, head bopping and back curvature (Schlageter-Tello et al., 2011). However, a visual locomotion scoring method performed by an expert is not feasible in today's intensive farming because it is too time-consuming. As a result, cows that are mildly lame often remain undiagnosed and not treated until they become severely lame (Zimmerman, 2001).

Different scientific approaches have been used in order to develop a fully automated and continuous lameness detection system based on behavioural parameters, kinetic and kinematic analysis and image processing techniques. Since lameness can affect the behaviour of injured cows (Cook and Nordlund, 2009), parameters such as lying times and lying bouts (Ito et al., 2010), milk yield, water and dry matter intake, feeding behaviour and activity (Kramer et al., 2009) can be used as indicators for lameness. Kinematic analysis measures the geometry of movement, without considering the forces that cause the movement, and calculates different aspects of gait such as stride length, stance and swing duration (Flower et al., 2005). Kinetic methods such as ground

* Corresponding author. Address: Division of M3-BIORES: Measure, Model and Manage Bioresponses, KU Leuven, Kasteelpark Arenberg 30, Box 2456, 3001 Leuven, Belgium. Tel.: +32 16321726; fax: +32 16321480.
E-mail address: daniel.berckmans@biw.kuleuven.be (D. Berckmans).

0168-1699/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.compag.2013.11.005

reaction force measurements (Rajkondawar et al., 2002) and load sensors (Pastell et al., 2008) assess lameness by evaluating the diversity in load distribution.

Various studies that have used computer vision to extract certain parameters related to lameness have not provided a reliable and fully automated solution. For example, Song et al. (2008) focused on trackway measurement, while Poursaberi et al. (2010) focused on the back arch curvature and Pluk et al. (2010) concentrated on step overlap and hoof release angles. While providing valuable insights in term of parameters, they all did not develop a fully automated detection system.

The back posture is a variable that can be used to detect lameness in dairy cattle and can be extracted by vision techniques (Poursaberi et al., 2010, 2011). As soon as the animal feels pain while standing or walking, it is reluctant to bear weight on the injured leg and consequently shifts the weight toward the contralateral limb (Neveux et al., 2006). As a result, the cow tends to increase the curvature of the back and to lower her head.

Following this approach, previous studies applied image processing algorithms based on side view recordings of a 2D camera. However, extracting the back arch of cows by using a side-view image processing algorithm presents different challenges when applied in commercial farm conditions.

First of all, not all the farms have a place to install a side-view camera pointing towards a corridor where the cows pass through in a single file. It is common, instead, to have selection gate where cows are guided into. Here, a 3D camera can be easily installed.

Furthermore, the technical challenges of extracting the back posture by using a 2D camera are firstly changes in light conditions which cause the colour of the cow to change and therefore add noise to the image and degrade the cow segmentation performance; secondly, the shadow is often detected as part of the segmented object and degrades segmentation performance; thirdly, continuous changes in the background (i.e., moving cows, passing tractors and farmers) may interfere with the segmentation process (Van Hertem et al., 2013).

Methods such as the active appearance model (Edwards et al., 1998) tried to overcome the 2D segmentation problems by developing more complicated and time-consuming algorithms that cannot be applied in real-time due to the amount of processing power and elaboration time they require.

Another way to solve these segmentation problems is to use different vision sensors that help to extract the desired information. For instance, a thermal camera was used instead of a regular camera to improve segmentation in order to evaluate the body condition scores in dairy cattle and showed promising results (Halachmi et al., 2008).

The objective of this study is to evaluate the use of a 3D camera from top-view to improve the back posture extraction in dairy cattle and to compare its performance in classifying lame and not lame cow with the 2D camera (side view) approach.

2. Materials and methods

2.1. Nomenclature

Back Posture Measurement, BPM; Receiver Operating Characteristic, ROC; Area Under ROC Curve. AUC; two-dimensional, 2D; three-dimensional, 3D; False Positive, FP; False Positive Rate, FPR; True Positive, TP; True Positive Rate, TPR; Sensitivity is the ability to correctly classify Lame cows. Specificity is the ability to correctly classify Not Lame cows. Accuracy is the proportion of instances that are correctly classified. Precision is the proportion of instances classified as lame that are really lame. Confusion matrix is a table used to evaluate classifier performance in which each column represents the instances in a predicted class, while each row represents the instances in an actual class.

A ROC curve (Metz, 1978) is a graphical plot of true positive rate on the *y*-axis and false positive rate on the *x*-axis. The ROC curve illustrates the performance of a binary classifier as its classification threshold varies. This allows determining the optimal threshold for different sensitivity and specificity levels. The AUC curve (Metz, 1978) is an index that measures the classification performance. The larger the AUC, the better is the classifier's performance. An AUC lower than 0.6, instead, implies that the classifier does not perform better than a random one. The quality of the ranking system measured by the AUC is shown in Table 1.

Decision tree is a schematic tree-shaped diagram used for classification. The classification when model and reference are transformed to 'Lame' and 'Not Lame' scores is called binary classification.

2.2. Experimental setup

2.2.1. Animals and housing

The experimental data were gathered in May 2012 in a commercial dairy farm located in Yifat, Israel. The herd size of the farm was 951 lactating Israeli-Holstein cows with an average milk production of 11,500 kg/year per cow. The cows were divided in 11 groups according to health and production status (group size: 96 ± 12 cows). All cows were milked three times a day in a 2×32 side-by-side parallel milking parlour.

2.2.2. Cameras

For this experiment, a 3D and a 2D camera were used.

The 3D Kinect camera (Microsoft corp., Redmond, WA) was chosen because it is an affordable and fast camera that is increasingly used in the last two years to develop real-time applications for human health, such as rehabilitation systems (Chang et al., 2011) and respiratory motion monitoring systems (Xia and Siochi, 2012). The depth sensor of the Kinect had a 57° horizontal and 43° vertical angular field of view and a maximum image throughput of 30 frames per second. The camera could provide a depth image size of 640×480 pixels with 1 cm resolution at 2 m distance from the cow (Andersen et al., 2012). The depth values were achieved by using an infrared projector that projected a known light pattern to the object, and an infrared sensor that detected the reflected light patterns, analysed the distortion and produced the depth image (PrimeSense, 2012).

Since the sensor was highly sensitive to sunlight, the experiment was carried out at night. Through an USB port, the camera was attached to a computer with 4-core processor of 3.1 GHz each, 8 GB of RAM and Windows 7 installed. OpenNI 1.5 framework was used to record the videos on the computer.

The 2D Nikon D7000 camera equipped with a Nikkor DX AF-S 18–105 mm G ED lens (Nikon Incorporation, Tokyo, Japan) was used to record the cow's gait from side view. Recordings of the cows passing were captured in a QuickTime H.264 compressed format with a frame rate of 25 fps at a resolution of 1920×1080

Table 1
The quality of the ranking system in relation to the Area under the Receiving Operators Characteristic curve (AUC) (Michalski et al., 2006).

AUC	Quality
$0.9 < AUC \leqslant 1.0$	Excellent
$0.8 < AUC \leqslant 0.9$	Good
$0.7 < AUC \leqslant 0.8$	Fair
$0.6 < AUC \leqslant 0.7$	Poor
$0.0 < AUC \leqslant 0.6$	Fail