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

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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.

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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

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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

pixels. Camera settings were set to an ISO value of 5000 and an aperture of 50 to guarantee sufficient video quality at night.

2.2.3. Measurement setup

The 2D and 3D cameras were placed in the area after a sorting gate to ensure that all cows could be recorded. The alley width in this area was 0.7–1.1 m to turn cow flow into a single file. The cows had to make a 90° turn at the beginning of the corridor. This allowed a sufficient delay between consecutive cows in order to record the animals individually. Cows walked through this alley after milking to return to their pen. The 3D camera was placed 3.15 m above the ground and was attached to an arm connected to the corridor (Fig. 1), while the 2D camera was put on a tripod placed 6 m from the corridor perpendicular to the route of cow passage.

2.2.4. Scoring methods

The 3D approach could not be compared directly to the 2D approach because a synchronisation between the two cameras was not possible. A direct comparison requires an equal body posture and therefore synchronised frames between the two cameras. Therefore, 2D and 3D approaches were compared and evaluated against the visual locomotion score of an expert veterinary.

A veterinary and expert on lameness (Repeatability: 85.6 ± 3, Kappa's coefficient: 0.64) scored visually all cows in the 2D video recordings by using the five points locomotion score of Flower and Weary (2006). Scores varied from 1 (normal walking) to 5 (severely lame) and were based on the observation of 5 gait attributes: flatness of back, steadiness of head carriage, tracking up, asymmetry of gait and reluctance to bear weight. The five points scoring scale was simplified into a binary score in order to classify the cows as lame or not lame. Score 1 and 2 referred to cows classified as 'Not Lame', while Score 3, 4 and 5 referred to cows that were 'Lame'.

2.2.5. Dataset

The experiment was conducted during the night of the 21st of May 2012, using the last 4 milking groups of cows that comprised 339 cows in total. These groups were chosen because the lameness prevalence was higher in these groups.

At the end of the experiment, 273 different cows were recorded by both the 3D and the 2D camera and scored by the veterinary. Since information about the cow's serial numbers could not be retrieved directly from the 3D depth images, the association between the 2D and 3D videos was established by using the order of the cows passing through the alley and the respective timestamp on both video recordings.

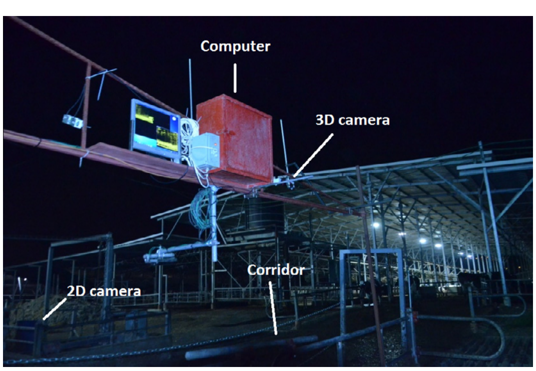

Fig. 1. Experimental setup. The corridor was built in order to force the cows to create a single file. The 3D camera was placed in top view of the corridor. The computer which the camera was connected to and where the videos were saved was placed in the box. The 2D camera was put on a tripod placed 6 m from the corridor perpendicular to the route of cow passage. Pictures were taken at night.

Two datasets out of the 273 cows recorded were created, one dataset of 181 cows for training the algorithm and one dataset of 92 cows for validation. The datasets were generated by dividing the cows in lame and not lame and by randomly selecting them for either training or validation dataset. In this way, the same prevalence of lameness was maintained in both datasets. The distribution of lameness classes based on the expert scores is shown in Table 2.

2.3. Lameness detection algorithm (2D)

2.3.1. Back posture measurement

The algorithm used to calculate the back posture and thus to evaluate lameness by using the 2D camera was described by Poursaberi et al. (2011) and hence will not be described extensively in this paper.

The selection of the different pixels of the back arch was performed manually due to the difficult image segmentation in videos recorded at night.

The videos from the 2D camera were loaded on Matlab (R2012b, The MathWorks Inc., MA). The frames were manually examined to select the moment in which the cow placed the hind limbs on the floor. The selected frames were further processed. The back arch of the cow and the position of the muzzle were manually selected using the *impoly* function (Fig. 2). The back arch was fitted with a 4th order polynomial curve by using the function *polyfit*.

The highest point (**R**) in the total curvature of the animal's back was used as a starting point to calculate the BPM. By using least square method, two ellipses were fitted to the left and right side of point **R** and their orientations θ_1 and θ_2 were calculated. The front ellipse represents the shape of the back around the shoulder, while the hind ellipse represents the shape of the back around the hip. The intersection between the two minor axes of both ellipses was determined and the resulting angle θ_3 was calculated. **L1** is the vertical distance between this intersection point and **R**.

In the front ellipse, the two vertexes $\mathbf{v_1}$ and $\mathbf{v_2}$ were determined where the major axis crosses the ellipse. A line that connects the position of the cow's muzzle with the closest vertex $\mathbf{v_i}$ was drawn.

Table 2
Distribution of lameness classes in the training and validation dataset as scored by the expert.

	Training dataset		Validation dataset	
	Number of cows	Percentage	Number of cows	Percentage
Not Lame	147	81	75	82
Lame	34	19	17	18

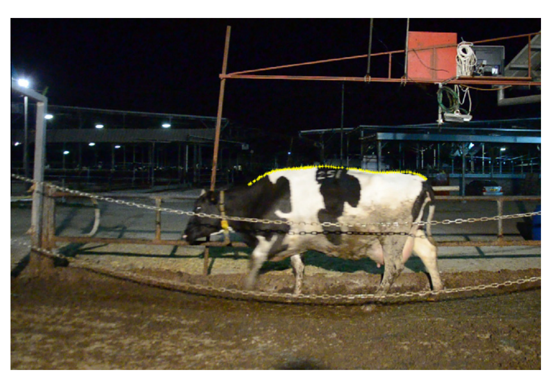

Fig. 2. The frame of the 2D camera was manually selected when the cow placed the hind limbs on the ground. The back arch of the cow (dots on the cow) was manually selected and used to measure the back posture.

L2 is the vertical distance between the cow's muzzle and the vertex $\mathbf{v_i}$.

The angle θ_4 between the horizontal line that connects **L2** with the major axis of the front ellipse, and the line that connects the cow's muzzle with the major axis of the front ellipse, was calculated.

The following formula was then used to calculate the BPM:

$$\mathrm{BPM}(2D) = w_1 * \frac{\theta_2}{\theta_1} + w_2 * \frac{\theta_4}{\theta_3} + w_3 * \frac{L_2}{L_1} \quad (1)$$

w_1, w_2 and w_3 are the weighing factors for the three terms of the BPM. The first term describes the relation between the front and hind ellipse, the second term includes the relation between both ellipses and the position of the head, while the third term relates the head position and the curvature of the back.

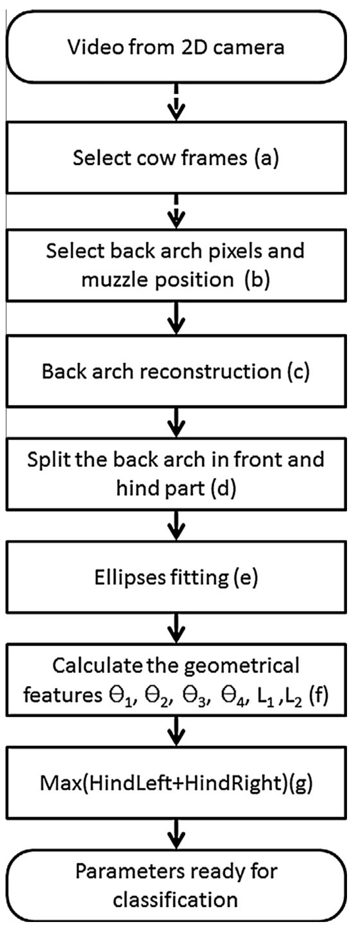

Fig. 3. The algorithm used to calculate the back posture in side view. The algorithm incorporated the following tasks: (a) Select frames when the cow placed the hind limbs on the ground (performed manually). (b) Manually selection of the back arch and muzzle pixels by using *impoly* function (Matlab, 2012). (c) Reconstruct the back spine by fitting a 4th order polynomial using the function *polyfit* (Matlab, 2012b). (d) The highest point (**R**) in the total curvature of the animal's back was used to separate the front from the hind part. (e) Two ellipses were fitted to the left and right side of point **R** using least-square fitting. The ellipsis' orientations θ_1 and θ_2 were calculated. The front ellipse represents the shape of the back around the shoulder, while the hind ellipse represents the shape of the back around the hip. The intersection between the two minor axes of both ellipses was determined and the resulting angle θ_3 was calculated. **L1** is the vertical distance between this intersection point and **R**. In the front ellipse, the two vertexes $\mathbf{v_1}$ and $\mathbf{v_2}$ were determined where the major axis crosses the ellipse. A line that connects the position of the cow's muzzle with the closest vertex $\mathbf{v_i}$ was drawn. **L2** is the vertical distance between the cow's muzzle and the vertex v_i. The angle θ_4 between the horizontal line that connects **L2** with the major axis of the front ellipse, and the line that connects the cow's muzzle with the major axis of the front ellipse, was calculated. (f) The weighted sum in the quotients θ_2/θ_1, θ_4/θ_3, L_2/L_1 was calculated. The maximum value of the sum of both hind placements was used for classification.

Two frames per hind hoof were taken when the hoof was fully placed on the floor. The sum of the two frames of each hoof was calculated and the maximum value was selected for lameness classification.

The entire image process flowchart is presented in Fig. 3. As it can be seen, the process is executed automatically only after the back arch was selected manually.

2.3.2. Lameness classification

The ROC curve was calculated in Matlab for both the training and validation dataset. The training dataset of the 2D model was used to calculate the weight w_i of the parameters and to determine the threshold value between lame and not lame cows. These thresholds were calculated by maximizing the following fitness function f:

$$f = 2 * \mathrm{sensitivity} + 3 * \mathrm{specificity} \quad (2)$$

The obtained threshold was then applied to the validation datasets in order to evaluate its performance.

2.4. Lameness detection algorithm (3D)

The algorithm for evaluating the back arch by using the 3D camera recordings was developed in Matlab (R2012b, The MathWorks Inc., MA).

2.4.1. Cow separation

The algorithm for cow separation was necessary in this experiment since no antenna was installed to trigger the start and stop of the 3D video recordings.

The 2D video allowed to manually associate the cow with its score because of the number marked on the cow's body. The 3D system, instead, lacked this possibility. Therefore, a continuous 3D video was recorded and the cows were separated automatically.

The first step in the 3D image processing algorithm thus consisted in detecting when a cow entered the recording area and in separating the successive animal (Fig. 4). Since the Kinect depth sensor calculated the distance between the object and the sensor, the minimal distance along the longitudinal direction was used to separate the cows.

When the cows walked in the view of the 3D camera, the value of the signal dropped and only increased again when the cows left the view of the camera (Fig. 5).

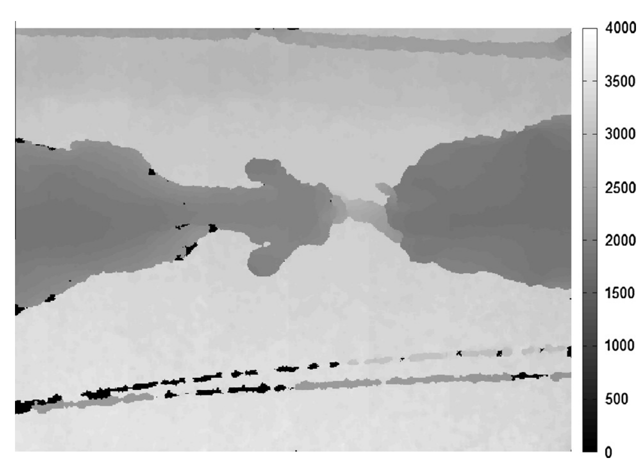

Fig. 4. Depth image extracted from the 3D camera, showing the cow traffic passing on the corridor. The pixel intensity represents the disparity matrix output of the 3D camera. The darker the pixels are the closer to the camera.

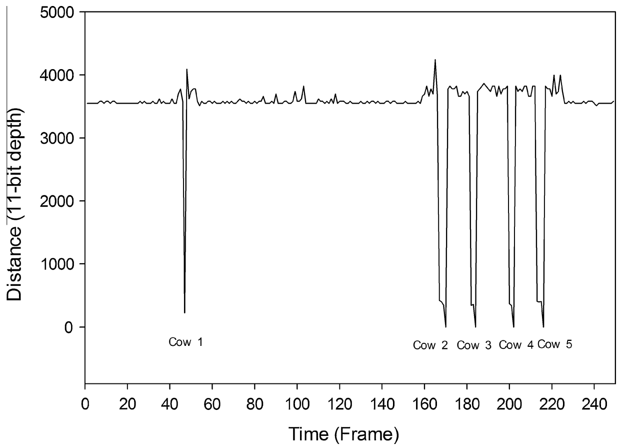

Fig. 5. Signal representing the distance from the object to the 3D camera sensor. Every minimum represents a cow passing through the sensor and it is used to automatically separate one cow from another.

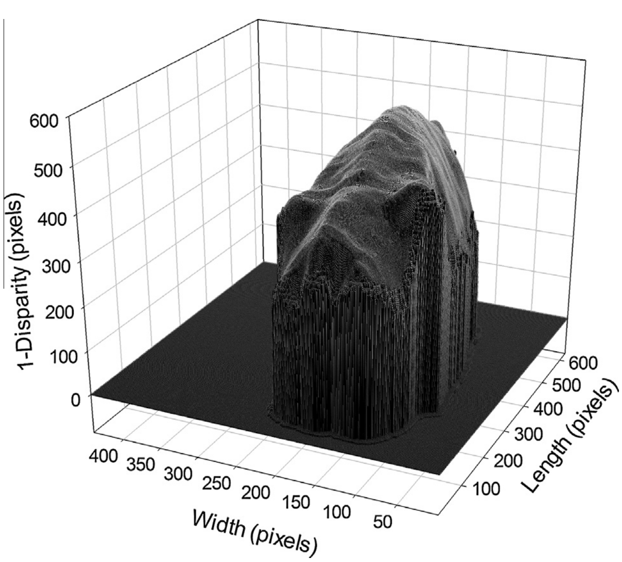

Fig. 6. Depth image after image segmentation reconstructed using mesh function in Matlab (2012b).

The drops and the increases were used as start and end frame of each video, with the minima representing a cow passing through the camera view. The entire video was therefore split in 339 videos, one for each cow that passed under the 3D camera.

2.4.2. Back posture measurement

The videos recorded from the 3D camera were loaded on Matlab.

For each frame the image was segmented by applying a minimal (1400) and maximal (2200) threshold to the depth matrix. All the objects whose area was smaller than 8000 pixels (85% of the average area of a cow in pixels) were removed by using the function *bwareaopen*. If the body of the cow was fully in the image and no object was on the border of the image, the frame was used for further processing (Fig. 6).

The contour of the cow was calculated by using the function *bwtraceboundary* and the distance between the symmetrical axes of the binary image was used to extract the head from the body of the cow: the first valley starting from the back of the cow was detected by using the function *findpeaks* and was considered the starting of the neck. The body orientation was calculated by using the function *regionprops*. The highest pixels around the orientation axes (10% of the cow width) represented the back spine.

The back spine was reconstructed by fitting a 4th order polynomial by using the function *polyfit* (Fig. 7).

The highest point (***R***) in the total curvature of the animal's back was used as a starting point. Two ellipses were fitted using least square fitting to the left and right side of point *R* and their orientations $\boldsymbol{\theta_1}$ and $\boldsymbol{\theta_2}$ were calculated. The intersection between the two minor axes of both ellipses was determined and the resulting angle θ_3 was calculated. $\boldsymbol{L_1}$ was the vertical distance between this intersection point and ***R***.

The average of each parameter calculated in the different frames was used for lameness evaluation.

The entire image process flowchart is presented in Fig. 8.

2.4.3. Lameness classification

The parameters extracted from the 3D algorithm differed from the parameters described by Poursaberi et al. (2011) in his algorithm approach. In order to not lose information by using only one out of the four extracted parameter, the present study selected all four parameters and used them directly in a decision tree classifier.

Decision tree learning (Quinlan, 1986) is a simple, but powerful classifier and it was chosen to classify the four parameters into lame and not lame. Decision tree learning is widely used as a predictive model that maps observations about an item to conclusions about the item's target value. In these tree structures, each branching node represents a choice between two or more alternatives. If the parameters are continuous, as they were in this study, the choice of which path to follow is based on thresholds that are calculated during the training phase.

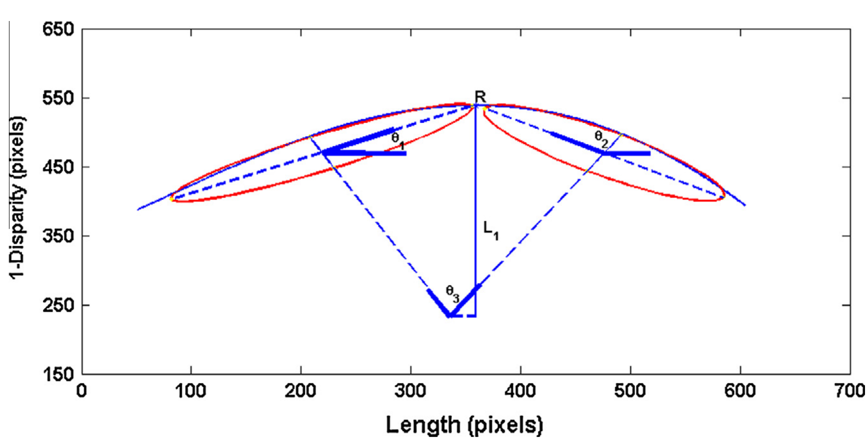

Fig. 7. Parameters θ_1, θ_2, θ_3 and L_1 extracted from the reconstructed back curvature of the cow.

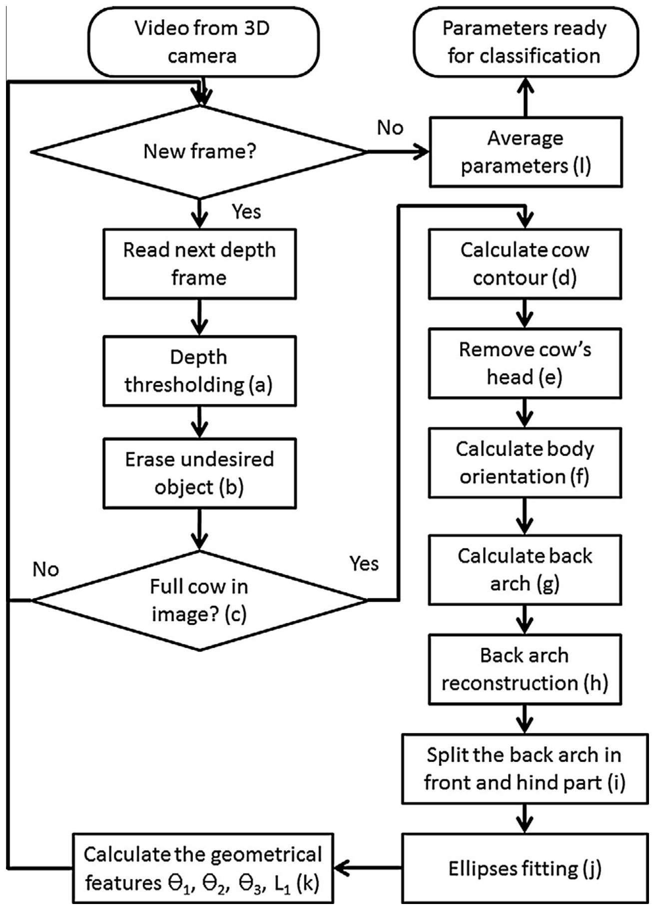

Fig. 8. The algorithm used to calculate the back posture with a 3D camera from top view. The algorithm looped over all the frames of the 3D video and for each frame performed the following tasks: (a) Apply threshold to the depth matrix. All the pixels whose value was not between 1400 and 2200 were set to zero (background). (b) All the objects whose area was smaller than 8000 pixels were removed using the function *bwareaopen* (Matlab, 2012b). (c) Check if the full body of the cow is inside of the image (No object was on the border of the image). If the full body of the cow is detected, proceed; otherwise load the next frame. (d) Calculate the contour of the cow by using the function *bwtraceboundary* (Matlab, 2012b). (e) Calculate the distance between the symmetrical axes of the binary image. Calculate the first valley starting from the back of the cow using the function *findpeaks* (Matlab, 2012b). This valley represents the starting point of the neck. Remove the head. (f) Calculate the body orientation by using the function *regionprops* (Matlab, 2012b). (g) Calculate the highest pixels around the orientation axes (10% of the cow width). This represents the back spine. (h) Reconstruct the back spine by fitting a 4th order polynomial using the function *polyfit* (Matlab, 2012b). (i) The highest point of the curve was used to separate the back arch in the front and back parts. (j) For both back parts an ellipse was used fitted by least squares fitting. (k) The orientation of the front (θ_1) and hind ellipses (θ_2) were calculated. The intersection between the two minor axes of both ellipses was determined and the resulting angle θ_3 was calculated. L_1 was the vertical distance between this intersection point and the highest point of the back spine reconstructed. (l) The average of the parameters was calculated and used for lameness classification.

Every branching node is part of a path to a leaf node. In this study, the leaf node represented the particular classification of the lameness score, based on the given parameters (θ_1, θ_2, θ_3 and L_1). These thresholds of the decision tree were obtained by maximizing the information gain of the training dataset (Quinlan, 1986) and evaluated on the validation dataset.

2.5. Data analysis

2.5.1. 3D cow separation

The algorithm of 3D cow separation was confirmed manually by reviewing the 3D video comparing manual observation and algorithm output.

2.5.2. 3D algorithm execution time

Since the aim of the 3D system was to build a fully automated real-time system to measure the back posture and relate it to lameness, the time of execution was also calculated. The profiling of the 3D code starts after each frame is loaded in the memory of the computer and ends when all the features are computed. The workstation used for the profiling is a workstation with a dual-core processor of 2.40 GHz and 3 GB of RAM with Windows 7 installed.

2.5.3. Classification evaluation

Matlab 2012b was used to evaluate the classifier performance for both the 2D and 3D lameness detection system. The evaluation criteria applied to assess the performance of the algorithms can be seen in Table 3.

Since the aim is to detect lameness, the true positives were defined as cows classified as *Lame* by both the expert and the algorithm, while true negatives were defined as cows classified as *Not Lame* by both the expert and the algorithm.

3. Results

3.1. 3D cow separation

The manual check confirmed that all 339 split videos of the algorithm were generated correctly and that the algorithm thus detected all cows passing under the camera.

3.2. 3D algorithm execution time

The 3D algorithm used only the frames where the body of the cow was fully visible in the image. The average was 2.56 ± 0.9 frames per cow. If the cow was in the image, it took on average 174 ± 0.01 ms per second to process the image, segment and extract the parameters. Otherwise, it took 19 ± 0.01 ms.

3.3. Classification evaluation

Tables 4 and 5 illustrates the result of the decision tree classifier applied to the training dataset of the 3D algorithm.

As it can be seen from the confusion matrix (Table 4), 140 'Not Lame' and 30 'Lame' instances were correctly classified. Overall, 94% of the instances were correctly classified with a TPR weighted average of 94%, a FPR weighted average of 10%, a precision weighted rate of 94%, and an AUC of 0.96.

Table 3
Performance measure used for the classifier.

Measure	Formula	Description
True Positive (TP) Rate *or* Sensitivity	TP/(TP + FN)	The proportion of positive instances that are correctly classified as positive
False Positive (FP) Rate	FP/(FP + TN)	The proportion of negative instances that are erroneously classified as positive
Specificity	1 − FP rate	The proportion of negative instances that are correctly classified as negative
Accuracy	(TP + TN)/(TP + FP + TN + FN)	The proportion of instances that are correctly classified
Precision	TP/(TP + FP)	The proportion of instances classified as positive that are really positive
Error rate	(FP + FN)/(TP + FP + TN + FN)	The proportion of instances that are incorrectly classified

Table 4
Confusion matrix of the decision tree classifier on the training dataset.

		Classified by the algorithm	
		'Not Lame'	'Lame'
Classified by the expert	'Not Lame'	140	7
	'Lame'	4	30

Table 6
Confusion matrix of the decision tree classifier on the evaluation dataset.

		Classified by the algorithm	
		'Not Lame'	'Lame'
Classified by the expert	'Not Lame'	70	5
	'Lame'	3	14

When applied to the validation dataset of the 3D algorithm, the results are shown in Tables 6 and 7.

As it can be seen from the confusion matrix (Table 6), 70 'Not Lame' and 14 'Lame' instances were correctly classified with an overall accuracy of 90%.

When comparing the results of the validation dataset of both the 3D and 2D algorithm (Table 8), it is possible to notice that the results are close, with the 2D algorithm performing slightly better than the 3D algorithm. The accuracy, the precision and the AUC of the 2D algorithm are respectively 1%, 1%, and 2% better than the 3D algorithm.

4. Discussion

Computer vision techniques have the advantage of providing continuous information without manipulating the animals or applying sensors to them. Furthermore, cameras are relatively cheap. As a result, computer vision is increasingly applied in order to extract valuable information from the animals for various purposes.

Even though computer vision techniques can be used to detect lameness, a reliable and fully automated segmentation of walking cows as well as the extraction of useful parameters by means of computer vision techniques are difficult to obtain in commercial dairy farms.

As this study illustrates, however, a 3D camera from top view can be useful in the development of a fully automatic measurement of back posture. First of all, it is easier to be applied into existing commercial farms. Moreover, it can help to overcome segmentation problems such as shadows and dynamic backgrounds which occur in a 2D side view approach.

The 3D camera method also proved to be suitable for an automated lameness detection system since it reached results comparable to the 2D camera method when the back arch segmentation was performed manually.

The 2D camera approach performs slightly better in the evaluation dataset compared to the 3D camera, having a 1% better accuracy.

This might have been caused by the fact that the 2D model calculated the parameters only from images in which a cow placed the hind hooves on the ground.

This might actually limit lameness detection in general because the focus should be on both front and hind hooves and because hooves cannot be differentiated in realistic farm conditions where manure is covering the animals' feet.

In fact the 3D top view approach provides advantages compared to the 2D approach.

The major advantage of the 3D approach is the fact that it can help to overcome segmentation problems such as shadow and dynamic background which occurs in the 2D side view approach. As a consequence it does not need a complex algorithm to segment the cow and it can be therefore applied in real time.

The average time for processing each frame is 174 ± 0.01 ms. Thus, the video can be analysed in real time at more than 5 frames per second. Furthermore, this performance will increase when implemented in a programming language other than Matlab and optimized for speed.

An advantage of the 3D top view approach, not implemented in this manuscript, is the fact that animals can be classified even if they are walking side by side, while a 2D approach relies on single file cow flow.

However, the use of the 3D camera has also limitations. The camera was developed for indoor use. While being insensitive to artificial light, the camera is very sensitive to natural light. Therefore, the experiment, which was conducted in an outdoor area, had to be carried out at night. This problem could be overcome by building a roof over the camera to create a shadow on the camera's field of view. However, this is not a practical solution and future studies should test 3D cameras with different technologies in order to avoid restrictions caused by light sensitivity. Another limitation of this camera is the small field of view. In fact, on average only 2.56 ± 0.9 frames per cow had the complete back on the image and could be extracted and used for lameness classification.

Furthermore, no information about the gait analysis can be extracted from 3D images. Thus, the 3D approach relies, so far, solely on the measurement of the back, which is extracted from only a few frames. This is the biggest difference in terms of methodology between the 2D and 3D approach.

Future studies may solve the problem by adding multiple cameras in a row in order to enlarge the field of view and to retrieve dynamic information about the back posture while the cow is moving. This approach may render the system more accurate and reliable. Notwithstanding these limitations, the main objective of this study was to test the feasibility and performance of applying a 3D camera instead of a 2D camera in order to automatically detect lameness. The study demonstrated that the 3D approach is indeed as reliable as the 2D approach.

Lame cows tend to increase the curvature of the back, but it is not the only sign that the expert uses to score lameness: steadiness of head carriage, head bopping, tracking up, reluctance to bear weight and asymmetry of gait are further variables to be taken into consideration when detecting lameness visually. The use of only one variable can explain the misclassified instances. However, it can be argued that the back arch proved to be suitable for lameness detection when only one single variable can be used in real farm conditions.

Cows are naturally different from each other. The back posture of the animals is therefore never identical and the animals are

Table 5
Result of the decision tree classifier using the training dataset.

Classified by the expert	TP Rate	FP Rate	Accuracy	Precision	AUC	Error rate
'Not Lame'	0.952	0.118	0.939	0.971	0.957	0.061
'Lame'	0.882	0.048	0.939	0.811	0.957	0.061
Weighted average	0.939	0.104	0.939	0.942	0.957	0.061

Table 7
Result of the decision tree classifier using the evaluation dataset.

Classified by the expert	TP Rate	FP Rate	Accuracy	Precision	AUC	Error rate
'Not Lame'	0.959	0.176	0.891	0.958	0.95	0.109
'Lame'	0.824	0.093	0.891	0.667	0.95	0.109
Weighted average	0.891	0.161	0.891	0.904	0.95	0.109

Table 8
Performance analysis of the classifier for the 2D and 3D training and evaluation dataset.

Dataset	Specificity (%)	Sensitivity (%)	Accuracy (%)	Precision (%)	AUC	Error rate
2D training	97	88	96	96	0.97	0.044
3D training	95	88	94	94	0.96	0.061
2D evaluation	95	76	91	91	0.97	0.087
3D evaluation	91	82	90	90	0.95	0.109

bound to react individually to lameness (Viazzi et al., 2013). In further research, individual models have to be used that consider the normal posture of each cow and that detect a deviation from the normal posture on an individual level.

Further studies should also evaluate the system's performance when applied to a bigger number of animals, to different breeds and to farming conditions that are different from those in Israel (for example open cowshed, no cubicle housing, no concrete floor).

5. Conclusion

The use of an automated algorithm to automatically measure the back posture and detecting lameness in dairy farms which was based on 3D camera recordings was tested in outdoor farm conditions in Israel on 273 cows. The algorithm on the validation dataset of 92 has an accuracy 90%. These results were comparable to the 2D camera recordings and the manual segmentation of the back arch. These results suggest that the 3D camera approach can be used to overcome the limitations of a 2D approach by making image segmentation fully automated and by developing an algorithm which can be applied in real time. Therefore, the 3D approach can be valuable for the development of a fully automated system that detects lameness in dairy cows.

Acknowledgements

The authors would like to thank farm personnel from Kibbutz Yifat for their cooperation in the project. Thanks go to Aaron Antler of ARO for building the experimental setup in the farm. The authors would like to thank Doron Bar, Dani Amram and Roni Meyer from SCR Engineers Israel for their technical help. Antler's and SCR's work were partly funded by the Israeli Agricultural Ministry Chief Scientist Fund, Project Numbers 459-4426-10, 459-4369-10 and 459-4398-951.

This study is part of the Marie Curie BioBusiness FP7-PEOPLE-ITN-2009-2014.

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