Online Lameness Detection in Dairy Cattle Using Body Movement Pattern (BMP)

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***Abstract*— In this paper a method for real time lameness detection in dairy cattle based on back posture analysis is presented. The system utilizes image processing techniques to automatically detect lameness based on new definition called Body Movement Pattern (BMP). The traditional Locomotion Scoring (LS) system that is widely used for manual lameness detection by expert people failed to classify the selected cows from a commercial farm in Estonia. The proposed system not only performs the detection in automatic way but also categorizes the level of lameness with high accuracy. Two ellipses are fitted on the back posture and the parameters of the ellipses in relation to the head position are used as features for classification of the lameness degree. The new method has been tested on more than 1200 cows with success rate of 92%.**

Keywords- Lameness; Dairy cattle; Image processing; Body Movement Pattern.

I. INTRODUCTION

Lameness is a frequent and common disease which affects the normal behavior in dairy cattle. Lameness normally influences negatively on milk production and animal welfare [1]. Moreover, fertility problems, economic cost, refuse to join milking procedure voluntary are other side effects of lameness. Early detection of lameness is important for effective treatment and ailment prevention as it might prevent the lameness from developing into a chronic situation. It would be desirable if a system can detect lameness automatically in order to have a health management system in dairy herds. Visual observation of abnormal locomotion by expert is usually performed for lameness detection. In a commercial farm with a high number of cows, this procedure is expensive if the farmer wants to do it regularly. In the other word, the probability of lame cow identification in a timely fashion will be reduced if observation is not done usually. Normally, many existing lameness scoring systems utilize a 5-point scale scoring method [2-3] and most of the rest are just modified versions. It is important to notice that observing and scoring of lameness in cattle is subjective and depends on the scorer's skill and perception.

Computer vision technology and other electronic techniques are used in the dairy industry increasingly. Image processing techniques offer the possibility to quantify the visual information continuously, without contact and human presence. In our previous publication [4] a fully automatic vision-based system for lameness detection based on back posture analysis has been proposed. The system was based on side view video of cows walking individually and freely one by one through a corridor. The back arch was automatically extracted and a circle was fitted through 3 points on the back and the average of the inverse radius of fitted circle was used as a feature for lameness classification. The system worked very reliable on Holstein Frisian cows, under controlled experimental conditions, when cows passed the corridor one by one apart from each other. Problems have been experienced under real farm conditions in Estonia, when cows were filmed after leaving the milking parlor, passing through a corridor very close to each other in a line of 10 to 20 animals (Figure1). An improved method for lameness detection is presented in this paper, which provides reasonable results under farm condition when cows walk in a line close to each other. The new method contains two steps: separation of individual cows walking in a line and classification of the lameness degree based on back posture and head position. The separation of cows is not discussed in this paper and main focus is on feature extraction. In the development of the new method, the head position was taken into account because it was observed that some cows, being lame, did not show an arched back while some healthy cow showed an arched back.

II. MATERIAL AND METHOD

In this section, the technical descriptions of the back posture detection and feature extraction are presented. First, frame by frame the images are converted from sRGB color space to XYZ. The difference between foreground and background (called Dif) gives a coarse estimation of the moving object. Since the color image is converted to gray-scale image for analysis, the cow's body color has most of the time high correlation with background (wood lumber-slats). So, a simple background subtraction does not always show the whole moving objects.

A. Back posture extraction

To determine the existence of a cow, first the parallel bars which guide the cows through the corridor are detected. This is done simply by

$$\mathrm{Sc} = e^{(\mathrm{Bg}+\log \mathrm{Bg}-e^{(\mathrm{Bg}-\log \mathrm{Bg})})} \tag{1}$$

Figure 1. An example of condition when cows walk in a line.

where Bg is the stationary background frame. The upper bar is used as a reference because in all cases according to the body size, the back of the cow is located above this bar. Considering a margin based on the reference, only the image area containing the cow's back is used. A binary template (T) is defined based on the shape of the back (Figure2). This template is a simple trapezoid shape which can present the shape of the back in such a way that the upper part is recognized as back posture, the lower part is a cross-section with the bar, the left side is a junction of the back together with the tail and the right one is a junction of back and shoulder. The area containing the back posture is binarized with a threshold based on cow's skin intensity in XYZ domain. The detected binary objects are filtered to remove small objects. Objects which have an area more than a fixed value (here 1000 pixels) are selected as cow (called BW). The normalized cross correlation (NCC) in addition with the sum of squared difference (SSD) is used to determine which objects in the binary image are detected as cow. The NCC and SSD are represented by

$$\mathrm{NCC} = \mathrm{Re}\Big(\mathrm{ifft2}\big(\mathrm{fft2}(\mathrm{Dif}) .* \mathrm{fft2}(\mathrm{T}_{90}, \mathrm{size}(\mathrm{Dif},1), \mathrm{size}(\mathrm{Dif},2))\big)\Big) \tag{2}$$

$$\mathrm{Im} = \mathrm{Dif} \times \mathrm{BW};\quad \mathrm{S1} = \mathrm{Csum}(\mathrm{Im},1); \mathrm{S2} = \mathrm{Csum}(\mathrm{S1},2); \tag{3}$$

$$\mathrm{S3} = \mathrm{S2} \times \mathrm{BW};\quad \mathrm{SSD} = \mathrm{S3} + \mathrm{sum}(\mathrm{T}) - 2 \times \mathrm{NCC} \tag{4}$$

where $Csum$ is the cumulative summation along different dimension. The maximum of SSD determines the position in image which has highest correlation between image and template. Based on separation algorithm, each cow's position is obtained [7]. Different studies [2-5] have proven that the back posture can provide information regarding lameness. In [4] a fully automatic system was described to analyze the shape of an arched back. The algorithm successfully could classify different level of lameness in two different databases (in total 184 cows, average success rate 97%). The algorithm worked less reliable under real farm conditions in Estonia, due to the described problems. To improve the algorithm, the combination of back posture and head position for lameness detection was considered.

1) *Segmentation of cow*

The coarse segmentation that means locating each cow separately is done based on the algorithm which has been described above. The bounding box (rectangle) is representing the minimum region in each frame a cow occupies as long as the cow is recognized in the video (see Figure2e).

Fine segmentation means extracting the body contour to find the back and head position in the image. In [4] it was stated that a lack of contrast between background and foreground makes it difficult to do segmentation with a simple background subtraction algorithm. Therefore, having elaborate techniques for segmentation is necessary. The procedures to find the back and head position are different. Based on the separation algorithm, the image region containing the back is searched for the contour line of the back. The conjunction of back and withers in direction to the neck leads to the position of the head. Since the background is more or less stationary, each frame of the video is subtracted from background frame for detection. To analyze the back posture, it is important to first select the frames in which the hind hoofs of cows are in contact with the floor. Two frames for each hind hoof in contact with the floor are sufficient for the analysis of the body movement pattern based on back posture and head position [4]. These four frames are extracted automatically based on the method in [6]. Then each of these four images (I) is analyzed as follows:

$$\mathrm{x} = \log(\mathrm{I});\quad \mathrm{Im} = 1 - \frac{\left|\mathrm{e}^{\mathrm{Bg}+\mathrm{x}} - \mathrm{e}^{\mathrm{I}-\mathrm{x}}\right|}{\left|\mathrm{e}^{\mathrm{Bg}-\mathrm{x}} + \mathrm{e}^{\mathrm{I}+\mathrm{x}}\right|};\quad \mathrm{y} = \log(\mathrm{Im}); \tag{5}$$

$$\mathrm{Imout} = \frac{\left|\mathrm{e}^{\mathrm{Bg}+\mathrm{y}} - \mathrm{e}^{\mathrm{I}+\mathrm{y}}\right|}{\left|\mathrm{e}^{\mathrm{LogIm}-\mathrm{x}} + \mathrm{e}^{\mathrm{I}-\mathrm{y}}\right|} \tag{6}$$

The $Imout$ retrieves missing edges in the back contour which have been lost during background subtraction. The Sc image is binarized and this mask is used to refine the filtered image in $Imout$. The succeeding smoothing of the back contour (called BP) is done first by filtering BackRect (where BackRect is the area containing back arch obtained from separation) by using a median filter. Then, from tail to neck the distance (D) between the highest pixel compared to all pixels in back arch is calculated. All pixels which have a distance less than a determined threshold are selected (reference points (P)). If needed, the reference points are used as start points for interpolation. A 4th-order curve was fitted through the reconstructed edges based on a least square fitting algorithm. Figure3 shows an example of edge reconstruction.

To detect the head position, the image is searched in the direction of the withers and neck. The image area around the withers is selected to find the slope of the neck. To find the position of the head, a new image is cropped from the original image inside the determined rectangle (see Figure2e) as follows:

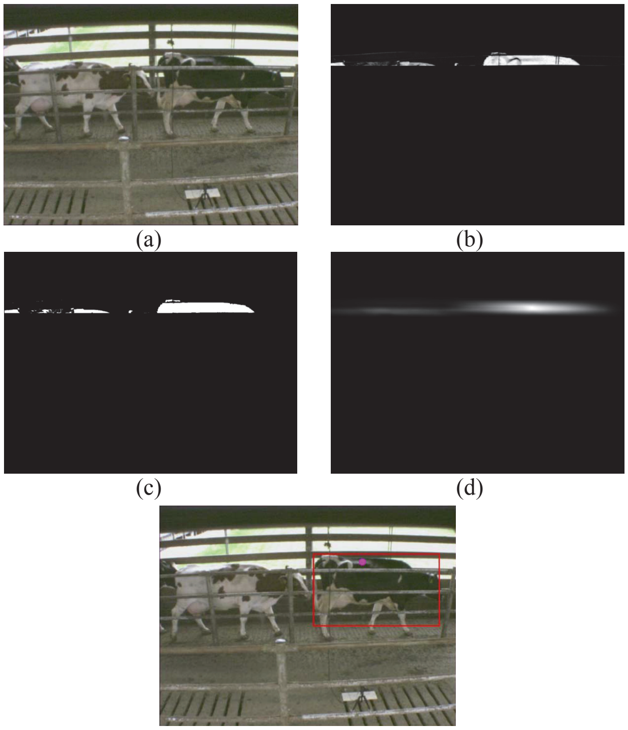


Figure 2. Different step for cow localization, (a) input image, (b) Dif, (c) BW, (d) detected cow (white marker on surrounded cow in red rectangle).

$$\text{BackRect} = [x_{b1}:x_{b2}, y_{b1}:y_{b2}]; \quad \text{CowRect} = [x_{c1}:x_{c2}, y_{c1}:y_{c2}]; \tag{7}$$

$$\text{NewImg} = \text{I}(x_{b1}:x_{c2}, y_{b2} - .1 \cdot (y_{b2} - y_{b1}):y_{c2}) \tag{8}$$

where CowRect is the rectangle framing the entire cow in each image. The angle between neck and forehead is normally between 80 and 150 degrees. So in NewImg the edges which satisfy this range are selected. Among selected edges, the longest one that is located in the right side of neck edge is assigned to forehead edges and the end pixel of this line is supposed as muzzle. Nevertheless if the back ground (here wooden bars) contrast with cow skin color, only a simple subtraction determines a coarse estimation of head position but in most cases when the skin is brown, it would be very hard to find the position easily. Figure4 shows two examples (for healthy and lame cow) and definition of all parameters.

B. Feature extraction

In this algorithm the head position is considered as a feature in addition to the back posture. The ellipses parameters are calculated because it is assumed, they fit a back arch curvature more precise compared to a circle as presented in former studies [4].

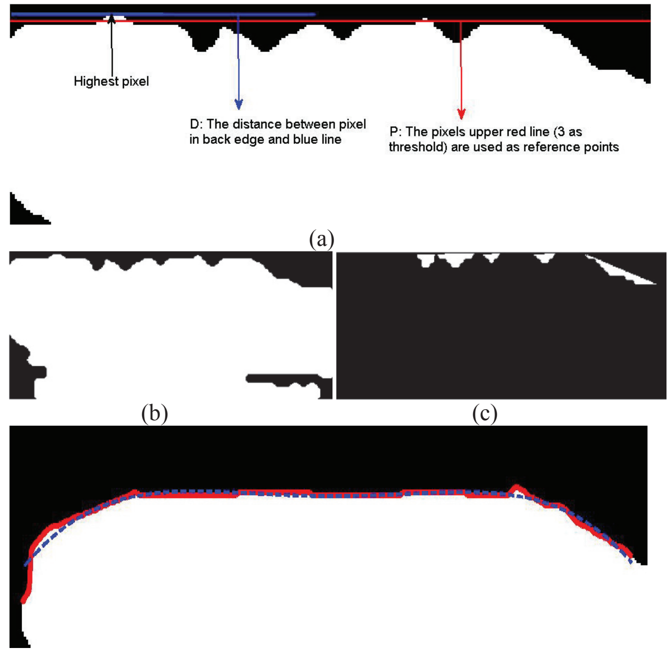
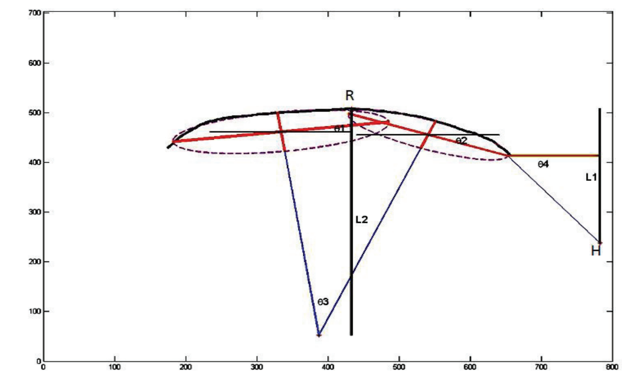


Figure 3. The definition reference points (a), binary image used for back posture extraction(b), reconstructed parts based on peaks and linear interpolation (c), the output of algorithm, the original back posture (red) and fitted 4th-order curve (blue) which is used for lameness assessment (d).

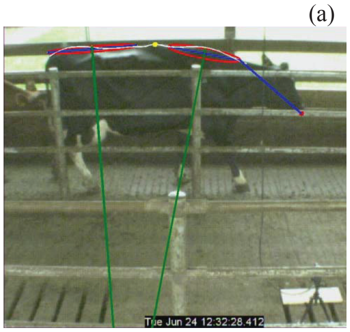
In the presented algorithm it was considered that the shape of back can be categorized in three main classes. Class 1 which represents the back of a sound cows has more or less a straight back line. Class 2 which represents moderately lame cows (scores 2 and 3 in 1-5 scale, score 2 in 1-3 scale) has a bended curve that is symmetric. The term "symmetry" means the curvature on the left side from the highest point is nearly the same as on the right side. Finally Class 3 represents severely lame cows having non-symmetrical curves. It means extend of the "curvature" calculated from the highest point in the back towards the neck is more than toward tail. The highest point (R) in the total curvature is used as reference point. Two ellipses are fitted to the left and right side of point R. These two ellipses represent the shape of the back around shoulder (front ellipse) and hip (hind ellipse). Each ellipse can be described by the longitudinal axis (length) and the lateral axis (width). The intersection between the two lateral axes of both ellipses is found. Then a line (L) connects the position of muzzle of cow (H) with the longitudinal axis of the front ellipse. Now, four angles are used as features: angle of the longitudinal axis of the hind ellipse (θ_1), angle of longitudinal axis of the front ellipse (θ_2), angle of the intersection between the two lateral axes of both ellipses (θ_3), and the angle between the horizontal line connecting L1 with the longitudinal axis of the front ellipse and the line connecting H with the longitudinal axis of the front ellipse (θ_4). L1 is the vertical distance between H and R and L2 is the vertical distance between the intersection of the two lateral axes of both ellipses and R. The Body Movement Score (BMS) which used for classification is as follows:

$$\mathrm{BMS} = \alpha \times \frac{\theta_2}{\theta_1} + \beta \times \frac{\theta_4}{\theta_3} + \gamma \times \frac{L_1}{L_2} \qquad (9)$$

where α, β, γ are weighing factors for the three terms of the BMS. 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, where the third term relates the head position and the curvature of the back. The features are calculated for four frames per cow. Per hind hoof two frames were taken, where the hoof was fully placed on the floor. The summation of the two frames of each hoof is calculated and the maximum value is selected for evaluation of lameness.



(a)



(b)

(c)

Figure 4. Parameter definition for BMP (a). Two examples of BMP for healthy cow (b) and lame cow (c). It is clear that the parameters are different for healthy and lame cow.

III. RESULTS AND DISSCUSION

Two different databases were used in this study. The first database (D1) is the same that was used in our previous research [4]. It contained 156 videos with one single cow per video. The second database (D2) is a selection of 1200 out of 3217 cows. The selection of 1200 out of 3217 was a result of lameness degree. It was tried to select as many as possible cows showing signs of lameness (score>1) during the measurement period. The scoring scale was also simplified from 1-5 to 1-3. In this case, healthy is (1), moderately lame is (2) and severely lame cow is (3). In [4] the algorithm could classify lameness with 96.7% success rate and Only 5 misclassifications occurred. Positive regarding the misclassified scores was its one-level-error. It means, four cases were wrongly classified to an upper class (score) and one case was wrongly classified to a lower class. The algorithm also detected all lameness cases since lame cows (Score 2 and 3) were not assigned to Class 1 (healthy cow). The algorithm worked properly under well defined experimental conditions such as cows walking one by one undisturbed through a corridor. Assuming the manual score as "golden standard" and reference, the automatic system misclassified 88 out of 1200 cow measurements, which means an overall accuracy of 92.67%. From 688 healthy cows 646 and from 512 lame cows (score 2 and 3) 466 cows were classified correctly with the new algorithm. Figure5 shows the distribution of BMS versus given scores by expert. As it is clear, all misclassifications are very close to the thresholds. Regarding the misclassifications in score 2, the automatic system scored lower than the human expert. Again, all misclassifications were one-level-errors. Accuracy is more than 90% and the algorithm delivers very reliable results under commercial farm conditions. After the algorithm has been improved and tested on the data from the commercial farm (D2), it was of high interest to re-check whether the improved version also works with the same reliability on the data gathered under controlled experimental conditions (D1). Results showed that the new algorithm could also classify the lameness scores of the cows under experimental conditions correctly. Four misclassifications occurred in the total dataset of 156 cow measurements (better than previous method). In total 97.4% correct classifications were achieved with the improved algorithm. The algorithm can only be as accurate as the reference because the reference is the golden standard to which the output of the algorithm can be compared with. Experts normally consider more than one variable in their manual scoring method, even variables, like tenderness, which tend to be rather subjective and difficult to assess. The introduced automatic system is proposed to measure very accurately only one variable to assess lameness. Problems which also have been addressed in this paper are mainly related to practical conditions on farm, which effect the application of the algorithm.

IV. CONCLUSION

A new method for lameness assessment in dairy cattle at commercial farm has been addressed in this paper. It introduced a new joint analysis of back posture and head position, so called Body Movement Pattern. The algorithm has been tested over real conditions at farm for lameness detection in dairy cattle. It can be concluded that the back posture is a highly relevant and reliable variable for automatic lameness detection. Future work will mainly focus on implementation on farm on long-term and make it run online and continuously. It will also be investigated whether the automatic lameness detection system is also suitable to follow the course of lameness in individual cows.

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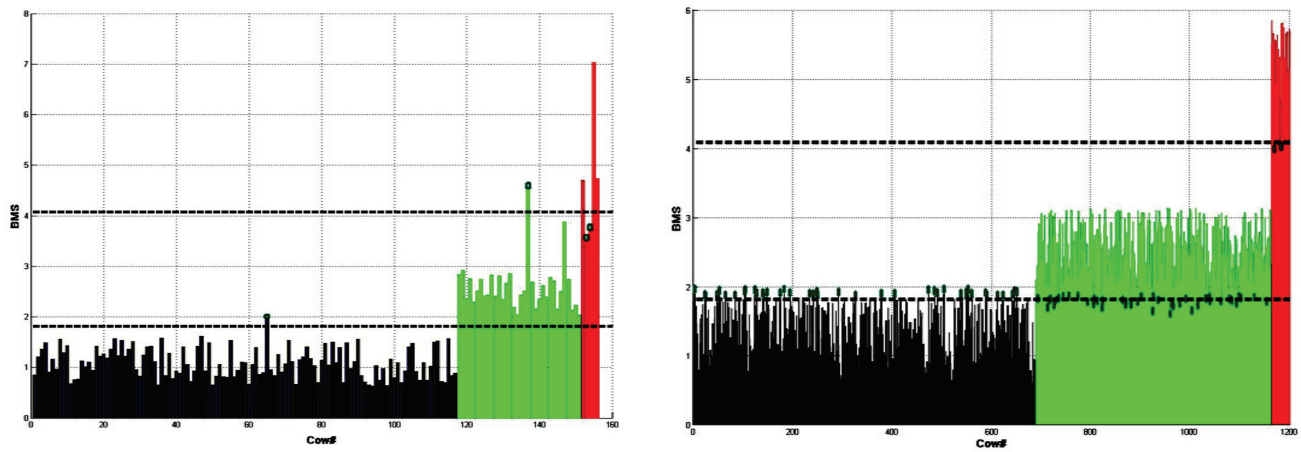

(a) (b)

Figure 5. The classification of scores from expert scorers and algorithm for D1 (a) and D2 (b). The horizontal and vertical axes are cow number and scores from algorithm.