ICIC Express Letters
Part B: Applications
Volume **14**, Number **10**, October **2023** ISSN 2185-2766
pp. 1107–1114

A NON-INVASIVE METHOD FOR LAMENESS DETECTION IN DAIRY COWS USING RGB CAMERAS

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Received February 2023; accepted April 2023

Abstract. *Lameness is a major health issue affecting dairy cows, causing pain, discomfort, and abnormal movements that can lead to decreased productivity and other diseases. Early detection and treatment are crucial to prevent the development of more serious conditions. In this paper, we present a method for detecting lameness in dairy cows using an RGB camera and analyzing their walking behavior. Our proposed technique achieves an accuracy of 84.6% in classifying cows as healthy or lame. We conducted a series of real-life experiments to validate our classification results, comparing them with expert diagnoses. Our method has the potential for use in routine farming conditions to detect lameness early and improve cow welfare and productivity.*
Keywords: Lameness, Walking behavior, Motion curve, Walking cycle, Dairy cows

1. **Introduction.** In recent years, the increasing number of cows per household and the aging of dairy farmers have put significant pressure on the industry [1]. Timely detection of diseases is crucial but challenging due to the limited time for individual cow health monitoring [2]. Late detection of diseases can lead to reduced milk yields, lower quality, and economic losses due to the removal of cows from the herd. The National Council of Dairy Herd Examiners reports that approximately 130,000 cows were expelled in 2019, with 70,000 being due to three major diseases: mastitis, reproductive disorders, and limb-hoof disease [3]. Among these three diseases, limb and hoof diseases are the most easily detected, but late detection can result in further production losses due to the development of other diseases such as mastitis and reproductive disorders.

Currently, experts diagnose lameness through visual judgment using a five-point scale, which can result in varying scores [4]. While studies using accelerometers and 3D cameras have shown promise in accurately detecting lameness, they are costly and can cause physical and mental stress to the cows while also damaging the equipment they are attached [5-7].

A recent literature survey [9] indicates that there is no one-size-fits-all locomotion scoring system for dairy cows, and the optimal choice of system depends on various context-specific conditions. In some cases, quantifying the severity of lameness is necessary, and thus a locomotion scoring system with an appropriate number of levels is required. However, in other cases, a simpler scoring system with fewer levels may suffice, being faster and simpler to apply. Therefore, it is recommended that the method and definition of lameness are explicitly stated and described in all studies reporting lameness in dairy cows. This paper focuses on early-stage lameness detection to maintain the well-being of dairy cows.

DOI: 10.24507/icicelb.14.10.1107

A review paper [10] highlights that computer vision-based lameness detection systems are not yet popular on farms, and their accuracy and applicability need to be improved. This review paper discusses the problems and development prospects of this technique from three aspects: detection methods, verification methods, and application implementation. There is a need to modify image processing techniques to make them more practical and easier for farmers to utilize. The authors in [11] have attempted to summarize the research progress of computer vision in the detection of lameness, and there have been some studies on lameness for individual cows using an individualized version of the body movement pattern score, which uses back posture to classify lameness into three classes [14]. Some researchers have attempted to find the relationship between walking speed and lameness problems, but much needs to be explored in this direction [15].

To address these issues, this study proposes a diagnostic method for early detection of limb and hoof diseases in dairy cows using image processing with RGB cameras. The proposed method aims to reduce the burden on dairy farmers and provide a quantitative evaluation of lameness without causing physical or mental stress to the cows or damaging the equipment. Although we have only presented a few related works in this paper, we recognize that a comprehensive review of the literature is necessary to fully justify the motivation behind exploring cattle lameness detection.

This paper consists of five sections. Section 2 summarizes the proposed method. Section 3 describes the experimental environment and evaluation method. Section 4 presents the experimental results and discussion, and Section 5 concludes and discusses future prospects.

2. **Proposed Method.**

2.1. **Flowchart of the proposed methodology.** The overall flowchart for measuring cow walking behavior is shown in Figure 1. A pre-processing video is created to track the cow's gait from the cow area image obtained from the input image. From the obtained video, gait tracking is performed to extract cow characteristics, and to classify and evaluate whether a cow is lame or healthy.

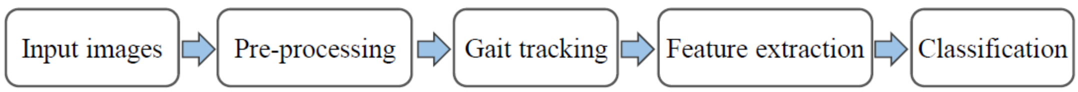


FIGURE 1. Flowchart of the proposed method

2.2. **Image of cow area.** The image of the cow area obtained beforehand from the input image is used. The captured video is resized to 1920 × 1080 and processed when the entire cow's body is in the angle of view. The video at 25 fps is used for the gait features. The input images and cow region images used are shown in Figure 2.

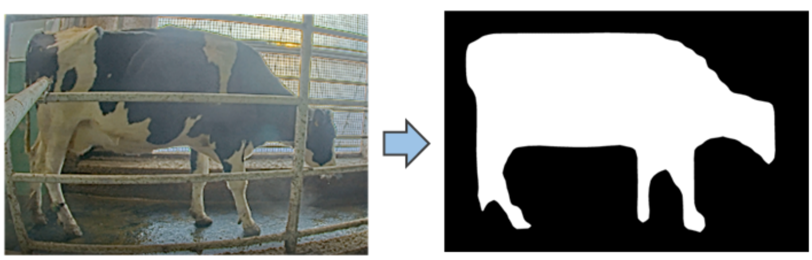


FIGURE 2. Input image and mask image

2.3. **Video preprocessing.** The moving legs are tracked from the input image and the walking video using the cow region image. Figure 3 shows the preprocessing for tracking moving legs. First, frame-to-frame subtraction is performed from the input video. Next, the image of the cow region is taken as a video (mask video), and noise is removed by taking the logical product of the video after inter-frame subtraction and the mask video. The mask video is also subtracted between frames in the same way as the input video. Finally, by taking the logical OR of the inter-frame subtracted video and the mask video, a video for tracking the legs as the region of interest is obtained. After converting each frame of the input video into a grayscale image, the current frame f_t, the two previous frames f_{t-2}, and the one previous frame f_{t-1} are differenced to obtain two different images, with the pixel value being 0 (black) when it is smaller than the threshold value 10 and 1 (white) when it is larger than the threshold value. If there is a white area (1) at the same pixel position in the two different images, the pixel value is kept; otherwise, it is set as a black area (0). The image thus obtained is called the inter-frame difference image. Figure 4 shows the process flow of the inter-frame difference image. If only the video is based on frame-to-frame subtraction, not only the moving area of the cow but also the noise portion will remain in the video. In order to remove the noise, noise reduction is performed. As a method of noise removal, only the cow region is obtained by taking the logical product of the frame-to-frame subtraction video and the mask video.

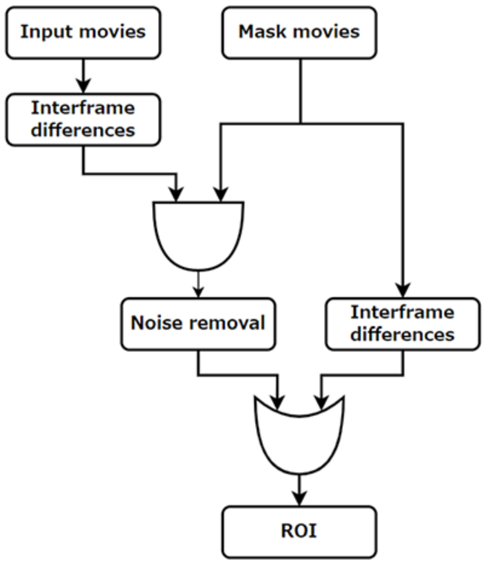


FIGURE 3. Flowchart of preprocessing related to gait tracking

2.4. **Walking tracking.** Gait tracking is performed from the obtained video of the region of interest. The leg with the largest amount of movement is found in the image and its value is obtained as the leg to be tracked. Figure 5 shows a flowchart of gait tracking. A bounding box (BB: Bounding Box) is set up for the video in the region of interest. The BB used here is an outline region surrounding the cow region obtained from the mask image (Figure 6(a)), with coordinates as R_1, R_2, R_3, and R_4, counterclockwise from the upper left corner of the BB. To extend this BB to the leg region only, the vertical height and coordinate points are transformed using the following formula. This is applied to the image of the region of interest to obtain an image of BB with coordinates L_1, L_2, L_3, and L_4 as shown in Figure 6(b).

$$L_{1,x} = R_{1,x} - 50 \tag{1}$$

$$L_{2,x} - L_{1,x} = 1000 \tag{2}$$

$$L_{3,y} - L_{1,y} = 181 \tag{3}$$

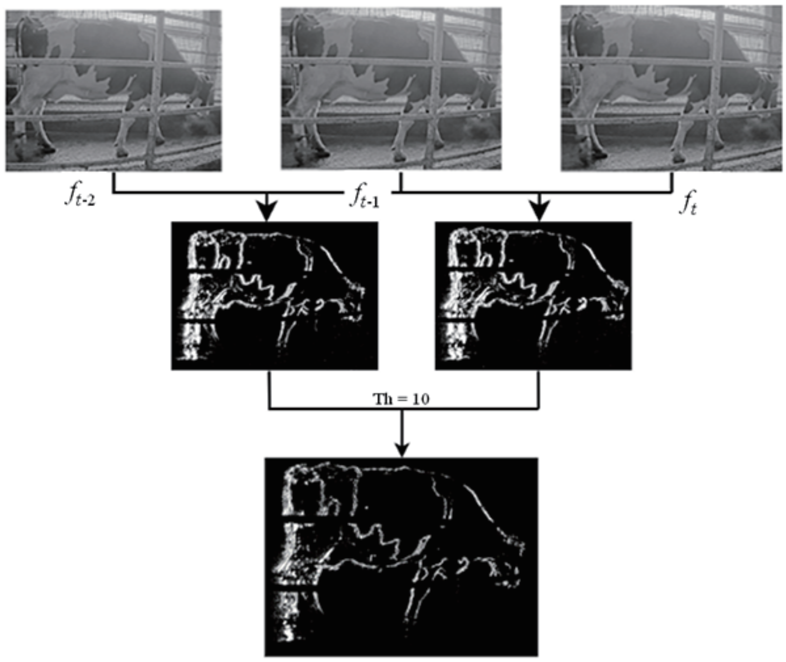


FIGURE 4. Difference between consecutive frames

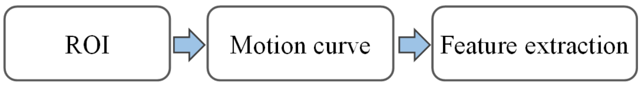
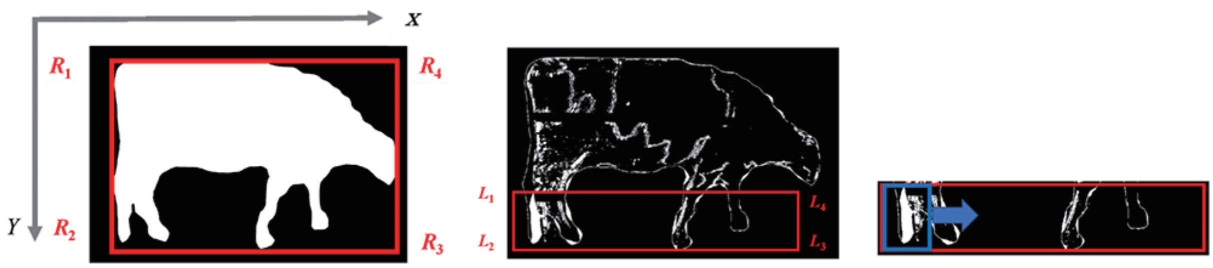


FIGURE 5. Flowchart of gait tracking



(a) (b) (c)

FIGURE 6. (a) Bounding Box (BB); (b) BB extended to leg area; (c) BB_1 provided in BB

The legs that are moving in each frame are tracked from the BB extended to the leg area. As shown in Figure 6(c), a blue BB (BB_1 for the sake of explanation) is added to the extended BB, and BB_1 is shifted by one pixel from the left in the BB, and the coordinates of BB_1 are taken when it reaches the right end and is the largest white pixel in the BB. The size of BB_1 to be newly used is 181 in height and 100 in width, as shown in the figure, which is the size of one leg. If there are multiple coordinates of BB_1 for the maximum white pixel, the average value is taken to determine a single coordinate. The coordinate points obtained in each frame are used to obtain the movement curve shown in Figure 7 [7]. The vertical axis represents BB_1's position in the BB, and the horizontal axis represents the frame in the cow's gait.

From the data obtained by the motion curve, feature values are extracted. After detecting the peak points P_1, P_2, and P_3, the number of frames between P_1 and P_2, P_2 and P_3, and P_1 and P_3 are obtained as f_l, f_r, and f_1, respectively. f_1 represents one cycle when all feet move one step, and f_l and f_r represent as the half period of f_1. f_2 is obtained

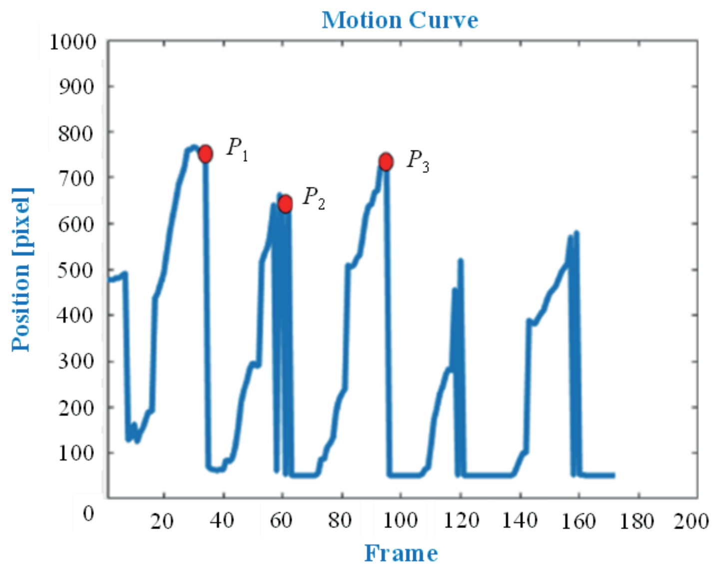


Figure 7. Motion curve

from the difference between f_l and f_r. Equations (4) to (7) describe the formulas for the characteristic quantities. The feature values f_1 and f_2 are used to classify lameness.

$$f_l = P_2 - P_1 \tag{4}$$

$$f_r = P_3 - P_2 \tag{5}$$

$$f_1 = P_3 - P_1 \tag{6}$$

$$f_2 = |f_l - f_r| \tag{7}$$

3. **Experiment.** This experiment was conducted at a demonstration farm in Kunneppu-cho, Hokkaido. A 4K camera was installed in the walkway on the way back from the milking parlor so that cows could be filmed from the side, with a resolution of 3840 × 2160 and a frame rate of 25 fps. Figure 8 shows the environment in which the camera was installed. The camera was installed at 1.5 m from the camera to the fence and at a height of 0.9 m. The video used was taken in November 2021, when cows were milked twice a day, once in the morning and once at noon, and were able to walk normally without stopping on the walkway on their way home. The camera used in the experiment was the AXIS P1448-Le, and MATLAB 2021b was used to process the acquired video. As an evaluation method, the lameness score determined by two experts is used to classify whether the cow is lame or not. Lameness score 1 is classified as normal and lameness score 2 or higher is classified as lame.

Figure 8. Experimental environment

4. **Results and Discussion.** In this experiment, cows were classified into two groups using the two feature values of one cycle of gait and the left-right difference obtained in 2.4. Table 1 shows the experimental data. The kernel function of the SVM is a linear SVM. Here, linear kernel refers to the type of mathematical function used to transform the data into a higher-dimensional space, where it can be more easily separated into classes. Generally, the C parameter in SVM is a regularization parameter that controls the trade-off between achieving a low training error and a low testing error in the SVM model. A smaller C value will result in a wider margin separating the classes, potentially allowing for more errors on the training set, but with better generalization performance on the testing set. On the other hand, a larger C value will result in a narrower margin, potentially overfitting the training set and leading to worse performance on the testing set. In simpler terms, the C parameter controls how much the SVM algorithm prioritizes finding the best possible decision boundary between classes versus allowing some mistakes in the training data in order to get better performance on new, unseen data. Thus, a smaller C value will prioritize the latter, while a larger C value will prioritize the former. Then, the grid search is used to find the optimal hyperparameters of a model which results in the most 'accurate' predictions. Assume the number of partitions for k-fold cross-validation is set to 5. The experimental results are shown in Tables 3(a) and 3(b),

Table 1. Experimental data

	Not Lameness	Lameness	Total
Number of movies	13	13	26
Number of cows	12	11	23

Table 2. Results of group identification

	Accuracy [%]	Recall [%]	Precision [%]
Result	84.6	76.9	90.9

Table 3. SVM and expert classification

(a) Lameness cow

Cow ID	SVM	Expert classification
4337	Not Lameness	Lameness
4128	Lameness	Lameness
4132	Not Lameness	Lameness
3855	Lameness	Lameness
3866	Lameness	Lameness
3868	Lameness	Lameness
4336*1	Lameness	Lameness
4336*2	Lameness	Lameness
3819	Not Lameness	Lameness
4142	Lameness	Lameness
4076	Lameness	Lameness
4161*1	Lameness	Lameness
4161*2	Lameness	Lameness

(b) Not Lameness cow

Cow ID	SVM	Expert classification
4043	Not Lameness	Not Lameness
4119	Lameness	Not Lameness
4125	Not Lameness	Not Lameness
4149	Not Lameness	Not Lameness
4165	Not Lameness	Not Lameness
4172	Not Lameness	Not Lameness
4346	Not Lameness	Not Lameness
4350	Not Lameness	Not Lameness
4361*1	Not Lameness	Not Lameness
4361*2	Not Lameness	Not Lameness
4367	Not Lameness	Not Lameness
4372	Not Lameness	Not Lameness
4374	Not Lameness	Not Lameness

*1 (Taken on 27th)

*2 (Taken on 28th)

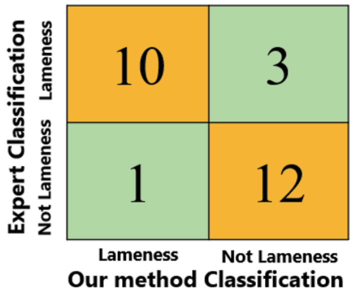


Figure 9. Confusion matrix with experimental results

and the accuracy, reproducibility, and fit rates are presented in Table 2. The confusion matrix resulting from the experiments is displayed in Figure 9.

Table 2 shows that 84.6% of the cows could be classified as lame or healthy correctly. The feature used in this study focused on the periodicity of walking motion, and its validity was demonstrated. In particular, the left-right difference in gait was a prominent feature of lameness.

5. **Conclusion.** This paper proposed a method to discriminate between healthy and lame cows by analyzing cow gait videos using image processing techniques. The current method performed classification on 23 cows and 26 videos. As described in the discussion, the classification accuracy was 84.6%. The features used in this study focused on the periodicity of gait movements, and their validity was demonstrated. In particular, the left-right difference in gait was a prominent feature of claudication. However, further improvement in accuracy is an issue for the future. The cause is the contamination of the cow's walking path. Cows were seen slipping on the walkways as they passed feces. Cleaning of the aisles is also done during milking, but since eight cows are milked at a time, contamination during that time would have an impact. We believe that lameness can be detected more accurately by using the relationship between back curvature and head position [8], in addition to gait features, as a solution to this problem.

For the future, we are considering using the relationship between head position and back curvature as an additional feature, as well as forefoot and hindfoot stride lengths. In addition, we aim to classify not only by lameness or normality but also by lameness level. We are aiming for more accurate detection by analyzing features using data obtained from multiple days.

Acknowledgment. This work is supported in part by "The Development and Demonstration for the Realization of Problem-Solving Local 5G" from the Ministry of Internal Affairs and Communications and the Projects of "The On-farm Demonstration Trials of Smart Agriculture" from the Ministry of Agriculture, Forestry and Fisheries (funding agency: NARO). We would like to express our sincere gratitude to the concerned persons of Hokkaido Hokuren Kunneppu Demonstration Farm for their knowledge of cow lameness and for their cooperation in providing walking videos.

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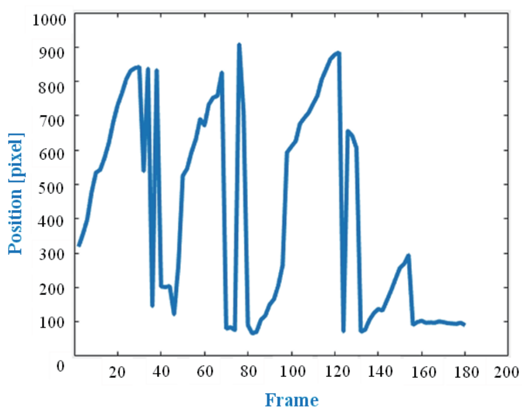
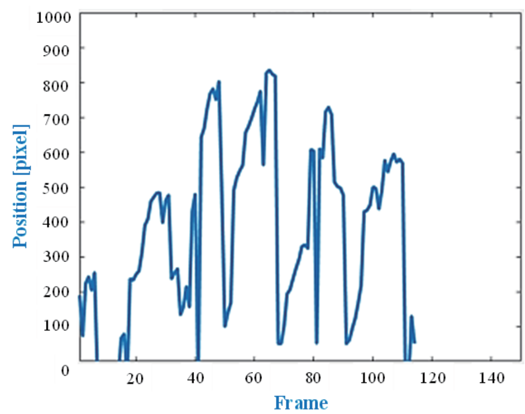
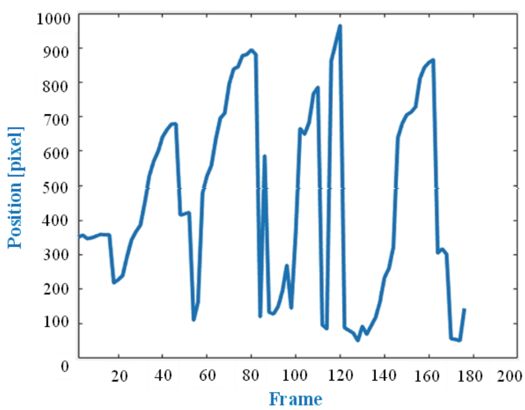
Appendix.



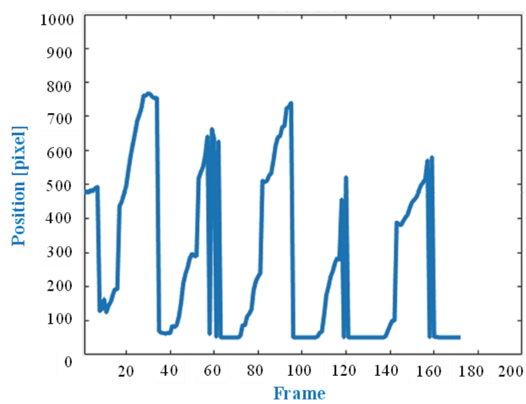
Lameness level 1



Lameness level 2



Lameness level 3



Lameness level 4

FIGURE 10. Motion curve (Lameness levels 1-4)