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QUANTIFYING BODY MOVEMENT VARIABILITY FOR CATTLE LAMENESS DETECTION USING DEPTH IMAGING

Thi Thi Zin* and Pyke Tin

Graduate School of Engineering
University of Miyazaki
1-1, Gakuen kibanadai-Nishi, Miyazaki 889-2192, Japan
pyketin11@gmail.com
*Corresponding author: thithi@cc.miyazaki-u.ac.jp

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Abstract. *This paper proposes a framework for detecting cattle lameness by quantifying the variability of body movement using depth imaging data collected while cows walk from the milking center to the resting area. The framework identifies critical factors that determine lameness scores based on the root mean square successive differences, various types of information entropies, and geometric measures of the collected depth data. To analyze lameness status, we developed an operational simulation model that combines Monte Carlo simulation with popular probability distribution functions such as uniform, normal, Poisson, and Gamma distributions. The simulation results suggest that detection performance and the characteristics of lame and non-lame cows significantly affect body movement variability. By using real-life data, we aim to validate this conjecture in future work.*
Keywords: Cattle lameness detection, Depth imaging, Body movement variability, Information entropy, Monte Carlo simulation

1. Introduction.

Lameness is a widespread welfare issue that has adverse effects on animal welfare, milk production, and farm economics worldwide. Limb disorders cause severe cow mobility, posture, and gait [1,2]. On the other hand, lameness in dairy cattle leads to significant economic losses and strongly deteriorates cow welfare. These losses include high treatment costs, reduced milk production, decreased fertility resulting in prolonged calving intervals, and early culling [3-6]. Unfortunately, farmers often underestimate the economic effect and prevalence of lameness in their herds, which results in late detection and treatment of the condition [7,8]. Correct and timely detection of lame cows is essential for reducing economic losses, improving animal welfare, and lowering on-farm lameness prevalence.

Traditionally, detecting lame cows has been done by farm experts using visual locomotion scoring, which is a labor-intensive, time-consuming, and experience-dependent method. Furthermore, the irregular practice of performing visual locomotion scoring can lead to inaccurate diagnoses and untreated lameness. To address these issues, research has focused on the development of automated lameness detection systems using a variety of sensor techniques, such as cameras, pressure mats, and accelerometers [11,12].

Automated lameness detection methods can be categorized into three main types: kinematic, kinetic, and indirect methods [13]. Among them, computer vision detection systems using the kinematic method, which measures the geometry of movement without considering the forces that cause the movement, have become increasingly popular. Most computer vision-based lameness detection systems utilize traditional 2D or 3D cameras

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or thermal infrared cameras. However, in this paper, we propose using a depth camera installed at the top of the pathway from the milking center to the resting area for automated lameness detection.

The hypothesis of this paper is that the variables used to detect lameness are conditioned by large variations among the successive differences in depths of individual cows' back arch postures. Therefore, an automated lameness detection system should account for this variation, which we term Body Movement Variability (BMV). The main contribution of this study is to develop an image-based lameness detection system that allows us to apply BMV on an individual level and uses back posture to classify lameness levels.

The remainder of this paper is structured as follows. Section 2 provides a literature review of existing automated lameness detection systems and discusses their limitations. Section 3 describes the proposed method for detecting lameness using a depth camera and introduces the concept of body movement variability. Section 4 presents the experimental setup and methodology used in this study. Section 5 presents discussions on methodology and concluding remarks followed by conclusions in Section 6.

2. Literature Review.

Recent research has focused on using image processing techniques to extract features for lameness characteristics from videos [14]. Automated lameness detection has been investigated through several academic research papers, with most researchers focusing on providing useful cow- and herd-level information to address information gaps, particularly regarding mild and moderately lame cows [15-17]. Deep learning techniques have shown great potential in improving feature extraction accuracy compared to traditional image processing methods, and there has been a growing interest in using them for the automatic detection of lameness in cows [5,14].

Automated methods of lameness detection typically fall into three categories: kinematic, kinetic, and indirect methods, with sensor system selection being a major consideration [5]. A computer vision system using kinematics has shown promise in measuring movement geometry without considering the forces that cause the movement. This system has a moderate price and non-contact information acquisition method and has demonstrated that lame cows compared with healthy cows have shorter stride lengths, longer stride duration, slower average speeds, and lower mean vertical distance. Another computer vision technique recorded stride length, back arch, and swing duration, suitable for detecting cow lameness [14,18].

Despite the advantages of computer vision lameness detection systems, there are still some problems that have limited their widespread use, such as accurately obtaining characteristic data, selecting appropriate methods for computer vision-based lameness detection, and exploring multi-feature fusion approaches to detect cow lameness [5,19]. To address these issues, utilizing deep learning techniques to extract cow lameness features from videos can improve feature extraction compared to traditional image processing methods. Additionally, a new approach for lameness detection is to use the Back Movement Variation (BMV) of a cow, defined as the variation of the differences between two successive depth measures of a cow's back arch. This approach offers a new way to detect cow lameness, with details described in the following sections.

To classify lameness levels according to various characteristics, statistical analysis of the data, such as linear correlation analysis, regression analysis, or machine learning techniques can be used. However, it is important to consider potential problems with research methods of lameness detection in cows by computer vision, including the need for new methods and features more suitable for computer vision-based lameness detection and the use of complementary methods to improve the accuracy of detection and classification [20,21].

Therefore, in this paper, we propose a new direction for lameness detection using the BMV of a cow. As in the above paragraph, the BMV is defined as the variation of the differences between two successive depth measures of the cow's back arch. We will describe the details of this method in the following sections. Additionally, we suggest exploring new methods and features more suitable for computer vision-based lameness detection and using complementary methods to improve the accuracy of detection and classification.

3. **Materials and Methods.** In this section, the depth image data collection process and the operational lameness detection model of our proposed method are mainly described.

3.1. **Depth image data.** The setup for data collection was placed in the passageway from the milking center to the hall with the feeding system. All measurements were taken on a walking animal from top view by using a depth camera located over the passage at approximately 3 meters above the ground. An illustrative continuously measuring and collecting lameness data is shown in Figure 1.

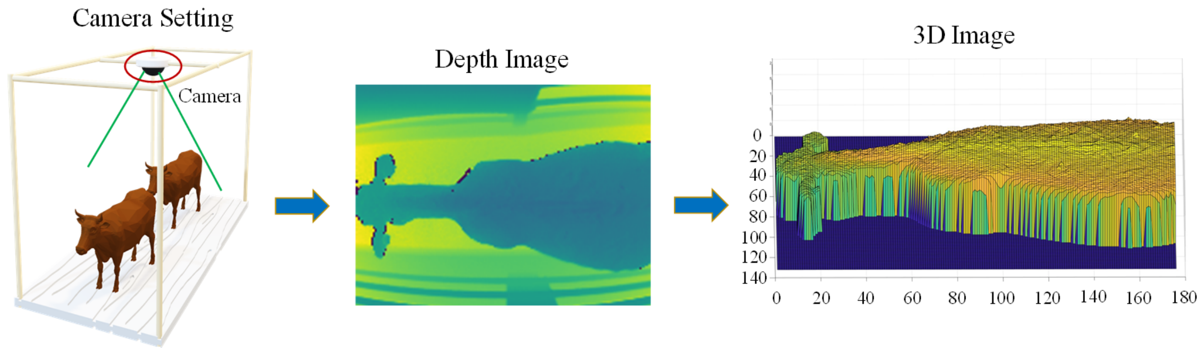

Figure 1. Illustration of depth image data collection

3.2. **Operational lameness detection model.** In real-life situations, most lameness data or data sequences exhibit some form of a pattern, whether regular or irregular. To understand trends in data, statistics – a mathematical tool – can be used. Variability in statistics is the degree to which data in a set varies or how much difference there is in a single set of data. It also refers to the consistency of the pattern in a set of data. General descriptions of a set of data, such as the mean, may not always provide the full picture of what is going on with the data. Measures of variability, on the other hand, enable researchers to determine the consistency of results to make assumptions about what is being studied. Several measures of variability are available to help researchers determine how much variability is present in a set of data, considering potential outliers. The most common measures of statistical dispersion include mean deviation, variance, standard deviation, range, and interquartile range. These measures have been used to study the variability of heart rates to diagnose healthy and unhealthy individuals, in mental health care to differentiate between normal and abnormal cases, and in other areas.

In this paper, we propose using the measure of variability to detect lameness scores in cows. Specifically, we define the BMV of the cow as the variability of successive shortest-depth intervals, which we refer to as SS intervals. We then calculated three types of measures for lameness detection scoring: Mean SS $\left(\overline{SS}\right)$, Standard Deviation SS $(SDSS)$, and Root Mean Square of Successive Differences $(RMSSD)$, collectively known as linear measures.

3.2.1. *Linear measures for lameness.* The formulations of the linear measures for lameness are described in the following lists.

i) *Mean SS interval* $\left(\overline{SS}\right)$: Let the SS interval time series include successive shortest depths intervals, i.e., $SS = (SS_1, SS_2, \ldots, SS_N)$. Then, the Mean SS interval $\left(\overline{SS}\right)$ and the Body Fluctuation Rate (BFR) are defined as follows:

$$\overline{SS} = \frac{1}{N}\sum_{n=1}^{N} SS_n, \quad \text{BFR} = \frac{T}{\overline{SS}} \tag{1}$$

where SS_n denotes the value of the nth SS interval and T represents the time duration for individual cow recording.

ii) *Standard Deviation of SS intervals* (*SDSS*): *SDSS* is the square root of variance. Since variance is mathematically equal to the total power of spectral analysis, *SDSS* reflects all the cyclic components responsible for variability in the period of recording. *SDSS* is defined as follows:

$$SDSS = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left(SS_n - \overline{SS}\right)^2} \tag{2}$$

iii) *Root Mean Square of Successive Differences* (*RMSSD*) calculating the shortest depth interval SS; that is defined as follows:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N-1}\left(SS_{n+1} - SS_n\right)^2} \tag{3}$$

These measures described in Equations (1)-(3) were used for scoring lameness levels by thresholds in a suitable manner. Similarly, we established some non-linear measures for cow body fluctuations variability for cow lameness detection.

3.2.2. *Non-linear measures for lameness.* The proposed body movement variability can also be measured by using non-linear methods. Specifically, we applied various types of entropy from information theory. In 1948, Shannon (Mathematician) proposed the concept of entropy which is known as Shannon Entropy (SE) to measure how the information within a signal can be quantified with absolute precision as the amount of unexpected data contained in the message. Although there are several common entropies, we utilized two of them: Multiscale Entropy (MSE) and Distribution Entropy (DistEn) for lameness detection.

i) *Multiscale entropy analysis*: The MSE analysis is a new method of measuring the complexity of finite length time series. We have developed and applied MSE for the analysis of dairy cows' depth data time series. The computational procedure for MSE can be used with a variety of measures of entropy for which we prefer to estimate entropy using the Sample Entropy (SampEn) measure. SampEn is a refinement of the approximate entropy family of statistics. Both have been widely used for the analysis of physiologic datasets. In order to define multiscale entropy, we first reconstructed the given depths data by averaging the data points within non-overlapping windows of increasing length, τ. The schematic illustration for scales 2 and 3 is shown in Figure 2. Each element of the time series y_j^τ is calculated according to Equation (4) where τ represents the scale factor and $1 \le j \le N/\tau$. The length of each time series is N/τ.

$$y_j^\tau = \left(\frac{1}{\tau}\right)\sum_{i=(j-1)\tau+1}^{j\tau} x_i \tag{4}$$

For scale 1, the constructed time series is simply the original time series. SampEn with unity delay is calculated for each time series and then plotted as the function of the scale factor τ to obtain the corresponding multiscale entropy.

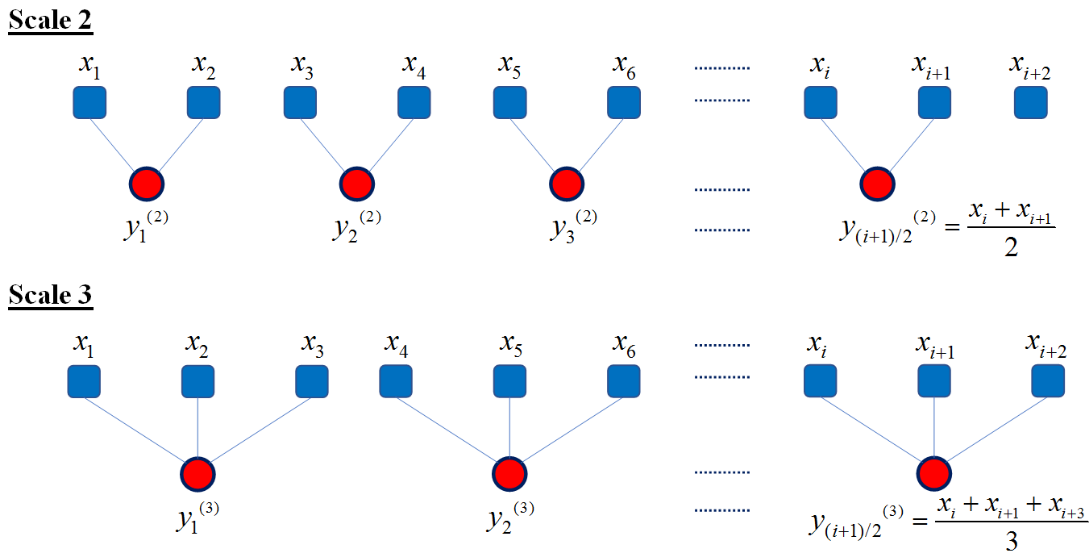

FIGURE 2. Schematic illustration of the procedure for scales 2 and 3

ii) *Distribution entropy analysis*: In this section, we developed the DistEn in order to analyze the depth data for dairy cow lameness problems. DistEn is a recently introduced measure of signal "complexity". It is calculated from the empirical Probability Distribution Function (ePDF) of vector-to-vector distances of the signal. DistEn is a function of three parameters: data length N, embedding dimension m and the number of bins M used in the probability distribution. In most cases, DistEn is known to be less influenced by changes in N and M. Additionally, DistEn performs better than other entropy measures, especially for short-length signals. In this paper, we explored the depth data relevance of DistEn cow lameness pattern analysis.

3.2.3. *Definition of distribution entropy.* DistEn is calculated based on the ePDF of distances among vectors formed from a given time series. For given time series data $\{x(n) : 1 \leq n \leq N\}$ of length N and embedding dimension m, DistEn is calculated as follows.

1) Form $(N-m)$ vectors of length m each, given by $\{X_i^m : 1 \leq i \leq (N-m)\}$, where

$$X_i^m = \{x(i+k) : 0 \leq k \leq m-1\} \tag{5}$$

2) Take each X_i^m vector of step 1) as a template vector and find its distance from every vector X_j^m where the distance is given by the following equation:

$$d_{ij}^m = \left\{\max\left|X_i^m - X_j^m\right| : 1 \leq j \leq (N-m),\ j \neq i\right\} \tag{6}$$

3) When step 2) is repeated for all ith template vectors where $1 \leq i \leq (N-m)$, a distance matrix D of dimension $((N-m) \times (N-m-1))$ is formed as shown below:

$$D = \begin{pmatrix} d_{12}^m & \cdots & d_{1(N-m)}^m \\ \vdots & \ddots & \vdots \\ d_{(N-m)1}^m & \cdots & d_{(N-m)(N-m-1)}^m \end{pmatrix} \tag{7}$$

From Equation (7), it is evident that elements in D are being repeated twice, i.e., $d_{ij}^m = d_{ji}^m$.

This is true because the distances are absolute values as can be seen from Equation (6). Thus, in formulating DistEn, it becomes sufficient to use either the upper triangle or lower triangle of D. Here, we used the upper triangle only and denote the resulting matrix as D', where

$$D' = \begin{pmatrix} d_{12}^m & \cdots & d_{1(N-m)}^m \\ \vdots & \ddots & \vdots \\ & \cdots & d_{(N-m)(N-m-1)}^m \end{pmatrix} \tag{8}$$

The elements of the distance matrix D' are now divided equally into M number of bins and the corresponding histogram is obtained. Now, at each bin t of the histogram, its probability is estimated as follows:

$$p_t = \frac{\text{count in bin } t}{\text{total number of elements in matrix } D'}, \quad 1 \leq t \leq M \tag{9}$$

where p_t is the probability of the ith bin in the histogram.

By the definition of Shannon entropy, the normalized DistEn of a given time series $x(n)$ is defined by the following expression:

$$\mathrm{DistEn}(m, M) = \frac{-1}{\log(M)} \sum_{t=1}^{M} p_t \log(p_t) \tag{10}$$

The distribution entropy used in our model was calculated by the following step-by-step procedures.

1) Collect depth data for lame and non-lame cows, separately.
2) For illustration, we generate these data by using random number generator in Excel.
3) Compute the distance between two data points for collected or generated data.
4) Group the set of data points into a predefined number of bins.
5) Suppose there are m number of bins, such as $b_1, b_2, b_3, \ldots, b_m$.
6) Compute the probabilities p_i defined as follows:

$$p_i = \frac{\text{number of distance measures in } b_i}{\text{total number of distances in all bins}} \tag{11}$$

7) Compute the distribution entropy by using the following formula:

$$\mathrm{DistEn} = -\sum_{i=1}^{m} p_i \log p_i \tag{12}$$

4. **Experimental Works Simulation Procedure.**

4.1. **Depth data collection.**

An Intel Depth Sensing Camera is mounted at a height of 3 meters and positioned face down at an angle towards the pathway between the milking station and resting area. The camera's angle is carefully calibrated to ensure it can capture the entire length of the cattle's backs as they walk past. Once the camera is set up and calibrated, it captures depth data of the cattle's backbones as they walk along the pathway to the milking station. This data is used to monitor the cattle's lameness. The data collection subsystem is illustrated in Figure 1.

To illustrate the proposed methodology in the materials and methods section, we collected the depth video images of a cow from a top view. Then, the differences of successive depths were formed as a sequence of SS intervals. The illustrative sequence of depths is described in Figure 3, which uses the 3D image of the sample cow from Figure 1.

4.2. **Simulation setting and procedure.**

The simulation process to calculate the lameness condition of the cows is described in the following step-by-step procedure. According to the sample depth data, we observed that the depth data sequence lies between 250 millimeters and 550 millimeters for non-lame cows and between 50 millimeters and 450 millimeters for lame cows. Thus, we use the following steps for simulation.

Step 1: To obtain non-lame data, we generate a sequence of random numbers between 250 and 550 using the uniform distribution.

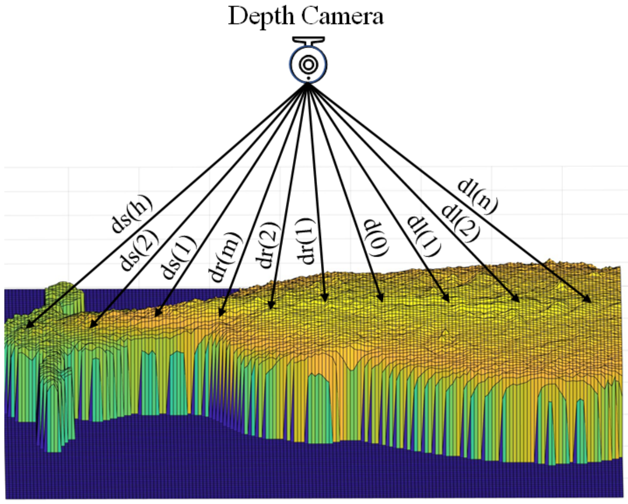

FIGURE 3. A sequence of depth data

Step 2: To obtain lame data, we generate a sequence of random numbers between 50 and 450 using the uniform distribution.

Step 3: Let $\{x_j\}$ be a sequence of generated random numbers. These numbers can be considered as a sequence of realization of a certain random variable. Therefore, we can derive a probability distribution.

Step 4: Calculate mean and variance using the following formulas:

$$\text{mean} = m = \frac{1}{N}\sum_{j=0}^{N} x_j, \quad \text{variance} = \sigma^2 = \left(\frac{1}{N}\sum_{j=0}^{N}(x_j - m)\right)^2$$

Step 5: Calculate the probability distribution:

$$p_j = \frac{x_j}{\sum_{j=0}^{N} x_j} \text{ for } j = 0, 1, \ldots, N$$

Step 6: Compute Root Mean Square of Successive Differences (*RMSSD*) of Depths values using Equation (3).

Step 7: Compute DistEn for illustration using Equation (12).

The illustrated computations for non-lame cows and lame cows are shown in Table 1 and Table 2, respectively. According to the calculation results from Table 1 and Table 2, we found that lame cows had higher *RMSSD* than non-lame cows, but the non-linear measure entropies were lower in lame cows than in non-lame cows.

Furthermore, we calculated some common statistical shape measures, such as skewness, kurtosis, standard deviation, and variance, using the simulation data shown in Table 1 and Table 2. Since the standard deviation and variance are classical measures, we only present the formulas to calculate skewness and kurtosis.

$$\text{Skewness: } skew = m_3 \Big/ \left(m_2^{3/2}\right)$$

where $m_3 = \sum(x - m)^3/n$ and $m_2 = \sum(x - m)^2/n$, and m is the mean and n is the sample size, as usual, m_3 is called the third moment of the data set, and m_2 is the variance which is the square of the standard deviation.

The other common measure of shape is called kurtosis. As skewness involves the third moment of the distribution, kurtosis involves the fourth moment. The outliers in a sample, therefore, have even more effect on the kurtosis than they do on the skewness, and in a symmetric distribution both tails increase the kurtosis. The moment coefficient of kurtosis of a data set is computed almost the same way as the coefficient of skewness: just change

TABLE 1. Illustrated computation for non-lame cow

	Generated Data (x)	Linear measure		Non-linear measure			
		Mean (m)	$(x-m)^2$	Sum	$P = x/\text{Sum}$	logP	Entropy
	400	429.450	867.303	8589	0.047	−4.424	0.206
	408		460.103		0.048	−4.396	0.209
	528		9712.103		0.061	−4.024	0.247
	524		8939.703		0.061	−4.035	0.246
	541		12443.400		0.063	−3.989	0.251
	326		10701.900		0.038	−4.720	0.179
	539		12001.200		0.063	−3.994	0.251
	433		12.603		0.050	−4.310	0.217
	315		13098.800		0.037	−4.769	0.175
	506		5859.903		0.059	−4.085	0.241
	550		14532.300		0.064	−3.965	0.254
	380		2445.303		0.044	−4.498	0.199
	549		14292.200		0.064	−3.968	0.253
	543		12893.600		0.063	−3.984	0.252
	422		55.503		0.049	−4.347	0.214
	316		12870.900		0.037	−4.765	0.175
	318		12421.100		0.037	−4.755	0.176
	402		753.503		0.047	−4.417	0.207
	304		15737.700		0.035	−4.820	0.171
	285		20865.800		0.033	−4.914	0.163
Sum	8589	Mean	9048.246	Sum	1	–	4.286
Mean (m)	429.450	*RMSSD*	95.122	Average entropy			0.214

the exponent 3 to 4 in the formulas:

$$\text{Kurtosis: } a_4 = m_4 \big/ m_2^2 \text{ and } m_2 = \sum (x-\bar{x})^2 \big/ n$$

From the simulation data in Table 1 and Table 2, we found that the corresponding shape measures and standard deviation and variance are shown in Table 3.

It can be interpreted as follows: Since the kurtosis for the lame cow is greater than that of the non-lame cow, the lame cow data has more outliers than the non-lame cow. Similarly, the non-lame cow data is negatively skewed, and the lame data is positively skewed. By looking at the variances, lame cow data is more fluctuating than non-lame cow data.

After calculating the shape measures and other statistical values, we can use them to determine the lameness condition of the cows. The following procedure outlines how we use these values in our simulation.

Step 1: Take the *RMSSD* value obtained from the depth data of the cow.

Step 2: Check if the *RMSSD* value is within the range of non-lame cows or lame cows. If the value is within the range of non-lame cows, then the cow is considered to be non-lame. If the value is within the range of lame cows, then the cow is considered to be lame.

Step 3: If the *RMSSD* value is outside the range of non-lame or lame cows, we can use the statistical shape measures to further classify the lameness condition. For example, if the *RMSSD* value is higher than the range of lame cows and the skewness value is positive, then the cow is considered to be severely lame.

Table 2. Illustrated computation for lame cow

	Generated Data (x)	Linear measure		Non-linear measure			
		Mean (m)	$(x-m)^2$	Sum	$P = x/\text{Sum}$	logP	Entropy
	229	249.100	404.010	4982	0.046	−4.443	0.204
	103		21345.210		0.020	−5.596	0.116
	401		23073.610		0.080	−3.635	0.293
	312		3956.410		0.063	−3.997	0.250
	428		32005.210		0.086	−3.541	0.304
	343		8817.210		0.069	−3.860	0.266
	117		17450.410		0.024	−5.412	0.127
	282		1082.410		0.057	−4.143	0.235
	317		4610.410		0.064	−3.974	0.253
	103		21345.210		0.020	−5.596	0.116
	234		228.010		0.046	−4.412	0.207
	332		6872.410		0.067	−3.908	0.260
	365		13432.810		0.073	−3.771	0.276
	94		24056.010		0.019	−5.728	0.108
	191		3375.610		0.038	−4.705	0.180
	222		734.410		0.045	−4.488	0.199
	174		5640.010		0.035	−4.840	0.169
	441		36825.610		0.089	−3.498	0.310
	66		33525.610		0.013	−6.238	0.083
	228		445.210		0.046	−4.450	0.204
Sum	4982	Mean	12961.290	Sum	1	–	4.160
Mean (m)	249.100	*RMSSD*	113.848	Average entropy			0.208

Table 3. Shape measures

	Skew	Kurtosis	Standard deviation	Variance
Non-lame	−0.24294	−0.70098	122.3935	14980.16
Lame	0.370586	−0.51958	184.1996	33929.5

Step 4: Based on the lameness classification, appropriate measures can be taken to prevent further deterioration of the cow's condition. For example, if a cow is found to be lame, steps can be taken to provide it with appropriate medical care, change its diet, or reduce its workload to allow for proper rest and recovery.

By using this simulation procedure, farmers can easily monitor the lameness condition of their cows, identify potential health issues early on, and take necessary actions to prevent further complications. This can result in healthier and more productive cows, leading to higher milk yields and greater profits for farmers.

5. **Discussion on Methodology and Concluding Remarks.** The concept of BMV can be considered as an analogy to heart rate variability in medicine. However, unlike heart rate variability, which has been analyzed in both the time and frequency domains, BMV is based on depth data in image frames to investigate the lameness conditions of individual cows. To the best of our knowledge, no such investigations have been conducted in the literature for dairy cows. Therefore, our study is at an early stage, and much work needs to be done to confirm the validity of our approach.

Although we have performed the simulation model for illustrative purposes only, our calculation results from Tables 1 and 2 indicate that there is a higher *RMSSD* in lame cows and a lower *RMSSD* in non-lame cows. However, the non-linear measure entropies were lower in lame cows than in non-lame cows. These findings will be further analyzed using real-life data in future works.

Early detection of lameness at all stages of lactation is essential for the milk production of a dairy farm. In this paper, we have introduced the concept of BMV for cow lameness detection, using two types of variability measures: linear and non-linear measures. These measures have been successfully utilized in human health analysis in terms of heart rate variability. However, this concept is newly developed in animal health studies. We hope that our proposed concept will be beneficial in investigating lameness analysis by refining the measures from all technological perspectives.

In conclusion, we have discussed the potential of BMV as a novel method for the early detection of lameness in dairy cows. However, we acknowledge that our study is still in its infancy and that further work needs to be done to validate our approach. We plan to utilize real-life data and conduct performance evaluations to make comprehensive comparisons with current state-of-the-art methods. We hope that our work will provide a solid foundation for further investigation into this critical area of animal health.

6. **Conclusions.** Early detection of lameness at all stages of lactation is an important factor in the milk production of a dairy farm. In this paper, we have introduced BMV concepts for cow lameness detection. We considered two types of variability measures namely linear and non-linear measures. These measures were successfully utilized in human health analysis in terms of heart rate variability. However, this concept is newly developed in animal health studies. We hope that our proposed concept would be beneficial to investigate lameness analysis by refining the measures from all technological perspectives.

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