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Dairy cattle behavior classifications based on decision tree learning using 3-axis neck-mounted accelerometers

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Abstract
Demand has been increasing recently for an automated monitoring system of animal behavior as a tool for the management of livestock animals. This study investigated the association between the behavior of dairy cattle and the acceleration data collected using three-axis neck-mounted accelerometers, as well as the feasibility of improving the precision of behavior classifications through machine learning. In total 38 Holstein dairy cows were used, and kept in four different farms. A logger was mounted to each collar to obtain acceleration data for calculating the activity level and variations. At the same time the behavior of the cattle was observed visually. Characteristic acceleration waves were recorded for eating, rumination, and lying, respectively; and the activity level and variations were significantly different among these behaviors ($p < 0.01$). Decision tree learning was performed on the data set from Farm A and validated its precision; which proved to be 99.2% in cross-validation, and 100% in test data sets from Farms B to D. This study showed that highly precise classifications for eating, rumination, and lying is possible by using decision tree learning to calculate the activity level and variations of cattle based on the data obtained by three-axis accelerometers mounted to a collar.

KEYWORDS
behavior classification, dairy cattle, machine learning, three-axis accelerometer

1 | INTRODUCTION

The behavior of animals reflects their physical condition (Frost et al., 1997), thus monitoring animal behavior is important in livestock management. Especially in large-scale cattle herds, direct individual observation has limitations because it requires a great deal of labor to identify all individuals and grasp their respective states. Therefore, an automated behavior-monitoring system is needed. In response to this need various research studies have been conducted and published, such as: a one-axis accelerometer mounted to the collar of cattle (Ueda, Akiyama, Asakuma, & Watanabe, 2011), the detection of eating and estimation of feed intake by pendulum (Uemura, Wanaka, & Ueno, 2009), a bitemeter incorporated microphone and a mercury switch (Delagarde, Caudal, & Peyraud, 1999), a pressure sensor attached to the halter (Braun, Trösch, Nydegger, & Hässig, 2013), the detection of eating and rumination by one-axis accelerometer with a voice recorder attached to a horn (Tani, Yokota, Yayota, & Ohtani, 2013), the detection of rumination time by a logger attached to the collar (Schirmann, von Keyserlingk, Weary, Veira, & Heuwieser, 2009), and the monitoring of lying behavior using a pedometer (Mattachini, Antler, Riva, Arbel, & Provolo, 2013). However, these are limited to the detection of simple behaviors, which is unsuitable for understanding complex behaviors.

TABLE 1 Information on herds

Farm	A	B	C	D
Herd scale (head)	25	50	40	30
Herd scale/beds		< 100%		
Feed bank width/ head		Enough		
Feeding/day	1	1	2	2
Milking/day	2	2	2	2
Cows for experiment (head)	10	9	8	11
Parities (Mean ± SD)	2.5 ± 1.4	1.8 ± 1.2	ND	2.8 ± 0.9
Days after calving (Mean ± SD)	123 ± 64	239 ± 122	ND	225 ± 110

To solve this problem, recently the use of three-axis accelerometers as a behavior-monitoring tool has been increasing; they have also been used for monitoring daily physical exercise for human health management purposes (Ohkawara et al., 2011; Oshima et al., 2010). In cattle there have been various reports using this tool: the estimation of grass intake at pasture (Oudshoorn et al., 2013), the prediction of calving with ear tag sensors (Rutten et al., 2017), behavior detection by a sensor attached to the mandible (Watanabe, Sakanoue, Kawamura, & Kozakai, 2008), the detection of various behaviors and lameness using sensors attached to the neck and a leg (Scheibe & Gromann, 2006).

Using the aforementioned devices, numerous results have been reported on the usefulness of monitoring animal behavior: the association between subclinical disease and reduction in rumination time (Soriani, Trevisi, & Calamari, 2015), subclinical hypocalcemia (Jawor, Huzzey, LeBlanc, & von Keyserlingk, 2012), metritis (Hazzey, Veira, Weary, & von Keyserlingk, 2007; Urton, von Keyserlingk, & Weary, 2005), milk yield (Kaufman, Asselstine, LeBlanc, Duffield, & DeVries, 2018), ruminal acidosis (DeVries, Beauchemin, Dohme, & Schwartzkopf-Genswein, 2009), liver function (Calamari et al., 2014), the association between subclinical ketosis and rumination time (Kaufman, LeBlanc, McBride, Duffield, & DeVries, 2016a; Schirmann, Weary, Heuwieser, Chapinal, & von Keyserlingk, 2016), stall structure (Haley, Rushen, & de Passillé, 2000; Tucker, Weary, & Fraser, 2004), the association between subclinical ketosis and lying behavior (Kaufman, LeBlanc, McBride, Duffield, & DeVries, 2016b), the association between lameness and lying behavior (Calderon & Cook, 2011), changes in behaviors in regrouping (Schirmann, Chapinal, Weary, Heuwieser, & von Keyserlingk, 2011), cortisol level (Bristow & Holmes, 2007), and the prediction of calving by rumination time (Büchel & Sundrum, 2014; Pahl, Hartung, Grothmann, Mahlkow-Nerge, & Haeussermann, 2014; Schirmann, Chapinal, Weary, Vickers, & von Keyserlingk, 2013). Therefore, classifying the behavior of cows and measuring the time spent in each behavior has important significance in the management of cattle herds.

Additionally, the high precision of cattle behavior classifications using the three-axis accelerometer has been gaining attention. Nielsen (2013) classified foraging behavior using sensors attached to the head and a hind leg with a sensitivity of 86.8% and a specificity of 90.5%. Oudshoorn et al. (2013) classified foraging behavior using sensors attached to the halter with a sensitivity of 74% and a specificity of 82%. Shen, Chen, Zheng, and Zhang (2014) classified static behavior and dynamic behavior using sensors attached to the neck with a precision of 93.26%. Darr and Epperson (2009) detected lying time using sensors attached to hind legs with 100% accuracy.

However, attaching a sensor to a halter and a limb, or attaching multiple sensors, is troublesome. In addition, past studies have not succeeded in classifying important behaviors of dairy cattle (e.g., eating, rumination, lying, and so on.) at once, and with high precision. The development of a new system where a sensor is easily attached to a cow's body and provides high precision classifications of their behavior is required. The objective of this study was to validate the association between the behavior of lactating Holstein dairy cattle and the data obtained by an accelerometer; within a free stall environment using three-axis accelerometers, which can be easily mounted to the collars of cattle. In addition, the improvement of the precision of behavior classifications was investigated using machine learning (Valletta, Torney, Kings, Thornton, & Madden, 2017), a method that has been frequently applied to animal behavior classification in recent years.

2 | MATERIALS AND METHODS

2.1 | Animals

A total of 38 Holstein cows were used in this study. They were kept in free stall barns on four farms. Total mixed rations (TMR) were fed to the cows, and access to water and mineral blocks were ad libitum. No other feeds and supplements were given. Milking was conducted twice a day at a milking parlor on each farm. Herds scale, parities, and the days after calving are shown in Table 1. Although the record of the feed bank width per head was not made, it was judged that it exceeded the recommended value (> 46 cm) (Albright, 1993) from the visual observation. All the cattle used were healthy during this study.

2.2 | Three-axis accelerometer device

A logger-node (Bycen Co., Ltd, Kobe, Japan) was used to record acceleration. This logger-node was equipped with H30CD (Hitachi Metals, Ltd., Tokyo, Japan) as a three-axis accelerometer; its measurement range was ± 19.613 m/s^2 and its precision was 12 bit. Acceleration data were stored in a built-in microSD card and used for analysis. The size of the logger-node was 58 ×42 × 16 mm (H×W×xD) and weighed 40.7 g. At the time of measurement, it was placed inside a reinforced plastic case (measuring 4.2 ×9.0 × 14.0 cm, Pelican Products, Inc., Torrance, CA). The case was then attached to the collar of the cows (collars were approximately 120 cm wide × 4 cm high) with weight on ventral (600 g), adjusting the acceleration devices to always be placed on right side of each cow's neck (Figure 1). There was a space where the hand could easily be inserted between the collar and the skin. Data sampling frequency at the time of measurement was set as 20 Hz.

2.3 | Data collection

Changes in acceleration accompanying the movements of cows were recorded from 10:00 to 16:00 hr, for 6 straight hours. Simultaneously, cattle behavior was being visually observed every 1 min, and the behaviors were classified as eating, rumination, standing, lying, walking, drinking water, or other.

2.4 | Analysis of acceleration signal

Acceleration data sets for eating, rumination, and lying (Table 2) were extracted separately. The time window for extracting data was set at 1,024 points (51.2 s) as one epoch, and epochs were selected avoiding a mixture of artifacts. After conducting offset processing to reduce the means of applicable epochs for each three-axis accelerometer, analysis was performed.

Scalar value ($A\nu(n)$), the combination of three-dimensional movements (Figure 1), back and forth (longitudinal) movement (x), up and down (vertical) movement (y), and left and right (horizontal) movement (z), was calculated for each detected value (Formula 1); and total of scalar values for applicable epoch ($\sum A\nu(n)$) was set as the "activity level" (m/s^2).

$$A\nu(n)=\sqrt{x_n^2+y_n^2+z_n^2}\quad (n=1,2,\cdots,1024)\quad \ldots\text{Formula1}$$

Absolute difference ($D\upsilon(n)$) in $A\nu(n)$ between points was calculated (Formula 2), and its mean ($\overline{D\nu(n)}$) was set as the "variation" for the applicable epoch (m/s^2).

$$D\nu(n)=\sqrt{\{A\nu(n+1)-A\nu(n)\}^2}\quad (n=1,2,\cdots,1023)\quad \ldots\text{Formula2}$$

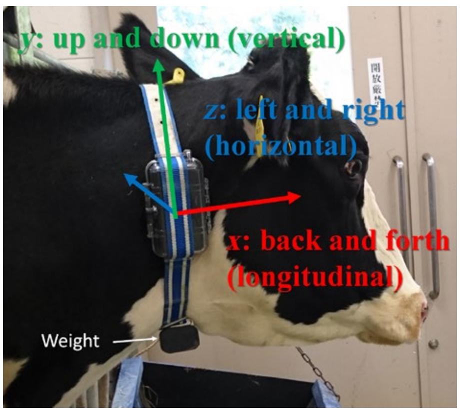

FIGURE 1 A data logger incorporated three-axis accelerometer mounted to cattle collar records longitudinal (*x*-axis), vertical (*y*-axis), and horizontal (z-axis) accelerations

2.5 | Statistical analysis

For the test of whether it is a normal distribution, we used one sample Kolmogorov–Smirnov test. And, for testing differences between different behaviors, we used a Kruskal–Wallis test as well as with multiple comparisons (Bonferroni correction). A P-value of less than 5% was considered significant.

The data set containing activity level and variations for eating, rumination, and lying in Farm A was considered training data, so decision tree learning was conducted following the method described by Valletta et al. (2017) for calculating a classification threshold value. The CART (Classification and Regression Tree) algorithm (Breiman, Friedman, Stone, & Olshen, 1984) was adopted, which uses Gini impurity to create splitting criteria (in order to measure impurity). In order to avoid overfitting, machine learning was performed which limited the splitting number to 4; the precision was confirmed by 10-fold cross-validation. Then, the sensitivity and specificity of the decision tree classification was calculated as it was applied to Farms B–D.

MATLAB R2017a (Mathworks, Natick, MA, USA) was used for the aforementioned hypothesis testing and decision tree learning.

3 | RESULTS

Visual inspection results of 10 cows in Farm A determined that the amount of time spent on eating/rumination/lying accounted for 94.8% of their total behavior (Table 3), so the analysis of the acceleration data focused on these three behaviors. Table 4 shows the final epoch number used for the analysis of the acceleration data. No avoidance behavior and dysphagia were observed in the cows due to mounted logger-node.

3.1 | Acceleration waveform

During eating, irregular and continuous accelerations in three directions were detected with a 2.0–5.0 m/s^2 amplitude (Figure 2). During rumination, homogeneous and regular acceleration with 0.8–1.2 m/s^2 amplitudes were detected in all three directions (Figure 3). Additionally, swallowing/regurgitating behavior observed during rumination occurred about once per minute at about 3-s intervals, with acceleration showing almost zero. However, acceleration was almost zero during lying (Figure 4).

TABLE 2 Definitions of eating, rumination, and lying used in this study

Eating	Sorting, chewing, and swallowing the TMR
Rumination	Rumination during standing or lying
Lying	Resting in the stall while lying (without ruminating)

TABLE 3 Percentage of each behaviors by visual observation (Farm A)

Behavior	%
Eating	26.6
Rumination	34.3
Rest (Lying)	33.9
Rest (Standing)	2.4
Walking	0.2
Drinking	2.6

TABLE 4 Epoch numbers used for final analysis

	Total epoch number		
Farm	Eating	Rumination	Lying
A	40	40	40
B	30	22	16
C	28	21	8
D	48	43	17

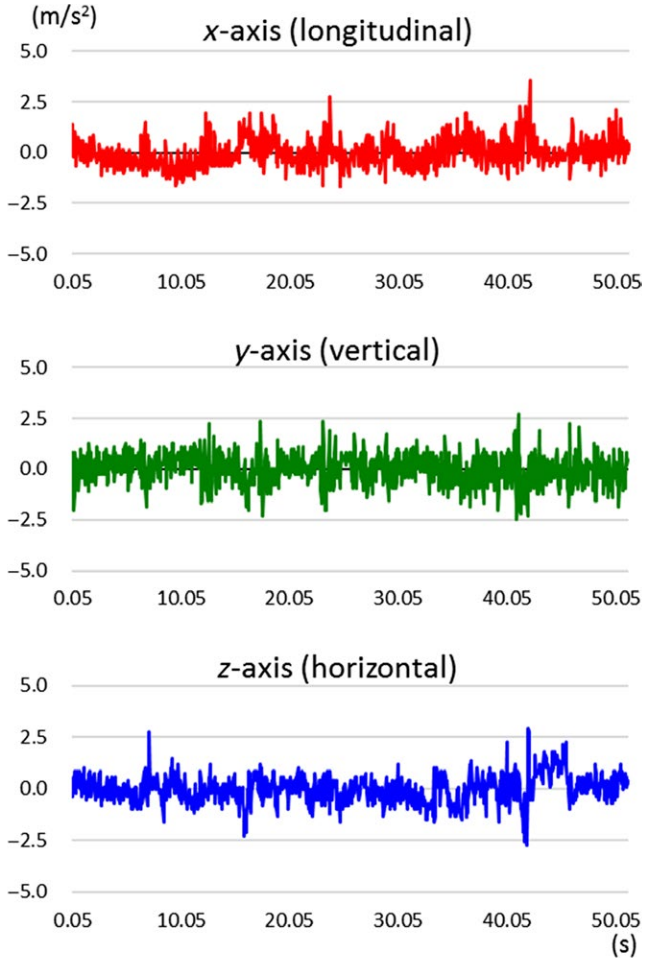

FIGURE 2 Accelerometer waves observed during eating (51.2 s) in longitudinal (top figure), vertical (middle figure), and horizontal directions (bottom figure). Irregular continuous accelerations were observed in all three directions with 2.0–5.0 m/s^2 amplitudes

3.2 | Activity level and variation (Farm A)

Activity level (median±interquartile range, skewness, and kurtosis) was determined for eating (3169.576 ± 2199.552 m/s^2, −1.310, and −0.611), rumination (391.140 ± 87.174 m/s^2, 0.481, and 0.973), and lying (183.320 ± 69.648 m/s^2, 0.732, and 0.406). Variations (median ± interquartile range, skewness, and kurtosis) were also determined for eating (0.407 ± 0.108 m/s^2, −0.527, and −0.029), rumination (0.168 ± 0.032 m/s^2, 1.655, and 0.821), and lying (0.055 ± 0.025 m/s^2, −0.622, and −0.064). The results of one sample Kolmogorov–Smirnov test showed no normality of distribution for both activity level and variations. The results of the Kruskal–Wallis test showed $p < 0.01$ for both activity amounts and variations, and significant difference ($p < 0.01$) was observed between each behavior in multiple comparisons (Figures 5 and 6).

3.3 | Decision tree learning

Figure 7 shows the decision tree learning obtained from the data set containing activity level and variations in Farm A. The activity level extracted by root node, 742.136 m/s^2 or higher, was classified as eating behavior. The secondary decision node classified variations as rumination at 0.103 m/s^2 or higher, and as lying at less than 0.103 m/s^2. Precision calculated by a 10-fold cross-validation was 99.2%. Based on the decision tree obtained, all the data from Farm A was correctly classified; both sensitivity and specificity were 100%.

3.4 | Sensitivity and specificity

When the test data from Farms B–D were applied to this decision tree, all of the data were correctly classified; both sensitivity and specificity were 100% (Table 5).

4 | DISCUSSION

Dairy cows kept in free stall environments are assumed to show different patterns of acceleration for each behavior such as eating, rumination, standing, lying, walking, drinking water, and mounting. Hancock (1954) described that the main behaviors of ruminant livestock animals were eating, rumination, and resting; it was confirmed by this study, which showed eating, rumination, and lying as their three main behaviors. As the classification of eating, rumination, and lying was thought to be particularly important, data analysis was focused on acceleration in these three behaviors. An investigation by *Watanabe* et al. (2008) also showed that behaviors outside of eating/rumination/lying were shorter, so these behaviors were excluded from analysis in this study.

In the previous studies involving three-axis accelerometers mounted to the head or neck of cows, sampling frequency settings varied: every 1 s (Oudshoorn et al., 2013; Watanabe et al., 2008), 0.5 s (Mattachini, Riva, Perazzolo, Naldi, & Provolo, 2016), 0.1 s (Dutta et al., 2014; Martiskainen et al., 2009; Shen et al., 2014; Werner et al., 2018), 0.02 s (Diosdado et al., 2015), and 0.01 s

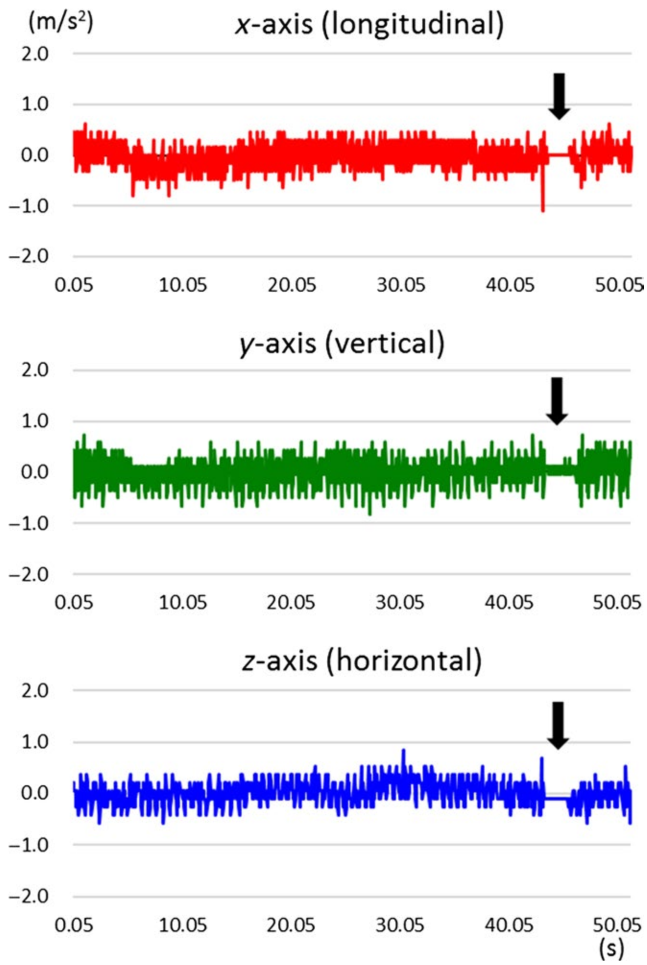

FIGURE 3 Accelerometer waves observed during rumination (51.2 s) in longitudinal (top figure), vertical (middle figure), and horizontal directions (bottom figure). Homogeneous and regular accelerations were detected with 0.8–1.2 m/s^2 amplitudes in all three directions. During swallowing/regurgitation, acceleration was almost 0 (arrows)

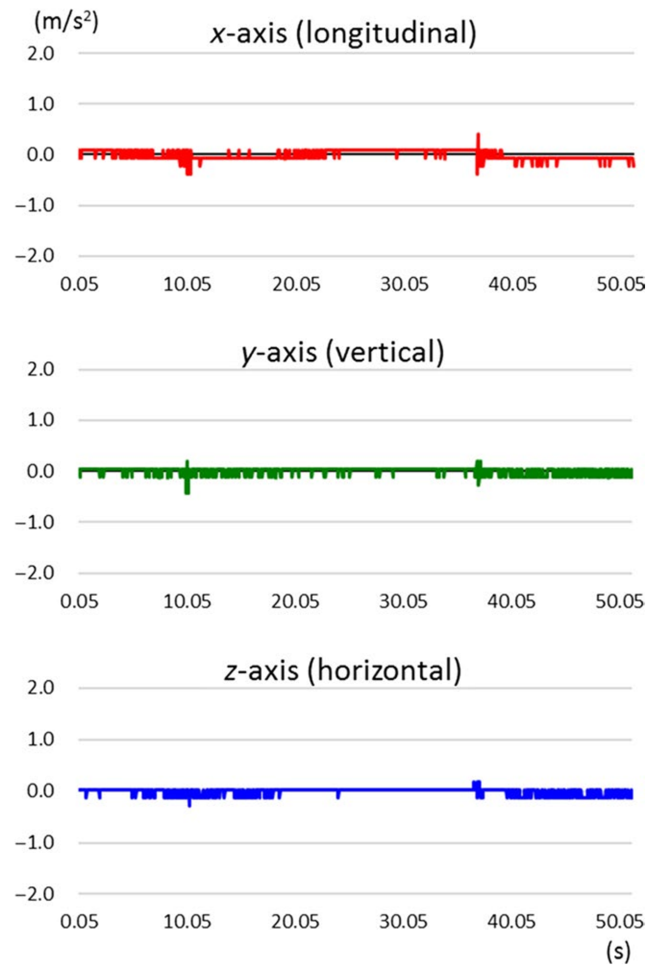

FIGURE 4 Accelerometer waves observed during lying (51.2 s) in longitudinal (top figure), vertical (middle figure), and horizontal directions (bottom figure). Changes in acceleration were minor, almost 0

(Scheibe & Gromann, 2006). For this study, sampling frequency was set at 20 Hz (per 0.05 s) which enabled proper behavioral classification.

Behavioral analyses using three-axis accelerometers attached to the mandible (Watanabe et al., 2008) and the collar (Scheibe & Gromann, 2006) reported that the amplitude of acceleration was ± 19.6 m/s^2. Therefore, this study's measurement range was set as ± 19.6 m/s^2. As a result, measurements were possible even during eating, which showed the biggest amplitudes; and so, the measurement range setting for this study was considered appropriate.

During eating, large and irregular acceleration variations were observed in all three directions (longitudinal, vertical, and horizontal). The cows' behaviors might have been captured as acceleration while they were trying to select and masticate TMR inside troughs—due to the fine movements of the head and neck with the contraction of mastication muscles, as well as the larger movements during TMR selection with the contraction of neck muscles. During rumination, cows repeat horizontal movements with the mandible by opening the oral cavity, dispersing the bolus of feed inside the oral cavity, and then grinding the bolus of feed by moving the mandible in the opposite direction (Bungo et al., 1999). Additionally, there were very few large movements of the head and neck during rumination, unlike in eating. Fine movements of the head and neck, caused by the rotational movements of the mandible, have homogeneity and periodicity in all three directions; thus, acceleration might have been detected as waveforms of smaller amplitudes as compared to eating. These acceleration waveforms were similar to the report by Scheibe and Gromann (2006). As there is no movement of the head and neck during lying, virtually no changes were observed in acceleration waveforms.

When behavior patterns are investigated using acceleration data, various parameters are sometimes calculated for setting time windows. In order to calculate total, mean, and deviations of accelerations, Watanabe et al. (2008) and Werner et al. (2018) set the time window as 1 min, and Shen et al. (2014) set the time window as 1 s. Different time windows have also used: 2 hr (Borchers et al., 2017), 10 s (Martiskainen et al., 2009), 5 s (Dutta et al., 2014), and 1–10 min (Diosdado et al., 2015). When changes in behavior patterns

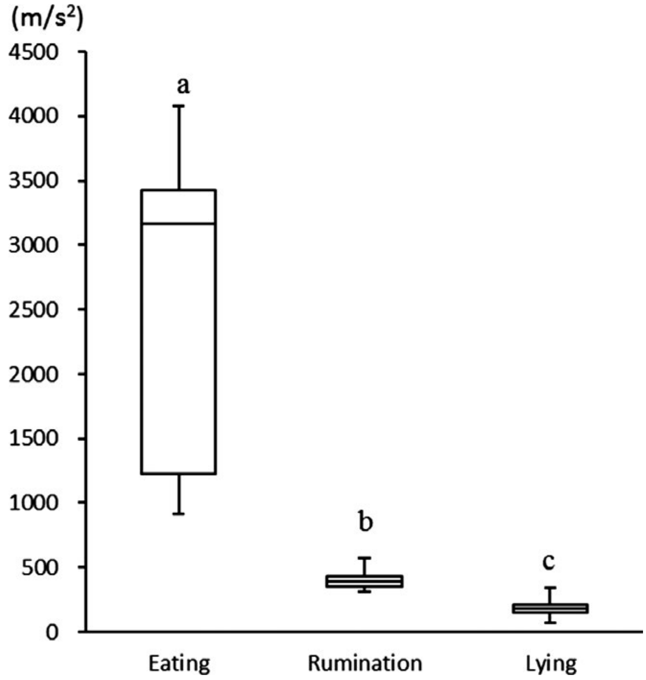

FIGURE 5 Comparison of activity level during eating, rumination, and lying. Different letters indicate significant differences ($p < 0.01$). Values are expressed as median ± interquartile range

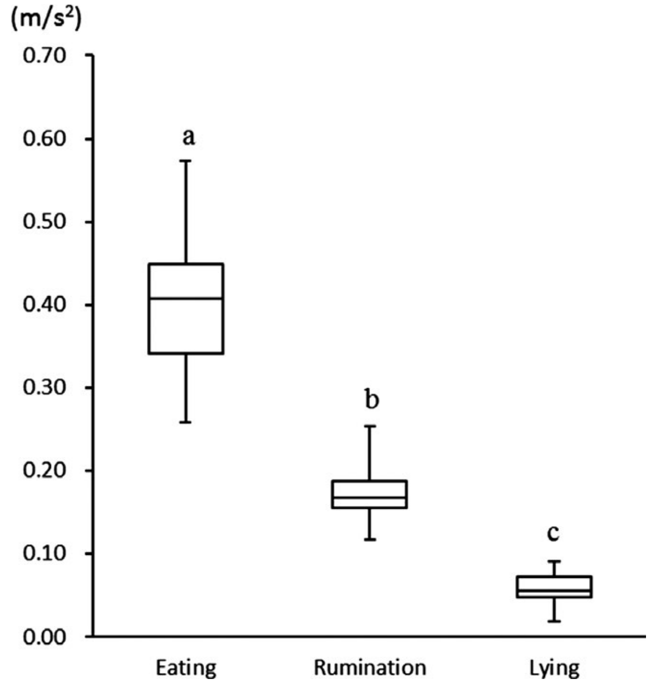

FIGURE 6 Comparison of variations during eating, rumination, and lying. Different letters indicate significant differences ($p < 0.01$). Values are expressed as median± interquartile range

are frequent, the time window should be set for a short range, but it results in a huge data set, making analysis more complicated. In this study, the time window was set as 51.2 s (1 epoch), and the parameters were calculated properly for eating, rumination, and lying.

Activity level and variations were calculated as parameters for behavior classification. Activity level is the total number of accelerations, and variations are the changes in the acceleration amount per 0.05 s. In other words, activity strength is reflected in the activity level, and variations indicate the degree of fast and repeated changes. Both parameters showed the amplitude tendencies as: eating > rumination > lying. Due to the large and irregular waveforms in eating behavior, the activity amounts and variations showed high values. Contrastingly, lying was reflected as low values for activity level and variations due to there being almost no movement. Values for rumination fell between the other two behaviors. This may have reflected the constant jaw movements during rumination without the large movements of the head and neck as was found in eating. There have been no reports about parameters equivalent to variations while monitoring cow behavior. In this study, significant differences were observed among the three types of behavior; thus variation is one of the most useful indices for analyzing cow behavior when using acceleration data.

In recent years, multiple studies have reported on cow behavior using accelerometers together with machine learning (Borchers et al., 2017; Dutta et al., 2014; Martiskainen et al., 2009). Although there are many methods of machine learning, this study used a simple decision tree. The advantage is that the decision tree method is easy to interpret by visualizing the classification process

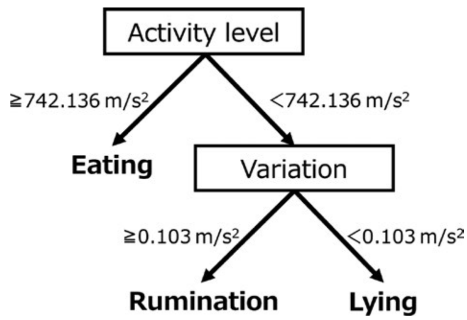

FIGURE 7 Classification and threshold values calculated with the decision tree

TABLE 5 Results of classification based on decision tree data

		Sensitivity (%)	Specificity (%)
Farm B	Eating	100	100
	Rumination	100	100
	Lying	100	100
Farm C	Eating	100	100
	Rumination	100	100
	Lying	100	100
Farm D	Eating	100	100
	Rumination	100	100
	Lying	100	100

as a tree structure (Valletta et al., 2017). In addition, the CART algorithm (Breiman et al., 1984) is one of the most commonly used algorithms as a decision tree method, and it was also used in this research. It used "activity level" and "variations" as parameters, as those parameters could be obtained beforehand and because they presented clear differences between eating, rumination, and lying. As a result, this study had excellent precision (99.2% by cross-validation), and superb sensitivity and specificity (100% in the test data from other farms). Another report of behavior classification using three-axis accelerometers and decision trees, Diosdado et al. (2015) showed similar results: 98.78% sensitivity and 93.1% specificity for eating, and 77.42% sensitivity and 98.63% specificity for lying behavior. However, Diosdado et al. used VeDBA (an equivalent to activity level) and SCAY (a component of gravitational acceleration in *y*-axis) as parameters. This suggests that in the classification of eating and lying behaviors, the frequency of rapid change (i.e., "variations") is more important than the gradient of the neck as a parameter added to the "activity level". It was considered to be one factor that high classification accuracy was in this research. Therefore, the "variations" parameter may be an element that reflects the behavioral characteristics of cattle efficiently, and it was possible to clearly classify rumination behavior in fact. However, further investigation is necessary to clarify this reason. Anyway, it suggests the usefulness of activity level and variations as parameters of behavior classification.

This study shows that collar-mounted three-axis accelerometers provide high precision data for calculating the activity level and variations used in classifying the behaviors of dairy cows kept in free stall barns as eating, rumination, or lying. In addition, decision tree method is recommended as a behavior classification algorithm using these data. This method will be a useful tool for cattle herd management in the future.

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