Status Discrimination of Dairy Cows using Activity Meter and Machine Learning

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Abstract

It is important to detect the estrus of a cow in order to maintain lactation and increase farmer productivity. In the existing method, the observation interval is long, and it is possible to overlook the estrus. In this study, we propose a method of discriminating the condition of dairy cow using acceleration data. It is intended to detect changes of behaviors in dairy cows at shorter intervals and to enable precise estrus detection. We attached a small acceleration sensor to a cow and collected data. We extracted features from the collected data and applied machine learning to predict the cow's condition. In this study, we attached sensors to dairy cows at Arimura Farm and the Konsen Agricultural Experiment Station, and collected data. One dairy cow at each farm had a sensor attached. We extracted the feature quantity and discriminated the state and the 10- fold cross validation. It was possible to judge the state with an accuracy of 90% or more in collected data on both farms. In addition, when the collected data on both farms were combined and learned, it became possible to judge the state with an accuracy of 94.8%.

keywords: Status Discrimination, Machine Learning, Random Forest, Sliding Window, Acceleration Data

1 Introduction

Because the amount of lactation in dairy cow is directly linked to dairy farming, it is very important to increase the amount of milk produced per cow. In general the amount of lactation in dairy cow increases immediately after parturition, reaches a maximum after a few weeks, and then gradually decreases. A curve showing the change in the amount of lactation is called a lactation curve (Figure 1) [1].

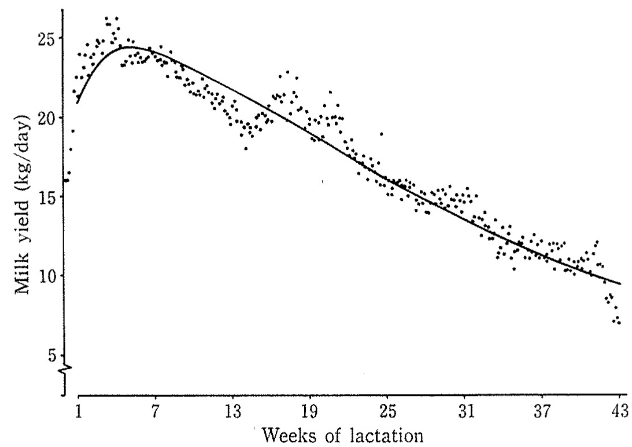

Figure 1: Lactation Curve

Since lactation increases again when delivering, shortening the period of emptying as much as possible leads to an increase in milk production. Therefore, increasing the probability of success of artificial insemination of dairy cow is a demand for conducting healthy farm management. We compare the proportion of empty cows to days in milk (DIM, lactation days) for farms with 15 % pregnancy rate and 35 % farms. On farms with a pregnancy rate of 35 % at DIM 150, the proportion of empty cows is about 10 %, whereas at farms with a pregnancy rate of 15 %, the proportion of empty cows exceeds 40 % [2].

The average fertility pregnancy value is about 13 to 16 million yen. If the proportion of empty cows is increased by 30% on a farm where 100 dairy cows are raised, it is a loss of 390 to 4.8 million yen. Meanwhile, semen used for artificial insemination also has large variations in monetary value depending on its kind and quality, and semen with excellent Holstein genes can cost hundreds of thousands of yen. When artificial insemination fails, the value of semen will be zero. Therefore, considering the cost of semen itself, it will not be a good idea to repeat artificial insemination many times without matching the timing.

Due to the mechanism of fertilization, in order to artificial insemination to succeed, it is necessary to inject semen 12 to 18 hours after observing estrus.

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However, because of the short time, it is difficult to raise the probability of successful artificial insemination. In other words, if we delayed or missed detecting sings of estrus, the success rate of artificial insemination will be greatly reduced. Two approaches are mainly considered as a method for knowing the start of estrus. The first is that farmers observe dairy cows and observe behavior specific to estrus, such as tolerance for mounting (mounting) and riding (standing), changes in cries, loss of appetite, and restlessness. Information about 21 days, which is regarded as a general estrous cycle and information such as increase of estrus behavior such as mounting and standing are used to find estrus. The actual estrus period is only about 2% of the estrous cycle and the standing time is often less than 0.2% of the total estrous cycle and therefore is often overlooked in normal observation. In addition, it is reported that milking cows are significantly less expressed than dairy cow and it is more difficult to detect the start of estrus (Table1)[2].

Table 1: Estrus Time and Estrus

	Breeding Cow	Milking Cow
Supplied Cow	114	307
Number of Standings	16.8	7.2
	± 12.8	± 7.2
Estrus Time	11.3	7.3
	± 6.9	± 72

The second approach is computer monitoring. It is possible to acquire ingredient data and food consumption of each dairy cow using equipment such as a milking robot, milk ingredient measuring device, and feeding machine. In this approach, rather than obtaining the estrus period by farmer observation, the start of the estrus is detected from the progesterone (luteinizing hormone) measured by the milk component measuring device. Estrogen and progesterone are hormones related to ovulation, but are generally in a trade-off relationship, and the amount of progesterone, which is easier to measure, is often used for monitoring.

Generally, dairy cows are milked twice a day. When we try to detect estrus by measurement with a milk component measuring instrument as described above, estrus occurs between milkings, and there are cases where estrus has almost ended at the time of the next milking. In order to overcome this issue, we attached a compact acceleration sensor to dairy cows, extracted features from the collected data, and propose a method to discriminate the activity of dairy cow by machine learning. By using this, it is possible to collect activity contents in time units and daily units of dairy cow. We observes this information to analyze changes in dairy cows at short time intervals and to detect estrus with higher accuracy. Because the device is very small and light, it does not limit activity or stress dairy cows.

2 Related Works

Machine learning is applied to dairy cow data in small amounts. Related studies are summarized as follows.

In 2006, D. Z. Caraviello et al. predicted the success of artificial insemination using an Alternating Decision Tree (ADTree) [3], a decision tree learning method [4]. In this study, an ADTree classifies whether pregnancy succeeds or fails using 300 or more dairy cow parameters at the 150th day of lactation (150 DIM) days. We performed 10-fold cross validation using 17,587 data points obtained from 9,516 head of cow, and it was possible to classify with 75% accuracy.

Machine learning not has been applied to research on dairy cow in addition to research targeting artificial insemination. Nazira Mammadove et al. predicted mastitis [6] by Support Vector Machine [5] in 2013.In this study, mastitis is predicted using features such as the milk yield of milking by an automatic milking machine and the electric resistance value of the breast, and shows a performance of sensitivity of 89% and specificity of 92%.An artificial neural network (neural network) is a machine-learning method utilized in a wide field. Artificial neural networks and their derivative machine learning algorithms have been applied to fields such as food processing and livestock management, although it includes engineering, economics and drug discovery. Wilhelm Grzesiak and colleagues predicted milk yield using an artificial neural network [7] in 2006 and found that the root mean square (RMS) is lower and R2 (determination coefficient) is larger than in the conventional milk yield prediction method. Similarly, applied research using the artificial neural networks includes predictions of reproductive value [8] carried out by Saieh Shahinlr et al. This study obtained the correlation between milk yield and fat mass and breeding value using an artificial neural net and neurofuzzy learning [9]. Both exhibited high performance of 0.9 or more.

3 Methodology

In this study, we collect data from an acceleration sensor attached to a dairy cow and apply it to machine learning to determine the cow's activity. This small, lightweight sensor doesn't limit the activity of cows, nor does it stress them.

3.1 Type of Activity State to be Determined

We discriminates five states. We discriminate whether a cow is standing or sitting or eating. When a cow is standing or sitting we discriminate whether the cow is rumitating or not. Rumitating is a characteristic behavior of cow, so I thought this would contribute to classification. It is summarized in Table2.

Table 2: Active Status to Determine

	Rumitating	not Rumitating
Standing	I	II
Sitting	III	IV
Eating	V	

3.2 Extraction of Data and Features to be Acquired

In this study, a small acceleration sensor is attached to dairy cows, and acceleration data is collected at 1 Hz for three-axis acceleration. This is because 1Hz is the shortest interval on the acceleration sensor used.

Next, feature data is extracted using acceleration data collected from sensors. The time series acceleration data of each of the three axes is separated into five-second windows, and the variance and average value between them are obtained. There are thus six feature quantities in total as shown below.

- Average x axis acceleration
- Average y axis acceleration
- Average z axis acceleration
- Variance x axis acceleration
- Variance y axis acceleration
- Variance z axis acceleration

In order to obtain more feature quantities from the collected data, we extract features using a one-second sliding window(Figure2). The black dot in the figure represents each data point every second. We didn't divide the data every five seconds. We slide the five-second frame by one second as in the figure. And we made features from every five-second frame.

Simultaneously with the data acquisition, the state of the cow is photographed with a video camera and recorded. Based on the recorded moving image, we labeled to each feature.

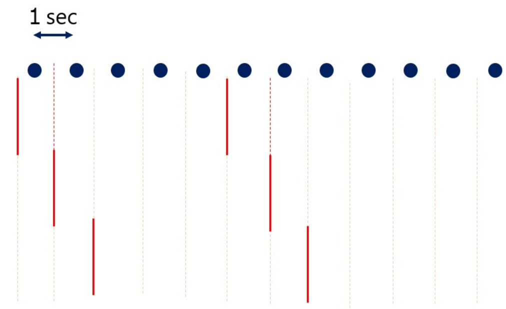

Figure 2: Sliding Window for Acquiring Features

These features are subjected to machine learning, and the activity state of the cow is discriminated. We used numerical analysis software, "MATLAB". This software can display the discrimination accuracy of multiple learning instruments side-by-side. The accuracy of each learning instruments can be compared, and the optimum one can be easily selected. Based on a comparison, we decided to use random forest in this study.

3.3 Random Forest

I used a random forest as a machine learning method. Random forest is a method to obtain high prediction accuracy using multiple decision trees. Random forest is one of ensemble learning methods. It select data randomly and grow a decision tree. It repeat this process specified number of times and determine the classification threshold by majority decision of the prediction result. Random forest does not need to scale feature and is easy to parallelize.

4 Experimental Results

We collected data by attached sensor on dairy cow. We experimented in two farms, "Arimura Farm" and "Konsen Agricultural Experiment Station".

4.1 Device Used

In this study, we attached a sensor on dairy cow, and collected acceleration data. This sensor is very small and light, so it does not limit dairy cow nor stress them. The device used is the IoT Smart Module(Alps Electric Co., Ltd).This device is compact, but it has a six-axis sensor, barometric pressure sensor, temperature / humidity sensor, and a UV / illuminance sensor. It can acquire the data at 1Hz and send it to nearby devices with Bluetooth. This is attached to the collar of a cow and collects data. Data transmitted from the IoT Smart

Module via Bluetooth is transmitted to the PC using Open Blocks IoT EX1(Plat' Home Corp.) as a relay, and data is stored in csv format on the PC. A sensor is attached to a cow's collar and collects data. Striped collars in Figure4 have sensors built in.

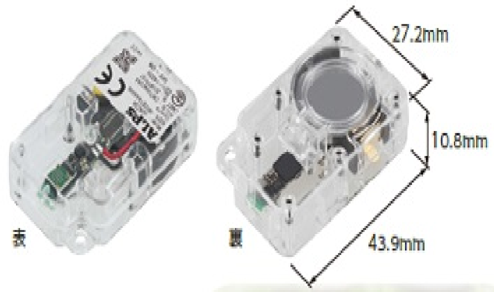

Figure 3: IoT Smart Module

Figure 4: Attach Sensor to Dairy Cow

4.2 Collected data

Data was collected at Arimura Farm for about 4 hours and at the Konsen Farming Experiment Station for about 3 hours. We collected data for each cow on each farm and extracted features from them using a sliding window. As a result, we obtained 11,580 data sets from the collected data at Arimura Farm and 8219 data sets from data collected at the Konsen Farming Experiment Station (data was lost in this section, so that part is excluded).

Dairy cows were able to act freely in the barn, and we tried to shoot with the video camera from a remote location so as not to affect their activity.

4.3 Result

At Arimura Farm and the Konsen Farming Experiment Station, data were collected on small farms by attaching a small acceleration sensor to dairy cow. Characteristic values were extracted from the collected data and labeling was performed. The data were learned in a random forest, and discrimination accuracy was obtained by performing a 10-fold cross validation test. The results are shown in the table below.

Results for data collected at Arimura Farm are in Tablel3. Accuracy is 93.9%. Roman numerals in Table3 correspond to the Table2. The column shows the predicted state and the row shows the actual state. For example, number of times data was predicted II state but actually it was I state was 28. Data collected at Arimura Farm does not contain data of dairy cows eating, it is classified into four classes. It is able to distinguish the cow standing and the cow sitting with high accuracy. The discrimination results for the data collected at the Konsen Farming Experiment Station are presented in Table4. Accuracy is 90.2%. The state in which the cow is ruminating and the state in which the cow is eating look similar. However, in this study, we were able to distinguish them with high precision. The above results show that classifiers generated using data collected from acceleration sensors attached to certain dairy cows in a farm can estimate the activity with high accuracy for the specific dairy cow. However, it has not been shown that classifiers generated using data collected from acceleration sensors attached to certain dairy cows can be used as they are for other dairy cows. Specifically, using the classifiers obtained from the data collected at the Konsen farm test site in this experiment, it is necessary to discriminate against the data collected by Arimura Farm. If you actually do that, the discrimination accuracy will be about 18%. There are several causes for this.

Table 3: Confusion Matrix(Arimura Farm)

		Predict Label			
		I	II	III	IV
True Label	I	1777	28	3	37
	II	88	368	4	47
	III	16	3	703	261
	IV	102	26	89	8028

The first is individual differences in dairy cows. There are differences in size and movement among the cows, possibly affecting discrimination accuracy. Second, there are differences in how the sensors are attached. In this experiment, there are no strict rules on how to attach the sensor, so the sensor direction may vary greatly depending on the data. If the sensor directions differ, the three-axis acceleration also changes greatly, and this may affect the discrimination accuracy. Third, there are regional differences. Three-axis acceleration has different properties depending on altitude and latitude / longitude. The latitude and longitude difference may affect the discrimination accuracy because the latitude is at least 10° and the latitude is about 15° apart at least at the two places where data was collected this time.

Table 4: Confusion Matrix(Konsen Agricultural Experiment Station)

Predict Label

		I	II	III	IV	V
True Class	I	1902	166	22	0	6
	II	289	1814	19	18	116
	III	30	9	1300	1	0
	IV	7	29	1	379	1
	V	3	84	5	0	2018

Ideal classifiers are not affected by regional or individual differences and can be discriminated with high precision regardless of how the sensor is worn. Therefore, we gathered data at Arimura Farm and at the Konsen Farming Experiment Station, and learned a total of 19,799 data sets in a random forest in the same way (Table 5). Accuracy was 94.8%. Acquisition data at Arimura Farm and acquisition data at the Konsen Agricultural Experiment Station gained higher accuracy than when learned alone. From this result, we think that it is possible to generate classifiers capable of discriminating the condition of dairy cow under any circumstances by collecting data and under learning conditions for different conditions of region, individual, and sensor attachment. We do not have current data to demonstrate this, so we plan to collect data under more conditions in the future, learn it, and verify its accuracy.

Table 5: Confusion Matrix(Both Farms)

Prediction Class

		I	II	III	IV	V
True Class	I	3690	28	221	2	0
	II	60	2561	39	101	2
	III	384	59	1873	7	0
	IV	1	107	0	8544	10
	V	0	5	0	7	2098

5 Conclusion

In this study, we aimed to improve the productivity of dairy cow using estrus detection and proposed a method of discriminating the activity of dairy cows from acceleration data. Features were extracted from acceleration data collected using small sensors attached to dairy cows, and their activity was determined by machine learning. Data was collected from each cow on two farms, Arimura Farm and the Konsen Farming Experiment Station. The characteristic quantity was extracted from the collected data and subjected to machine learning and 10-fold cross validation. The accuracy was 93.9% when we used the data collected at Arimura Farm. The accuracy was 90.2% when we used the data collected at Konsen Farming Experiment Station. We also tried discrimination by machine learning by combining data collected at both farms, and it was possible to perform state discrimination with an accuracy of 94.8% by 10-fold cross validation.

Combining and learning the data collected under multiple conditions may enable generating a classifier that can discriminate the state under any condition. We are going to collect more data under various conditions and conducts.

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