Efficient Estimation of Cow's Location Using Machine Learning Based on Sensor Data

Tomohide Sawada(✉), Tom Uchino, Niken P. Martono, and Hayato Ohwada

Department of Industrial Administration, Faculty of Science and Technology, Tokyo University of Science, Tokyo, Japan
{7422519,7421701}@ed.tus.ac.jp, {niken,ohwada}@rs.tus.ac.jp

Abstract. Indoor localization of dairy cows is important for determining cow behavior and enabling an effective farm management. In this study, a low-cost localization system was constructed by attaching accelerometers to dairy cows kept indoors in a barn in order to obtain radio wave strength. Using link quality indicator (LQI) data, we employed four machine learning models to predict the position of the cow: LightGBM, logistic regression, support vector machine (SVM), and neural network. The prediction performance and computational cost of the models were compared and evaluated. In the monitoring and building of the prediction models for cow's location, we considered various sizes of location (barn) compartments and evaluated the performance of each prediction model using with different compartments. The experimental results showed that LightGBM and neural networks have an accuracy of 46.6% at 9 m horizontal and 12 m vertical and an accuracy of 90% at 45 m horizontal and 15 m vertical. In terms of the computational score, we may consider whether to use neural network or LightGBM depending on the amount of data to be predicted at a time in the location estimation system.

Keywords: Indoor localization · Machine learning · Sensor data · Farm management · Cow location

1 Introduction

In Japan, almost all dairy cows are housed indoors at least for some part of their lives, and, in an increasing number of farms, indoor housing is practiced year-round. Farmers are preferring to keep their cows indoors throughout the year [8] since it allows them to provide high-yielding individuals with a nutritionally balanced diet fit for their needs, and this practice has important welfare benefits for both cows and their calves, such as protection from predators, parasites, and exposure to extreme weather conditions. However, the challenge is that farmers need to visually check the location of each cow, as there are typically more than 100 cows in a barn.

Y. Kambayashi et al. (Eds.): AICON 2022, LNICST 477, pp. 86–94, 2023.
https://doi.org/10.1007/978-3-031-29126-5_7

The motions and location of animals are important for their health monitoring. By monitoring the motions of animals, we may obtain early warnings of diseases and stresses by analyzing untypical behavior. Several commercial systems that can monitor cow behavior have been based on cow motions. However, these systems are relatively expensive [4]. Many studies have been conducted on the position estimation of indoor cows using the received signal strength indicator(RSSI) values, which can be obtained from Wifi access points (APs) and link quality indication (LQI), which can be obtained from ZigBee modules based on the IEEE 802.15.4 standard. There are several methods for indoor location estimation using radio wave strength, such as trilateration [11] and the fingerprint method, which can predict data most similar to past data.

In this study, we constructed a mechanical localization system by attaching accelerometers that can acquire radio wave strength to dairy cows kept indoors in a barn. The proposed system can support dairy farmers to visually estimating the position of their cows by illuminating the LEDs on the accelerometers and displaying their location on a web application, thereby assisting in quick response to sick cows and in health management tasks. We trained a machine learning model with pairs of radio wave strength and location labels obtained from multiple APs to create a model that can predict the location using radio wave strength data from multiple APs. Four machine learning algorithms were considered for position estimation: LightGBM, logistic regression, support vector machine (SVM), and neural network. The results were compared and evaluated both accuracy and computational cost. Finally, we considered various sizes of the predicted location compartments for actual operation of the location estimation system for dairy cows kept in a free stall barn and evaluated each model for each compartment size.

2 Related Works

There is growing interest in developing technologies that can help monitor the physiological and behavioral parameters of dairy cows [5], mainly attributed to the increase in herd size and the facilitation of herd and health management. A good dairy management system should include automated milking systems and automated feeders as well as sensors (e.g., pedometers and accelerometers) that can be mounted on a cow's legs, collars, or ears or placed in the rumen. Additionally, it should include real-time location systems that allow tracking of animal location within a barn.

These systems can be useful for detecting cows within the barn, for example, in estimating and predicting the time animals spend in relevant areas, such as the alley, feed bunk, or cubicle [5]. Location data can also be used to predict the activity performed by animals in important areas of the barn. Many indoor location estimation methods for cows have been studied and reviewed. In particular, location estimation using machine learning models has been extensively studied.

RADAR is a pioneering RF-based fingerprint indoor location estimation method that uses the K-nearest neighbour (KNN) and Euclidean distance as the location estimation index between the predicted and actual locations [3]. Previous studies have also introduced machine learning models, such as the support vector machine (SVM) [6,9], random forest (RF) [7], decision tree [10], and deep learning models to address the inherent problems in indoor positioning, showing good performance in analyzing the indoor positioning of animals. Various machine learning algorithms, such as deep learning, have been used for location estimation using RSSI values, and methods using it [1,2] have been devised. However, there have been few stduies on location estimation using LQI data. Moreover, the accuracy of these multiple algorithms and the computational cost of actually operating them have not been compared. Our work addresses these gaps. We employed LQI data from sensors and used several machine learning algorithms to create location prediction model for cows, and their performance was compared and evaluated.

3 Methods

3.1 Data Acquisition

The LQI data used in this study were obtained from accelerometers attached to approximately 100 Holstein dairy cows at Nakayama Farm in Nakashibetsu, Hokkaido, Japan. The period of data acquisition was from April 29 to 30, 2021, and the total number of data points was 126,696. The data range was a closed interval from 0 to 255. We used 70% of the total data by random sampling in the training sample, and 30% for the test sample. Some of the missing values were preprocessed before being used in the model building. In the barn where the data were obtained, a fixed transponder was installed to acquire the radio wave from the accelerometer, as shown in Fig. 1. The barn was 19.4 m long and 78.8 m wide, with a 5.4 m-wide aisle at the center. The actual length and width of each compartment where the dairy cows were kept was 12 m as seen from the entrance of the barn. In this study, the barn was divided into 160 sections, 80 sections on each side viewed from the barn entrance, and approximately 790 data were obtained from each section. The length and width of each section of the 160 compartments were 3 m and 3.94 m, respectively.

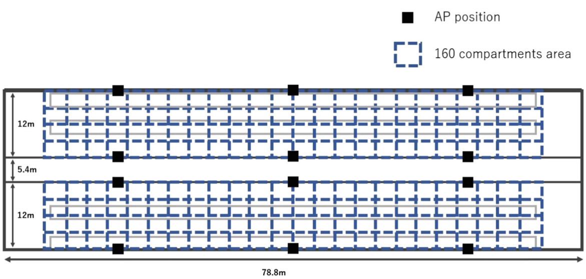

Fig. 1. Barn layout and AP position

The LQI value is the link evaluation value based on the bit error rate (BER), which is the loss rate of packets with a value between 0 and 255. The accelerometer used for acquiring the LQI values was attached around the neck of the dairy cow. For efficiency reasons, we set a separate accelerometer that can transmit acceleration data to a fixed relay once every 0.25 s for data acquisition.

At Nakayama Farm, where the data were obtained, the reception of acceleration data from the radio waves emitted by the accelerometer and the acquisition of LQI values were performed using a fixed repeater, as shown in Fig. 1. The repeater used in the experiment was a Raspberry Pi Zero WH connected to a 32-bit wireless microcontroller module TWELITE DIP (developed by Mono Wireless) that complies with IEEE802.15.4. After the fixed transponder sends the acceleration data from the accelerometers via Zigbee communication, the data were sent to the server. A server was installed at each barn, and Raspberry Pi 4 model B was used as the hardware. The servers measured the computational cost (the time cost of making predictions using the trained models), which was used to compare the accuracy of each machine learning model as well as their computational cost.

3.2 Data Preprocessing

As a preprocessing step for the completion of missing values, we set the LQI value to −1 when the transponder could not acquire a signal, i.e., when the LQI value could not be acquired. This is because the value range of the data includes 0, and −1 is used to distinguish them from the data whose values are close to 0, although they can be acquired by the transponders. To examine the grouping of the divisions, we divided the barn into two regions: the left and right sides from the barn entrance. We divided the barn vertically into two compartments (each 78.8 m in length and 12 m in width), 8 compartments (each 19.7 m in length and 12 m in width), and 20 compartments (each 15.76 m in length and 6 m in width), respectively, as shown in Figs. 2, 3 and 4.

Fig. 2. 2 partitions

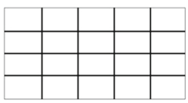

Fig. 3. 8 partitions

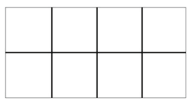

Fig. 4. 20 partitions

3.3 Machine Learning Model

In this study, Bayesian optimization was applied to decide the hyperparameter values of each method using Optuna to improve the performance of each model. The trained models with the hyperparameters optimized by Optuna were also used to determine the computational cost of the operation. In using the machine learning, the main purpose is to learn to minimize the cross-entropy error.

Equation 1 shows the dateset in building the machine learning model: the dataset is denoted by $\boldsymbol{D}$, the feature LQI value is $\boldsymbol{x}$, the area of the teacher data is $\boldsymbol{A}$, the number of parts is $\boldsymbol{d}$ ($\boldsymbol{d} \in \{2, 8, 20, 160\}, \boldsymbol{A} \in \{A_1, A_2, \ldots, A_d\}$) and the amount of data is M ($M = 126,969$).

$$D = \begin{pmatrix} LQI_{1,AP1} & \ldots & LQI_{1,APj} & \ldots & LQI_{1,AP12} \\ \vdots & & \vdots & & \vdots \\ LQI_{i,AP1} & \ldots & LQI_{i,APj} & \ldots & LQI_{i,AP12} \\ \vdots & & \vdots & & \vdots \\ LQI_{M,AP1} & \ldots & LQI_{M,APj} & \ldots & LQI_{M,AP12} \end{pmatrix} \tag{1}$$

$$\boldsymbol{D} \in \mathbb{R}^{M,12},\ \boldsymbol{x} \in \boldsymbol{D},\ \boldsymbol{A} \in \mathbb{R}^d.$$

Given the LQI value $\boldsymbol{x}$ of a certain target acquired by each relay from the data, considering the posterior probability $\boldsymbol{P}(A_j|\boldsymbol{x})$ that the target is in an areaA_j, and finding its likelihood, the model parameters are $\boldsymbol{\theta}$, the likelihood function is $\boldsymbol{P} = \boldsymbol{P}(\boldsymbol{A}|\boldsymbol{x})$, and $\boldsymbol{t}$ is a one-hot matrix of the teacher data. The likelihood function is obtained as follows:

$$L(\boldsymbol{\theta}) = \prod_{i=1}^{M} \prod_{j=1}^{d} {p_{ij}}^{t_{ij}} \tag{2}$$

We minimize the logarithm of the likelihood function$L(\boldsymbol{\theta})$ using a machine learning model to minimize the cross-entropy: $-ln(L(\boldsymbol{\theta}))$. To evaluate the learning model, the percentage of correct predictions is calculated for each of the three partitions considered for each learner: 2 partitions, 8 partitions, 20 partitions, and 160 partitions. For the 20-part and 160-part partitioning methods, a percentage of correctness is also evaluated by assuming that when one part is predicted, it is said to be correct if its neighboring part has the correct label.

For all the partitioning methods, 70% of the data randomly sampled from the entire dataset was used as training data and the other 30% was used as test data. The evaluation index for each trainer was also set to be the usual percentage of correct predictions. For the evaluation of the computational complexity, we measured the time required to make predictions on 1,000, 100, 10, and 1 data points for each of the partitioning methods considered by each trainer using a Raspberry Pi 4 model B.

Prediction models were build using four machine learning algorithms:

- **Logistic regression (LR).** LR is a simple but powerful algorithm for linear classification regression problems, binary classification problems, and multiclass classification; it is a model for classification rather than regression. In this study, given a feature $\boldsymbol{x}$, we performed a multiclass classification to determine whether the target belongs to areaA_i or not.
- **LightGBM.** The light gradient boosing machine(LightGBM) is a type of gradient boosting that uses the gradient descent method to minimize the loss function when constructing a weak learner among boosting methods that

sequentially construct weak learners and generate prediction models. The tree structure is such that the tree is grown leaf by leaf and the leaf with the lowest loss is selected, which has the advantage of high efficiency and memory consumption.

- **Support vector machines (SVM).** The SVM is one of the widely used and powerful algorithms that maximizes the margin between the hyperplane (decision boundary), which is the decision boundary to classify positive or negative cases, and the training sample closest to the hyperplane.
- **Neural network (NN).** A neural network comprises an input layer, an intermediate layer, and an output layer. It learns by gradually adjusting the weights of each layer to reduce the error between the correct label and the correct answer. In this study, we used TensorFlow to construct and train a neural network with the structure shown in Fig. 5.

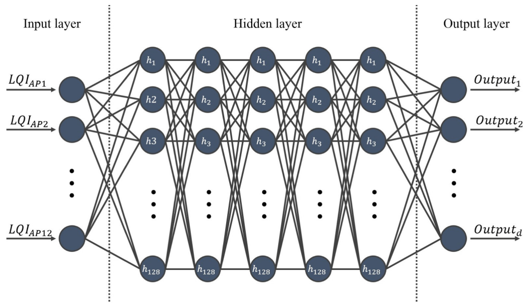

Fig. 5. Structure of the neural network model

4 Results and Discussion

Table 1 presents the accuracy of each of the segmentation methods used in the experiment, namely logistic regression, SVM, LightGBM, and neural network, for the 160-, 20-, 8-, and 2-part segmentations. Table 2 presents the loose accuracy rates for the 160-part and 20-part partitions, where the parts adjacent to the predicted part are also considered as correct. For the 160-part split, the results in Table 1 show that LightGBM has the highest percentage of correct predictions. In addition, Table 2 shows that LightGBM and the neural network have the highest percentage of loose correct predictions, and their numbers are almost similar. The accuracy of guessing the correct answer for each segment is less than 20% for all the training systems; however, when the loose accuracy, which is the percentage of correct predictions for segments adjacent to each segment, is used as an indicator, all the training systems achieve an accuracy rate higher than 40%, and the accuracy rate of LightGBM and neural network is close to 50%.

The results show that the accuracy, is 46.6% at 9 m (width) and 12 m (height). Using the 20 part splits, the highest percentage of correct predictions is obtained for LightGBM when looking at the results presented in Table 1. Moreover, from Table 2, the SVM has the highest percentage of loose correct predictions. The LightGBM and neural network are almost as accurate as the SVM. As for the accuracy of guessing each compartment, models other than logistic regression have an accuracy close to 50%, and above 90% for the loose correct rate. From these results, it can be said that an accuracy of 90% is achieved at 45 m (width) and 18 m (height).

Using the 8-partition classification, Table 1 shows that LightGBM has the highest percentage of correct predictions. The neural network and LightGBM have largely the same accuracy, being close to 60%. Finally, for the two-partition classification, Table 1 shows that LightGBM has the highest accuracy rate, and all the models except for logistic regression have an accuracy of more than 90%, with no significant difference in the accuracies between the SVM, neural network, and LightGBM.

Table 1. Percentage of correct predictions for each learner

ML model	2 partitions	8 partitions	20 partitions	160 partitions
Logistic regression	85.927	51.006	40.459	11.966
SVM	90.247	56.987	47.649	18.222
LightGBM	90.657	58.660	47.907	19.217
Neural network	90.379	58.163	47.147	18.183

Table 2. Loose correct rate for each learner

ML model	20 partitions	160 partitions
Logistic regression	89.979	40.990
SVM	91.360	44.679
LightGBM	91.344	46.694
Neural network	91.242	46.699

Table 3 shows the time required by the logistic regression, SVM, LightGBM and neural network segmentation methods to predict 1,000, 100, 10, and 1 data point(s) for 160 partitions, 20 partitions, 8 partitions, and 2 partitions. For the 160-part and 20-part partitions, in terms of the forecasting time required by LightGBM and neural network, which have a high forecasting accuracy, LightGBM is faster than the neural network except for forecasting 1,000 cases. LightGBM is faster than the neural network in predicting 1 to 100 data points. For the 8-part classification and 2-part segmentation, LightGBM, which is the best in terms of accuracy, is the fastest in all cases, except for the 160-part segmentation and 20-part segmentation. In the case of 160-part or 20-part segmentation, where more than 1,000 predictions are required in actual operation, it is necessary to select a trainer that can balance the ideal accuracy and computational cost between the neural network and LightGBM.

Table 3. Computational cost of predicting each classifier

ML model	Number of part divisions	1,000 case [msec]	100 case [msec]	10 case [msec]	1 case [msec]
Logistic regression	160	273	281	285	289
	20	46.7	50.9	54.9	58.7
	8	29.1	33.3	37.4	41.4
	2	14.7	19.2	23.5	27.9
SVM	160	8.88×10^4	8.94×10^3	903	106
	20	2.30×10^4	2.29×10^3	242	29.7
	8	1.86×10^4	1.87×10^3	189	24.9
	2	1.63×10^4	1.64×10^3	173	23.1
LightGBM	160	1.89×10^3	176	25.1	11.1
	20	290	33.3	8.38	6.01
	8	19.3	6.43	6.13	4.91
	2	19.3	6.43	5.12	4.91
Neural network	160	254	134	124	123
	20	230	133	126	123
	8	238	133	126	123
	2	236	134	124	122

5 Conclusions

This study developed a method for estimating the location of individual dairy cows indoors using a machine learning model and LQI values as the radio wave strength for the dataset. Four machine learning models, namely logistic regression, SVM, LightGBM, and neural network, were employed to build prediction models. As an evaluation of the accuracy of the models, we examined the percentage of correct predictions and the percentage of loose predictions in which a predicted segment is also considered to be correct if it is adjacent to the predicted segment. We also examined the prediction time required by each model on a real machine and compared the computational cost of operating the system to verify the best model for operating a location estimation system. Finally, we examined 160-part, 20-part, 8-part, and 2-part partitions as the classification partitions.

The proposed method could make loose correct predictions with an accuracy of 90% for the 20-part classification and 2-part classification and with accuracies of 46% and 56% for the 160-part and 8-part divisions, respectively. In terms of the computational complexity, it is necessary to consider whether to use the neural network or LightGBM for the 160-part or 20-part segmentation, depending on the amount of data to be predicted at a time in the location estimation system. In the future, for barns where dairy cows are kept, we plan to analyze the variation in the LQI due to environmental factors such as humidity and temperature, and consider improving the accuracy by adding environmental information as a new feature.

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