A study on outdoor localization method by recurrent deep learning based on time series of received signal strength from low power wireless tag

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Abstract: In order to detect estrus and abnormalities from the interactions of grazing cattle, we are developing a position estimation method using low-power wireless devices. In this paper, in order to obtain a natural trail of cow’s locations, we propose a localization method based on long short term memory. Our evaluations show that the proposed method suppresses unnatural trail and achieves the average location error of 5.25 m for the cow that is used for learning and about 6 m for the other cows.

Keywords: localization, Bluetooth, RSSI, deep learning, LSTM

Classification: Sensing

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1 Introduction

Focusing on the sociability of cattle, we study to detect estrus and abnormalities from the interactions of grazing cattle [1]. Such interactions are possibly extracted if the position of cattle can be localized every few seconds, which can be easily realized by attaching a global positioning system (GPS) device to each of cattle. Such GPS devices will, however, burden farmers with frequent battery replacements even if its capacity is large. Another way is to utilize low power wireless devices such as Bluetooth low energy (BLE) tags and to estimate the device location based on the values of received signal strength indicator (RSSI) at several receivers. For example, NTT TechnoCross mobicollect is a BLE tag system in which a tag works with CR2032 button battery of 220 mAh for one year [2].

One of the promising localization methods using such wireless devices is fingerprinting [3, 4, 5]. These methods can be further divided into two categories: “matching approaches” and “deep learning approaches.” When RSSI is used with the matching approach, it requires a database of pair data of location and corresponding RSSI data for each receiver at each location. We call such pairing information “fingerprint data” hereafter. This requires much effort, especially for a vast outdoor area. Further, as the size of the database becomes large, the search times when matching RSSI data with known fingerprint data become increasingly longer. On the other hand, the deep learning approach, which relies on a deep neural network (DNN), has the potential to reduce such efforts significantly.

Once the neural network has been trained on fingerprint data relation-
ships in the pasture, it can estimate positions much faster than the matching approach. For example, in [6], a virtual space is developed to mimic a pasture for grazing cattle. Then, a DNN is trained using fingerprint data generated from the virtual space and then fine-tuned by those taken from the real environment. As a result, it is shown that this deep learning approach achieves localization error of about 6 m on average. See [6] for more details.

Resultant trails by [6], however, appear somewhat awkward like zigzag walking as shown later. This will cause an unexpected effect on the analysis of the interactions among grazing cattle. To cope with this problem, we propose a localization method based on long short-term memory (LSTM) [7], which is a kind of recurrent neural network (RNN) suitable for time series data such as speech recognition [8] and sentence analysis [9]. The RNN takes time series of RSSI as input and outputs an estimated location. This paper is a improved version of [10].

The rest of this paper is organized as follows: Section 2 describes our experiment field. Section 3 explains the proposed localization method. Section 4 shows evaluation results. Finally, Section 5 concludes this paper.

2 Experimental environment

Fig. 1 (a) shows an overview of the pasture for our experiments. We adopt “mobicollet” as a BLE tag system, which is developed by NTT Technocross Corporation [2]. In order to cover the entire of the pasture, we deploy 20 BLE receivers around the pasture, and each is numbered from 1 to 20 in a clockwise direction. Among them, ten receivers equip with Yagi antenna whose half-value angle is 47 degree and the other do with the flat antenna whose half-value angle is 77 degree. In the figure, their directions and types are depicted. Unfortunately, however, Receiver 8 does not work on account of the antenna failure. Therefore, we use only 19 receivers except Receiver 8 actually.

In order for beacon frames to be received as successfully as possible, each cow has wrapped a belt with four BLE tags, two for each side, and one GPS device around her neck as shown in Fig. 1 (b). Each BLE tag transmits a beacon frame every two seconds. Fig. 1 (c) shows temporal characteristics of RSSI from two different BLE tags fixed at the same place. From this graph, it can be seen that RSSI fluctuates with time and the average is different between these BLE tags. Also, as shown in Fig. 1 (d), the antenna pattern of BLE tag is not uniform. This will make RSSI fluctuate as a cow bends her neck up and down or right and left. With BLE tags, the temporal fluctuation of transmission power and the directionality of the antenna may make it difficult to estimate the cow’s location using the RSSI at the receivers even if the cow stays at the same place. To mitigate this problem, we will adopt a localization method based on LSTM in the next section.

In order to obtain accurate locations, the GPS logger device, ARKNAV K-18U GPS Data Logger with 11,000 mAh battery [11], is also attached to each cow. In order to extend the battery operation time, it records a current
location intermittently every five seconds in the national marine electronics association (NMEA) 0183 format. Locations traced by the GPS device are a part of fingerprint data to train a DNN and an RNN, which will be explained in the next section.

3 Localization using LSTM

First, let us consider a DNN without any recurrent. As shown in Fig. 2(a), the DNN is trained using fingerprint data, given RSSI at the 19 receivers as the input and the corresponding location \((X,Y)\) obtained by the GPS device as the output. Fig. 2 (b) shows that the resultant trail as a series of the locations estimated by the DNN after trained. From this figure, we can see that the trail is zigzag and unnatural unlike the behavior of cattle. This may be because of the temporal fluctuation of transmission power and the directionality of the antenna of BLE tags as mentioned in Section 2. To mitigate this problem, we utilize LSTM [7] shown in Fig. 2 (c). The important is that the sixth middle layer is a recurrent layer unlike the DNN shown in Fig. 2 (a). The recurrent layer can memorize the past states for a moment so that the LSTM can learn time series of fingerprint data as the pattern of cow’s movement.

4 Evaluation

In this section, we evaluate the accuracy and generalization capability of the DNN and the LSTM. For this sake, fingerprint data of the cow with
Table I. Position estimation result.

| Recurrent         |   | Cow identifier |   |   |   |
|-------------------|---|----------------|---|---|---|
|                   |   | 20112  | 20215 | 20295 | 20120 |
| w/ (LSTM)         | Average | 5.25  | 6.22  | 5.78  | 5.53  |
|                   | Standard deviation | 3.32  | 3.69  | 3.79  | 3.73  |
| w/o               | Average | 6.08  | 6.63  | 7.32  | 7.18  |
|                   | Standard deviation | 3.59  | 3.92  | 5.85  | 4.23  |

Focusing on the cow with ID 20112 whose fingerprint data are used for learning, the average distance error is reduced by 0.86 (= 5.25/6.08) times. Even for the cows whose fingerprint data are used only as test data, the LSTM has smaller average distance errors and standard deviations than the DNN. Thus, we can conclude that learning time series data is effective even from a numerical viewpoint.
not used for learning, the LSTM has the average distance error about 6 m which is smaller than that of the DNN. In this sense, we can confirm that the LSTM has the generalization capacity.

5 Conclusion
In this paper, we proposed an outdoor position estimation method using LSTM. Thanks to the recurrent layer, LSTM can learn a movement of cows. As a result, the accuracy has improved. Through our evaluation, it was confirmed that the cow used for learning could be estimated with an average distance error of 5.25 m, and that other cows could also be estimated at about 6 m. Since the LSTM has generalization capacity, in practical operation, it is possible to estimate the position of all the other cows by the LSTM trained by the fingerprint data of a few cows even without attaching GPS to all cows.

As future research work, we would like to utilize the virtual space discussed in [6].

Acknowledgments
This research is supported by JST CREST JPMJCR1682.