Bluetooth Low Energy Livestock Positioning for Smart Farming Applications

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Abstract. Device localization provides additional information and context to IoT systems, including Agriculture 4.0 and Smart Farming. However, enabling localization incurs additional requirements and trade-offs that often do not fit into application constraints – use of specific radio technologies, increased communication, computational, and energy costs. This paper presents a localization method that was designed for Smart Farming and applies to a wide range of radio technologies and IoT systems. The method was verified in a real-life IoT system dedicated to monitor cow health and behavior. In a large multi-path environment, with a large number of obstacles, using only 10 anchors, the system achieves an average localization error equal to 6.3 m. This allows to use the proposed approach for animal tracking and activity monitoring which is beneficial for well-being assessment.

Keywords: Smart Farming · indoor localization · signal strength · Bluetooth Low Energy

1 Introduction

The number of IoT systems and devices rapidly increases, and IoT applications become more and more popular. For a large number of such applications, the ability to localize the devices is of additional value as it gives context to the application and increases usability and functionality. Since the deployment of global navigation satellite systems (GNSSs) the task of determining the device location becomes straightforward. However, its use requires to include GNSS receivers that increase device energy consumption, demand larger batteries, and incur additional costs. Additionally, the GNSS does not work well in indoor environments and is practically unavailable underground and in multi-story buildings. Consequently, the IoT devices and communication technologies use other localization approaches including methods based on the angle of arrival, time of flight, or time difference of arrival. These methods may not require additional hardware however, incur increased costs in terms of energy, communication bandwidth, or processing time. As a result, enabling localization in an IoT system is a trade-off between constraints, desired parameters, and functionalities of the system. This includes the aforementioned costs and the resulting localization accuracy.

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Animal localization is a challenging topic for Smart Farming and precision agriculture. First of all, it allows to localize individual animal in the grazing fields or sheds, thus simplifying the everyday work of farmers and veterinary doctors. Additionally, location information over time provides information about animal activity, which is an indicator of health status. As presented in [1, 8, 9], changes in the activity may signal diseases or estrus and can be often detected before emergence of clinical symptoms. Contemporary radio technologies used in IoT systems enable localization through either radio signal strength (e.g. [4, 11]) or time of flight measurements (e.g. [5, 15]). While the former group gives less accurate localization, the latter is more energy demanding and requires more complex deployments. Additionally, the use of signal strength localization ensures applicability to a wide range of various radio technologies and can be adjusted to use other radio signal quality indicators (e.g. [6]).

This paper presents an animal localization algorithm based on signal strength measurements and dedicated for indoor environments. The algorithm provides accurate localization using small number of reference points (anchors) and requiring limited measurements during setup. The accuracy of the proposed algorithm was verified in a dairy cow farm located in Zagrodno, Poland, where a dedicated cow health monitoring system is deployed [13]. Using 10 anchors, in a 1 400 m^2 shed the average localization accuracy equals 6.3 m.

2 Related work

Signal strength localization has gained much attention in the last years [3, 7, 10]. This was the result of the fact that recently the number of low power IoT devices increased significantly, and this method does not incur additional complexity and cost.

Indoor localization using signal strength is often focused on office buildings where the number of anchors (reference devices with known localization) is large and they are deployed densely. The article by Wang et al. [14] is an example of such applications. The authors analyze localization in the office space of 44 by 22 meters. The results achieved are quite accurate with an average error equal to 1.8 m and maximum error slightly exceeding 10 m. However, this is achieved with up to 34 anchors deployed with an average distance between the neighboring anchors of 5 m. Additionally, the localization method proposed in [14] is based on fingerprinting and requires mapping the whole area before the localization can be used.

Signal strength-based localization is also interesting for industrial and agriculture applications, including Smart Farming A good example of such system is a localization in an industrial workshop [3] or the dairy farm [2, 4, 11]. In the latter example, the goal of localization is to monitor the activity of the animals and shorten the time required to locate an individual cow on a large farm or field. For these applications accuracy of a few meters is acceptable. Article by Trogh et al. [12] presents an indoor localization solution for dairy cows. The proposed approach uses Bluetooth Low Energy (BLE) and is based on path loss

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model. The model is derived from the floor plan of the localization area and does not require any measurements before the localization system can be used. During the evaluation, 11 anchors were deployed in 30 by 13 m area, allowing to estimate cow location with an average error of 4.2 m (median 3.3 m). The results are good but the area is relatively small and is located in the center of the barn, far away from large obstacles (e.g. walls) thus minimizing the adverse effects of propagation phenomena.

Bloch et al. [2] investigate a localization system for dairy cows. The system estimates location based on RSSI measurements and two different approaches: log-distance path loss model, and fingerprinting of the localization area. The results of experiments conducted in 420 m^2 barn show slightly better results for the method based on fingerprinting. The resulting average localization error was equal to 3.3 meters while the maximal error was slightly above 10 m. Although the accuracy is considered good, it was achieved with dense deployment of the anchors – the total amount of 10 anchors were deployed in the area, with an average distance between neighboring anchors of 10 m.

Takahiro et al. [11] analyzed localization of animals in an open field of approximately 11 400 m^2. Each animal wore four BLE transmitters and a GNSS receiver attached to its collar. Transmitted BLE signals were received by 20 receivers deployed in the area perimeter and used for estimating the animal location, using a neural network. The average localization error achieved was slightly above 6 m. This is considered a good result taking into account the size of the area and a relatively small number of anchors. However, this was achieved with redundancy and in preferable radio propagation conditions, as the experiments were conducted in an open field and as many as four BLE devices per animal were used.

Signal strength-based localization was also analyzed by Cardoso et al. [4] who attempted to determine a position in an open square area of 440 m^2. Using only four anchors the average localization error of the proposed algorithm was equal to 2.48 m, and the maximum error to 6.5 m. However, the proposed algorithm was evaluated only in a a few locations along the diagonal of the area with some of the locations close to the anchors. Because test locations were not spread across the localization area, the results are not considered reliable.

Hindermann et al. [5] investigated the use of ultra-wideband (UWB) radios and time-of-flight measurements for localization in a 12 by 25 m barn. They have used only four anchors and achieved a localization error that was 0.5 m in most scenarios and test locations. The results are impressively good and allow not only to track activity but also to analyze the interactions between the animals. However, the approach uses radio technology that has relatively high energy demands and requires additional hardware, cabling, and costs. Time-of-flight based localization is also available in a commercial solution from Smartbow [15]. In the experiments conducted in approx. 2 100 m^2 area using 17 anchors the resulting accuracy was below 2.93 m during 95% of time. Similar to the previous approach, this technology also requires additional hardware, cabling, and costs.

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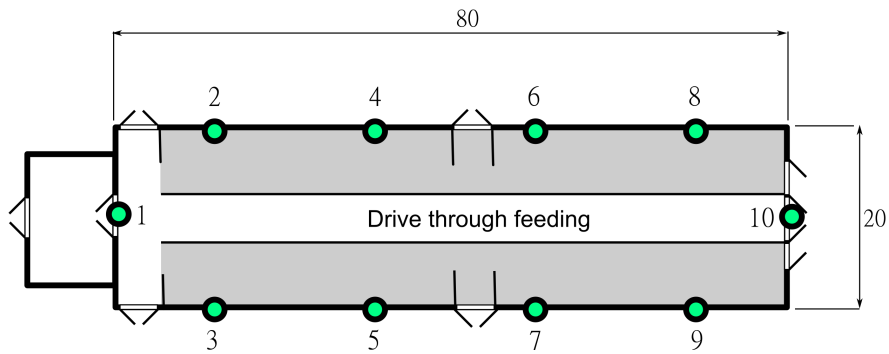

Fig. 1. The map of the area used for the evaluation of the proposed localization algorithm. Gray areas mark sections where animals reside and can walk freely. Green circles mark the locations of the anchors numbered 1 to 10.

The aforementioned localization approaches have limited applicability to large-scale smart farming applications. This is either due to the use of specific radio technologies, the requirement to derive radio propagation models that are inaccurate in indoor applications, or the use of complex and time-consuming procedures to set up the localization system (build a radio map of the area for fingerprint-based methods). This article proposes a different approach that uses a limited measurement campaign to derive a geometrical model which translates RSSI values to rings – a range of distances from the anchors. This is in contrast to the propagation models where RSSI value determines a single distance which is "good on average". The contribution of the paper is as follows:

- proposal of a geometrical approach to signal strength based localization, that can be used with various radio technologies,
- evaluation of the proposed localization method in real-life system (animal monitoring) deployed over a large indoor area.

3 System architecture and localization algorithm

The proposed localization algorithm is designed to be integrated with typical IoT architecture. The end devices (tags) report measured data to neighboring anchors. Anchors receive the transmitted data and take radio signal measurements including RSSI and possibly other parameters (e.g. link quality indicator - LQI). Anchors aggregate the data and the measurements over time and transmit this information (together with the tag identifier and timestamp) to central server located in the cloud. When measurements from anchors are collected, the server runs a localization algorithm to determine tag location.

The experimental evaluation presented in this paper was run in the system of the aforementioned structure deployed to monitor the behavior, activity and well-being of dairy cows [13]. The test barn of 20 by 80 meters (Fig. 1) hosts

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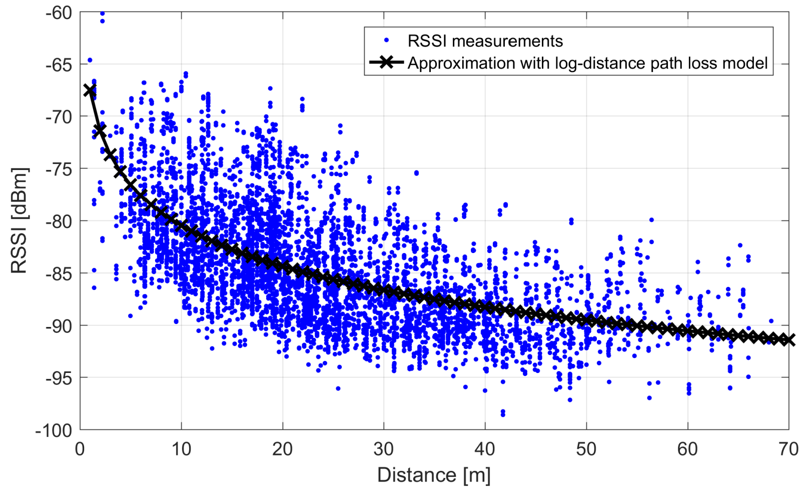

Fig. 2. RSSI values measured in the experiment for different locations and distances from the anchors. Black line marks log-distance path loss model approximating the measured values.

approximately 80 mature cows all wearing the monitoring tags. The tags are BLE devices mounted on collars, take periodic measurements of animal activity, calculate aggregates, and transmit them inside advertisement packets broadcasted periodically every 250 milliseconds. Ten anchors deployed in the barn receive the aggregated measurements and record radio signal parameters – RSSI and strength of the radio signal when receiving the radio message. The signal parameters are then aggregated separately for each tag in non-overlapping, 30 seconds wide time windows. The aggregates include the average value and standard deviation of RSSI measurements, the number of messages received from a tag, and total signal strength (TSS) which is an accumulated strength of all the radio messages received from a tag. Aggregates are transmitted and stored on the server which runs the localization procedure.

3.1 Localization based on radio propagation model

A typical localization approach based on RSSI attempts to determine distance vs. RSSI dependency using a selected propagation model. Unfortunately, the simple propagation models do not adhere to indoor environments where signal propagation is complex, affected by obstacles, and various propagation phenomena. For example, consider the RSSI measurements presented in Fig. 2. It can be noticed that the same value of RSSI was measured for significantly different distances. Due to high variance of the distances (for a given RSSI value) an approximation with a propagation model would result in a single relation that is good on average but fails to accurately estimate the real distance. For the mea-

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surements presented in Fig. 2, using the least square method, the approximated log-distance path loss model equals:

$$\hat{d} = 10^{\frac{\mathrm{RSSI}+67.9961}{-12.5215}}, \tag{1}$$

where RSSI is the measurement and $\hat{d}$ is the estimated distance to the anchor. The position of the tag can be estimated from multilateration [5] given distances to at least 3 anchors. Unfortunately, inaccuracies in distance estimation result in large localization errors.

3.2 Proposed localization procedure

To avoid the limitations and achieve good accuracy this article proposes to use a more general approach where a range of RSSI measurements determines a range of possible distances. Considering the previous example (Fig. 2) it can be noted that for RSSI values exceeding -75 dBm the distance is almost always smaller than 20 m. Similar for RSSI between -80 dBm and -75 dBm the distance varies from approx. 4 to 25-30 m. Similar dependencies can be observed for smaller RSSI values. Simultaneously, a RSSI vs distance relationship can be divided into three sections depending on the vicinity to the anchor: immediate, near, and far zone. For BLE transmission the measured RSSI values in the immediate zone are above approximately -80 dBm. In this zone, the signal strength drops quickly with the distance. In the near zone the RSSI varies between approximately -80 dBm and -90 dBm, and the RSSI vs distance relationship flattens. In the far zone the RSSI drops below -90 dBm and there is almost no correlation between RSSI and the distance.

Based on the aforementioned observations the proposed RSSI vs. distance model defines ranges of distances (rings) that depend on RSSI value. The possible RSSI values are divided into disjoint ranges and for each range, the corresponding distances are assigned. (Fig. 3). The distances are then approximated with the probability distribution that is used to calculate the minimum and maximum value of the distance for this RSSI range. Because for each RSSI range the distribution of the distances was close to normal distribution the minimum and maximum distances were calculated based on the mean and the standard deviation of the distances:

$$\begin{aligned} \mathrm{D}_{i,\min} &= \mathrm{mean}(\mathbf{D}_i) - 1.5 \cdot \mathrm{std}(\mathbf{D}_i), \\ \mathrm{D}_{i,\max} &= \mathrm{mean}(\mathbf{D}_i) + 1.5 \cdot \mathrm{std}(\mathbf{D}_i), \end{aligned} \tag{2}$$

where $\mathbf{D}_i$ denotes the distances for the i-th RSSI range, mean and std are an average and a standard deviation respectively. It is worth to notice that the resulting distance ranges (rings) overlap. This is because of the large variance of RSSI measurements for each distance. The actual model for the evaluation scenario was derived in a small measurement campaign and is presented in Table 1. The model differs for various anchors because their location and impact of the environment on the RSSI measurements is different. Additionally, for some of the anchors (eg. 1, 5, 10) the minimal distance does not increase with lowering

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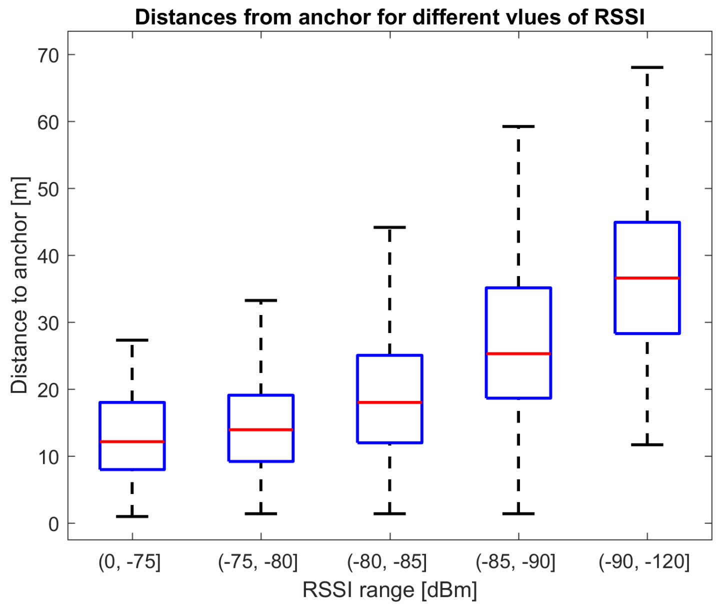

Fig. 3. The values of the distance for disjoint RSSI ranges. The RSSI measurements were collected at different locations by 10 anchors.

RSSI. This is likely because the measured RSSI is sometimes attenuated by the animal wearing the tag (as the tag is mounted on a side of a neck).

The localization procedure takes the RSSI_i and TSS_i measurements for every anchor $i = 1, 2, \ldots, n$. Based on the model the algorithm uses the RSSI_i to determine the $\mathrm{D}_{i,\mathrm{min}}$ and $\mathrm{D}_{i,\mathrm{max}}$ distances to the i-th anchor. Afterwards, for each (x, y) coordinate of the localization area, the algorithm defines a discrete function $f(x, y)$. The function is a weighted sum of TSS_i values if (x, y) coordinates belong to the i-th ring (if the tag distance to the i-th anchor falls between $\mathrm{D}_{i,\mathrm{min}}$ and $\mathrm{D}_{i,\mathrm{min}}$):

$$f(x, y) = \sum_{i=1}^{n} w(x, y) \cdot \mathrm{TSS}_i, \tag{3}$$

where

$$w(x, y) = \begin{cases} 1 \text{ iff } \mathrm{D}_{i,\mathrm{min}} \leq d_i(x, y) \leq \mathrm{D}_{i,\mathrm{max}}, \\ 0 \text{ otherwise}, \end{cases} \tag{4}$$

and $d_i(x, y)$ denotes the Euclidean distance from the i-th anchor to (x, y) point.

The resulting function $f(x, y)$ defines the likelihood of the tag location – in particular, it is unlikely that the tag is located in the region where the function value is small. Therefore, in the next step, the algorithm finds a threshold T that is used to distinguish (x, y) coordinates with the highest likelihood. Based on

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Table 1. The RSSI-ring model for the anchors. The measured value of RSSI determines a range of possible distances to the anchor ($D_{i,\min}$–$D_{i,\max}$). The ranges define rings around anchors pointing estimated location of the tag.

Anchor i	Distance ranges [m] for various RSSI measurements [dBm] ... ≥ -75	$-75 >$ ... ≥ -80	$-80 >$ ... ≥ -85	$-85 >$ ... ≥ -90	$-90 >$ ...
1	9–15	2–26	6–37	10–47	25–63
2	5–16	4–27	4–36	10–48	24–53
3	5–9	4–17	4–30	11–40	27–54
4	6–21	5–25	7–26	10–35	19–40
5	4–25	2–21	7–23	12–38	20–40
6	3–24	8–30	13–35	16–36	28–32
7	6–20	4–29	5–28	7–34	17–33
8	10–17	7–26	7–25	13–45	29–52
9	5–11	5–18	5–31	8–48	21–51
10	4–22	4–37	10–57	21–61	42–63

experimental evaluation the threshold is equal to the 85-th percentile of $f(x, y)$ values for all (x, y). Using the threshold T algorithm calculates:

$$\hat{f}(x, y) = \begin{cases} f(x, y) \text{ iff } f(x, y) > T, \\ 0 \quad\quad\quad \text{otherwise.} \end{cases} \tag{5}$$

The final location of the tag is determined as a center of mass of $\hat{f}(x, y)$, i.e:

$$\hat{x} = \frac{\sum_{(x,y)} x \cdot \hat{f}(x, y)}{\sum_{(x,y)} \hat{f}(x, y)}, \quad \hat{y} = \frac{\sum_{(x,y)} y \cdot \hat{f}(x, y)}{\sum_{(x,y)} \hat{f}(x, y)}. \tag{6}$$

4 Evaluation and analysis

The evaluation was conducted for 33 tags mounted on animals, during normal operation of the farm, without affecting the natural behavior of the cows. During the experiment 67 animal locations were measured using a laser range finder, with an estimated accuracy below 1m. In each test location, all anchors have reported to the server several aggregated measurements containing the average value of RSSI, total signal strength (TSS), and a number of raw RSSI measurements. Overall the server received almost 5000 data points from all cows and all locations, that were used for evaluation of the proposed localization method.

Figure 4 shows one of the test points. The blue and red marks in the figure denote real and estimated location of the animal, respectively. The error in location estimation equals 5.3 m. It can be seen that the highest value of the $f(x, y)$ function (white areas in the figure) span along the X axis (width of the barn) causing the resulting $(\hat{x}, \hat{y})$ to be biased towards the center of the barn. A similar bias is observed for all the test points and is a consequence of the proposed localization approach – first, the rings are wide and overlap largely;

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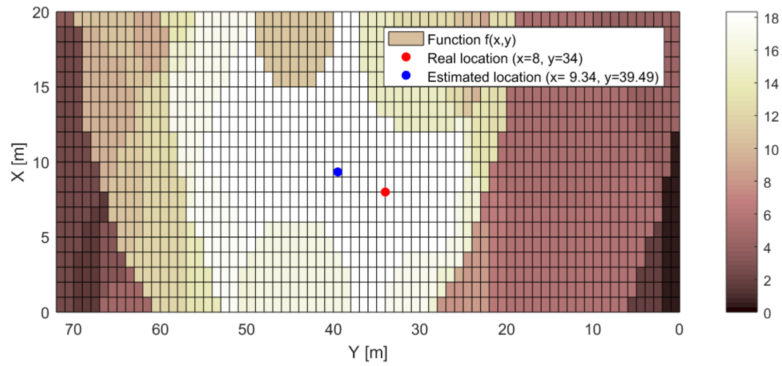

Fig. 4. Example of localization using single RSSI-ring model for each anchor. The colors of the surface represent values of the $f(x, y)$ function, red and blue marks denote real and estimated location of the tag, respectively.

Table 2. The localization error of the proposed approach when using different number and sets of anchors. The reported results were achieved for a single RSSI-ring model for each anchor (cf. Tab. 1)

Anchors		Euclidean error [m]			
number	list	min	average	median	max
10	1-10	0.6	8.3	7.8	24.7
8	2-9	0.6	8.5	7.5	37.7
6	1,4-7,10	0.9	9.2	8.6	23.5
6	1-3,8-10	0.7	9.4	9	23.1
4	2,3,8,9	1.8	9.8	9.4	25.2

second, because the anchors are located on the edges of the area, the center of the ring's mass tends to be located in the center of the barn.

Table 2 presents statistics on the accuracy of the proposed localization method in terms of Euclidean error. The results are presented for a different number and set of anchors used in the localization procedure. This simulates localization accuracy for scenarios where fewer anchors are available in the system. The best results are achieved when all 10 anchors are used. In this case, the mean error is slightly above 8 m, and for over 50% of the test points (median) the error does not exceed 7.8 m. The accuracy of the localization drops as the number of anchors is reduced. While the mean error when using 8 anchors (except anchors 1 and 10) increases by approx. 2.5%, the error for 6 and 4 anchors is higher by 16% and 37%, respectively. Also the median and the maximal error increases as the number of anchors drops.

The localization accuracy can be further improved if we take into account that dairy cows on a farm are divided into groups. Due to the different feeding, the groups reside in different sections of the barn and never mix. Consequently, for each cow in the barn we know if she resides in the top or bottom section of

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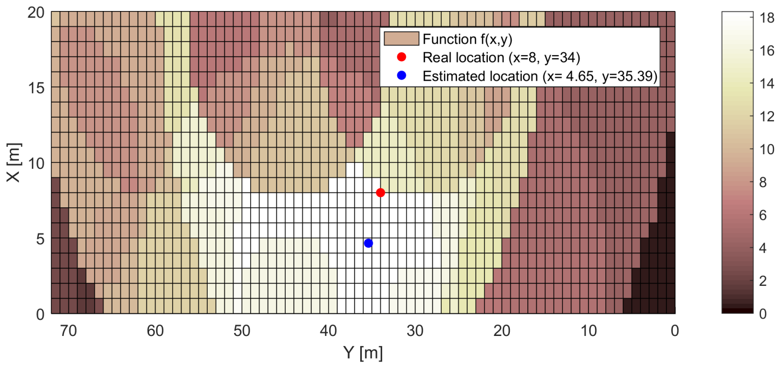

Fig. 5. Example of localization with improved approach – using two RSSI-ring models for each anchor

Table 3. Comparison of the localization error in the improved approach (two RSSI-ring models per anchor) and the log-distance path loss model based localization

Method	Euclidean error [m]			
	min	average	median	max
Path loss based	0.43	10.3	9.9	33.18
Our (first approach)	0.6	8.3	7.8	24.7
Our (improved approach)	0.8	6.3	5.4	20.8

the barn (cf. Fig. 1). This allows building separate RSSI-ring models for cows on the same and on the other side of the barn with respect to anchor location. As a result, each anchor will have two RSSI-ring models: one for animals on the same side of the barn and the other for the animals on the other side. Figure 5 presents localization result for the same test location as in Fig. 4, but using the improved approach. The maximal value of $f(x, y)$ function is now limited to a significantly smaller area and is almost entirely included with the bottom section of the barn. For the test location presented in Fig. 5 the resulting localization accuracy improves as the error drops from 5.3 to 3.6 meters (32%). The improvement is also observed for all the test locations lowering the average, median, and maximal errors to 6.3, 5.4, and 20.8 meters, respectively (Tab. 3).

The reported errors are also significantly better compared to the traditional approach based on the log-distance path loss model (Tab. 3). For example, if one uses the log-distance path loss model (1) and multilateration procedure from four closest anchors (with the smallest values of RSSI), then the average and median errors for the experimental scenario equal 10.3 and 9.9 m, respectively. This means that the improved algorithm reduces the average and mean localization error by approximately 39% and 45%, respectively.

The localization error is smaller for tags located closer to the center of the barn and increases as they approach the edges. This is presented in Fig. 6 that shows a localization error for the whole area. The surface is an extrapolation

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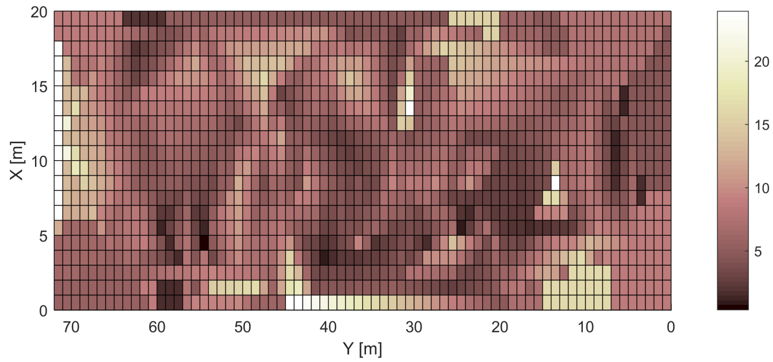

Fig. 6. Localization error in different locations of the area for the improved approach (two RSSI-ring models for each anchor). The colors denote the Euclidean error.

Table 4. Comparison of the localization error for different methods based on signal strength measurements

Approach	Location	Area size [m^2]	# Anchors	Area per anchor [m^2]	Average error [m]
[4]	outdoor	440	4	110	2.48
[11]	outdoor	11 400	20	570	6
[12]	indoor	390	11	35	4.2
[2]	indoor	420	10	42	3.3
Path loss model	indoor	1 440	10	144	10.3
Our improved	indoor	1 440	10	144	6.3

of the errors in all the measurement points. Locations are the least accurate when tags are located close to anchor no 1 (left of the localization area). This is possibly due to the fact that anchor number 1 was located 8 m away from the edge of the localization area. Consequently, the ranges estimated for this anchor were always large and could have affected the localization result.

Table 4 shows a comparison of the localization error of the proposed approach and solutions presented in the literature, which are based on signal strength measurements. Because the density of anchors significantly affects the accuracy therefore apart from comparing average error we also compare the average area covered by each anchor, which is calculated as a ratio of the area and the number of anchors deployed. Compared to other RSSI-based systems for indoor localization of farm animals [2, 12] the proposed approach yields slightly larger errors, but operates in a significantly larger area, using a small number of anchors, and does not require time-consuming fingerprinting. Lower average error is achieved in outdoor deployments [4, 11] where radio propagation conditions are preferable and all RSSI-based methods perform better. Additionally, the reported results were achieved using complex system [11] and through evaluation in specific test locations [4].

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5 Conclusions

Using BLE and RSSI for indoor localization is one of the most challenging approaches. This is because the averaged RSSI measurements are affected by the radio channel used, attenuation due to obstacles, multi-path propagation, and other phenomena. This makes it impossible to derive a radio propagation model that will accurately relate the value of RSSI to the distance between the transmitter and receiver. Large area, a large number of animals obstructing signal propagation, and unfavorable location of the tags (on the side of animal neck) harden typical approaches. Methods based on path loss models are highly inaccurate and susceptible to variations of RSSI measurements. Methods based on fingerprinting, on the other hand, require time-consuming measuring campaigns that are troublesome and impractical for real-life, large scale applications. The proposed approach overcomes the limitations of previous methods. The geometric localization is less susceptible to variations and inaccuracies in RSSI and it requires a relatively small measurement campaign compared to fingerprinting. Additionally, the proposed method uses small number of anchors and achieves accuracy that is acceptable for a large range of applications, including animal tracking and monitoring their activities.

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