

Regular Paper

Localization with Portable APs in Ultra-Narrow-Band-based LPWA Networks

MIYA FUKUMOTO¹ TAKUYA YOSHIHIRO^{1,a)}

Received: May 12, 2020, Accepted: November 5, 2020

Abstract: For IoT applications LPWA is a useful communication choice that enables us to connect tiny devices spread over the land to the Internet. Since many low-price IoT devices usually need to work with limited power budget, this kind of low-power long-range communication technique is a strong tool to populate IoT deployment. Since LPWA devices are less functional, localization of devices are addressed as one of the important practical problems. UNB (Ultra Narrow Band)-based LPWA networks such as Sigfox are one of the major LPWA services for IoT applications, which have a long communication range more than 10 km. However, due to the long-range communications and the property of UNB-based modulation, it is not possible to use state-of-the-art localization techniques with high-accuracy; UNB-based LPWA should use simple methods based on RSSI (Radio Signal Strength Indicator) that involves large position estimation errors. In this paper, we propose a method to improve accuracy of device localization in UNB-based LPWA networks by utilizing portable Access Points (APs). By introducing a distance-based weighting technique, we improve the localization accuracy in combination with stationary and portable APs. We demonstrated that the portable AP and the new weighting technique effectively works in UNB-based LPWA networks.

Keywords: wireless mesh networks, scheduling, slotted CSMA, routing

1. Introduction

Internet of Things (IoT), which collects sensor data from tiny devices, is getting great interest in these days. For this purpose several Low-Power Wide-Area networks (LPWA) have appeared and they are providing services to collect data from the large surface of the globe with low cost. Since those services have covered the major region of land people are living, now people can utilize sensor data obtained by sensors set on the area. LPWA covers a large area of lands by long-distance communications with low signal power by making use of 800–900 MHz bands. Especially, UNB (Ultra Narrow Band)-based LPWA systems such as Sigfox [10] provide very long communication range of 10–50 km in return for their low data rate as low as 100 bps. UNB-based LPWA services are suitable for applications that connect low data-rate sensors with low economical cost.

However, one of the difficulties in this kind of UNB-based LPWA systems lays in the localization capabilities. First of all, note that GNSS (Global Navigation Satellite System)-based methods are usually not applicable because tiny devices are usually battery powered, less functional, and need to save power by sleeping most of the time. This limitation forces us to use the localization methods based on measurements of communication radios in LPWA networks. The localization methods are classified into several types [1]. Time-based methods such as ToA (Time of Arrival) and TDoA (Time Difference of Arrival) are the methods based on the arrival time of frames transmitted by tiny devices

at multiple APs (Access Points) of LPWA networks, which enables relatively accurate localization of devices especially if the device is located at line-of-site (LoS) position for the LPWA base stations. However, due to the nature of UNB communications, arrival time is not accurately measured [2] so that the methods are hard to deploy in UNB-based LPWA systems. As a result, we need to use RSSI-based approaches for localization.

Unfortunately, localization accuracy in RSSI-based approaches are not high since RSSI values easily fluctuate according to multi-paths effects. Additionally, with the long communication range of UNB-based LPWA, the localization errors are easily more than the order of Kilometers. As above, improving accuracy in RSSI-based localization with long range communication is a challenging task with strong practical demand.

In this paper, we propose to use portable APs to improve the localization accuracy in RSSI-based position estimation of tiny IoT devices. In order to collect additional RSSI measurements from closer position to tiny devices, we carry a portable AP on a vehicle equipped with it, and move around a target area. Although these measurements contain a considerable level of error, we utilize them to improve the accuracy in position estimation by introducing a weighting technique that not only appraises the importance of each measurement but also takes balance between measurements of stationary APs and mobile APs. Field evaluation results showed that our proposed method significantly improved the localization accuracy, and additionally, we analyzed the results to retrieve the interesting properties of the proposed method.

The rest of this paper is as follows. In Section 2, we describe

¹ Faculty of Systems Engineering, Wakayama University, Wakayama 640-8510, Japan

^{a)} tac@wakayama-u.ac.jp

the related work. In Section 3, we present a short introduction of UNB-based LPWA service Sigfox. In Section 4, we present the proposed method. In Section 5, we describe our evaluation methods and results, and finally conclude this work in Section 6.

2. Related Work

Several approaches for localization based on radio measurements have been proposed so far, and we have several survey papers on it in the literature [1]. Arrival-time-based methods would be the most major approach among them. The methods utilizing ToA measure the time of the transmitted radio arriving at multiple receiver nodes [3]. From the air time of the radio, the distances from APs as well as the position of the device are estimated. TDoA-based methods measure time difference of arrival time at multiple APs, from which the position is estimated [4]. However, as is already mentioned, in UNB-based communication the arrival time is not accurately obtained. Thus, ToA and TDoA approaches are not applicable, although those are the methods with the highest accuracy among typical approaches for localization.

AoA (Angle of Arrival) approach detects the angle of the radio source to estimate the location of source devices [5]. This technique requires directive antennas or antenna arrays, which increase the cost of APs. In addition, the accuracy is not so high if we apply this approach into long-range communications; the position errors will not be small enough.

As above, in UNB-based systems, the most preferable approach for localization is RSSI-based approach [6]. As the radio strength decays according to distance, we can estimate distance from RSSI measured at multiple APs. However, since RSSI easily fluctuates according to multi-path effects, the accuracy of estimated distance is in general not high enough. Fingerprinting is a promising technique in utilizing RSSI measurements [7], [8]. In this technique, we first measure the RSSI values at various locations, and typically compute the nearest location for a newly given measurement to estimate the location of the measurement.

Although the localization methods based on fingerprinting are known to have good performance in many cases, it would not work well in UNB-band systems because of errors in estimated distance; inaccuracy in RSSI grows so large when the communication distance goes large. As we will show later, the average error in location is as large as several hundreds of Kilometers in case of Sigfox. There are very few studies that treats localization in UNB-based LPWA systems [9]. Sallouha et al. proposed a fingerprint-based localization for UNB-based LPWA systems, in which anchor nodes that have reference RSSI profiles used in fingerprinting are introduced. However, this work intends to classify the area of device positions, i.e., devices are located at one of the areas where each area has considerable distance with one another. Different from the work, we intend to reduce localization errors when devices are uniformly distributed in a large region. Practically, to identify the specific location rather than the rough region in which devices are located on has significant importance. Even if it costs more, to obtain more precise location of devices has practical merits in many applications.

3. Sigfox

Sigfox [10] is the most popular commercial LPWA service based on UNB-based communication. Sigfox uses 100 Hz channels, and Binary phase shift keying (BPSK) is used for modulation techniques to provide 100 bps bit rate. With the UNB-band transmissions with low bit rate modulation, Sigfox achieves a very long communication range of 50 km in rural and 10 km in urban areas in catalog. Reference [11] reported that Sigfox test link achieves 25 km communication in Ireland. Services use ISM band. Specifically, 868 MHz band in EU, 902 MHz in US, and 920 MHz in South America, Australia, New Zealand, and Japan. Typically, 200 kHz bandwidth is divided by 100 Hz bands to provide more than 2,000 orthogonal channels. By randomly selecting the channels with short packets (up to 12 bytes payload), Sigfox avoids collisions among devices distributed in the large area of its coverage.

Sigfox provides a location estimation service called Atlas [12]. This service is available for all devices connected to Sigfox so that positions are estimated for all devices even if they are not equipped with GPS functionality. In Atlas, positions are estimated basically based on RSSI observed at all APs that received the signal of the devices, though other data could be incorporated in the position estimation. Accordingly, the error in position estimation is as large as several hundreds of meters, or occasionally several Kilometers.

4. Proposed Method

4.1 Overview

RSSI-based localization is a basic methodology in localization that is available without any special equipment. However, the accuracy is not high because RSSI values are strongly affected by multi-paths effects. Due to the property of multi-path effects, the localization errors basically grow large in proportion to the distance between devices and APs.

We treat battery-powered stationary tiny devices that do not have GPS functionality. To improve the accuracy in position estimation, we propose to measure RSSIs of the signals transmitted by tiny devices by portable APs moving on vehicles. We suppose that a portable AP has a UNB-based LPWA NIC (Network Interface Card), GPS functionality, and an uplink NIC such as 3G or LTE so that the portable AP behaves as an AP that is able to both receive the devices' data and store them to the cloud storage with the position of data reception. By using RSSI values of both stationary and portable APs, we improve the accuracy in localization. Note that the stationary APs have lots of RSSI measurements per device although they include large errors due to long-distance communications. On the other hand, portable APs have a small number of RSSI measurements that may include small errors when the distances between devices and APs are small at some measurements. In our proposition, we introduce weights between those measurements of stationary and portable APs to improve the localization accuracy.

4.2 RSSI-based Localization

In RSSI-based localization, position of a device is estimated

using RSSI measurements at multiple (usually more than three) APs. Since radio decays in accordance with distance, distance between the device and an AP is estimated based on the RSSI measurements at the AP. As path loss model, the formula called Friis's equation [13] is generally used, in which signal strength decays in proportion to the square distance. Friis's equation is shown as follows,

$$RSSI = A - 10n \log(d), \quad (1)$$

where $RSSI$ is the measured RSSI value, A is the transmission power, n is the communication coefficient, and d is the distance from the device and the AP.

If we have RSSI measurements at three APs, we can identify the estimated location as the intersection of three circles. However, to mitigate the errors in RSSI measurements, it is usual to use measurements of more than three APs. In this case, we usually estimate the position by minimizing the square errors of the estimated distances at each AP. Namely, the following formula is applied,

$$\hat{X} = \arg \min_X \sum_{k=1}^n (d_k - d_k^{(X)})^2, \quad (2)$$

where \hat{X} is the estimated position of the device, d_k is the estimated distance at the k -th AP, and $d_k^{(X)}$ is the distance between k -th AP and the position X .

4.3 Introducing Weight Based on Distance

As mentioned above, RSSI-based distance estimation errors in general increase as the distance increases. Namely, the position estimation errors are small for small-distance APs while they are large for large-distance APs. As shown later in this paper, this trend is seen in the real data. Accordingly, we propose first to weight APs according to the estimated distance in estimating the optimal estimation position based on square errors. The following is the formula for weighted position estimation as an extension of formula (2).

$$\hat{X} = \arg \min_X \sum_{k=1}^n w_k (d_k - d_k^{(X)})^2, \quad (3)$$

where w_k is a weight for k -th AP, and n is the number of APs. As one of the natural setting, we set $w_k = \frac{1}{d_k}$, meaning that the weights of distant APs are relatively low in estimating positions. Note that for each of k -th APs, we have a lot of RSSI measurements on each device. As the estimated distance d_k , we use the average of RSSI measurements applied to formula (1).

4.4 Weighting among Stationary and Portable APs

We use both stationary and portable APs for localization so that we have to consider portable APs in weighting. Since the RSSI measurements with portable APs are corresponding to different positions, we cannot determine the weight for each portable AP device. The solution for this is to introduce weights for each measurement in case of portable APs. In other words, we regard each measurement as an observation from distinct portable APs. Note that, although errors in portable APs could be large since each position has only one sample, the errors could be small when the

distances from devices are small. In addition to this, we introduce a coefficient p that balances the weights between stationary and portable APs. As a result, the proposed formula for position estimation is as follows.

$$\hat{X} = \arg \min_X \sum_{k=1}^n p w_k (d_k - d_k^{(X)})^2 + \sum_{l=1}^m w_l \cdot (d_l - d_l^{(X)})^2, \quad (4)$$

where l represents each measurement of portable APs, w_l is the weight for measurement l , and m is the number of measurements on portable APs.

5. Evaluation

5.1 Overview

We obtain RSSI measurements of several devices through Sigfox infrastructure through four stationary APs and one portable AP in Wakayama city in Japan. Wakayama is a local city in Japan with a population of 360 thousands. The evaluation area is the north part of Wakayama city which is covered by four stationary APs A , B , C , and D shown in Fig. 3.

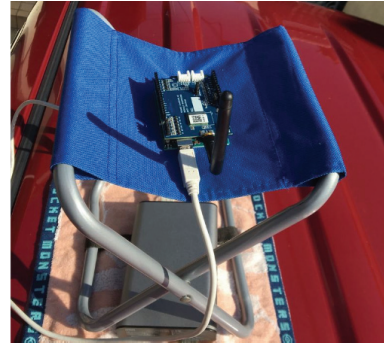


Fig. 1 Client devices used for parameter estimation.



Fig. 2 Portable APs for parameter estimation.

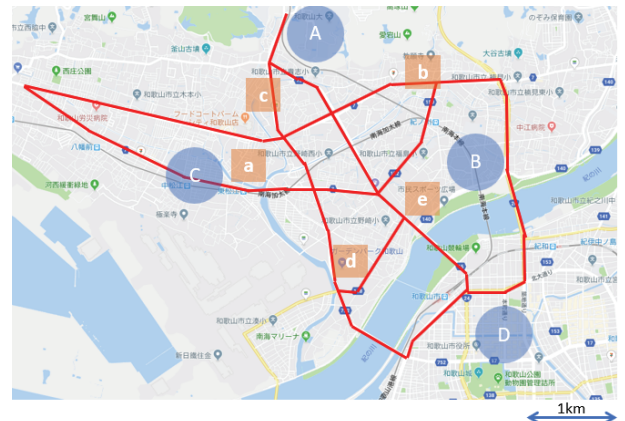


Fig. 3 The evaluation area in Wakayama City.

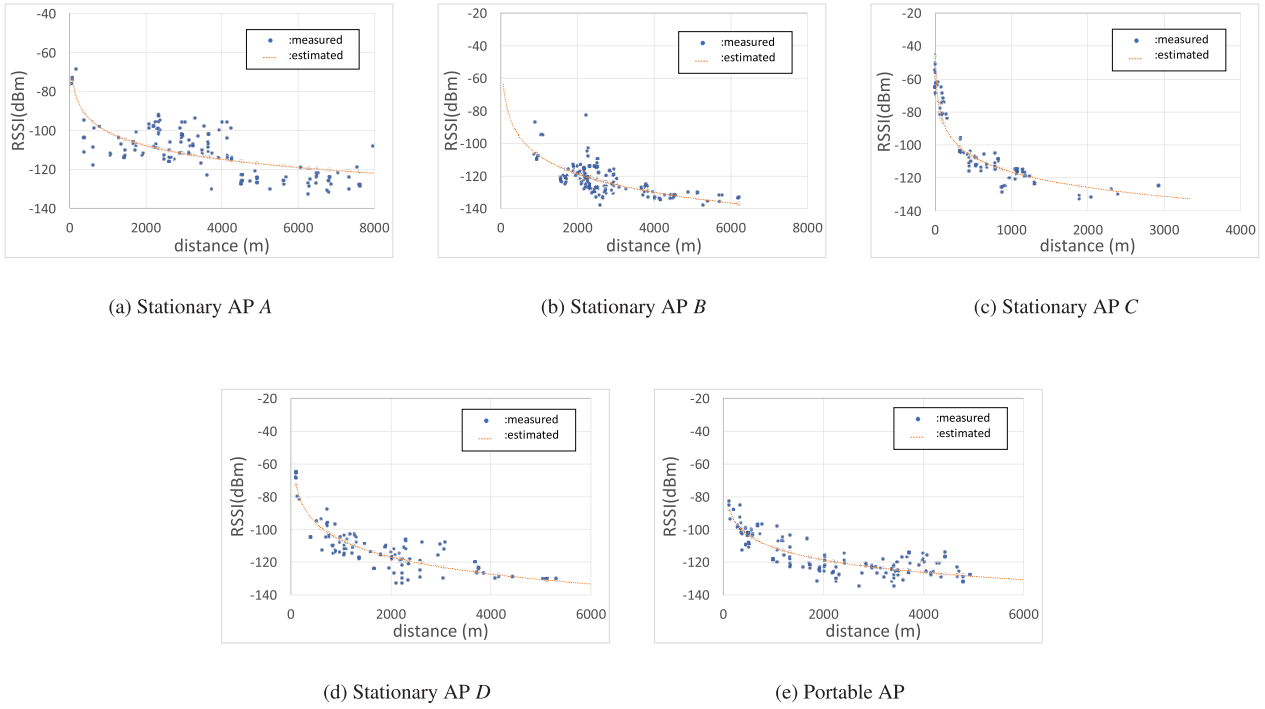


Fig. 4 Preliminary experiment results for parameter determination.

We first estimate parameters for each of the stationary and the portable APs, and then evaluate the proposed methods by measuring RSSI values of each client device. In Fig. 3, lines represent the routes of a vehicle that is equipped with a client device or a portable AP. The positions of client devices localized in our evaluation are shown as *a*, *b*, *c*, *d*, and *e* in Fig. 3. Note that precise positions of APs and client devices are not possible to indicate because of privacy issues. So, in Fig. 3 we show only the rough positions of them. Client devices are built based on Arduino Uno R3, and equipped with UnaShield V2S, which is a network interface module for Sigfox (Fig. 1). As a portable AP, we use Access Station Mini (TAPMV3.0) shown in Fig. 2.

5.2 Parameter Estimation

We first estimate parameters *A* and *n* of formula (1) for each of the stationary and the portable APs. In general, those parameters are determined depending on the specification of antennas. This time, because we could not specify the model of stationary APs, we estimate them for each of the stationary and the portable APs. We have four stationary APs and one portable AP to estimate parameters. The stationary nodes are located as shown in Fig. 3, and the portable AP is set on the roof of a two-story house located somewhere in this area as shown in Fig. 2. Then, we drive a vehicle equipped with the client device along the routes shown in Fig. 3 randomly.

We obtained the set of RSSI measurements of more than 100 positions, so that we obtained pairs of RSSI measurement and the corresponding distance for each AP. We apply them to formula (1) and obtained the values of *A* and *n*. Each measurement for each stationary and mobile AP as well as the fitting curves are shown in Fig. 4, and the parameters computed as a result are shown in Table 1.

The distribution of errors in the estimated distance based on the

Table 1 The estimated values of *A* and *n*.

APs	A	B	C	D	Portable
<i>A</i> (dBm)	-30.2	4.7	-2.6	-35.1	-23.8
<i>n</i>	2.35	3.74	3.26	2.53	3.09
# of Data Pairs	161	154	109	147	90

estimated parameters *A* and *n* are shown in Fig. 5. Specifically, we compute the estimated distance for each RSSI measurement, and plot the difference between the estimated distance and the true value. We see that, roughly, errors increase in proportion to estimated distances for every AP, and variances also increase as the estimated distance increase. Especially in A, the proportional trend is clearly seen because A is on top of a hill so that multiple paths between devices and the AP rarely exist. Although we see the noise due to the multi-path effect in all APs, we can conclude that the proportional trend seen in the results supports the weight $w_k = \frac{1}{d_k}$ deployed by the proposed method.

5.3 Evaluation Method

We located four stationary APs and five client devices in Wakayama city as shown in Fig. 3, and one portable AP moves around the area on a vehicle. From the measurements of those 5 APs, we estimate the location of 5 client devices. The conditions of the client locations are shown in Table 2. Four of the five devices are set on the balcony of apartments, and one is located at a parking lot on the ground floor. We drove a vehicle equipped with the portable AP on the roof of it along the routes shown in Fig. 3 randomly, and obtained several tens of RSSI measurements. Note that those client devices are set at the locations for a few weeks so that stationary APs obtain sufficient number of RSSI measurements. From the obtained RSSI measurements, we compute the position of those five devices with the proposed method with the parameters determined in the previous section, and evaluate the accuracy of the estimated position.

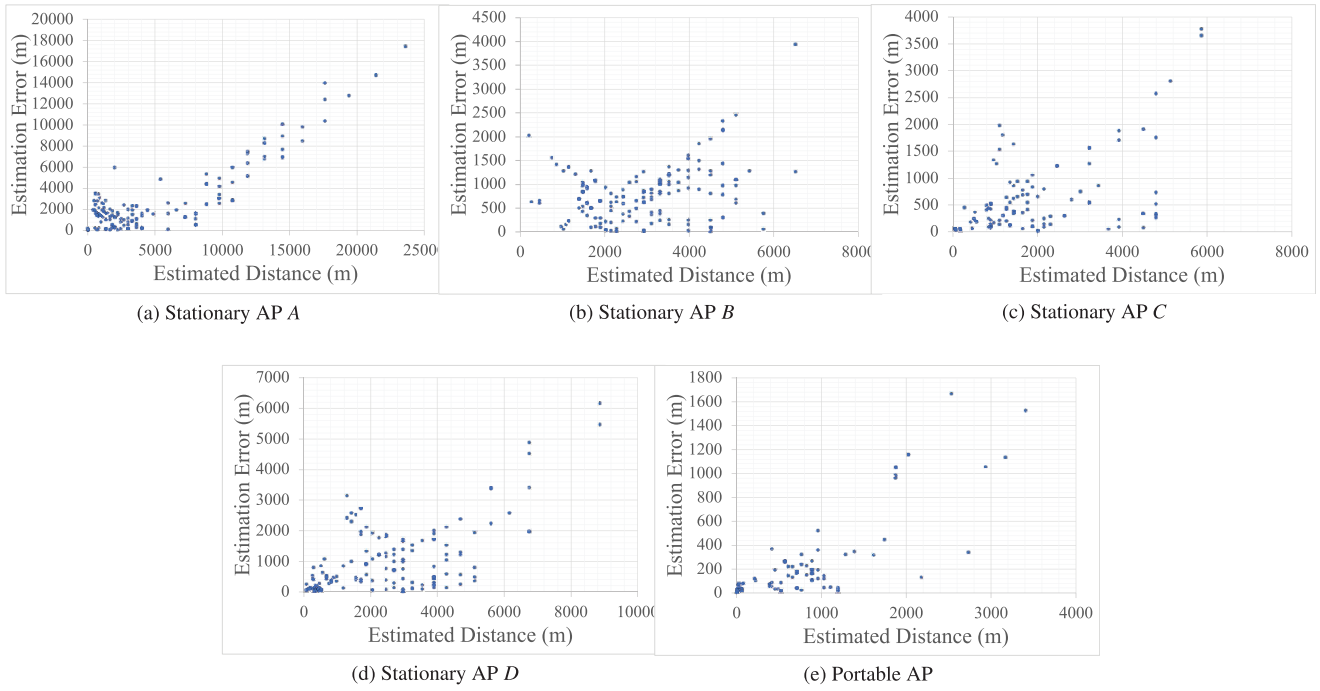


Fig. 5 Distribution of errors in estimated distances.

Table 2 Located conditions of client devices.

Client Devices	a	b	c	d	e
Conditions	balcony (3rd floor)	balcony (3rd floor)	balcony (7th floor)	parking lot	Balcony (2nd floor)

Table 3 Comparison of position errors (meter).

	Atlas	Stationary (unweighted)	Stationary (weighted)	Proposed ($p = 3$)	Proposed ($p = 1$)	Proposed ($p = 0.5$)
Device a	396	956	531	208	293	357
Device b	1,095	5,437	2,633	82	79	78
Device c	3,065	2,805	3,278	678	482	442
Device d	1,770	3,908	3,873	277	260	238
Device e	1,383	1,086	373	267	73	74
Average	1,541.8	2,838.4	2,137.6	302.4	237.4	237.8

We compare the proposed method with Sigfox Atlas, and the proposed method without portable APs to show the effect of portable APs as well as distance-based weighting. Also, to examine the balance of stationary and portable APs in weighting, we compare the performance of the proposed method with different parameter values of p in formula (4). Furthermore, to clarify the required number of RSSI measurements of the portable AP, we examined the transition of the accuracy in estimated positions as the number of RSSI measurements increases.

5.4 Results

The comparison results are shown in Table 3. First of all, we see that the proposed methods are far accurate in position estimation compared to both Sigfox Atlas and the proposed method without portable APs. This means that the effect of portable APs are significant in improving the accuracy of position estimation. Next, we see that the performance of Atlas is overall better than the case without portable APs. The reason for this is not sure, but it seems that Sigfox Atlas utilizes some other techniques or data in position estimation. Additionally, the proposed method with stationary nodes performs better when the weighting technique is applied. Especially, the accuracy for device e is greatly improved,

which is because device e and AP B were very close.

For the balance of weights between stationary and portable APs, we see that performance is better when p takes smaller values 1 or 0.5, i.e., performance improves when the weight of stationary APs is small. This means that the effect of portable APs is significant although stationary nodes have many measurement data and so have statistical advantage. However, we see the case (of device a) in which the large value of $p = 3$ is the best compared to the smaller values of p . This means that the effect of portable APs is still not stable because of the small amount of measurements for each position.

Next, we show the effects of the number of measurements of portable APs in Fig. 6. In this evaluation, we randomly choose the specified number of measurements among all, and compute the estimation error. Figure 6 is created as the average of 5 repetitions for each number of measurements. Also, this time we tested the case of the proposed method without weights to see the effect of distance-based weighting in the proposed method. From the results, we first see that the distance-based weighting significantly improves the accuracy, which clarified that the weighting is effective in improving accuracy. As for the effect of measurement count, we see that accuracy significantly improves for every

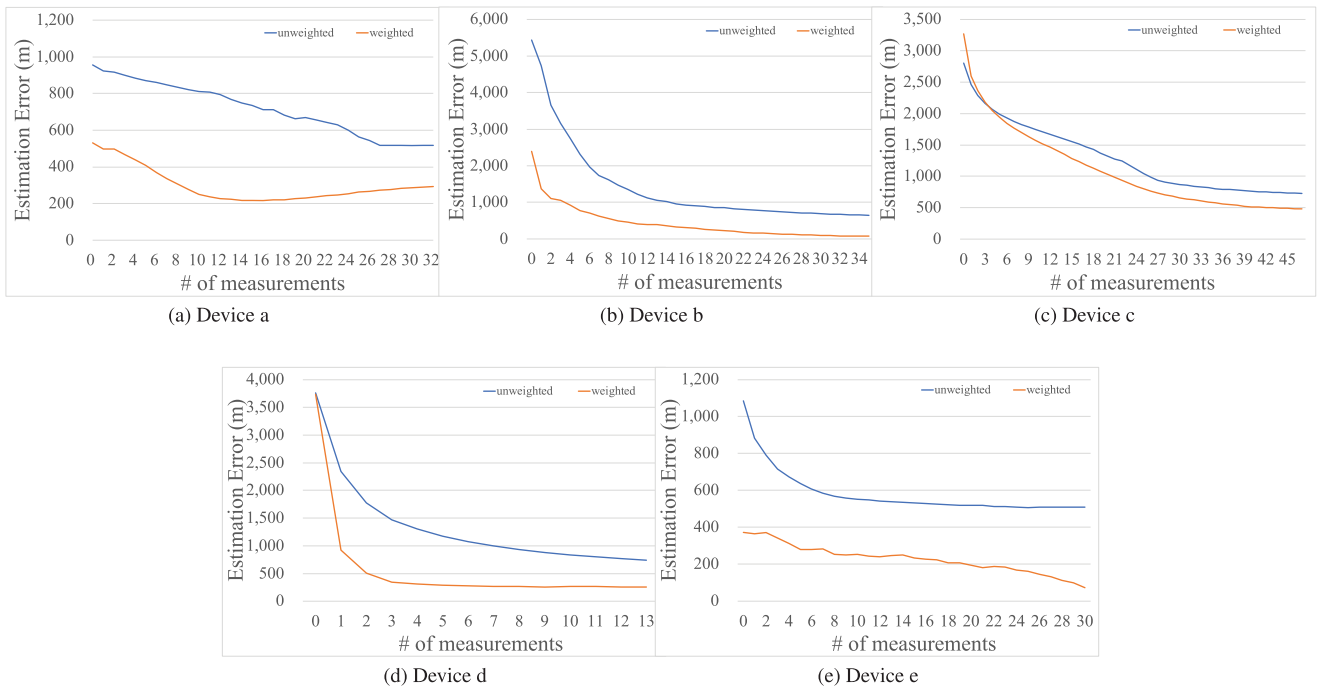


Fig. 6 Estimation error with the number of measurements of portable APs.

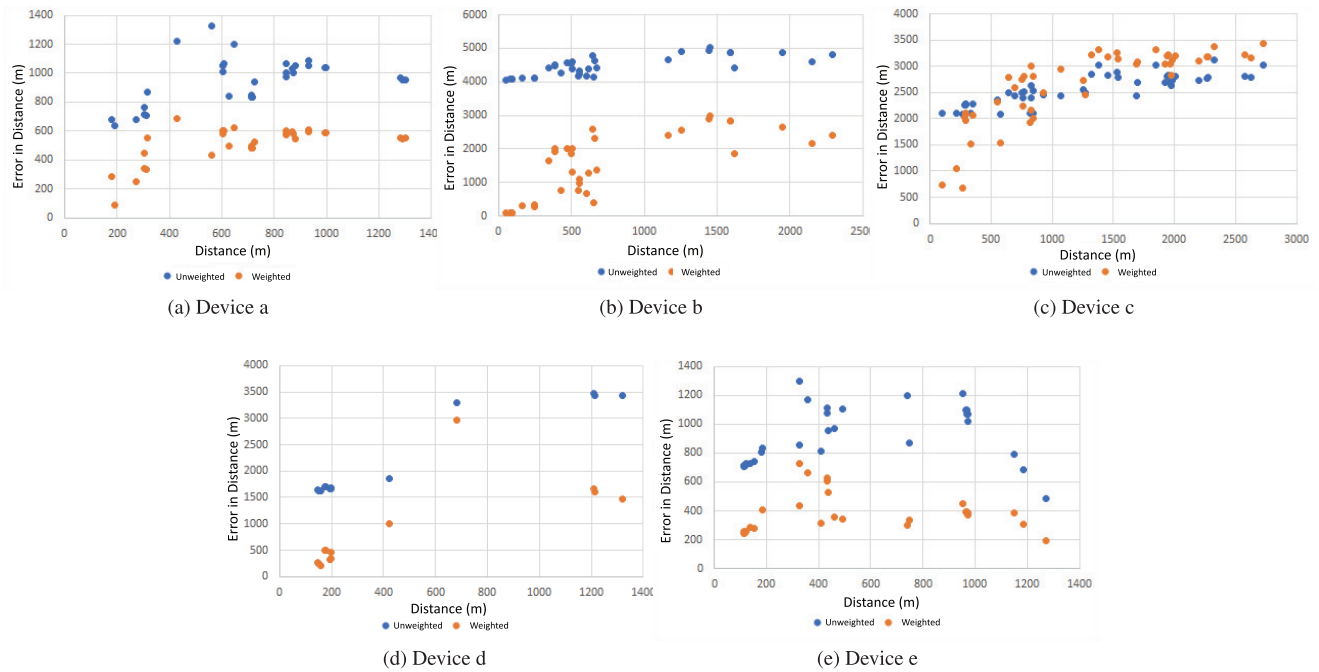


Fig. 7 Estimation performance with distance.

device as the number of the measurements of portable APs increases. This shows that, in many cases, as many as 50 measurements would be sufficient to ensure a certain level of accuracy. However, note that the number of measurements are not always the most important point. See Fig. 6 (a), in which the accuracy is the best when the number of measurements is around 15, and the accuracy goes worse as the number of measurements increases. This means that the accuracy could depend on some specific measurements such as the values measured at a very close position to the device. In the case of device *a*, because the balcony faces south, positions at which the portable AP captures the signal of device *a* is limited.

Other findings from Fig. 6 is that, with only device *c*, the difference in performance between weighted and unweighted is small. This is because device *c* is located on the 7th floor of a building so that it is not affected largely by multi-path effects. The distance-based weighting is effective especially in the case where the multi-paths effects are large.

In Fig. 7, we see the contribution of the portable AP according to the distance from the device. We computed the estimated distance with all measurements of stationary APs and a single measurement of the portable AP with various distances to the device, and plot the location error in distance. The results show that the error is smaller as the distance between the device and

the portable AP is smaller if the distance is less than 500 meters. Additionally, except device c, the errors are far smaller in the case with weighted location estimation. This again means that the weighting method works well in location estimation. The reason it does not perform with device c is that device c is located on the 7th floor of a building. Since there are a few high buildings around there, the device c case includes less effects of obstacles due to multipaths etc. This would make less difference errors especially for the cases with large distances.

5.5 Discussion on Elevation

In this section, we discuss the effect of elevation on accuracy in location estimation. The evaluation area shown in Fig. 3 is mostly flat so that almost all APs and devices were set on low-elevation places. Exceptionally, the area around AP A is a hill and the elevation of A is about 110 meters. Also, the device c is located at 7th floor. Now we would discuss the effect of elevation from the results that are already presented in the previous sections.

See Fig. 4 (a). AP A has a specific trend where RSSI values are relatively high between 2,000 to 4,000 meters in distance. The reason of this is that the elevation of A is high so that line-of-site locations have high intensities, while the region within 2,000 meters from A is not directly reachable due to woods around A. Next, see Fig. 7 (c), and we find that only device c had a low effect of the weighting method, which is because the error level is relatively high when the distance is small due to elevation of device c. In both cases, a large elevation difference between an AP and a device resulted in a high error level in the proposed method although the physical distance is not large. Actually, this effect is seen in Table 3; see the weighted and unweighted results of stationary APs. The position error is significantly small for device e, which is because the location of device e is close to AP B. However, although device c and a are close to APs A and C, respectively, the position error is not that small, which we consider is caused by the elevation of device c and AP A.

From above, we conclude that elevation effects on the accuracy of position estimation, and we should care about it when we utilize the proposed method.

6. Conclusion

This paper presents a method to improve the RSSI-based localization accuracy for UNB-based LPWA networks. Although RSSI-based localization includes large errors due to multi-paths effect, this is the most preferable method in UNB-based LPWA network. We proposed to introduce portable APs equipped on the roof of a vehicle that moves all around the target area. Our idea is to combine RSSI observations from stationary and portable APs to improve accuracy of localization. Note that stationary APs suffer from a large error in distance estimation because of the large distance from small devices, while portable APs would suffer from a shortage of measurements. By combining the RSSI measured by stationary and portable APs, we achieved far more accurate localization than the conventional method. Evaluation results in Wakayama city demonstrated that the proposed method performs far better than the conventional method.

The contribution of this paper is summarized as follows.

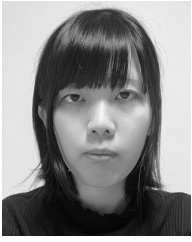
First, we demonstrated through real-environment evaluation in Wakayama city that the portable APs effectively improve the localization accuracy although the number of measurements are small and the measurements could include large error in it. Second, we newly proposed the distance-based weighting technique for long-range LPWA systems, and showed the positive effect in improving accuracy. Third, we showed the trend on localization accuracy under various number of measurements by portable APs, and showed that a relatively small number of measurements would achieve a certain level of accuracy as a case study in Wakayama city.

As future work, it could be interesting to compare with the fingerprint-based methods. Although fingerprint technique requires a large amount of measurements on RSSI statistics at various positions, we could compare the performance under the condition of the same number of measurements.

Acknowledgments The authors sincerely appreciate the kind cooperation of Kyocera Communication Systems Co., Ltd. for providing us various information and devices for this research.

References

- [1] Laoudias, C., Moreira, A., Kim, S., Lee, S., Wirola, L. and Fischidone, C.: A Survey of Enabling Technologies for Network Localization, Tracking, and Navigation, *IEEE Communications Surveys & Tutorials*, Vol.20, No.4, pp.3607–3644 (2018).
- [2] Gezici, S., Tian, Z., Giannakis, G.B. and Kobayashi, H.: Localization via Ultra-Wideband Radios: A Look at Positioning Aspects for Future Sensor Networks, *IEEE Signal Processing Magazine*, Vol.22, No.4, pp.70–84 (2005).
- [3] Guvenc, I. and Chong, C.C.: A Survey on TOA Based Wireless Localization and NLOS Mitigation Techniques, *IEEE Communications Surveys & Tutorials*, Vol.11, No.3 (2009).
- [4] Xu, B., Sun, G., You, R. and Yang, Z.: High-accuracy TDOA-Based Localization without Time Synchronization, *IEEE Trans. Parallel and Distributed Systems*, Vol.24, No.8 (2013).
- [5] Xu, J., Ma, M. and Law, C.L.: AOA Cooperative Position Localization, *IEEE Global Telecommunications Conference (GlobeCom2008)* (2008).
- [6] Zanella, A.: Best Practice in RSS Measurements and Ranging, *IEEE Communications Surveys & Tutorials*, Vol.18, No.4 (2016).
- [7] Bshara, M., Gustafsson, F. and Biesen, L.V.: Fingerprinting Localization in Wireless Networks Based on Received-Signal-Strength Measurements: A Case Study on WiMAX Networks, *IEEE Trans. Vehicular Technology*, Vol.59 (2010).
- [8] Chen, Y., Sakamura, M., Nakazawa, J., Yonezawa, T., Tsuge, A. and Hamada, Y.: OmimamoriNet: An Outdoor Positioning System Based on Wi-SUN FAN Network, *The 11th International Conference on Mobile Computing and Ubiquitous Networking (ICMU2018)* (2018).
- [9] Sallouha, H., Chiumento, A. and Pollin, S.: Localization in Long-range Ultra Narrow Band IoT Networks using RSSI, *Proc. International Conference on Communications (ICC '18)* (2018).
- [10] Sigfox: Sigfox connected objects: Radio specifications (2019).
- [11] Nolan, K.E., Guibene, W. and Kelly, M.Y.: An evaluation of low power wide area network technologies for the internet of things, *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*, pp.439–444 (2016).
- [12] Sigfox Location: available from (<https://build.sigfox.com/location>) (accessed 2019-06).
- [13] Friis, H.T.: A Note on a Simple Transmission Formula, *Proc. I.R.E. and Waves and Electrons* (1946).



Miya Fukumoto received her B.E. from Wakayama University in 2019. She is currently working with Unisystem Co. Ltd. She is interested in wireless networking and communications as well as localization techniques on them.



Takuya Yoshihiro received his B.E., M.I. and Ph.D. degrees from Kyoto University in 1998, 2000 and 2003, respectively. He was an assistant professor at Wakayama University from 2003 to 2009. He has been an associate professor in Wakayama University from 2009. He is currently interested in graph theory, distributed algorithms, computer networks, wireless networks, medical applications, bioinformatics, etc. He is a member of IEEE, ACM, IEICE, and IPSJ.