공학석사학위논문

Fingerprint map 을 이용한 LoRa ToA 기반 위치 추정 방법

LoRa ToA-Based Localization Using Fingerprint Map

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Abstract

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Localization is one of the essential elements in Internet of Things (IoT) applications. Especially, LoRa which is one of the Low-power wide area network (LPWAN) technologies has suitable features for localization such as low power consumption, long range, and low cost of employment. However, the existing LoRa localization methods have limitations in terms of localization possible area and accuracy. In the area where there are less than three gateways, it is impossible to estimate location using the existing algorithms. And the existing LoRa localization algorithms show large estimation error in noisy environment such as urban. In this paper, we propose LoRa ToA-based localization using Fingerprint map to tackle the issues. First, we propose localization algorithm to estimate location even in the area where there are less than three gateways. In addition, to calculate ToA-based distances which are used in the algorithm, we propose a LoRa Time Synchronization Protocol that is suitable for LoRa network. Second, we use

fingerprint map to reduce localization error caused by noisy environment. Since we construct fingerprint map utilizing static end-devices, the overhead to use the fingerprint map can be alleviated. The simulation results show that, compared with other schemes, the proposed localization scheme significantly expands localization possible area and improves the localization accuracy.

Keywords : LoRa, ToA Based localization, LoRa Time Synchronization Protocol, Fingerprint Map, Static End Device, Distance Correction

***Student Number* : 2017-25700**

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Chapter 1
Introduction

Low-power wide area network (LPWAN) is a wireless wide area network technology that allows long range communications with low power among connected devices. Due to its ability to offer affordable connectivity for the massive number of devices, LPWAN is considered as one of the key-enabling technologies for Internet of Things (IoT) where billions of devices are connected [1].

Localization is an essential element in the most IoT applications. There are several studies on the localization that utilize GPS, Wi-Fi, Bluetooth or other technologies. Unfortunately, few of solutions can be used to support IoT applications. For instance, although GPS can be useful for localization in remote regions, but the power and cost associated with a GPS are having an adverse effect for IoT devices. For the localization with WLAN or WPAN systems such as Wi-Fi and Bluetooth, a number of access points are required to cover a large region [2]. Hence, these technologies greatly increase the cost of deployment.

On the other hand, LoRa is one of the LPWAN technologies with advantageous features for localization. First, LoRa uses chirp spread spectrum modulation (CSS) to support long distance communication. CSS is robust to channel noise and resistant to multipath fading even at low power. Second, all

gateways which receive a packet from end-device record the timestamp of the received packet [4]. Based on the timestamps and gateway locations, the location of the target device can be estimated using Time Difference of Arrival (TDoA) algorithm. Due to these useful properties, it would be desirable to localize devices with the LoRa.

However, even though these useful properties, there are two problems on the existing LoRa localization algorithms. The first problem is localization is limited according to the number of gateways. And the second problem is the performance is greatly degraded in noisy environment such as urban.

The TDoA algorithm requires at least three gateways which receive signal from a device. Thus, it is impossible to estimate the location of a device when less than three gateways are available. The authors in [5] used pedestrian dead reckoning (PDR) technique for localization with a single access point (AP). However, the PDR technique cannot be applied for LoRa localization since the sensors are rather expensive and have high power requirements.

Several researches on LoRa localization show that the performance is highly degraded in noisy environment. The work in [6] proposed the TDoA-based localization and several experiments were carried out. The localization error is over 1 km. On the other hand, in [7], the authors utilized LoRaWAN datasets to perform the RSSI fingerprinting-based localization [8] in urban area. It has localization error of 400 meters. In both works, the performance is highly influenced by noisy environment since there is no process to mitigate

errors caused by multipath fading. Moreover, in the case of [8], there is an additional overhead that the fingerprint map is needed to be updated frequently since the method is sensitive to the environment change.

In this paper, we propose a LoRa Time of Arrival (ToA) based localization algorithm aiming to find the accurate location in all areas. Unlike the existing LoRa localization method, our method uses ToA-based algorithm. The proposed algorithm estimates the location with ToA-based distances. The basic ToA-based Algorithms also need at least three distances to estimate location. In the area that less than three gateways receive the signal from a device, we use the proposed algorithm that can estimate location with two or a single distance. In addition, we propose a LoRa Time Synchronization Protocol (LTSP) to calculate ToA-based distance in LoRa. The existing method such as [9] is inefficient to calculate ToA-based distances in LoRa network. It is because the method only calculates propagation delay between a transmitter and a receiver in order to estimate the range.

To improve localization accuracy, before we do localization, we correct the ToA-based distances through the fingerprint map. The ToA-based distances are not accurate in noisy environment. Localization with the inaccurate distances can lead to large localization errors. Thus, in off-line phase, we estimate ToA-based distances at reference points (RPs) and store them in database with real distances. In online phase, the ToA-based distance of the target device is corrected by fingerprint map. Then, each corrected distance is used for localization. However, as we mentioned above, there is

overhead to maintain the fingerprint map. To solve this problem, we use static end-devices (smart metering device, environment monitoring device, smart parking, etc.), as RPs. As we use static end-devices as RPs, the overhead can be alleviated.

The rest of the paper is organized as follows. We describe a system model in Section II and followed by LTSP in Section III. The proposed algorithm is further described in Section IV. Some experimental results and discussions are presented in Section V. We then conclude the paper in Section VI.

Chapter 2

System Model

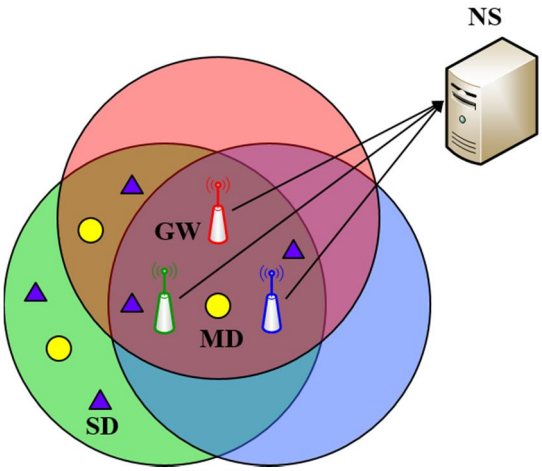

Fig. 1. System model

As shown in Fig. 1, our proposed LoRa networks consist of network server (NS), gateway (GW), and end-device (ED). The ED is further classified into static end-device (SD) and mobile end-device (MD). The location of SD is fixed and the NS knows its the location, whereas the MD is a device to be localized. We consider there are N deployed GWs within a transmission range. These GWs are synchronized with each other by using a GPS receiver and the SDs are randomly deployed within the service area.

Chapter 3

LoRa Time Synchronization Protocol

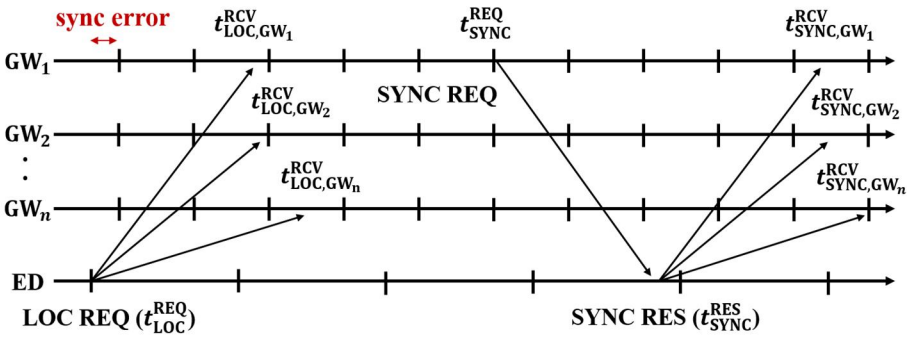

Fig. 2. Example of LTSP operation

The goal of LTSP is to calculate distances between a device and multiple GWs within a single operation. As seen in Fig. 2, there are synchronization error and clock drift between ED and GWs. We can calculate ToA-based distance using the message departure time, the message arrival time at GWs, and synchronization error. In this section, we introduce ToA-based distance calculation process considering synchronization error and clock drift. The calculating distances procedure are follows:

1) The ED sends a localization request message to neighbor gateways with its local time $t_{\mathrm{LOC}}^{\mathrm{REQ}}$

2) Among GWs which receive the message, only one GW sends a synchronization request message
3) The ED reports the time that the message is received $t_{\mathrm{SYNC}}^{\mathrm{RES}}$ to GWs
4) NS calculates the synchronization error and clock drift
5) Thus, NS can calculate propagation delays between ED and GWs

By considering the whole process of message exchange process, we can obtain the following three equations:

$$t_{\mathrm{LOC,GW}_i}^{\mathrm{RCV}} = t_{\mathrm{LOC}}^{\mathrm{REQ}} + \Delta t + \alpha_{\mathrm{GW}_i}\,, \tag{1}$$

$$t_{\mathrm{SYNC}}^{\mathrm{REQ}} + \alpha_{\mathrm{GW}_i} = t_{\mathrm{LOC}}^{\mathrm{REQ}} + \Delta t + \left(t_{\mathrm{SYNC}}^{\mathrm{RES}} - t_{\mathrm{LOC}}^{\mathrm{REQ}}\right) \times \beta\,, \tag{2}$$

$$t_{\mathrm{SYNC}}^{\mathrm{RCV}} = t_{\mathrm{LOC}}^{\mathrm{REQ}} + \Delta t + \left(t_{\mathrm{SYNC}}^{\mathrm{RES}} - t_{\mathrm{LOC}}^{\mathrm{REQ}}\right) \times \beta + \alpha_{\mathrm{GW}_i}\,, \tag{3}$$

where Δt is synchronization error, α_{GW_i} is propagation delay between ED and GW-i, and β is time lapse ratio between ED and GW. Based on the Eq. (1), (2), and (3), we can calculate Δt. Therefore, the ToA-based distance between MD and GW-i can is calculated as follow:

$$D_i^{\mathrm{ToA}} = c \times \{t_{\mathrm{LOC,GW}_i}^{\mathrm{RCV}} - (t_{\mathrm{LOC}}^{\mathrm{REQ}} + \Delta t)\}\,, \tag{4}$$

where c is signal propagation speed.

Chapter 4
Proposed Localization Algorithm

In the proposed scheme, the localization process consists of two phases: (1) off-line phase, and (2) online phase. In the off-line phase, we create a fingerprint map by using SDs. In the online phase, the location of MD is estimated as following steps.

1) First, MD calculates ToA-based distances.
2) Next, the distances are corrected by fingerprint map
3) Then, we perform the localization based on the corrected distances in Step 2 with different algorithms, which to be further discussed in the following section.

In the following section, we will describe the distance correction and algorithms for different cases.

A. Distance Correction

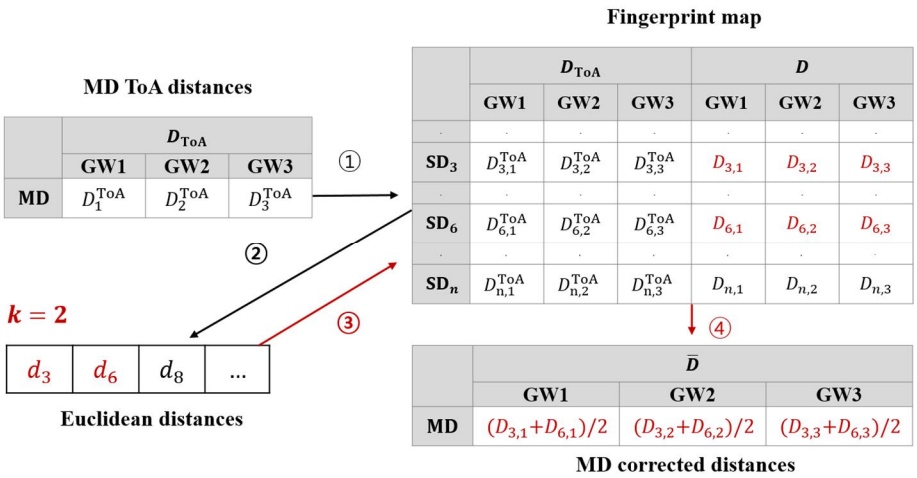

Fig. 3. Example of distance correction ($K = 2$)

To ensure the accuracy of the localization, a correction process must be in place. In this work, we use fingerprint map to correct ToA-based distances. The fingerprint map is constructed during the off-line phase, where ToA-based distance and real distance between SDs and GWs are collected respectively. An example of distance correction is depicted in Fig. 3. Let $D_{i,j}^{\mathrm{ToA}}$ denotes the ToA based distance, and $D_{i,j}$ be the real distance between SD-i and GW-j. For each SD-i and GW-j, $D_{i,j}^{\mathrm{ToA}}$ and $D_{i,j}$ are stored in fingerprint map as a set of RPs. In online phase, ToA-based distances between MD and GW-j, denoted as D_i^{ToA}, are calculated and corrected using K Nearest Neighbors (KNN) algorithm. KNN algorithm is one of the notable fingerprint based algorithm, where the K nearest RPs are selected according to

the Euclidean distance. Let D_{MD} and D_{SD} represent the ToA-based distance vectors of MD and SD respectively. Euclidean distance in ToA-based distance between MD and SDs is defined as

$$d = \sqrt{\sum(D_{\mathbf{MD}} - D_{\mathbf{SD}})^2}, \tag{5}$$

where d denotes the dissimilarity of ToA-based distances between the SD and MD. Intuitively, the smaller d value indicating the smaller gap between SD and MD. In this work, the K SDs with smallest d value are selected. Then the MD's ToA-based distances are corrected as based on:

$$\overline{D}_j = \frac{1}{K}\sum_{i=1}^{K} D_{i,j}, \tag{6}$$

where $\overline{D}_j$ is the corrected distance between MD and GW-j. After all distances are corrected, these distances are used in the localization algorithm

B. Case Ⅰ: Area that three GWs receive MD signal

In this case, we consider localization in area where three GWs receiving the signal from MD. Since we have corrected the distances between MD and GWs, we can estimate the location with Least Squares method (LS) in [10].

C. Case Ⅱ: Area that two GWs receive MD signal

As shown in Fig. 4, the intersection between two circles (with radius $\overline{D}_2$ and $\overline{D}_3$) will give us two intersection points. Since one of these two points is in a

transmission range of the other gateway, we will exclude it and select another point as the final location.

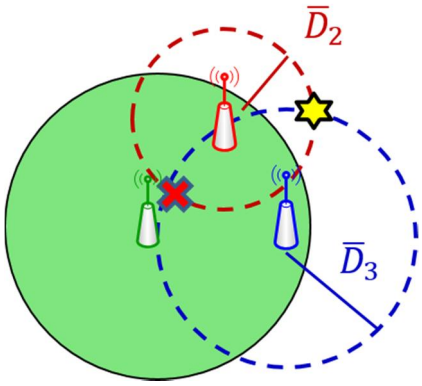

Fig. 4. Example of localization in Case Ⅱ

D. Case Ⅲ: Area that a single GW receives MD signal

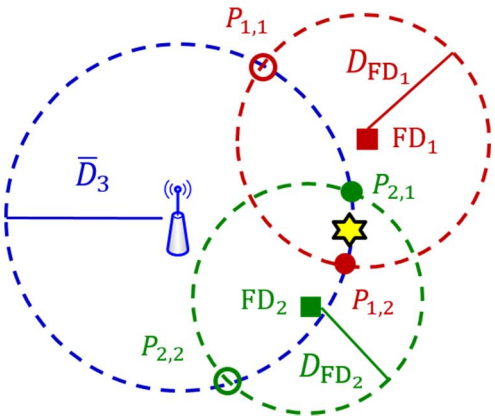

Fig. 5. Example of localization with two FDs in Case Ⅲ

Even though we exclude the coverage range of other GWs, it is still unfeasible to estimate the location of device with a single distance. To tackle this problem, we propose to use SDs (Class B) as a forwarding device (FD). FD is a normal SD in FD mode where it can listen MD message during certain period and forward it to GW. In LoRa, the purpose of Class B is to have an end-device available for reception on a predictable time. All gateways must synchronously broadcast a beacon providing a timing reference to the end-devices. Based on this timing reference the end-devices can periodically open receive windows called ping slot. A network can initiate downlink using one of these ping slots [6]. As NS sends a FD request message to SDs in ping slot, SDs (Class B) are changed into FD mode. As well as GW, FDs receive a message from MD. Thus, we can get $\overline{D}$ and D_{FD_i} which are corrected distance between MD and GW and ToA-based distances between MD and FD-i, respectively. After calculating the distances, we find intersection points sets $\{P_{1,1}, P_{1,2}\}$, $\{P_{2,1}, P_{2,2}\}$, $\cdots$, $\{P_{n-1,1}, P_{n-1,2}\}$, $\{P_{n,1}, P_{n,2}\}$ where $P_{i,j}$ is j-th intersection point between circle with radius $\overline{D}$ and circle with radius D_{FD_i}. One intersection point in each set is selected and sum of distance differences is calculated. The n intersection points with minimum sum of distance differences are also selected. Having a minimum sum of distance difference means the location which FDs expect is similar. Finally, the median of n points will be determined as final location. An example of localization with two FDs in Case Ⅲ is depicted in Fig. 5. The procedures to calculate D_{FD_i} are as follows:

1) The MD sends a localization request message and the server know that it is in Case Ⅲ
2) The NS sends localization interval request message to make SDs (Class B) FD mode at next localization time and MD sends localization interval information in interval response message
3) At next localization time, server sends forward request message to SDs (Class B) in ping slot.
   ① To do localization, at least two FDs which can listen MD message are needed. Thus, at first localization time, we divide coverage range with 40° and select one SD randomly in each partition.
   ② After the localization, server selects n SDs near from last location
4) The FDs are listening and MD sends localization request message
5) The FDs which receive the message forward it and the rest procedures in LTSP are followed
6) Repeat the above steps from step 3 to step 5

The above procedure is described in Fig. 6.

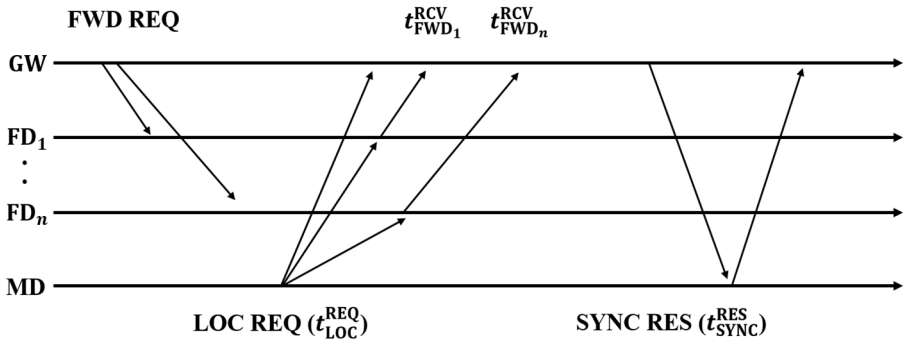

Fig. 6. Procedures of calculating D_{FD_i} in Case Ⅲ

As we follow the procedures, we will obtain

$$t_{\mathrm{LOC}}^{\mathrm{REQ}} + \Delta t + \alpha_{\mathrm{MD,FD}_i} = t_{\mathrm{FWD}_i}^{\mathrm{RCV}} - \alpha_{\mathrm{FD}_i,\mathrm{GW}}, \tag{7}$$

where $\alpha_{\mathrm{MD,FD}_i}$ is propagation delay between MD and FD-i, $t_{\mathrm{FWD}_i}^{\mathrm{RCV}}$ is arrival time of forwarded message from FD-i, and $\alpha_{\mathrm{FD}_i,\mathrm{GW}}$ is propagation delay between FD-i and GW.

To calculate D_{FD_i}, we should know $\alpha_{\mathrm{MD,FD}_i}$. We know $t_{\mathrm{LOC}}^{\mathrm{REQ}}$, Δt, and $t_{\mathrm{FWD}_i}^{\mathrm{RCV}}$ through above procedures and $\alpha_{\mathrm{FD}_i,\mathrm{GW}}$ since FDs are SDs which are used in fingerprint map. Thus, we can calculate $\alpha_{\mathrm{MD,FD}_i}$ and D_{FD_i}.

Chapter 5

Performance Evaluation

A. Simulation Setting

In this section, we evaluate the performance of a proposed localization algorithm through a simulation presented in Fig. 1. Our simulation is based on the urban and rural scenarios with respect to the number of number of GWs that receive message from device:

1) For urban scenario, we set the locations for three GWs (each with 5 km coverage range) at (0,0), (3000,0), and (1500,2500).
2) For rural scenario, we set the locations for three GWs (each with 10 km coverage range) at (0,0), (8000,0), and (4000,6920) for the rural scenario.

Note that the unit used in our simulation is meter.

The SDs are located randomly and used for fingerprint map. The accuracy of fingerprint-based method is highly affected by the number of RPs. To check the impact on the performance of the algorithm, we set SDs density to 0.01 SD/m^2, 0.0004 SD/m^2, 0.0001 SD/m^2, 0.00004 SD/m^2. 20% of total SDs are Class B SDs and the number of FD is set to 3. When the proposed scheme is compared with other algorithms, we set density 0.0004 SD/m^2 and 0.0001 SD/m^2 respectively considering urban and rural environment. The MD

moves at walking speed (1 m/s) for 1 hour. The localization interval is set to 5 minutes. For a given trial, the distance measurements for NLOS [7] are

$$r_i = r_i^0 + \epsilon_i + \alpha_i, \tag{8}$$

where r_i are the estimated distance, and r_i^0 are the true distance, and ϵ_i denoting measurement noise are independently and identically distributed (i.i.d.) zero mean Gaussian random variable of variance σ^2, and α_i is NLOS error which follows uniform distribution.

We compare the performance of our algorithm with the basic TDoA localization algorithm and the algorithm in [6] which is called GFG. GFG creates a grid of possible locations of the end device and creates subgrids in the grid. The distances from each gateway to the center of subgrids were computed and stored in dataset. In online phase, distances calculated by TDoA algorithm were compared with the distances in the database. The center location of subgrid that provide minimum error is determined as final location. The following results are obtained from 10000 simulation runs.

B. Simulation Result

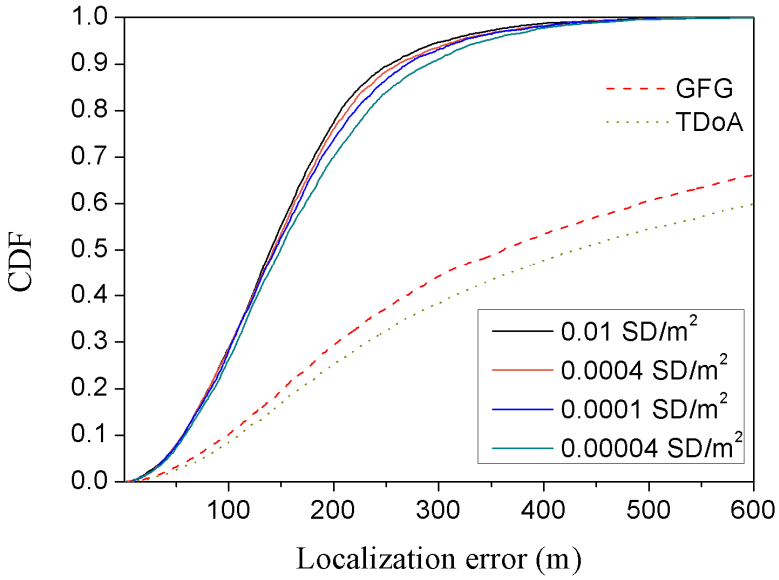

Fig. 7. CDF of localization accuracy in Case Ⅰ of urban scenario

Fig. 7 shows the cumulative probability distribution of localization errors for each algorithm in Case Ⅰ of unban scenario. As observed from the figure, although the number of SDs used for fingerprint map decreases in the proposed scheme, the localization accuracy is not degraded greatly. The proposed scheme has significantly low localization error, compared with GFG and TDoA. Since the inaccurate ToA-based distances biased by NLOS error are corrected through the fingerprint map and the corrected distances are used for ToA-based localization algorithm. Thus, the performance is much better than other schemes. On the other hand, GFG and TDoA has considerably high

localization error. This is because there is no process to mitigate NLOS error in both GFG and TDoA. The methods use the inaccurate values to estimate location and lead to high localization error.

		Proposed scheme				GFG	TDoA
SDs density (SD/m^2)		0.01	0.0004	0.0001	0.00004		
Case Ⅰ	mean (m)	150.94	154.15	157.26	164.90	775.51	1360.51
	Std. (m)	82.99	86.28	88.50	94.07	1268.04	4385.12
Case Ⅱ	mean (m)	217.74	221.44	222.68	228.98	×	×
	Std. (m)	118.98	120.26	123.06	127.92	×	×
Case Ⅲ	mean (m)	247.00	247.31	250.43	250.87	×	×
	Std. (m)	242.28	249.45	251.12	252.50	×	×

Table 1. Statistical characteristics of the localization accuracy in urban

Table 1 shows mean and standard deviation of the error in all cases of urban scenario. In case Ⅱ and Ⅲ, [6] and TDoA methods cannot estimate location since at least three GWs are needed for localization. However, the proposed scheme can estimate the location in the cases. In both Case Ⅱ and Ⅲ, although the number of SDs decreases, the localization accuracy results are not changed greatly. Moreover, the proposed scheme has high localization accuracy 221.44 m and 247.31 m in Case Ⅱ and Ⅲ, respectively. In a GW coverage range, from the perspective of localization possible area, the area

that we can estimate location is widened by 51% compared with GFG and TDoA.

		Proposed scheme			GFG		
Sync error (ns)		10	200	400	10	200	400
Case Ⅰ	mean (m)	158.35	171.16	205.60	780.75	805.89	1023.46
	Std. (m)	88.03	103.33	128.54	1280.28	1302.65	1568.16
Case Ⅱ	mean (m)	224.44	256.85	348.24	×	×	×
	Std. (m)	121.70	159.89	207.52	×	×	×

Table 2. Statistical characteristics of the localization accuracy according to the time synchronization error in urban

Time based localization requires strict synchronization between the GWs. It is critical that the GWs are synchronized with nanoseconds (ns) accuracy. If it fails to achieve precise time synchronization between devices, the failure to obtaining the correct values directly affects location estimation error. In the work [13], GPS synchronization performance was evaluated. Although a maximum time synchronization error value of 423 ns was measured, most time synchronization errors were within 200 ns, corresponding to 60 m localization error. Table 2 shows mean and standard deviation of the error according to the time synchronization error in urban scenario. We assumed the system having time synchronization error of 10 ns, 200 ns, and 400 ns. And

we set SDs density to 0.0001 SD/m^2 in the proposed scheme. Compared to the performance of GFG, the proposed scheme has better performance. In the average synchronization error 200 ns, the proposed scheme has good performance compared with GFG. The proposed scheme has 171.16 m and 256.85 m in Case Ⅰ and Case Ⅱ respectively. At last, we can see that although the time synchronization error is changed, the performance is not degraded significantly in the proposed scheme.

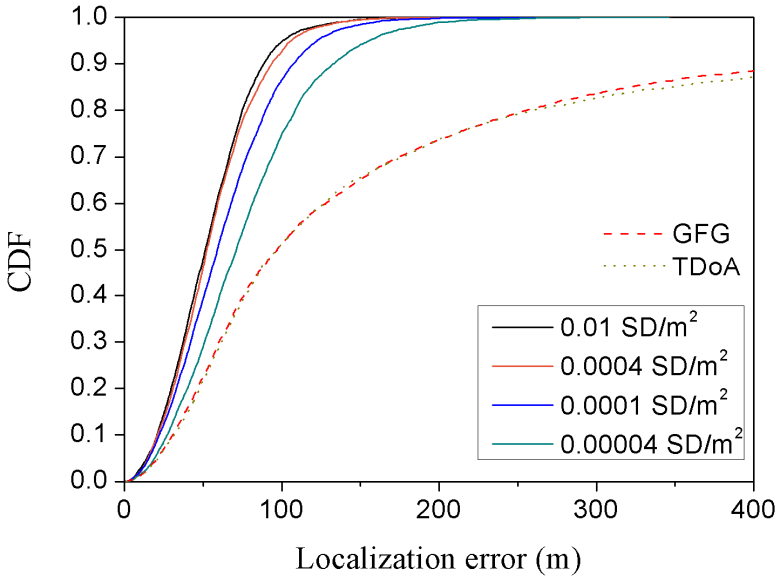

Fig. 8. CDF of localization accuracy in urban scenario

Fig. 8 shows CDF of localization accuracy in Case Ⅰ of rural scenario. In general, the localization error of rural scenario is smaller than the localization

error of urban scenario. And there is no big difference on localization error between GFG and TDoA. It is because the NLOS error of rural scenario is smaller than the NLOS error of urban scenario. Similar to the result of urban scenario, although the number of SDs decreases in the proposed scheme, the localization accuracy is not degraded greatly. The proposed scheme provides better performance than GFG and TDoA. This is because, although the NLOS error is lower than the NLOS error of urban scenario, still the inaccurate values affected by NLOS error are used for localization.

		Proposed scheme				GFG	TDoA
SDs density (SD/m^2)		0.01	0.0004	0.0001	0.00004		
Case Ⅰ	mean (m)	53.82	55.61	63.86	76.65	205.21	207.66
	Std. (m)	27.55	28.48	33.85	42.65	336.79	319.82
Case Ⅱ	mean (m)	64.69	66.49	73.34	89.63	×	×
	Std. (m)	29.44	31.13	38.15	49.76	×	×
Case Ⅲ	mean (m)	117.43	118.27	119.66	121.01	×	×
	Std. (m)	120.44	120.52	123.78	123.43	×	×

Table 3. Statistical characteristics of the localization accuracy in rural

Table 3 shows mean and standard deviation of the error in all cases of rural scenario. Like the urban scenario, GFG and TDoA methods cannot estimate location in case Ⅱ and case Ⅲ. Although the number of SDs

decreases, the localization accuracy result in Case Ⅱ and Ⅲ are not changed greatly. And the proposed scheme has a high localization accuracy 74.34 m and 119.66 m in CaseⅡ and Ⅲ, respectively. The localization possible area in a GW coverage range is widened by 75% compared with GFG and TDoA

		Proposed scheme			GFG		
Sync error (ns)		10	200	400	10	200	400
Case Ⅰ	mean (m)	63.13	83.89	133.03	201.96	339.64	588.96
	Std. (m)	33.69	44.49	59.97	316.29	550.80	952.64
Case Ⅱ	mean (m)	76.56	126.31	227.67	×	×	×
	Std. (m)	40.22	64.29	77.23	×	×	×

Table 4. Statistical characteristics of the localization accuracy according to the time synchronization error in rural

Table 4 shows mean and standard deviation of the error according to the time synchronization error in rural scenario. Compared to the performance of GFG, the proposed scheme has better performance. In the average synchronization error 200 ns, the proposed scheme has good performance compared with GFG. The proposed scheme has 83.89 m and 126.31 m in Case Ⅰ and Case Ⅱ respectively. Like the urban scenario, we can see that

although the time synchronization error is changed, the performance is not degraded significantly in the proposed scheme.

Chapter 5
Conclusion

We have suggested a LoRa ToA-based localization using fingerprint map. To make localization possible in all areas, we have designed LoRa Time Synchronization Protocol (LTSP) and proposed ToA-based algorithm for each case. In addition, the proposed scheme uses fingerprint map to reduce the localization error. As we use static end-devices as reference points, we can reduce the overhead to maintain the fingerprint map. The simulation results show that the localization accuracy is improved compared with the existing LoRa localization algorithms in both urban and rural scenarios. In addition, the localization possible area is also widened by the proposed scheme.

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요 약

위치 추정은 Internet of Things (IoT) 어플리케이션들의 필수 기능 들 중에 하나이다. 특히, LoRa 는 저전력, 장거리, 그리고 저비용과 같은 IoT localization 에 적합한 특징들을 가지고 있다. 하지만, 기존 LoRa 위치추정 방법에는 위치 추정 가능 지역이 제한된다는 점과 정확도가 낮다는 문제점이 있다. 게이트웨이가 3개 미만인 지역에서는 기존 Lora 위치 추정 방법으로 위치 추정이 불가능하다. 또한, 실제 도심과 같이 noise 가 심한 환경에서는 정확도가 매우 낮다.

이러한 문제점들을 해결하기 위해, 본 논문에서는 Fingerprint map 을 이용하는 LoRa ToA 기반 위치 추정 방법을 제안한다. 첫 번째로, 우리는 게이트웨이의 개수에 제한 없이 어느 곳이든 위치추정을 가능하게 하는 알고리즘을 제안한다. 추가로, 알고리즘에 사용될 ToA 기반 거리를 구하기 위해, 기존 방식이 아닌 LoRa 적합한 LoRa 시간 동기화 프로토콜을 제안한다. 두 번째로, noise 가 심한 환경으로 인해 발생하는 오류를 줄이기 위해 fingerprint map 을 이용한다. 우리는 기존 고정되어 있는 단말 기기들을 활용하기 때문에, fingerprint map 을 사용함으로써 발생하는 오버헤드를 줄일 수 있다.

제안 방법에 대한 성능 측정 결과, 제안하는 방법은 기존 LoRa 위치 추정 방법으로 추정이 불가능한 지역에서도 추정을 가능하게 함으로써 추정 가능 범위를 넓혔고, 심한 noise 로 인해 생기는 오류도 보정함으로써 정확도를 크게 향상시켰다.

주요어 : LoRa, ToA 기반 위치 추정,
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