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A Fingerprint-Based Indoor Localization System Using IEEE 802.15.4 for Staying Room Detection

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ABSTRACT

Nowadays, indoor localization systems using IEEE 802.11 have been actively explored for location-based services, since GPS cannot identify floors or rooms in buildings. However, the user-side device is usually large and consumes high energy. In this paper, the authors propose a fingerprint-based indoor localization system using IEEE 802.15.4 that allows the use of a small device with a long-life battery, named FILS15.4. A user carries a small transmitter whose signal is received by multiple receivers simultaneously. The received signal strengths are compared with the fingerprints to find the current location. To address signal fluctuations caused by the low-power narrow-band signal, FILS15.4 limits one room as the localization unit, prepares plural fingerprints for each room, and allocates a sufficient number of receivers in the field. For evaluations, extensive experiments were conducted at #2 Engineering Building in Okayama University and confirmed high detection accuracy with sufficient numbers of receivers and fingerprints.

KEYWORDS

Detection Accuracy, Fingerprint, Fluctuation, IEEE 802.15.4, Indoor Localization System, MQTT, Raspberry Pi

1. INTRODUCTION

Nowadays, various location-based services have appeared in indoor and outdoor environments, such as medical facilities, shopping malls, and airports (Huang, 2018). Then, indoor localization systems using short-range wireless signals have been actively explored since the *global positioning system (GPS)* does not offer sufficient accuracy in identifying the floor or room of a user (Curran, 2011). For them, various wireless technologies including *RFID*, *ultra wide-band (UWB)*, *IEEE 802.11Wi-Fi*, and *Bluetooth* (Ogun, 2018; Yao, 2017; Blasio, 2017 have been studied along with various localization techniques such as *time of arrival (ToA)* and *time difference of arrival (TDoA)*, *angle of arrival (AoA)*, *trilateration*, and *pattern matching* for solving the indoor positioning problem (Brena, 2017).

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Among localization techniques, the *fingerprinting* method has gained the most attention due to its ability to achieve reasonable accuracy (Davidson, 2016). It does not require any additional device such as the directional antenna in *AoA*, the precise time synchronization in *ToA* and *TDoA*, or the complex distance calculation using the propagation models (Ammar, 2014).

This method achieves advantages by adopting the *radio map pattern matching* that consists of offline *calibration* and online *detection phases*. In the *calibration phase*, the *radio map* for every localization point in the target field is made by measuring the *received signal strength (RSS)* when the user is there. Then, in the *detection phase*, the current measured signal strengths are compared with every fingerprint in the *radio map*, and the closest one is selected as the current position.

The *IEEE 802.11* protocol has been most popular among wireless technologies because it has been extensively deployed worldwide to offer wireless local-area networks (WLANs) for Internet access services. A *smartphone* can be used for the user-side transmission device, and an *access point (AP)* can be used as the system-side reception device, where a huge number of APs have been allocated in indoor environments.

However, the user-side device in this protocol consumes much energy to offer high-speed data communications, which needs an expensive and heavy battery. Then, it becomes difficult to always keep and activate the device during the long-time service. In addition, the detection accuracy depends on the type or brand of the device, which may transmit or receive the different levels for *RSS* (Alshami, 2017).

The *IEEE 802.15.4* protocol has been defined to realize low-rate communications with nearby small devices. *ZigBee* is the most popular application of this protocol for monitoring and controlling devices (Jindal, 2015). It needs a small-size antenna and consumes much smaller energy than *IEEE 802.11*, making it suitable for long-time use with a coin battery. The transmitter and receiver are small and relatively inexpensive. Therefore, it becomes possible to assign the transmitter to every user in the system and to cover a large field by allocating many receivers.

In this paper, the authors propose a *fingerprint-based indoor localization system* using the *IEEE 802.15.4* protocol, which is named *FILS15.4* for convenience. A user in the system always carries a small *transmitter* whose signal is simultaneously received by multiple *receivers* that are allocated and fixed in the target field. Each receiver is connected with *Raspberry Pi* through *USB* to transmit the received data to the *server PC* periodically, using the *message-queueing telemetry transport (MQTT)* protocol on a cloud. At the server, the signal strength, *LQI (link quality indicator)*, of every received data is compared with the corresponding value in every stored fingerprint to detect the current location. The programs are made using *Python,* and the *SQLite* database is adopted in the server.

Unfortunately, the wireless signal in *IEEE 802.15.4* often fluctuates when people move or doors are opened/closed in the field because of the low-power and narrow-band transmission. To cope with fluctuations, *FILS15.4* limits one room as the localization unit since walls between rooms can cause significant attenuations of wireless signals. Therefore, each room is more likely to have a unique combination of LQI vectors. Besides, plural fingerprints are prepared to one room when required, and their values are optimized by applying the parameter optimization algorithm to the measured data (Kaku, 2021). Furthermore, a sufficient number of receivers are allocated in the field to increase the average LQI at each location in the field.

For evaluations of *FILS15.4*, we conduct extensive experiments using the prototype system at two floors of #2 Engineering Building in Okayama University using three, four, and five receivers and different numbers of fingerprints in different topologies. The results show that with a sufficient number of fingerprints, the average detection accuracy is 82.64% for three receivers, 97.37% for four receivers, and 99.71% for five receivers. Thus, the sufficient detection accuracy of the proposal is confirmed by increasing the number of receivers and fingerprints.

The rest of this paper is organized as follows: Section 2 notes preliminaries to this study. Section 3 presents a comparison of various localization techniques and wireless technologies. Section 4 presents the proposed *FILS15.4*. Section 5 discusses the signal fluctuation problem with solutions. Section 6 evaluates the proposal through experiments. Finally, Section 7 concludes this paper with future works.

2. PRELIMINARIES

This section shows an overview of studies in wireless technologies and localization techniques for indoor localization systems in the literature. The MQTT protocol is also introduced.

2.1. Wireless Technology

The studies for accurate *indoor positioning systems (IPS)* have taken much interest in academics and industries. Various combinations of wireless technology and a positioning algorithm have been explored for reliable IPS during the past decade.

2.1.1. Radio Frequency Identification

In early studies of indoor localization systems, *RFID* was used as wireless technology. By equipping an object with an *RFID tag*, the reader can automatically detect it within its range. In (Saab, 2011), Saab et al. developed a standalone indoor localization system using passive RFID tags. After reading the *RSSI* of the tag attached to an object, the *log-normal shadowing model* and filtering methods such as *Kalman filter* are used together to estimate the distance from the object to the reader. However, this system cannot find the object's exact position since it can only estimate the distance between the tag and the reader.

2.1.2. Bluetooth

In (Cruz, 2011), Cruz et al. developed an indoor localization system using *Bluetooth*. It reads the nearby *Bluetooth* signals from a mobile phone, where the radio pattern is stored as the reference information for each location. Then, based on the *k-nearest neighbor* method with the *Euclidean distance*, it compares each reference with the current signal vector to detect the location, which is called the *fingerprinting technique*. Since then, it has gained significant interest and has been continuously explored using different wireless technologies and scenarios. However, this original system only achieved 50% accuracy in the location estimation due to the device movements.

2.1.3. IEEE 802.11 Wi-Fi

Among wireless technologies, IEEE *802.11 Wi-Fi* is most popular in indoor localization system studies due to its wide development in almost any indoor environment. In (Bruno, 2014), Bruno et al. studied the path-loss parameter estimation for this system using WLAN. In (Yang, 2015), Yang et al. proposed a method for time-*of-arrival (ToA)* and angle-*of-arrival (AoA)* measurements to determine the distance between an access point and a mobile device. In (He, 2016), He et al. reviewed recent advancements of the fingerprinting method using IEEE *802.11* since the combination has attracted great interest.

2.1.4. IEEE 802.15.4

The IEEE *802.15.4* protocol defines the low-rate wireless network. The communication range is shorter than IEEE *802.11* but longer than Bluetooth. The device is small and inexpensive and consumes low energy, making possible use of a coin battery for a long time. *ZigBee* implements this protocol and has gained interest because of its low-power, low-range, and low-data transmission features. In (Luoh, 2013), a ZigBee-based indoor localization system was proposed with the radial *basis function network (RBFN)* to determine the location with the fingerprinting method. In (Urad, 2017), the nearest *neighbor* and *Bayesian* were adopted, which promised less than or equal to the

0.81m accuracy. Therefore, the authors believe that the *IEEE 802.15.4* protocol is a good candidate for indoor localization systems.

2.2. Indoor Localization Techniques

Researchers have been exploring various techniques which work best for indoor localization. Many of them rely on the *received signal strength indicator (RSSI)* to determine the distance between the transmitter and the receiver. Some others exploit the angle of the coming signal or the radio pattern at one specific position.

2.2.1. Time of Arrival (ToA) and Time of Difference Arrival (TDoA)

ToA calculates the distance between the transmitter and the receiver based on the measured transmission time of the radio signal. First, the signal leaving from the transmitter and arriving at the receivers should be time-stamped. Second, using the propagation speed of the signal in the environment, their distance is estimated.

TDoA calculates the propagation time from the transmitter to different receivers. Each signal is time-stamped, and the arrival time difference among the receivers is used to estimate the distance between the transmitter and these receivers (Ammar, 2014).

They require precise time synchronization among the transmitter and the receivers to achieve reliable accuracy. Thus, they can work at limited types of devices that can be precisely synchronized.

2.2.2. Angle of Arrival (AoA)

AoA calculates the estimated position based on the signal reception angle from the transmitter. This technique requires directional antennas to estimate the position using triangulation like in GPS (Yassin, 2015). Adopting adequate antennas with precise directions can provide an accurate estimation. However, this technique is rarely applied due to the cost of such antennas.

2.2.3. Signal Propagation Model-based

Signal propagation model-based is much more popular due to its simplicity and cost-efficiency. This technique exploits the signal strength at the receiver. It uses a propagation model such as the path-loss model to estimate the distance between the transmitter and the receiver in the indoor environment (Zanella, 2016).

However, achieving reliable accuracy using this technique poses great challenges. The multipath nature of the wireless signal propagation in indoor environments can cause the estimation error by the model (Gu, 2009). Besides, the proper model is different by layouts and objects in this technique (Sadoudi, 2015).

2.2.4. Fingerprinting

The *fingerprinting* method has gained the most attention due to its ability to achieve reasonable accuracy (Davidson, 2016). It adopts *radio map pattern matching*. In the *calibration phase*, the *radio map* in the target field is made by measuring the RSS (Wang, 2017). In the *detection phase*, the current signal strengths are compared with every fingerprint in the *radio map*, and the closest one is selected as the current position (Alfakih, 2019).

2.3. Message-Queueing Telemetry Transport (MQTT)

The *message-queuing telemetry transport (MQTT)* protocol is one of the well-known transport protocols for device-to-device communications in IoT systems. It works with the *publish/subscribe* principle, where each device takes a role as the *publisher*, *subscriber*, or both at transmitting data. In the middle of both sides, a *broker* acts to relay it. Figure 1 illustrates the *publish/subscribe* messaging principle in MQTT.

In (Ali, 2019), Ali et al. built the *Wi-Fi-based* indoor localization system using *MQTT* for sending measured data to the server. Then, (Mekki, 2019) and (Mohaghegh, 2020) reported *Bluetooth-based* systems using *MQTT*.

3. COMPARISON OF INDOOR LOCALIZATION TECHNIQUES

In this section, the authors compare the features of typical indoor localization techniques and wireless communication standards that have been adopted in indoor localization system (ILS) studies. Then, we discuss its advantages and drawback and our solutions to our proposal.

3.1. Comparison of Indoor Localization Techniques

First, we compare the features of the four typical indoor localization techniques in Table 1.

Table 1. *Comparison of indoor localization techniques.*

feature	Fingerprinting	Signal propagation model-based	Time of Arrival (ToA)	Angle of Arrival (AoA)
accuracy	high	low	high	low
least # of signal	3	3	3	2
time synchronization	no	no	yes	no
directional antenna	no	no	no	yes
implementation cost	low	low	high	high

In Table 1, the *least # of signals* indicates the least number of different propagation wireless signals at the receivers necessary to detect the user's location correctly. In our proposal *FILS15.4*, the different propagation of the wireless signals is obtained by receiving it from the one transmitter attached to a user with at least three receivers that are located at different locations. On the other hand, in Wi-Fi-based systems, the different signals are obtained by receiving the wireless signals from at least three transmitters located at different locations by the one receiver attached to the user.

ToA needs accurate time synchronization between the transmitter and the receiver because the distance between them is calculated by the difference between the radio signal transmission time at the transmitter and its reception time at the receiver. This requirement increases the implementation cost of *ToA*.

AoA needs the accurate detection of the signal reception angle from the transmitter using the accurate directional antenna. However, conventional devices such as personal computers and smartphones typically only have omnidirectional antennas. Thus, this requirement increases the implementation cost of *ToA*.

The *signal propagation model-based method* needs the mathematical model for accurately estimating the RSS at every necessary location in the indoor environment. However, the required accurate model may not exist because it is difficult to estimate the signal attenuations from various obstacles or materials. Moreover, RSS is often affected by environmental changes such as human movements, door opening or closing, other interfering wireless signals, and even temperature/moisture changes. Therefore, this method is likely to have low accuracy.

On the other hand, the *fingerprinting method* does not need such special hardware/software and can reduce the implementation cost. Furthermore, references in (Mrindoko, 2016) and (Choi, 2017) show that this method gives a robust accuracy by building the radio map of the known locations in the target field by collecting the received signal strength information under various environmental changes. Therefore, we choose the *fingerprinting method* as the indoor localization technique in this paper.

3.2. Comparison of Wireless Technologies

Next, we compare the features of the four IEEE wireless communication standards that have been adopted in indoor localization system (ILS) studies and their ILS implementations using the fingerprinting method in Table 2.

As shown in Table 2, the transmission power of the *802.15.4* standard in our proposal *FILS15.4* is much smaller than the powers of the other standards, and thus, the battery consumption becomes much smaller. A small coin battery can work for a long time. As a result, the transmitter becomes very small, light, and inexpensive compared to a smartphone, which is the great advantage of *FILS15.4*, since every user must always keep the device.

However, the small transmission power in *802.15.4* also causes the drawback of larger signal fluctuations at the receiver. As a result, the received signal becomes very small and needs a high gain to be amplified for the *link quality indicator (LQI)*.

Table 2. Comparison of IEEE wireless standards and ILS implementations.

feature	802.15.4 (in proposal)	802.15.4 (ZigBee)	802.15.1 (Bluetooth)	802.11 (Wi-Fi)
channel bandwidth	2MHz	2MHz	1MHz	22MHz
transmission power	2.5dBm	14dBm	20dBm	24dBm
max. data rate	250Kbps	250Kbps	1Mbps	78Mbps
modulation	O-QPSK	O-QPSK	GFSK	BPSK, QPSK, M-QAM
spread spectrum	DSSS	DSSS	FHSS	DSSS, OFDM
frequency	2.4GHz	2.4GHz	2.4GHz	2.4GHz, 5GHz
transmission range	100m	100m	10m	100m
ILS	FILS15.4 (proposal)	Intelligent ZigBee (Luoh, 2014)	IPNS (Cruz, 2011)	DORA (Molina, 2018)
technique	room unit, multiple fingerprints	RBFN	kNN	kNN
accuracy	99%	100% at 3m 90% at 1.47m	90% at 2m 80% at 3m	80% at 5m 99% at 15m
user device	Mono Wireless $\left(2.5\times 2.5\times 1cm\right)$	FT6251 module $\left(6.1\times 13.6\times 2.3cm\right)$	cellular phone $\left(9.6\times 5.2\times 2.2cm\right)$	smartphone: iPhone $\left(14.7\times 7.2\times 1.7cm\right)$
battery	$3V$ coin battery	$1.5V\times 2$ AA battery	Li-ion battery	Li-ion battery
battery consumption	low	low	moderate	high
user device cost	low	low	high	high

Besides, the channel bandwidth of this standard is much smaller than that of the *802.11 (Wi-Fi)* standard. The narrow-band signal is susceptible to *flat fading* that causes amplitude changes of received signals over a short distance (Bensky, 2019).

The narrow-band signal reduces multipath effects and makes the LQI be sensitive to uncontrollable factors such as human movements and interfered wireless signals in the service field. As a result, the LQI can often fluctuate.

In (Hara, 2005), Hara et al. evaluated the propagation characteristics of *802.15.4* for the location estimation and confirmed large fluctuations of received powers by indoor attributes. Furthermore, they mentioned that the number of RSSI measurements is essential in improving the location estimation.

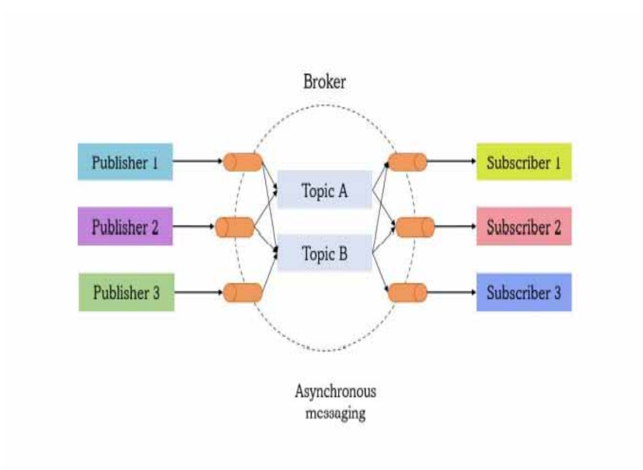
In (Turner, 2013), Turner et al. studied the effects of human movements on the signal strength in indoor wireless sensor networks. They found significant impacts on signal fluctuations when the number of people and their movement paces are taken into consideration. A slow movement definitely reduces the signal strength, a fast one slightly decreases it, and the increase of the number of people significantly reduces it.

To overcome the LQI fluctuation problem, *FILS15.4* regards one room in the field as the detection granularity instead of the exact coordinate of the user location. LQI differences among different rooms can be sufficiently large to absorb LQI fluctuations through high signal attenuations by walls. Besides, multiple fingerprints are prepared for each room to handle the different LQI, where the fingerprint values are optimized using the *parameter optimization method* in (Kaku, 2021). Furthermore, more than three receivers are usually deployed in the field.

4. PROPOSAL OF *FILS15.4*

In this section, the authors present the system architecture, logic, and implementation procedure of *FILS15.4*.

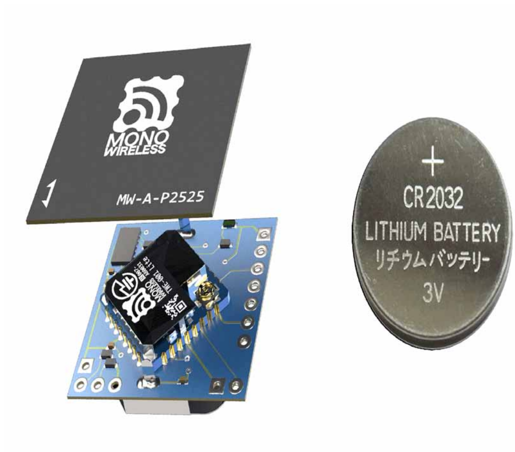
Figure 1. Publish/subscribe messaging principle



4.1. System Architecture

The overview of the system architecture is shown in Figure 3. In the implementation, the authors adopt commercial transmitters and receivers that follow the *IEEE 802.15.4* protocol and works at 2.4 GHz, provided by *Mono Wireless* (Monowireless, 2020). For the transmitter, *Twelite 2525* is used as the small-size transmitter with 2.5 × 2.5 cm that can be powered with a coin battery, shown in Figure 2. *Mono Stick* is used for the receiver and connected to a *Raspberry Pi* single-board computer to transmit the received data using *MQTT* to the *server*. Multiple receivers (R_1 to R_n) are installed at the target area.

Figure 2. *Twelite 2525 transmitter*



The fingerprinting method uses the LQI of the received signal at the receiver. Thus, the LQI is collected from the first eight symbols of the received packet (Baccour, 2012) and transmitted to the server. The server collects the data from every receiver and finds the user's current location through comparisons with the stored fingerprints. The *SQLite* database (SQLite, 2009) is adopted to manage the collected data. The programs at *Raspberry Pi* and the server are made using *Python*.

In our implementation, the transmitter samples the LQI every 500 ms and sends them together to the server continuously. The server processes the detection every one minute.

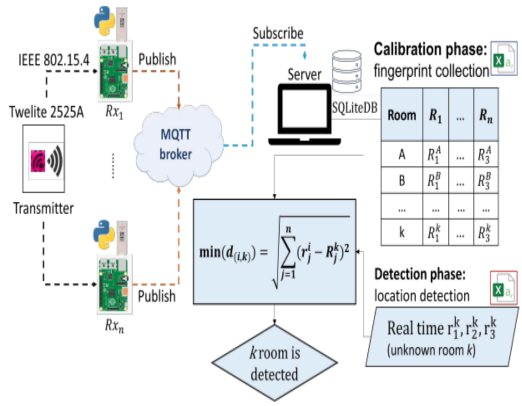
4.2. Location Detection Mechanism

The location detection using fingerprints consists of the *calibration phase* and the *detection phase*.

4.2.1 Calibration Phase

In this phase, the *fingerprint* at every location to be detected in the target field is generated and stored as the *radio map* in the database. One fingerprint is actually a vector of n LQI values from the n receivers. For this purpose, the transmitter is kept at each location for at least 60 min. The average LQI among the measured ones is used for the initial fingerprint value. Then, this fingerprint value is optimized by applying the *parameter optimization method* (Kaku, 2021) to the measured data.

Figure 3. System illustration



4.2.2 Detection Phase

In this phase, the current location of the target user in the field is detected using the currently measured LQI.

a. *Euclidean Distance Calculation*

First, the Euclidean distance between the currently measured average LQI vector and the fingerprint for each location in the *radio map* is calculated by the following equation:

$$d_{(i,k)} = \sqrt{\sum_{j=1}^{n} \left(r_j^i - R_j^k\right)^2}$$

where:

$d_{(i,k)}$: distance between i -th measured data and k -th fingerprint for room

r_j^i : i -th measured LQI at receiver j

R_j^k : k -th measured LQI at receiver j

i : measured data index

j : receiver index

k : fingerprint index

b. *Location Detection*

Next, the fingerprint with the smallest Euclidean distance is selected, and the location corresponding to it is selected as the current location.

To improve the detection accuracy, the authors also consider the fact that when the transmitter is located near a transmitter, such as in the same room, the average measured LQI at the transmitter becomes significantly high. To use it, the authors introduce the c*andidate list* to list up the candidate location indices that can cause the high average measured LQI when the transmitter is located and select one location from the locations in the list. In this paper, 90 is used as the threshold to apply this function. It is noted that the range of the LQI in a room with a receiver is 90 to 140.

4.3. Implemented Procedures in FILS15.4

The implemented procedures for the startup and the phases of FILS15.4 are described.

4.3.1. System Startup

The following procedure describes the steps to start up the system:

1. Allocate the required number of *Mono Sticks* receivers connected with *Raspberry Pi* at the proper locations in the target field.
2. Activate the *Raspberry Pi* to run the program to receive the LQI from the *Twelite 2525* transmitters at *Mono Sticks* in the $500\,msec.$ interval and continuously send or *publish* it to the server via the MQTT broker.
3. Place the *Twelite 2525* transmitters at the selected locations for the fingerprints in the field.
4. Run the program in the server to receive or *subscribe* the LQI data from the MQTT broker, manage it in the *SQLite* database, and calculate the fingerprints for the *calibration phase* or detect the current locations of the transmitters for the *detection phase*.

4.3.2. Calibration Phase

The following procedures describe the steps to apply the *calibration phase*:

1. Move the transmitters at the locations corresponding to the fingerprints in the field and collect the LQI data from the receivers in the server.
2. Calculate the average LQI for every receiver at every location for $60\,sec.$, and generate the initial value of the corresponding fingerprint.
3. Apply the *parameter optimization method* to optimize the fingerprint values from the initial.
4. Store the generated fingerprint values in the database for use in the *detection phase*.

4.3.3. Detection Phase

The following procedures describe the steps to apply the *detection phase*:

1. Move the transmitter to the target location in the field and collect the LQI data from the receivers.
2. Calculate the average LQI for every receiver for $60\,sec.$.
3. If the average LQI from at one receiver is larger than or equal to the threshold (90), select the corresponding candidate location indices in the *candidate list*, and calculate the *Euclidean distances* only for their fingerprints.
4. Otherwise, calculate the *Euclidean distances* for all the fingerprints.
5. Find the location index whose fingerprint gives the least *Euclidean distance*.
6. Save the data and detection result in the database.

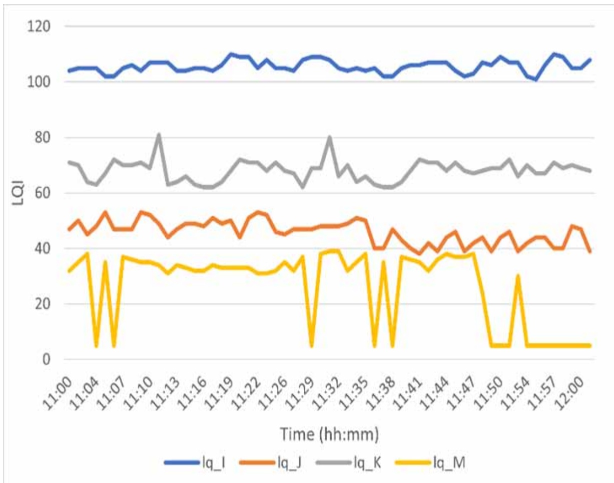
5. DEVICES FOR LQI FLUCTUATION PROBLEM

In this section, the authors present the devices in *FILS15.4* to deal with the LQI fluctuation problem.

5.1. Observation of LQI Fluctuation Problem

The measured LQI value at a receiver often fluctuates in the adopted devices on the *IEEE 802.15.4* protocol due to the low-power narrow-band wireless signal. It can appear when a person moves around, a door is opened/closed, and other wireless devices such as Wi-Fi are turned on/off in the field. As the example, Figure 4 illustrates the fluctuated measured LQI values for one hour when four receivers were placed at I, J, K, M, and one transmitter was placed in D307 in Figure 6.

Figure 4. Measured LQI value fluctuations



The LQI at receiver I is the highest, around $101 - 111$, and is more stable than the LQI at the other receivers because it is located in the same room as the transmitter. Based on this observation, we adopt a *candidate list* that includes the same room as the receiver to improve the detection accuracy by limiting the possible locations for the high LQI.

The LQI at receiver M is the lowest and is more fluctuated than the LQI at the other receivers because it is located farthest from the transmitter and is separated by several walls. As a result, the connection between transmitter and receiver was often lost, especially when humans moved along the corridor or the door of D307 was closed. It is noted that the least LQI value 5 indicates the connection lost in the device specification.

The LQI at receiver K in the corridor is higher than the LQI at receiver J in D306, although only one wall separates each room from D307. The cabinets were placed along the wall between D306 and D307, whereas no cabinets were against the corridor.

By comparing them with the LQI at receiver I, significant differences can be observed between the receiver located in the same room as the transmitter) and receivers in different rooms. Furthermore, the LQI at receiver K takes several stable values around 63, 69, and 80, while the LQI at receiver J takes them around 40, 45, and 50. These different stable values can be caused by human movements in the corridor and the related rooms, including opening/closing the doors.

5.2. Devices of FILS15.4

Based on the observations of the LQI fluctuation problem, the following devices are adopted in *FILS15.4* to improve the detection accuracy:

1) The resolution of the location detections is limited to a space closed by walls such as a *room*, instead of the coordinate as in most existing research so that the average LQI difference between the different locations can absorb the LQI fluctuation.
2) The increasing number of receivers are allocated in the field so that it can be as near as possible to the target location.
3) The increasing number of fingerprints are prepared for each location so that the fluctuated LQI values can be matched with some fingerprints for the same location.

5.2.1 Room Detection Resolution

In practical applications of indoor location systems, it is often sufficient to find the currently staying room of the target user. For example, in a large hospital, there are a lot of small rooms for treatments, exams, or hospitalizations, where it is demanded to find the staying rooms of doctors, nurses, patients, or guests. Even in a large shopping mall, it is usually divided into several sections, and each section can be regarded as one room.

In our experiments in the next section, eight rooms on the second floor and seven rooms on the third floor in our building are considered as the target locations of *FILS15.4*. Among them, the Refresh Corner (RC), the Corridor, and the Toilet are connected without walls or doors. Thus, it is more difficult to distinguish the user location among them.

5.2.2 Increasing Number of Receivers

The LQI fluctuation can be significant when the distance between the transmitter and the receiver, including the increase of separating walls, is relatively long. Even the connections can be lost. On the other hand, the measured LQI values are stable when the distance is short. Thus, a receiver should be allocated as closely as possible to a possible user location to reduce the LQI fluctuation and improve the detection accuracy.

Besides, when a receiver is allocated in the same or very close room from the transmitter, the *candidate list* approach can increase the accuracy by limiting the possible rooms. The increasing number of receivers can contribute to them.

5.2.3 Increasing Number of Fingerprints

The LQI fluctuation may often happen since humans usually move around and open/close doors in the field. Multiple fingerprints with different LQI values for one room can deal with the different measured LQI values of the fluctuation. Then, the *parameter optimization method* in (Kaku, 2021) is adopted to automatically find the proper values for a new fingerprint from an existing fingerprint using extensive measured LQI data.

6. EVALUATIONS

In this section, we evaluate *FILS15.4* through experiments using the prototype system.

6.1. Experiment Fields

We constructed the testbed system of *FILS15.4* on the second and third floors in the #2 Engineering Building in Okayama University. Figure 5 illustrates the second floor's layout with eight rooms marked by white, where seven possible locations are selected for receivers, which are marked by the alphabet. Figure 6 illustrates the layout of the third floor with seven rooms marked by white, where six possible locations are selected for receivers, which are marked by the alphabet.

Figure 5. Second floor layout

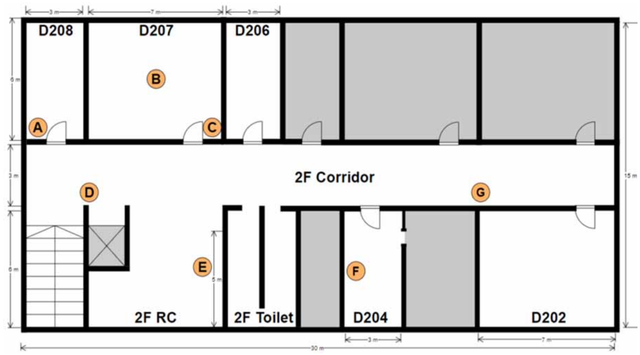


Figure 6. Third floor layout

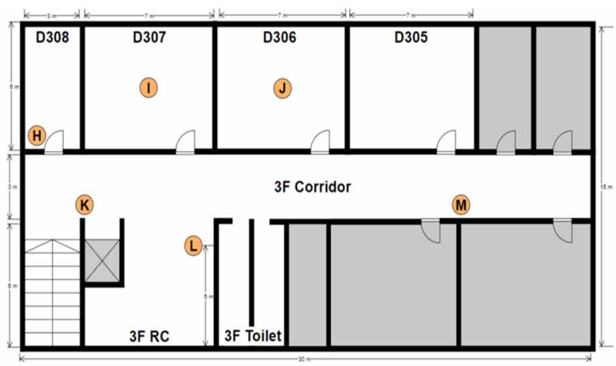


Table 3. Receiver locations in fields.

# of receivers	floor	location
3	2F	B, D, G
	3F	J, K, M
4	2F	B, D, F, G
	3F	I, J, K, M
5	2F	A, B, E, F, G
	3F	H, I, J, L, M

6.2. Experiment Scenario

For the receiver locations, three, four, or five among the possible ones are selected to allocate the receivers, as shown in Table 3. These receivers are connected with the server in D207 using the WLAN in the building through the MQTT broker. For the transmitter locations, the center of each room is selected, where one transmitter is allocated statically at least for 96 hours. It is noted that people sometimes moved around in the field.

Then, the measured LQI data for the first 48 hours were used to obtain the fingerprint values using the parameter optimization method. The LQI data for the remaining 48 hours were used to evaluate the room detection accuracy of *FILS15.4* using the obtained fingerprint values. Thus, the different LQI data was used for the fingerprint optimization and detection accuracy evaluation.

6.3. Effects of Increasing Number of Receivers

First, we discuss the effects of the increasing number of receivers in improving the stability of the measured LQI stability. Because the nearest receiver of the transmitter is most important in our proposal, we compare the average and the standard deviation (SD) of the measured LQI values at the nearest receiver that shows the highest average LQI value when the transmitter is located in each room.

Tables 4 and 5 show the average of the measured LQI values at the nearest receiver when the transmitter was located in each room on the second and third floor, respectively. In general, the average LQI at the nearest receiver becomes higher as the number of receivers is increased. However, in some rooms where no receiver is allocated, it becomes smaller because of the increase of interference from the receivers.

Table 4. *Average of nearest receiver LQI at 2F*

Room	Average of the highest LQI		
	3 Rx	4 Rx	5 Rx
D202	46.49	49.61	44.26
D204	52.61	124.19	144.88
D206	45.28	55.78	50.95
D207	94.71	94.71	117.06
D208	75.66	88.51	113.72
2F RC	68.21	73.79	101.23
2F Toilet	46.19	50.46	63.65
2F Corridor	96.55	94.67	103.71
Average	65.71	78.96	92.43

Table 5. *Average of nearest receiver LQI at 3F*

Room	Average of the highest LQI		
	3 Rx	4 Rx	5 Rx
D305	81.46	81.52	82.14
D306	119.85	115.51	116.78
D307	70.47	108.27	139.71
D308	75.99	74.18	75.27
3F RC	48.21	72.91	135.92
3F Toilet	43.03	56.05	64.81
3F Corridor	109.81	101.62	110.23
Average	78.41	86.47	103.55

Table 6. SD of nearest receiver LQI at 2F

Room	SD of the highest LQI		
	3 Rx	4 Rx	5 Rx
D202	9.8546	8.3404	5.2129
D204	15.3546	1.7707	1.7665
D206	10.8956	12.7634	10.2481
D207	11.4321	10.8502	10.3921
D208	9.9875	11.3708	5.6549
2F RC	9.9642	12.6798	6.6425
2F Toilet	15.3654	14.0118	12.6191
2F Corridor	14.2365	14.1391	15.4801
Average	12.1363	10.7408	8.5021

Table 7. SD of nearest receiver LQI at 3F

Room	SD of the highest LQI		
	3 Rx	4 Rx	5 Rx
D305	8.4643	8.6495	8.5314
D306	6.3144	6.5960	6.1472
D307	14.4321	10.6090	10.5236
D308	12.5349	12.4302	11.8778
3F RC	11.5451	10.8749	6.2712
3F Toilet	11.4135	11.5183	11.1566
3F Corridor	12.5424	12.9485	11.6554
Average	11.0352	10.5181	9.4619

Tables 6 and 7 show the standard deviation (SD) of them on the second and third floors, respectively. In general, the SD at the nearest receiver becomes smaller as the number of receivers is increased. However, in some rooms where no receiver is allocated, it becomes larger when the number of receivers is increased from three to four. Again, the reason will come from the increase of interference from the receivers.

6.4. Effects of Increasing Number of Fingerprints

Next, we discuss the effects of the increasing number of fingerprints in improving detection accuracy. In the beginning, one fingerprint was assigned to every room, and the values were optimized by the *parameter optimization method* (Kaku, 2021). Then, a new fingerprint was assigned to the room whose detection rate was worst (or was smaller than 90%), and the values were optimized. This process was repeated until the total number of fingerprints became 40.

Figure 7 shows the changes in the average detection rate among all the rooms on the second and third floors when the total number of fingerprints was increased for three, four, and five receivers. These results show that the detection accuracy is improved as the number of fingerprints increases, and at a certain number of fingerprints, it is saturated. The total number of fingerprints at the saturated accuracy for the third floor is smaller than that for the second floor because the target rooms on the third floor are close to each other, while D202 on the second floor is isolated from the others, as shown in Figures 5 and 6.

Figure 7. The effect of increasing fingerprint on the average detection accuracy

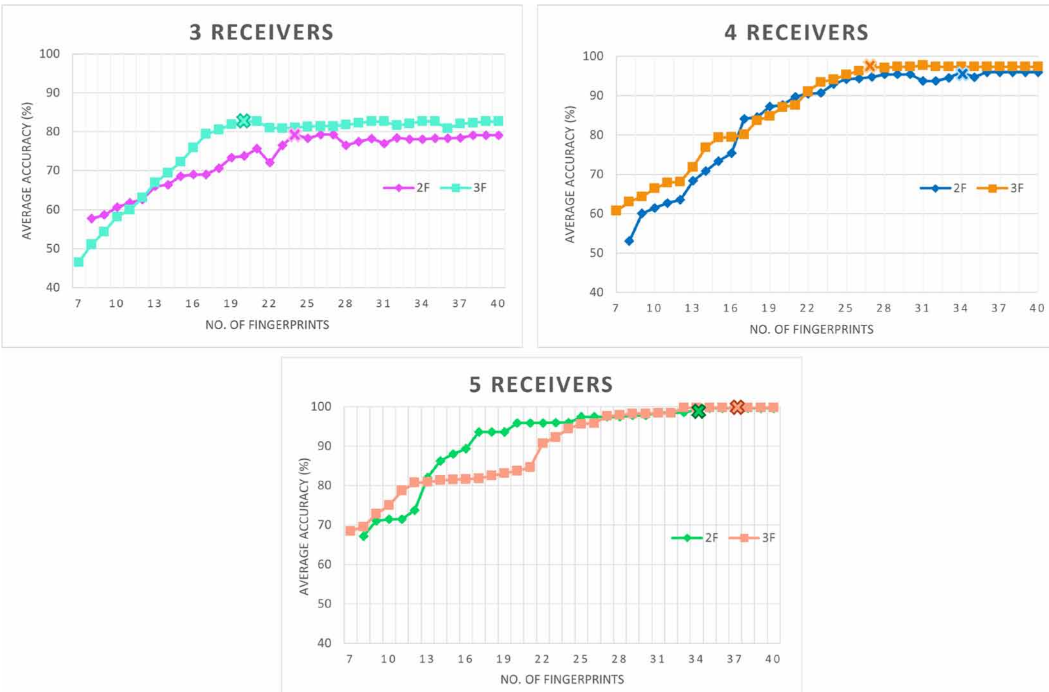


Table 8. *Number of fingerprints for each room at 2F*

Room	# of fingerprints		
	3 Rx	4 Rx	5 Rx
D202	2	4	4
D204	2	2	2
D206	2	3	4
D207	4	5	7
D208	3	4	2
2F RC	3	5	2
2F Toilet	4	7	8
2F Corridor	4	4	6
Total	24	34	35

6.5. Room Detection Accuracy Results

Finally, we discuss the room detection accuracy of *FILS15.4* when the number of receivers is increased from three to five, and the least number of fingerprints at the saturated detection accuracy is used. Tables 8 and 9 show the number of fingerprints for each room.

6.5.1. Results at Second Floor

Table 10 shows the average detection rate for each room on the second floor. It is noted that the results are obtained from the measured LQI data that is different from the data for generating the fingerprint values as the *cross-validation*. The average detection rate is improved from 72.98% to 99.57% by increasing the number of receivers from three to five.

Using three receivers, the detection rate for D206, D208, RC, and Toilet is less than 80% because no receiver was allocated there. Then, using the five receivers, the detection rate for any room exceeds 98%, which indicates sufficient accuracy, even if no receiver was allocated in the room.

Table 9. *Number of fingerprints for each room at 3F*

Room	# of fingerprints		
	3 Rx	4 Rx	5 Rx
D305	2	2	4
D306	1	1	1
D307	4	4	6
D308	2	3	4
3F RC	3	4	2
3F Toilet	4	8	8
3F Corridor	4	4	8
Total	20	27	33

Table 10. Detection rates at 2F

Room	Detection rate (%)		
	3 Rx	4 Rx	5 Rx
D202	87.67	97.74	99.65
D204	80.22	98.56	99.86
D206	72.41	95.68	98.70
D207	87.67	94.58	99.86
D208	68.42	93.23	99.78
2F RC	69.05	94.17	99.95
2F Toilet	95.46	98.65	99.03
2F Corridor	70.41	92.87	98.83
Total	79.28	95.95	99.57

6.5.2. Results at Third Floor

Table 11 shows the average detection rate for each room on the third floor. Again, *cross-validation* was applied here. The average detection rate is improved from 82.64% to 99.71% by increasing the number of receivers from three to five.

Using three receivers, the detection rate for D307, D308, RC, and Toilet is less than 80% because no receiver was allocated there. Then, using the five receivers, the detection rate for any room exceeds 98%.

Table 11. *Detection rates at 3F*

Room	Detection rate (%)		
	3 Rx	4 Rx	5 Rx
D305	94.78	98.87	99.87
D306	98.57	99.47	99.82
D307	70.37	97.43	99.56
D308	66.85	93.72	99.60
3F RC	68.38	93.32	99.73
3F Toilet	97.10	99.35	99.56
3F Corridor	77.45	96.30	98.50
Total	82.64	97.37	99.71

7. CONCLUSION

This paper proposed the *fingerprint-based indoor localization system* using the *IEEE 802.15.4* protocol named *FILS15.4*. It adopts 2.5 × 2.5 cm transmitters and USB-connected receivers with *Raspberry Pi*, where the received data is transmitted to the server using the *MQTT* protocol. The signal strengths *LQI* at the multiple receivers allocated in the field are compared with the stored fingerprints to find the current location in the server.

To improve the detection accuracy under signal fluctuations caused by human movements, *FILS15.4* limits one room for the resolution, allocates a sufficient number of receivers and prepares plural fingerprints to one room whose values are optimized by the *parameter optimization method*.

For evaluations of *FILS15.4*, extensive experiments were conducted using the prototype system on two floors of the #2 Engineering Building in Okayama University. The cross-validation results confirmed the sufficient detection accuracy of 99.57% and 99.71% for each floor with the increasing numbers of receivers and fingerprints.

In future works, the investigation of further improvements in detection accuracy will be considered by excluding the receiver when the signal fluctuation is high, optimizing the number of allocated receivers and their locations in the field. Then, we will evaluate the detection accuracy in various fields for long periods while the weather, the season, and human movements can be changed.

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