International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 15, No.1 (Feb-2024)

http://dx.doi.org/10.12785/ijcds/150164

A Dynamic Indoor Localization with Movement Validation and Fingerprinting Technique under IEEE 802.15.4 Network

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Received 2 Oct. 2023, Revised 1 Feb. 2024, Accepted 2 Feb. 2024, Published 5 Feb. 2024

Abstract: The study of indoor localization has been extensively studied, either in terms of wireless technologies or localization techniques. The accuracy is then challenged when the monitored object is actively moving. Previously, we studied a continuous and low-power fingerprint-based indoor localization system using IEEE 802.15.4 *(FILS15.4)*, which has been integrated into a smart environmental IoT platform. Although fingerprint-based localization offers a great advantage in its simplicity, it relies on real-time signal strength measurements and databases. Thus, it suffers challenges in accuracy when the object is continuously moving. In this study, we focus on developing dynamic positioning, where users continuously move from one room to another. Due to human movements, the fluctuation of the link quality indicator (LQI) can affect the detection accuracy. To avoid false detection, we propose a movement validation method by checking the variance of the LQI and accelerometer to differentiate the cause of fluctuations and increase the detection accuracy. For experiments, we run the test-bed of *FILS15.4* on a two-floor layout. Five to six receivers were allocated to detect multiple users. The results show that the system yields 96.2% accuracy using six receivers simultaneously. Thus, it gives sufficient detection accuracy even for dynamic conditions.

Keywords: Indoor positioning, personal area network, dynamic localization, link quality indicator, accelerometer, IoT

1. INTRODUCTION

Location-based services in indoor settings have become increasingly popular in recent years. The global positioning system (GPS), despite being widely used for outdoor positioning and navigation, is unable to accurately detect the user's floor or room information, leaving it unusable in indoor environments [1][2]. As a result, several strategies utilizing various wireless technologies have been investigated. The mentioned technologies encompass the IEEE 802.11 standard (commonly known as Wi-Fi), Bluetooth Low Energy (BLE), Zigbee, ultra-wideband (UWB), as well as other combinations of these technologies [3][4]. Several positioning techniques have also been considered, including the *time difference of arrival (TDoA)*, *angle of arrival (AoA)*, *lateration*, and *pattern matching* such as *fingerprinting* [5].

Due to the widespread availability of Wi-Fi *access points* in buildings, Wi-Fi fingerprinting attracted the most interest [6] among the other wireless communication standards. Unfortunately, the device's battery lifetime, which is also relatively big and hefty, is burdened by constant Wi-Fi scanning to determine the user's location. Also, the signal reception sensitivity between different kinds and brands of the device can influence Wi-Fi fingerprinting's accuracy [7].

Fingerprinting itself becomes popular due to its straightforward implementation by mapping out the received signal strength and its corresponding location to create a radio map reference [8]. The target area is usually categorized into a certain resolution (i.e. coordinate or grid). Each one of them should have a different radio pattern from several receivers allocated in the target area. The IEEE 802.15.4 standards for wireless personal area networks, on the other hand, provide a compact, lightweight, and reasonably priced transmitter and have a long life when powered by a coin battery. Currently, we have been working on a *Fingerprint-based Indoor Localization System* using the *IEEE802.15.4* protocol named *FILS15.4* for convenience [9]. Devices from *Mono Wireless* are adopted in *FILS15.4* and work under the *IEEE802.15.4* known as the *wireless personal area network (WPAN)* protocol [10]. Due to its low-power and narrow-band characteristics, *WPAN* has a limitation where the propagation dynamics can be easily influenced by human movements or other environmental changes [11].

Previously, we observed that the LQI reception varies greatly from room to room. Consequently, rather than using location coordinates, limiting the detection resolution to

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one room is preferable in *FILS15.4*. Subsequently, the addition of assigned receivers and fingerprints for each room enhanced the precision of detection in two distinct configurations. However, allocating receivers for each floor separately will raise the development costs in multi-story buildings. Hence, the proper receivers distribution for a two-floor environment as a basis for establishing multi-floor buildings has not been researched, especially in actual cases when the monitored users roam around the field.

In the previous work in [12], we combined two adjacent floors as one target field. Multiple receivers were utilized together to detect rooms on both floors to maintain high detection accuracy and avoid high development costs in multi-floors implementation. However, the transmitters were limited to stationary conditions by placing each in a room.

In this paper, we extend the study to a dynamic case where we increase the number of users who are moving around in the field while carrying transmitters. Human motions like standing, sitting, or walking can cause the LQI fluctuation to rise, which could lower the detection accuracy. The accelerometer embedded in the transmitter can be used to detect the user's movement. Unlike the typical method in detecting the direction of movement as presented in [13], we propose a much simpler method by using the variance of the accelerometer and LQI to distinguish the fluctuation induced by movement and other environmental sources in order to prevent false detection.

A series of comprehensive experiments were carried out, including several users on various days at the 2nd and 3rd floors as a two-floor environment. We compare and evaluate different receivers' arrangement both in *stationary (off-body)* and *dynamic (on-body)* situations. The results show that with six receivers allocated on a two-floor environment, the system achieved over 96.2% of average accuracy for multiple users in dynamic situations.

The following parts of this paper are structured as follows: Section 3 presents the system implementation. Section 4 presents the observation of the FILS15.4 device on the human body. Section 5 explains the use of LQI and accelerometer variance to filter the fluctuation causes to maintain high detection accuracy. Section 6 presents the evaluation result on a two-floors environment. Section 7 provides the final remarks and outlines future research directions in this publication.

2. RELATED WORKS

Researchers have shown significant interest in conducting studies on precise indoor positioning systems (IPS). Over the past decade, researchers have investigated different combinations of wireless technology and a positioning algorithm to achieve dependable Indoor Positioning Systems (IPS).

The IEEE 802.15.4 protocol establishes the network for low-rate wireless communication. The range of communication is intermediate between that of IEEE 802.11 and Bluetooth. The device is compact and cost-effective, with low power consumption, enabling long-term usage with a coin battery. The ZigBee protocol is utilized to implement this technology, which has garnered attention due to its characteristics of low power consumption, short range, and limited data transmission capabilities.

The paper by Luoh et al. (2013) introduced a ZigBee-based system for indoor localization [14]. The system utilized a radial basis function network (RBFN) to establish the location using the fingerprinting method.

In the study conducted by Urad et al. [15], the researchers utilized the closest neighbor and Bayesian methods, which demonstrated an accuracy of 0.81m or less. In this perspective, the *IEEE 802.15.4* protocol is well-suited for indoor localization systems.

Pino et al. in [16] presented a self-positioning system for Indoor Positioning Systems (IPS) using an IEEE 802.15.4 network, offering a solution where GPS or IEEE 802.11-based networks are impractical. It achieves a position estimation accuracy of 0.6 meters in a real-world scenario.

Mamun et al. in [17] introduced an automated method for constructing radio maps for RSS fingerprinting localization. The method utilizes a self-navigating automobile to efficiently gather RSS and location data, based on IEEE 802.15.4. Through experimentation in office environments, this technique enhances precision and uniformity in the generation of radio maps, hence diminishing human mistakes and saving time.

Booranawong et al. in [18] proposed an enhancement of accuracy of multi-lateration localization by mitigating the impact of RSSI signal fluctuations. They implemented a novel approach that integrates boundary consideration, zone selection, and position compensation. Through experimentation conducted in both a controlled laboratory setting and a real-world corridor environment, the utilization of a ZigBee network demonstrates a substantial decrease in localization mistakes. This improvement surpasses the performance of conventional approaches by more than 57%.

Recently, Wahab et al. in [19] evaluated the signal strength of IEEE 802.15.4 in indoor positioning, with a specific focus on the impact of access point positioning and environmental variables. The study evaluates and contrasts theoretical and empirical path loss models, demonstrating an error rate of less than 5.5%.

Based on the prior works concerning the feasibility of the IEEE 802.15.4, it is note that this wireless technology is a low-power alternative for indoor localization. The different technique and localization algorithm can be implemented in this standard with precise accuracy.

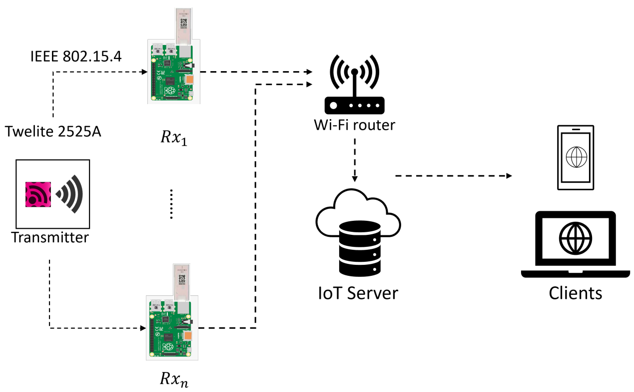


Figure 1. System overview

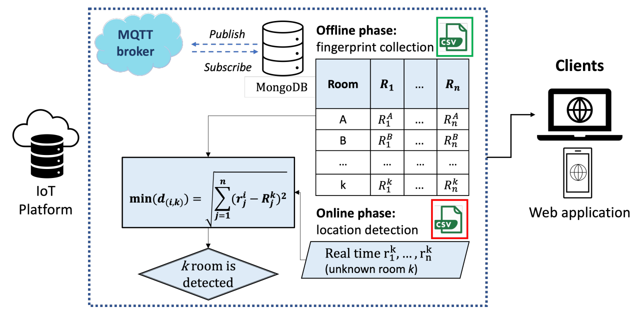


Figure 2. Detection process overview

3. THE FILS15.4

This section provides an overview of *FILS15.4*, encompassing its architectural design, localization method, and operational procedure.

A. System Architecture

FILS15.4 adopts sets of transmitters and receivers from Mono Wireless. The transmitter is a $2.5 \times 2.5 \times 1cm$ accelerometer which regularly sends packets to the receiver under the *IEEE 802.15.4* network. The receiver is connected to the Raspberry Pi via a USB port and establishes a connection to the server over an internet connection using the existing Wi-Fi network. The system gets packets containing accelerometer measurements and the corresponding LQI.

LQI itself indicates the data packet quality received by receivers which is similar to the *received signal strength (RSS)* [20]. In the adopted devices, it is represented by a number from 0 to 255 [21]. However, based on our extensive experiments, the LQI in complex indoor environments are bound to 150-160 at a 1-meter line-of-sight between the transmitter and the receiver.

The message-queuing telemetry transport (MQTT) protocol is commonly used for device-to-device communication in internet of things (IoT) implementations[22]. Furthermore, it has been applied in an IoT-driven indoor locating system as described in the publication by Mekki et al [23].

The server is deployed using the SEMAR IoT server platform [24]. The server retrieves the required data from each received packet, transfers it to the *MongoDB* database, calculates the average of LQI within a fixed time interval, and aggregates the results from all the receivers for use in the subsequent localization process. The system's architecture is depicted in Figure 1.

B. Localization Procedure

Typically, fingerprinting localization needs two phases. First, in the *offline phase*, the system gathers LQI measurements by placing transmitters at every target location. During a certain period of time, the allocated receivers in the area collect the LQI data and the server records it to generate a fingerprint radio map. Second, in the *online phase*, the current position of each transmitter is determined by calculating the *Euclidean distance* between the current LQI and each fingerprint in the database using Eq(1). The fingerprint label whose values give the minimum distance is selected as the detected room.

Figure 2 illustrates the whole process of storing the fingerprint radio map and detecting the current location of the user in the *SEMAR* server. An authorized user can access that information using a web application. The recorded LQI can also be downloaded to be processed by the *parameter optimization method* to determine the number and values of the fingerprint database [25].

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

Where $d_{(i,k)}$ represents the distance between the i-th measured data and the fingerprint for room k. Then r_j^i represents the i-th measured average LQI at receiver j. R_j^k represents the LQI fingerprint for room k at receiver j. While i is the index for the measured data and j is the index for the receiver, which varies from 3 to 6 in this study. Finally, k is the index for the fingerprint, representing different rooms.

C. System Operation Procedure

The working method of the system that is applied in *FILS15.4* is discussed.

1) Setup Phase

The initial setup of the system includes setting up several receiving nodes, consisting of *Mono Sticks* connected to *Raspberry Pi* devices, to be properly allocated within the target area. Then, the program in the *Raspberry Pi* to continuously receive data from any *Twelite 2525* transmitters automatically runs when it is powered. The transmitter is set to send a packet every $0.5second$. In the IoT server, the program for receiving data and running the localization is activated.

2) *Offline Phase*

The *offline* phase aims to collect a radio map of LQI within the target area by allocating the *Twelite 2525* transmitter at the center of every target room in the field. The receivers collect the LQI data within the required period and send it to the IoT server where the average LQI is calculated every 30*second*. The server combines values from all assigned receivers and labels them according to the transmitters' position. After a certain duration, the collected data is downloaded and processed using the *parameter optimization method* to generate the appropriate value and number of fingerprints for each room.

3) *Online Phase*

The *online phase* aims to detect the current location of the transmitter or user in the target field after a radio map has been recorded. In principle, the system compares the newly received fingerprint with the pre-built radio map to find the closest match using the *Euclidean distance*.

Thus, the process involves placing the *Twelite 2525* transmitter in an arbitrary room in the field. It continuously sends packets and is received by all receivers in the field and the LQI information is collected in every allocated receiver and collected by the system.

Since the IEEE 802.15.4 works well in a low range, a strong LQI likely indicates that the transmitter is located in the same room as the receiver. When the $r_i^k >= 95$, select the *location candidates* whose fingerprints satisfy the condition of $R_j^k > 95$. Then, the *Euclidean distance* of the current r_i^k is calculated against the selected fingerprint candidates to simplify the calculation process.

Otherwise, if $r_i^k < 95$, the current LQI combination is calculated against every fingerprint in the radio map. Select the fingerprint's label which gives the least *Euclidean distance* as the detected room. This algorithm reduces the complexity of the room selection among patterns recorded in the fingerprint database rather than calculating against all fingerprints in every detection process.

D. *Indoor LQI Measurement*

LQI itself indicates the data packet quality received by receivers which is similar to the received signal strength (RSS) [20]. In the adopted devices, it is represented by a number from 0 to 255 [21]. However, based on our extensive experiments, the LQI in complex indoor environments, an office room with furniture and human moving around, are bound to 150-160 at a 1-meter line-of-sight between the transmitter and the receiver.

Within our FILS15.4 research, we investigated the degradation of wireless signals in an indoor environment by utilizing IEEE 802.15.4. The selected experimental location is an 8×16 meter corridor with minimal obstacles, yet it was surrounded by concrete walls and had two entrance doors. These elements have a recognized influence on the intensity and quality of wireless signals.

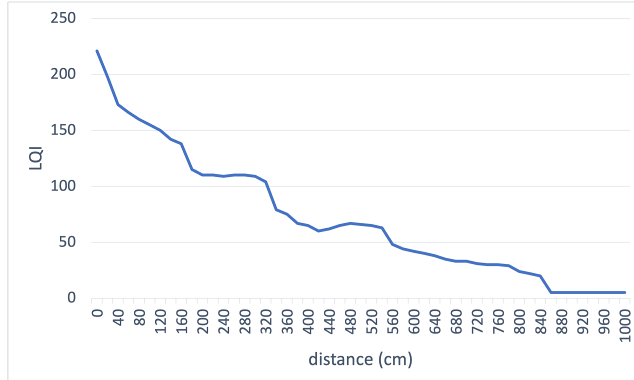


Figure 3. LQI measurement over distance

Signal quality was assessed by employing the LQI against distance as shown in Figure 3. Between $0-200$ cm, there was a significant decline in LQI, indicating the expected decrease in signal intensity as distance increases inside an interior setting.

At distances beyond 200 cm, the LQI experienced variations caused by ambient reflections, such as those originating from walls and doors. The findings indicated that the signal reception had a maximum effective range of 840 cm. Beyond this range, the LQI decreased to a minimum of 5, suggesting a decrease in signal reliability.

4. FILS15.4 DEVICES ON THE HUMAN BODY

In this section, we explain the different responses of FILS15.4 with and without attachment to a human body within the same target field.

A. *Target Field*

Figure 4 illustrates the floor layout that was used to evaluate the accuracy of detection of the *FILS15.4* system in dynamic situations on two floors of the #2 Engineering Building at Okayama University. The target field consists of twelve rooms, each of which is covered by five or six receivers.

However, because of its narrow bandwidth and low data rate, the *802.15.4* suffers from greater signal fluctuation [26], [27], [28]. Then, in [9], we discovered that the received LQI is considerably higher and more stable when a transmitter is situated in the same room as the receiver. Conversely, when there is a considerable distance between the transmitter and receiver, the reception of LQI is significantly reduced and sometimes results in signal loss.

Unfortunately, the movement of the transmitter inside the field significantly affects the signal's propagation patterns. When a transmitter is connected to a human body (on-body), it has the ability to cause heightened fluctuations in LQI. In contrast, previous research solely focused on assessing the efficacy of FILS15.4 in a controlled environment where transmitters remained stationary within a room, devoid of any movement or attachment to users.

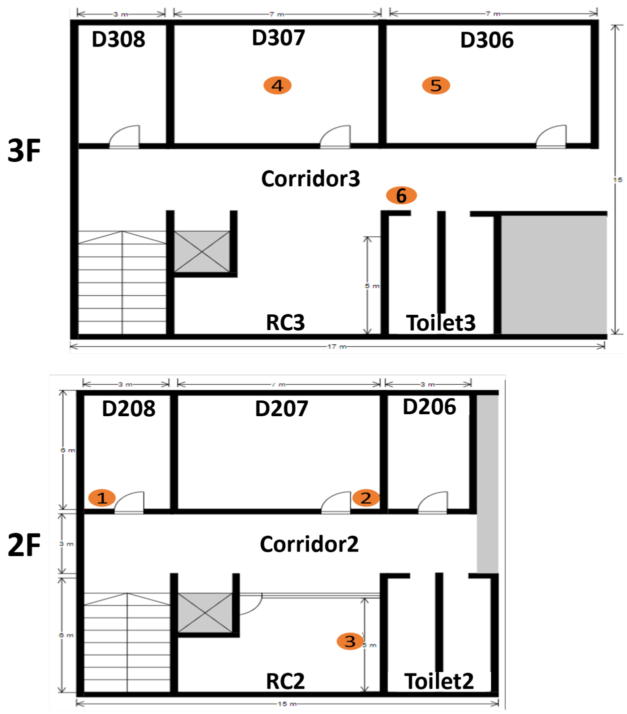


Figure 4. Two-floor target field

B. *Receiving LQI from Off-body Transmitters*

A comparison of the received LQI from transmitters in D207 and D308 is shown in Figure 5. Positioned at the center of the room, both were unattached and in a state of either *stationary* or *off-body*. It should be noted that a total of six receivers were assigned in a two-story setting. Receiver #2 was installed in Room D207, however Room D308 did not have any receivers.

Since D207 has receiver #2 in it, noted by *lq2*, it received the highest LQI between $110-120$ when the transmitter was there. Conversely, in D308 where a receiver was not installed, the receiver #1 situated in D208, as indicated by *lq1*, received the greatest LQI in the range of $98-102$. Within 10 minutes of observation, the signals in both rooms were relatively stable. Fluctuations only appeared in weak receptions ($LQI < 40$) caused by the far transmitter-receiver distance.

Such kind of experiment was presented in the earlier works [9], [12] with different numbers of receivers and types of layouts. The transmitters did not carry by any users and were placed stationary all the time.

C. *Receiving LQI from On-body Transmitters*

Then, in figure 6 we added a comparison to the received LQI from transmitters in D207 and D308, but under conditions when the sensors were attached to the humans or users *(on-body)* located in each room. The users were allowed to sit, stand, and walk while staying inside the room. However, in this short detection epoch, the users did not move between rooms.

It is apparent that the presence of users carrying the transmitters leads to an increase in the fluctuation of the LQI. The signals in both rooms had increased fluctuations due to the movements of the users throughout their occupancy in each space. The *on-body* transmitter in D207 has the highest LQI in the range of $100-125$ in *lq2*. Meanwhile, the highest LQI from D308 was between $70-100$ in *lq1*. Table I shows the LQI variance comparison between *off-body* and *on-body* transmitters in both rooms. However, when the transmitter and receiver were far apart and the LQI is much smaller, fluctuation is likely to happen. Thus, those variances can be neglected as in D207 at receiver #6 or D308 at receiver #2.

5. LOCALIZATION IN DYNAMIC CIRCUMSTANCES

This section exhibits the application of the FILS15.4 protocol in dynamic scenarios where users carry the transmitters. The movement encompasses all activities conducted within a room, such as sitting, standing, or engaging in any little motions, as well as strolling between different rooms.

A. *Devices of* FILS15.4 *on Dynamic User*

The transmitter obtained from Mono Wireless is equipped with a three-axis accelerometer sensor capable of detecting movement, shock, vibration, tilt, and other related phenomena. The accelerometer values are also included in the broadcast packet. Prior implementations were solely focused on averaging the LQI values within a detection interval without utilizing the accelerometer values.

In fact, the accelerometer alone cannot be used to detect the exact direction of movement. Thus, when the users are making any kind of movement, it is crucial to determine whether they are actually moving to another room. Figure 7 and Table II demonstrate the sequential movement of a user from one room to another. Initially, the user remains in a specific room and subsequently undergoes physical locomotion to reach a different room.

The observation was made of 11 detection epochs or 330 seconds. At first, between $1-5$ epoch $1-5$, the user was located at D207, as shown by the highest LQI received by *lq2*. Between the $7-11$ epoch, the user has moved to RC2, as *lq3* became the highest LQI. The user also passed Corridor2 and caused an extreme change in *lq2* and *lq3*. Due to the 30*second* detection interval, the detection result is likely incorrect.

The details of LQI and accelerometer variance when a user is transitioning between rooms are outlined in Table II. The idea behind showing only two of the greatest LQI values is the assumption that the stronger values are more important in determining the user's location. In epoch #6, the LQI variance peaked as the user transitioned from D207 to RC2. Accelerometer variance was 639 during this time. By epoch #7, the user had moved to a different room.

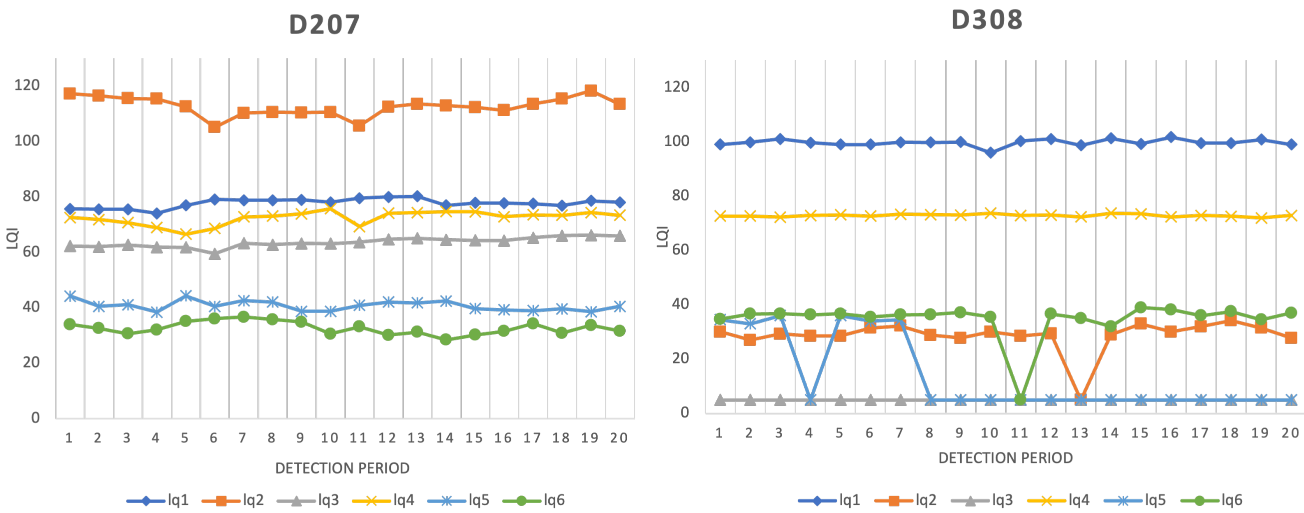


Figure 5. LQI comparison in off-body case

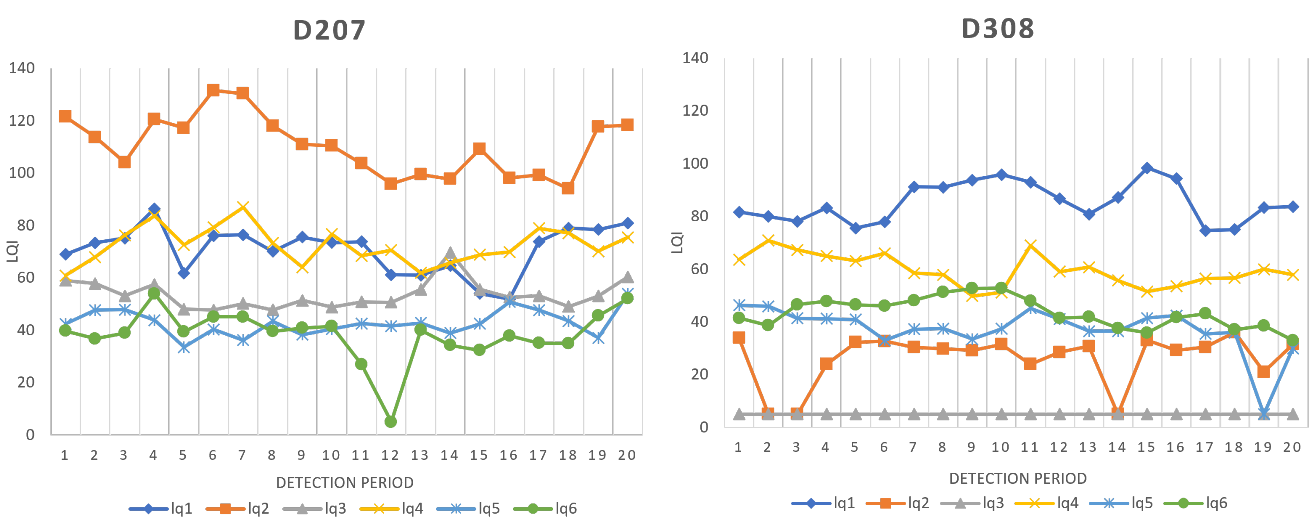


Figure 6. LQI comparison in on-body case

However, accelerometer variance does not always reflect user movement. Interestingly, the biggest variance occurred after the user settled in RC2. User movements that are abrupt may be the main cause of variance.

According to the data shown in table II, the threshold values for the LQI and accelerometer variance are established as 200 and 500, respectively. It should be noted that the transmitter emits a data packet at regular intervals of 500*ms*, containing information such as the LQI and accelerometer readings. The system calculates the average LQI value from each packet every 30 seconds. LQI variance is calculated from two detection epochs' average LQI. In the interim, the variance of the accelerometer is computed during a single detection interval, which spans a duration of 30 seconds, for each packet that is received.

B. Detection of Moving Transmitter and Signal Loss

When a transmitter is connected to an user, every time the user moves, the LQI reception changes more. As previously indicated in Section 4-C, it is worth noting that the user's motions within a given room have an impact on all LQI receptions, even the one with the highest value. In the event that the user relocates to a new room, it is anticipated that this action will result in a change in the highest received LQI within a single interval, thereby leading to an increased variation and the potential for false detection.

In section 3-C3, *FILS15.4* calculates the average of the current LQI within 30 second interval and determines the

TABLE I. LQI variance in rooms with and without receivers in off-body and on-body cases

room	receiver	case	lq1	lq2	lq3	lq4	lq5	lq6
D207	yes	off-body	2.66	**11.52**	2.90	5.83	3.27	5.31
D207	yes	on-body	81.87	**127.30**	29.08	48.24	25.04	101.15
D308	no	off-body	**1.50**	34.76	0.00	0.21	194.91	50.82
D308	no	on-body	**55.70**	95.43	0.00	35.99	76.68	32.87

TABLE II. Comparison of accelerometer variations from a moving user with LQI data.

detection epoch	detected room	#1 highest LQI		#2 highest LQI		max. variance	
		R_x	value	R_x	value	LQI	accelerometer
1	D207	R_2	122	R_4	92	8	1
2	D207	R_2	123	R_4	90	7	1
3	D207	R_2	123	R_4	89	9	1
4	D207	R_2	122	R_4	90	7	633
5	D207	R_2	121	R_4	92	184	62
6	D207	R_2	98	R_2	98	255	639
7	RC2	R_3	124	R_2	98	177	3892
8	RC2	R_3	125	R_2	98	22	1
9	RC2	R_3	124	R_2	99	8	1
10	RC2	R_3	124	R_2	99	144	515
11	RC2	R_3	124	R_2	100	110	574

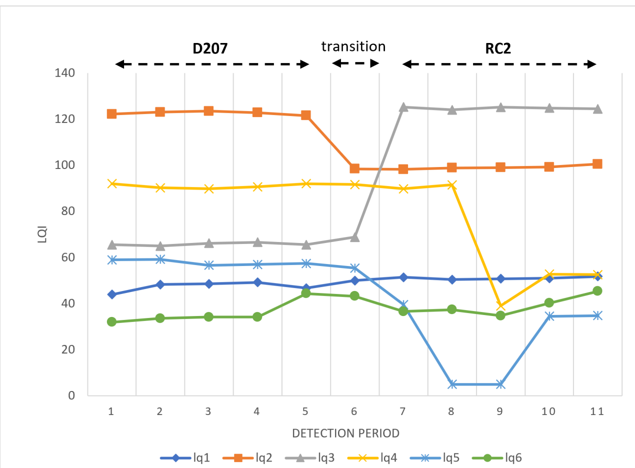


Figure 7. Average LQI changes from a moving user.

detected location from the room whose fingerprint has the closest distance of Eq. 1. In [9], the IEEE 802.15.4 devices were discussed to have fluctuation drawbacks especially when the distance between the transmitter and a particular receiver is quite far. At such time, packet loss is likely to occur and cause no LQI reception. Here, we use $r^i_j = 5$ as a constant when there is no packet is received at one receiver.

Consequently, *FILS15.4* faces greater challenges in accurately localizing the user's movements. False detection is likely to occur when a person remains in the same room but is detected in a different room and vice versa. This particular predicament arises as a result of the sudden shift in the dynamics of the LQI.

The determination of the direction of movement of the subject only based on accelerometer readings is not feasible. However, the significance of the movements can be assessed by examining the variance of the values along the three axes (x, y, z). The desired factor can be attained by calculating the magnitude of the accelerometer values, as denoted in Eq. 2.

$$accelero^i_j = \sqrt{|x^i_j|^2 + |y^i_j|^2 + |z^i_j|^2} \tag{2}$$

where x^i_j, y^i_j, and z^i_j represent the measured x, y, and z accelerometer values at receiver j, respectively.

Then, the variance of both *LQI* and $accelero^i_j$ between the two epochs is used to validate whether the user stays in the same room or moves to another room. To check the user's movement during the detection epoch, we apply a *value checker* algorithm as explained in algorithm 1.

When the user is moving in any direction, the accelerometer value should change over the course of a single detection interval. However, it is crucial to determine if the user is still in the same room or moved to a different room by comparing the present LQI with the previous one. The software should store the prior LQI value in order to facilitate comparison with the current LQI value.

Therefore, we define var_acc as the variation of $accelero_ji$ in one detection epoch with a threshold of 500. The variance of the Link Quality Indicator (*LQI*), denoted as $var_{r^i_j}$, is determined by calculating the variance between r^i_j and r^{i-1}_j. This calculation is used to identify any changes in the LQI values between two distinct detection epochs. A threshold value of 200 is employed in this analysis. Once the value of $var_{r_j^i}$ exceeds 200, the system subsequently verifies the value of var_{acc}.

Algorithm 1 Value checker

for i in the range of $30secs$. **do**
    Calculate r_j^i by averaging $i-th$ LQI at receiver j.
    Check r_j^{i-1}, previously detected LQI at receiver j
    if r_j^{i-1} exists **then**
        Calculate $var_{r_j^i}$ as the variance of r_j^{i-1} and r_j^i
        Calculate var_{acc} as the acc. var. in Eq. 2.
        if $var_{r_j^i} > 200$ **then**
            if $var_{acc} < 500$ & $r_j^i = 5$ **then**
                Packet loss may occur
                The user does not move.
                Grab previous detection result.
            else$var_{acc} > 500$
                User is moving to a different room.
                Detect current location with Euclid. dist.
            end if
        end if
        Detect current location with Euclid. dist.
    end if
end for

If the var_{acc} is smaller than 500 and the current r_j^i is equal to 5, it indicates that the user did not make any significant movement and packet loss may occur due to other factors (e.g. transmission failure) and although the user. In such condition, the system will not calculate the Euclidean distance and take the previously detected room as the output.

However, when the $var_{r_j^i}$ and the var_{acc} are both above the threshold, and the current LQI is not equal to 5, it suggests that the user is traveling to another room. Hence, the system will compute the present location utilizing the Euclidean distance. As the time it takes to travel between rooms varies proportionally to their distance, the system is unable to determine the current location. Despite potential inaccuracies in the detection outcome, the system will indicate the user's transition to a different room.

6. ASSESSMENT OF FILS15.4 IN PRACTICAL SCENARIOS

This section presents an evaluation of *FILS15.4* during dynamic conditions where users are carrying transmitters. During the experiment, users are allowed to move between rooms within the two-floor target area at the #2 Engineering Building of Okayama University.

A. Experiment Setup

The detection accuracy of *FILS15.4* under dynamic situations is evaluated using three cases where the number of receivers is varied, namely:

1. The received LQI from three receivers are used separately as the fingerprint on the same floor (receiver #1-3 for lower floor, and #4-6 for upper).
2. The received LQI from five receivers are used as the fingerprint on two-floor (receiver #1-5).
3. The received LQI from six receivers are used as the fingerprint on two-floor (receiver #1-6).

In cases 1 and 3, the total number of receivers are same. However, the fingerprint sets in case 1 consist of LQI from receivers located only on the same floor. Meanwhile, in cases 2 and 3, the fingerprint sets consist of LQI from receivers on both floors, the 2nd and the 3rd floor.

In the scenario, six users carry the transmitters and stay in the main rooms, namely D206, D207, D208, D306, D307, and D308. Those rooms are actually used for students and faculty members.

Each transmitter is attached to the user's *shoulder* and they are allowed to move naturally such as sit, stand, or move around within one room or to another room. The experiment is conducted over a duration of four hours and is subsequently replicated for a period of five consecutive days. A comparison is made between the detection accuracy of the three cases.

It is noted that the fingerprint database was generated under the stationary or *off-body* as in [12]. Thus, there is no need to generate a new fingerprint database specifically for dynamic cases (*on-body*). The fluctuation problem caused by the user's movement is expected to be overcome by the algorithm 1 which is explained in Figure 8.

B. Evaluation on Users Position

In a typical situation, during office hours, people would mostly spend their time working in a certain room. Thus, we assign six subjects to carry the transmitters and stay in six main rooms. Nevertheless, users may require breaks for personal necessities such as using the restroom, having a meal, preparing beverages at the refresh corner, or engaging in discussions in an alternate main room.

Table III shows the users' positions during the experiments. Most of the time, the users stayed in each assigned room and occasionally moved to other rooms such as Refresh Corner (RC), Toilet, or other main rooms through the Corridor. Based on the recorded duration of the experiment, the user required a time range of 3 to 12 seconds to move from one room to another room on the same level, while it takes 18 to 35 seconds to a different floor. These variation are based on the distance between the rooms.

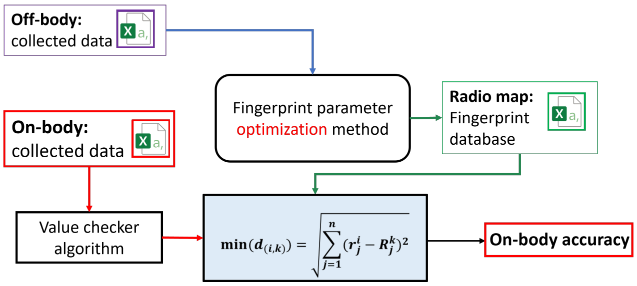


Figure 8. Dynamic user evaluation scenario.

Since the experiment was conducted over five days, table III shows a sample of room occupation in one out of five days of the experiment. Normally, users are less likely to stay in the corridor and the movement duration between rooms is mostly less than one detection epoch (30*seconds*). Thus, we intentionally add an additional 15 minutes for the users to stay in both corridors for the experiment.

C. Evaluation on Detection Accuracy in Dynamic Situations

The evaluation of the detection accuracy of *FILS15.4* was conducted with users wearing the transmitters on their shoulders. A total of six transmitters were utilized to collect data from six individuals. The quantity of receivers in the field adheres to the three scenarios elucidated in Section 6-A. Building upon the research conducted in [12], we conduct a comparative analysis of receiver usage in both single-floor and two-floor environments, specifically focusing on dynamic scenarios.

Table IV presents a comparison of the detection accuracy in three distinct scenarios based on the user locations given in Table III. We also analyze the detection accuracy with and without the *value checker* algorithm in Section 5-B. The algorithm is used to validate whether the user is moving to another room or not based on the variance of LQI and accelerometer.

First, the best detection accuracy in dynamic situations is shown when six receivers were simultaneously used in a two-floor environment (case 3). This result matched to our previous evaluation in [12] although it was under stationary *off-body* scenario.

Second, the system shows significant reliability by showing better detection accuracy when the variance of LQI and accelerometer are used to validate the user's movement. Without the *Value Checker* algorithm, any abrupt movements by users will cause LQI fluctuation and lead to false detections showed by 81.7% as the best detection accuracy by using six receivers simultaneously on two floors. The worst performance is shown when each floor uses three receivers separately with only 66.5% of average accuracy.

Meanwhile, when the *value checker* algorithm is used, the best performance shows significant improvements in every case. For case 3, the system yields its best at 96.0% of average accuracy. The detection accuracy was notably improved, even in rooms lacking receivers, specifically D206, D308, RC3, Corridor 3, and the Toilets on both floors.

7. CONCLUSION

This study undertook comprehensive experiments to evaluate the detection accuracy of *FILS15.4* in dynamic on-body settings. The transmitting sensor is affixed to several users while they are engaged in natural forms of movement, such as standing, sitting, or walking. The movements result in an increase in variations of the LQI within the detection epoch. The sudden fluctuations in LQI values undermined the accuracy of the detection. Hence, it is vital to distinguish the underlying reason for the change in LQI, particularly when the user is transitioning between different rooms.

Since the adopted device in *FILS15.4* has an accelerometer which detects any movement in *x, y, z* directions, it can be combined with the existing fingerprint-based localization algorithm. The variance of accelerometer values indicating the user's movement is combined with the variance of LQI to distinguish a condition when the user is moving to a different room or staying. The use of movement validation in the system for *dynamic scenario* resulted in a significant improvement in detection accuracy across all three scenarios when compared to the straightforward LQI-based fingerprint method. The system demonstrates optimal performance when six receivers are employed concurrently in a two-floor setting, resulting in an average detection accuracy of 96.2%. In contrast, traditional fingerprinting methods only achieve an accuracy of 81.7%.

In future works, we will extend the utilization of accelerometer for detecting seizure or fall. These development will be practical for monitoring elderly or people with disability who live or left unsupervised at home.

REFERENCES

[1] N. H. A. Wahab, N. Sunar, S. H. Ariffin, K. Y. Wong, Y. Aun *et al.*, "Indoor positioning system: A review," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 6, 2022.

[2] J. Kunhoth, A. Karkar, S. Al-Maadeed, and A. Al-Ali, "Indoor positioning and wayfinding systems: a survey," *Human-centric Computing and Information Sciences*, vol. 10, no. 1, pp. 1–41, 2020.

[3] B. Molina, E. Olivares, C. E. Palau, and M. Esteve, "A multimodal fingerprint-based indoor positioning system for airports," *Ieee Access*, vol. 6, pp. 10 092–10 106, 2018.

[4] A. M. S. Chong, B. C. Yeo, and W. S. Lim, "Automatic data acquisition system for wi-fi fingerprint-based indoor positioning system," *International Journal of Innovative Computing, Information and Control (IJICIC)*, vol. 18, no. 1, pp. 231–252, 2022.

[5] F. Liu, J. Liu, Y. Yin, W. Wang, D. Hu, P. Chen, and Q. Niu, "Survey on wifi-based indoor positioning techniques," *IET communications*, vol. 14, no. 9, pp. 1372–1383, 2020.

TABLE III. Users' position and movement during the experiment

user	time start	time finish	position	duration (h:mm)
A	14:10	15:34	D206	1:24
	15:34	15:36	Toilet2	0:02
	15:36	15:38	RC2	0:02
	15:38	16:20	D206	0:42
	16:20	16:22	D207	0:02
	16:22	16:24	Toilet2	0:02
	16:24	17:55	D206	1:31
	17:55	17:58	RC2	0:03
	17:58	18:10	D206	0:12
B	14:10	15:47	D207	1:37
	15:47	15:50	D208	0:03
	15:50	16:22	D207	0:32
	16:22	16:25	Toilet2	0:03
	16:25	17:58	D207	1:33
	17:58	18:02	Toilet2	0:04
	18:02	18:05	RC2	0:03
	18:05	18:10	D207	0:05
C	14:10	15:48	D207	1:38
	15:48	15:50	D207	0:02
	15:50	16:22	D208	0:32
	16:22	16:25	Toilet2	0:03
	16:25	17:58	D208	1:33
	17:58	18:02	Toilet2	0:04
	18:02	18:05	RC2	0:03
	18:05	18:10	D208	0:05

user	time start	time finish	position	duration (h:mm)
D	14:10	15:12	D306	1:02
	15:12	15:16	D207	0:04
	15:16	16:44	D306	1:28
	16:44	16:47	Toilet3	0:03
	16:47	17:20	D306	0:33
	17:20	17:25	RC3	0:05
	17:25	18:10	D306	0:45
E	14:10	14:15	D307	0:05
	14:15	14:20	RC3	0:05
	14:20	14:58	D307	0:38
	14:58	15:00	D207	0:02
	15:00	15:02	Toilet2	0:02
	15:02	16:11	D307	1:09
	16:11	16:25	D308	0:14
	16:25	17:03	D307	0:38
	17:03	17:06	Toilet3	0:03
	17:06	18:10	D307	1:04
F	14:10	15:34	D308	1:24
	15:34	15:37	Toilet3	0:03
	15:37	16:47	D308	1:10
	16:47	16:52	D307	0:05
	16:52	17:18	D308	0:26
	17:18	17:21	RC3	0:03
	17:21	18:10	D308	0:49

TABLE IV. Detection accuracy for on-body transmitter (dynamic).

room	detection accuracy (%)					
	no value checker			with value checker		
	case 1	case 2	case 3	case 1	case 2	case 3
D206	70.8	79.1	81.9	85.9	92.3	96.5
D207	64.3	78.3	81.5	84	94.5	95.5
D208	73.6	79.3	82.8	94.5	96.6	98.5
RC2	72.8	79.5	82.4	93.4	93.3	95.6
Toilet2	67.7	76.1	80.2	75.1	90.6	94.4
Corr2	64.4	76.9	81.3	93.3	93.9	95.5
D306	72.6	80.6	82.6	99	95.4	99.3
D307	71.2	78.5	82.3	95.7	98.2	98.3
D308	73.9	79.3	82.4	86.6	96.5	96.6
RC3	45.7	77.7	81.7	84.5	90.6	94.2
Toilet3	52.1	76.7	80.8	81.3	90.2	94.3
Corr3	70.1	78.2	81.0	94.2	93.2	96.2
Avg.	66.6	78.4	**81.7**	88.9	93.8	**96.2**

[6] W. H. Ali, A. A. Kareem, and M. Jasim, "Survey on wireless indoor positioning systems," *Cihan University-Erbil Scientific Journal*, vol. 3, no. 2, pp. 42–47, 2019.

[7] I. H. Alshami, N. A. Ahmad, S. Sahibuddin, and F. Firdaus, "Adaptive indoor positioning model based on wlan-fingerprinting for dynamic and multi-floor environments," *Sensors*, vol. 17, no. 8, p. 1789, 2017.

[8] M. Uradzinski, H. Guo, X. Liu, and M. Yu, "Advanced indoor positioning using zigbee wireless technology," *Wireless Personal Communications*, vol. 97, pp. 6509–6518, 2017.

[9] P. Puspitaningayu, N. Funabiki, Y. Huo, K. Hamazaki, M. Kuribayashi, and W.-C. Kao, "A fingerprint-based indoor localization system using ieee 802.15. 4 for staying room detection," *International Journal of Mobile Computing and Multimedia Communications (IJMCMC)*, vol. 13, no. 1, pp. 1–21, 2022.

[10] Mono Wireless, "TWELITE CUE - Mono Wireless," https://mono-wireless.com/jp/products/twelite-cue/index.html, PublicationYear, [Online; accessed August, 2022].

[11] A. Booranawong, K. Sengchuai, and N. Jindapetch, "Implementation and test of an rssi-based indoor target localization system: Human movement effects on the accuracy," *Measurement*, vol. 133, pp. 370–382, 2019.

[12] P. Puspitaningayu, N. Funabiki, Y. Huo, Y. Panduman, X. Wu, M. Kuribayashi, and W.-C. Kao, "Accuracy investigations of fingerprint-based indoor localization system using ieee 802.15.4 in two-floor environment," in *2022 Fifth International Conference on Vocational Education and Electrical Engineering (ICVEE)*, 2022, pp. 89–94.

[13] R. A.-H. Hani Muhsen, Odeh Al-Amaydeh, "Algorithm Design for Accurate Steps Counting Based on Smartphone Sensors for Indoor Applications," *Advances in Science, Technology and Engineering Systems Journal*, vol. 5, no. 6, pp. 811–816, 2020.

[14] L. Luoh, "Zigbee-based intelligent indoor positioning system soft computing," *Soft Computing*, vol. 18, pp. 443–456, 2014.

[15] M. Uradzinski, H. Guo, X. Liu, and M. Yu, "Advanced indoor positioning using zigbee wireless technology," *Wireless Personal Communications*, vol. 97, pp. 6509–6518, 2017.

[16] E. S. Pino, C. Montez, O. T. Valle, E. Leão, and R. Moraes, "An indoor positioning system using scene analysis in ieee 802.15.4 networks," in *IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society*, vol. 1, 2019, pp. 2817–2822.

[17] M. A. Al Mamun, D. Vera Anaya, F. Wu, J.-M. Redouté, and M. R. Yuce, "Radio map building with ieee 802.15.4 for indoor localization applications," in *2019 IEEE International Conference on Industrial Technology (ICIT)*, 2019, pp. 181–186.

[18] A. Booranawong, K. Sengchuai, D. Buranapanichkit, N. Jindapetch, and H. Saito, "Rssi-based indoor localization using multi-lateration with zone selection and virtual position-based compensation methods," *IEEE Access*, vol. 9, pp. 46 223–46 239, 2021.

[19] M. S. Daniel Bin Wahab, A. Kiring, L. Barukang, H. T. Yew, Y. Y. Farm, and S. K. Chung, "Ieee 802.15.4 signal strength evaluation in an indoor environment for positioning applications," in *2023 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, 2023, pp. 325–330.

[20] S. Farahani, "Chapter 3 - zigbee and ieee 802.15.4 protocol layers," in *ZigBee Wireless Networks and Transceivers*, S. Farahani, Ed. Burlington: Newnes, 2008, pp. 33–135. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780750683937000030

[21] Mono-Wireless, "Estimation of electric field strength [dbm] from lqi value," https://mono-wireless.com/jp/tech/Programming/Tips_LQI.html, accessed January, 2020.

[22] M. B. Yassein, M. Q. Shatnawi, S. Aljwarneh, and R. Al-Hatmi, "Internet of things: Survey and open issues of mqtt protocol," in *2017 International Conference on Engineering MIS (ICEMIS)*, 2017, pp. 1–6.

[23] K. Mekki, E. Bajic, and F. Meyer, "Indoor positioning system for iot device based on ble technology and mqtt protocol," in *2019 IEEE 5th World Forum on Internet of Things (WF-IoT)*. IEEE, 2019, pp. 787–792.

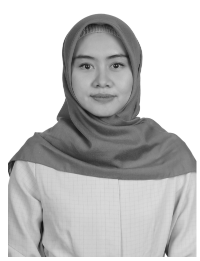
[24] Y. Y. F. Panduman, N. Funabiki, P. Puspitaningayu, M. Kuribayashi, S. Sukaridhoto, and W.-C. Kao, "Design and implementation of semar iot server platform with applications," *Sensors*, vol. 22, no. 17, p. 6436, 2022.

[25] Y. Huo, P. Puspitaningayu, N. Funabiki, K. Hamazaki, M. Kuribayashi, and K. Kojima, "A proposal of the fingerprint optimization method for the fingerprint-based indoor localization system with ieee 802.15.4 devices," *Information*, vol. 13, no. 5, p. 211, 2022.

[26] A. Bensky, *Short-Range Wireless Communication: Fundamentals of RF System Design and Application*, 3rd ed. Newnes, 2019.

[27] S. Hara, D. Zhao, K. Yanagihara, J. Taketsugu, K.-i. Fukui, S. Fukunaga, and K. Kitayama, "Propagation characteristics of IEEE 802.15.4 radio signal and their application for location estimation," in *Proceedings of the IEEE Vehicular Technology Conference*, 2005, pp. 97–101.

[28] J. S. C. Turner, M. F. Ramli, L. M. Kamarudin, A. Zakaria, A. Y. M. Shaka, D. L. Ndzi, C. M. Nor, N. Hassan, and S. M. Mamduh, "The study of human movement effect on signal strength for indoor WSN deployment," in *Proceedings of the International Conference on Wireless and Signal Processing (ICWiSe)*, Dec. 2013, pp. 30–35.



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