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Research Article

RoC: Robust and Low-Complexity Wireless Indoor Positioning Systems for Multifloor Buildings Using Location Fingerprinting Techniques

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Most existing wireless indoor positioning systems have only success performance requirements in normal operating situations whereby all wireless equipment works properly. There remains a lack of system reliability that can support emergency situations when there are some reference node failures, such as in earthquake and fire scenarios. Additionally, most systems do not incorporate environmental information such as temperature and relative humidity level into the process of determining the location of objects inside the building. To address these gaps, we propose a novel integrated framework for wireless indoor positioning systems based on a location fingerprinting technique which is called the Robust and low Complexity indoor positioning systems framework (RoC framework). Our proposed integrated framework consists of two essential indoor positioning processes: the system design process and the localization process. The RoC framework aims to achieve robustness in the system design structure and reliability of the target location during the online estimation phase either under a normal situation or when some reference nodes (RNs) have failed. The availability of low-cost temperature and relative humidity sensors can provide additional information for the location fingerprinting technique and thereby reduce location estimation complexity by including this additional information. Experimental results and comparative performance evaluation revealed that the RoC framework can achieve robustness in terms of the system design structure, whereby it was able to provide the highest positioning performance in either *fault-free* or *RN-failure scenarios*. Moreover, in the online estimation phase, the proposed framework can provide the highest reliability of the target location under the RN-failure scenarios and also yields the lowest computational complexity in online searching compared to other techniques. Specifically, when compared to the traditional weighted k-nearest neighbor techniques (WKNN) under the 30% RN-failure scenario at Building B, the proposed RoC framework shows 74.1% better accuracy performance and yields 55.1% lower computational time than the WKNN.

1. Introduction

Indoor positioning systems (IPSs) refer to wireless network infrastructure systems that provide location information to any requesting user inside an indoor operating area such as airports, shopping centers, and hospitals. These systems are currently experiencing a tremendous growth and becoming a vital part of life in the digital age [1]. The use of unlicensed frequency spectrum ranges and inexpensive wireless communication technologies has facilitated the deployment of IPSs [2]. They can be applied to various domains including for indoor navigation and tracking in the health-care sector, in industrial areas, and at trade fairs [3, 4]. However, most of these IPSs only have success performance requirements under normal operating situations whereby all of the wireless equipment works properly. There remains a lack of system reliability that can perform in rescue situations, such as localization that supports rescuers in an earthquake scenario or firefighters in a fire situation. Under these emergency situations, some wireless network equipment (i.e., reference nodes) may fail due to some parts of the building being damaged. Therefore, the key performance requirement of the IPS under such node-failure situations is the reliability of the estimated target locations under either a normal situation or when some reference nodes (RNs) have failed. Moreover, under such unexpected situations, the computational complexity during the online searching process is an important performance requirement for the IPSs.

The general indoor positioning approaches can be divided into three groups: Triangulation, Proximity, and Scene Analysis [5]. First, Triangulation uses the geometric characteristics of triangles to estimate the target location. It has two types, namely, lateration and angulation. The lateration method determines the position of a target by using the relationship of distances between various transmitters and receivers. The accuracy performance of the lateration method depends on the precise time synchronization of all transmitters and receivers. Thus, lateration requires the high cooperation and synchronization of all devices in the system [2, 3]. Examples of IPSs based on the lateration approach are Time of Arrival (TOA) and Time Difference of Arrival (TDOA). Another technique that is based on Triangulation is angulation. This technique estimates the position of an object by exploiting the relationships of angle direction lines between the transmitter and receiver. The angulation method can estimate the position of a target in a three-dimensional (3D) coordinate system, in which no time synchronization between transmitter and receiver is required. However, it requires complex antenna hardware to measure the angle of incidence. Moreover, the precision of the angle measurement may be limited by the multipath effect and the non-line-of-sight (NLOS) propagation of signals [2, 3]. An example of an IPS based on the angulation approach is Angle of Arrival (AOA).

Second, Proximity is a simple indoor positioning approach that provides symbolic relative location information. This approach is relatively simple to implement and requires low complexity hardware. Proximity is often used in the IPSs that deploy Radio Frequency Identification (RFID) technology. However, this method provides the lowest accuracy performance of these three mentioned approaches. It can only identify the approximate position of the target by successfully communicating with one or more transceivers [4, 6]. The proximity is often applied in specific applications such as the exhibitor check-in process and information advertising for visitors in a museum [2, 4].

Third, Scene Analysis uses the characterization of an indoor radio propagation that is associated with the particular location. This technique requires a calibration training phase called the offline calibration phase to compile a radio map (e.g., the location fingerprinting) of the service area, before the indoor positioning algorithm is used to determine the estimated location during the online estimation phase. The advantage of this technique is that it is simple to deploy with no specialized hardware required. It can employ various wireless technologies such as Wireless Local Area Network (WLAN) and Bluetooth Low Energy (BLE). Moreover, this technique can provide high accuracy and precision performance without being affected by multipath fading and shadowing. However, the drawback of this technique is that it is very time-consuming to perform the exhaustive data collection for a wide operation area [1, 2, 7]. Examples of IPSs that are based on Scene Analysis are the probabilistic, neural networks, and location fingerprinting (i.e., Euclidean distance technique).

From the property aspects of those three indoor positioning approaches, in this article, we focus on the development of IPSs based on Scene Analysis, in which the location fingerprinting technique is considered. This technique is simple to implement and does not require specialized hardware with no time synchronization necessary between transmitter and receiver. Moreover, it may be implemented in the software format which can reduce the complexity and cost significantly compared to the lateration and angulation methods [2, 7]. We employ the IEEE 802.15.4 wireless sensor networks (WSNs) with ZigBee. They are lightweight devices with ultra-low power consumption that can detect several environmental parameters such as temperature and relative humidity [8]. In this paper, we also exploit the association of environmental data, which are the temperature and the relative humidity, as a part of Scene Analysis that can be used to coarsely separate the area of location for an object.

According to the literature reviewed in Section 2, to fulfill the gaps and to extend the ability of the IPSs under unexpected situations (e.g., earthquake and fire situations), reliable estimated target locations and a short time to estimate them are required. Thus, in this article, we propose a novel integrated framework for the IPSs based on the location fingerprinting technique which is called the Robust and low Complexity indoor positioning systems framework (RoC framework). The RoC framework consists of two essential indoor positioning processes: the system design process and the localization process. Our proposed framework can achieve the robustness of the system in terms of the system design structure and the reliability of the target location in the localization process. In particular, the RoC framework can provide low computational complexity during the online searching time without compromising the positioning accuracy. The major contributions of our integrated framework include the following:

(1) Development of a robust system design that is provisioned to support RN-failure situations

(2) Development of a robust floor determination algorithm that can efficiently work under RN-failure situations

(3) Reduction of computational complexity during the location estimation process by using temperature-level classification

(4) Development of a novel Active Euclidean distance approach that can solve the missing received signal strength (RSS) problem

The remaining organization of this article is as follows. First, Section 2 summarizes and compares related works on design with robustness and low complexity of the IPSs. Second, we describe our proposed RoC framework for the IPSs in Section 3. Third, Section 4 explains about the experimental environment, the hardware specifications used for data collection, and the setup parameters used in this work. Fourth, the experimental results are presented and discussed in Section 5. Finally, Section 6 concludes the performance achievement of our proposed framework and future research plan.

2. Related Works

Similar to any information technology systems, the development and deployment of wireless indoor positioning system (IPS) can be divided into two processes: the system design process and the localization process. First, in the system design process, a system designer has to gather all necessary requirements such as dimension of the building and determine various wireless network parameters that will affect the performance of the IPS. To ensure a required performance or design goal for the IPS, a well-designed methodology is indeed the essential process. For instance, the required number and placement of reference nodes (RNs) must be determined based on predefined criteria during this process. Second, after the system is successfully installed, the IPS can be used to estimate any target locations in the localization process. Using localization algorithms in this second process, the physical environmental information such as received signal strength information (RSSI) or time of arrival (TOA) measured at the target is analyzed to calculate its position on a coordinate system. Note that the localization process for location fingerprinting approach is further divided into offline calibration phase and online estimation phase. The offline calibration phase is when the location fingerprints are collected to create a location fingerprinting database, while the online estimation phase is when the location determination is actually performed by comparing or matching the location fingerprinting database with the current location pattern such as RSSI pattern of the target.

To ensure the success performance requirements of the IPS based on the location fingerprinting approach, an effective framework that can achieve the consistent relationship between the system design process and the localization process is required. On the other hand, the positioning performance of the system might be dropped if both processes do not have a consistent relationship with each other. For example, the main objective of the node placement design for Triangulation is to place a sufficient number of RNs in optimum locations so that the signal test points (STPs) must be able to receive signals from at least *three* RNs installed in the service area [2]. They are different from the structure design for Scene Analysis (e.g., the location fingerprinting technique), which need as many received signals as possible to make a location estimate. For the Scene Analysis structure design, the STPs must be able to receive signals from at least *four* RNs installed inside the service area to handle the symmetrical RSS problem [9].

For the system design, existing research in the literature has focused on different performance requirements of the system design. The authors of [10–12] presented the system design structure for the IPSs based on Triangulation. They focused on the improvement of the positioning performance under a limited number of RNs and minimizing the number of RNs. Redondi et al. [10] proposed an RN-placement method for the IPSs based on the Cramer–Rao lower bound (CRLB) approach. Their design goal was to minimize localization errors when operating with a limited number of RNs due to fixed budget constraints. Merkel et al. [11] presented an optimal RN-placement approach for the IPSs based on distributed range-free localization. Achieving the optimal coverage of a certain area while simultaneously minimizing the necessary number of RNs was their focus. Tong et al. [12] proposed an optimum RN placement for the TOA technique by minimizing the Cramer–Rao Bound (CRB) of localization error. The objective of their system design was to achieve the highest localization accuracy when the reference nodes have uniform angular distribution around the service area.

The authors of [13–16] presented their RN-placement design for the IPSs based on Scene Analysis such as the location fingerprinting techniques. They focused on the performance requirements including the reduction of data redundancy and the guarantee of signal coverage. To obtain better location accuracy, Sharma et al. [13] developed an RN-placement method that attempts to minimize the total number of similar fingerprints (SFs). Fang and Lin [14] proposed a framework for relating the positioning performance with the RN placement. To achieve their design objective, their algorithm determined a suitable set of RN locations such at the signal-to-noise ratio (SNR) was maximized. Chen et al. [15] proposed a novel RN-placement algorithm for the IPSs based on the location fingerprinting technique. They focused on maximizing the fingerprint difference (FD) while still guaranteeing the coverage requirement by using the least number of APs. Kondee et al. [16] proposed a novel RN-placement technique using the Binary Integer Linear Programming (BILP) approach to design efficient wireless indoor positioning systems based on the location fingerprinting technique. The main goal of their system design was to install the RNs and improve the location determination performance for a single-floor area and the multifloor building.

In the existing system design literature, most research focused on the IPS performance requirements, including minimizing the number of installed RNs, guaranteeing radio signal coverage requirements in the service area, and minimizing the total number of similar fingerprint locations. A system design for robust IPSs that supports the RN-failure scenario caused by hardware failures or software errors has only been investigated once in our previous work in [17] but not in any other existing literatures. Additionally, physical environment parameters such as temperature and relative humidity inside buildings were not exploited for IPSs. Based on these knowledge gaps, the design of RN placement for robust IPSs and the utilization of temperature and humidity data to improve localization are still open research issues. Therefore, first, in the system design process, we propose a robust system design model for wireless indoor positioning systems based on location fingerprinting techniques. Our proposed model aims to place a suitable number of RNs and to determine their locations whereby their placement is provisioned to support robust system operation both during a normal situation and when some RNs have failed. Table 1 shows a summary of system design approaches for indoor positioning systems.

Table 1: Recent system design approaches for indoor positioning systems.

Category	Scheme	Localization algorithm	Optimization method	Design objectives	Design limitations	Service areas	Robustness (support in RN-failure situation)
Triangulation	[10]	RSS-based	Tabu search	To minimize localization error	The design does not consider minimizing the number of RNs	Single floor	No
	[11]	Distance-based	Genetic Algorithm	To maximize signal coverage and minimize number of RNs	The selected fitness evaluation influences the localization results	Single floor	No
	[12]	TOA	—	To minimize localization error	The RN placement has only a uniform angular distribution	Single floor	No
Scene analysis	[13]	KNN	Simulated Annealing	To minimize total number of similar fingerprints	The dynamic nature of the indoor environment is not considered in the system design	Single floor	No
	[14]	WKNN	—	To maximize signal RSS and minimize noise	The design does not consider the signal coverage in the physical surroundings	Single floor	No
	[15]	KNN	Simulated Annealing	To maximize fingerprint difference	Complicated indoor layouts influence the minimum number of RNs	Single floor	No
	[16]	Euclidean distance	Simulated Annealing	To maximize summation of maximum RSS	The RN placement design lacks system reliability	Single-floor and multifloor	No
	Proposed design	Active Fusion	Simulated Annealing	To minimize number of RNs and find their optimum locations to be provisioned to support RN-failure situations	The design considers only the discrete candidate sites for installing RNs	Single floor and multifloor	Yes

Next, in the localization process, we investigate the existing indoor positioning research that has focused on robust localization estimation algorithms. The authors of [18, 19] presented robust floor determination algorithms that considered the movement of objects across the floors. Gupta et al. [18] studied robots moving between floors by using incorporative information from the pressure sensor and the Wi-Fi access points (APs). Their floor determination algorithm is based on the RSS received from the APs that utilize a Maximum Likelihood (ML) to estimate the floor location of the robots. Lee and Park [19] presented a technique to estimate the robot position in each floor by using gyroscopes to recognize the robot motion status on the stairs. The authors of [20–23] presented robust and reliability positioning techniques for the IPSs based on Scene Analysis. They focused on handling the problems of different mobile devices and reducing the impact of environmental dynamics on the accuracy performance. He et al. [20] studied the problem of indoor localization in the case of equipment heterogeneity and an indoor dynamic environment. They proposed a Hierarchical Edit Distance (HED) algorithm based on the location fingerprinting technique. This algorithm can improve the robustness of systems under various environment dynamics and different factors of the target device such as Wi-Fi chipsets. Zayets and Steinbach [21] proposed a novel location fingerprinting technique which operates by extracting and analyzing individual multipath propagation delays. They presented the localization algorithm based on the Multipath Component Analysis (MCA) to be robust against changes in the environment. Taniuchi and Maekawa [22] proposed a new Wi-Fi indoor positioning algorithm by which the system can be robust over unstable Wi-Fi APs. Their algorithm was based on the location fingerprinting technique that used the ensemble learning approaches to handle the problems of Wi-Fi positioning caused by unstable and uncontrollable infrastructure such as the movement of people. Guan et al. [23] presented a localization algorithm that reduces the influence of symmetry by considering extrarestrictions from redundant APs. They used a novel clustering method to robustly estimate the target location from the fingerprint location candidates.

According to the literature reviewed on the robust localization process, although some existing works have studied the robust and reliable location problem [18–23], they focused on robustness issues, including robust tracking of floor changes when the robots moved in the staircase, improving the robustness of dynamic changes to the indoor environment which lead to the instability of fingerprint information, and reducing the influence of different mobile devices. In particular, they did not consider the robustness in terms of faulty RNs during the online estimation phase. Thus, in the localization process, we propose a fault tolerance positioning algorithm that can overcome the problem of RN failures. The contributions of our proposed robust positioning algorithm include both the robust floor determination algorithm and the robust location estimation (x, y).

Other existing IPS research focused on improving the time complexity performance. The authors of [24–27] presented a recent research on the development of the indoor positioning performance in terms of computational complexity for Scene Analysis. Xue et al. [24] proposed an improved neighboring fingerprint location selection method for Wi-Fi indoor localization. They proposed a clustering algorithm based on k-means to classify the nearest neighboring fingerprint location according to its physical distance to the test point. Zhou and Van [25] proposed a location fingerprinting algorithm based on fuzzy c-means (FCM) clustering. Their algorithm employs offline clustering to reduce the online computational complexity of the matching process. Lee et al. [26] proposed a novel Support Vector Machine based Clustering (SVM-C) approach for the large database searching problem. Their proposed algorithm was further able to reduce the mean localization errors and reduce the computational complexity of location estimation. Saha and Sadhukhan [27] presented a novel hierarchical clustering strategy for the location fingerprinting technique that would reduce the searching time in the online estimation phase. Their proposed clustering strategy selects an appropriate cluster in the localization process based on the descending order of APs having the strongest signal strength in the observed RSS vector.

According to the literature reviewed on the development of computational complexity for the IPSs based on location fingerprinting techniques, recent works have aimed at improving overhead searching during the online estimation phase by using a classification approach. They have utilized effective cluster analysis, such as FCM, SVM-C, k-means clustering, and hierarchical clustering. However, their computational complexity approaches could take a long time to search for the closest location solution, in which the worst-case complexity of their clustering algorithms are $O(ndc^2)$, $O(n^3)$, $O(ndc)$, and $O(n^3)$ [28, 29], respectively, where n refers to the number of data points, d represents the number of dimensions, and c represents the number of clusters. Note that we consider the worst-case complexity during the online estimation phase, which is the maximal complexity of the algorithm over all possible inputs. Thus, in this article, we present a low-complexity algorithm based on the classification approach to reduce online searching time without compromising the positioning accuracy. Our proposed clustering algorithm utilizes a temperature-level filter based on a binary search algorithm. The time complexity of the proposed algorithm was lower than those four existing clustering algorithms, in which our algorithm has the worst-case complexity of $O(\log n)$ [29]. Table 2 shows different indoor positioning systems considering robustness and complexity.

In summary, we developed an integrated framework for the IPSs based on a location fingerprinting approach called the RoC framework. The proposed framework consists of two main processes, the system design process and the localization process. The proposed framework is developed to provide robustness in terms of the system design structure, both during a normal situation and when some RNs fail. Moreover, in the online estimation phase, we have developed the framework to be able to achieve the reliability of the target location under the RN-failure scenarios and provide low-computational complexity using additional temperature and relative humidity data. Furthermore, our proposed framework can be applied to various service area structures ranging from single-floor to multiple-floor environments.

3. Development of Indoor Positioning Systems

In this section, we describe our RoC framework for the IPSs based on location fingerprinting techniques. First, in Section 3.1, an overview of the RoC framework for wireless indoor multifloor positioning systems is described. Then, in Section 3.2, the development of the system design process is explained. Finally, in Section 3.3, the localization process of our proposed framework is described.

3.1. An Overview of RoC Framework for Wireless Indoor Positioning Systems. Figure 1 shows an overview of the RoC framework for the IPSs based on the location fingerprinting techniques, including the system design process and the localization process. Figure 1(a) represents the first process of the framework as the system design process. This process starts with the design of the wireless network infrastructure in which the RNs are the wireless nodes of the network. The aims of the process are to put in place a suitable number of RNs and to determine their optimum locations. Note that the RN's locations may be on a single floor or on multiple floors. In particular, the proposed system designs provisions to support robust operation, both during a normal situation and when there are some RN failures (which will be discussed in Section 3.2). Note that this part of the framework was originally presented in detail in our previous work [17]. Figure 1(b) represents the second process of the RoC framework as the localization process based on location fingerprinting techniques. This process is divided into two phases: the offline calibration phase and the online estimation phase. During the offline calibration phase, each fingerprint location (i.e., represented by the points on a map) records the physical environment of the service area into the fingerprint database. In this article, we use three aspects of physical environment information for creating the database. These aspects consist of the RSS values received from each RN, the temperature value, and the relative humidity value. Note that in [17], only RSS values were considered. Both the temperature value and the relative humidity value are used to classify the similar physical environments of each subarea, which are called the temperature level (TEMP level) (which will be discussed in Section 3.3.1). During the online estimation phase, whenever there is a request for a target location, the mobile target will measure the three environment

Table 2: Different indoor positioning systems considering robustness and complexity.

Category	Scheme	Focus on	Location results	Localization algorithm	Robustness	Complexity	Additional sensor
—	[18]	Robustness	Floor	ML	The algorithm provides robustness in terms of the movement of objects across the floors	Low	Pressure sensor
—	[19]	Robustness	Floor	Particle filter	The algorithm provides robust tracking of floor changing when the robots moved in the staircase	High	Gyroscopes
Scene analysis	[20]	Robustness	x, y	HED	The system can provide the robustness of systems under the environment dynamics	Medium	—
	[21]	Robustness	x, y	MCA	The algorithm is can tolerate against changes in the environment	Medium	—
	[22]	Robustness	x, y	Ensemble learning	The system can handle the problems of the Wi-fi positioning caused by the unstable infrastructure	High	—
	[23]	Robustness	x, y	Probabilistic based	The algorithm can reduce the influence of symmetry RSS signal	Low	—
	[24]	Complexity	x, y	k-means	—	Medium	—
	[25]	Complexity	x, y	FCM	The algorithm can classify the data into clusters which are robust to the multipath effect	Medium	—
	[26]	Complexity	x, y	SVM-C	—	High	—
	[27]	Complexity	x, y	Hierarchical clustering	The strategy is more robust in highly fluctuating RSS measurements	High	—
	Proposed algorithm	Robustness and complexity	x, y, floor	RMoS floor + Active Fusion	The algorithm can overcome the problem of RN failures	Low	Temp. and humid. sensor

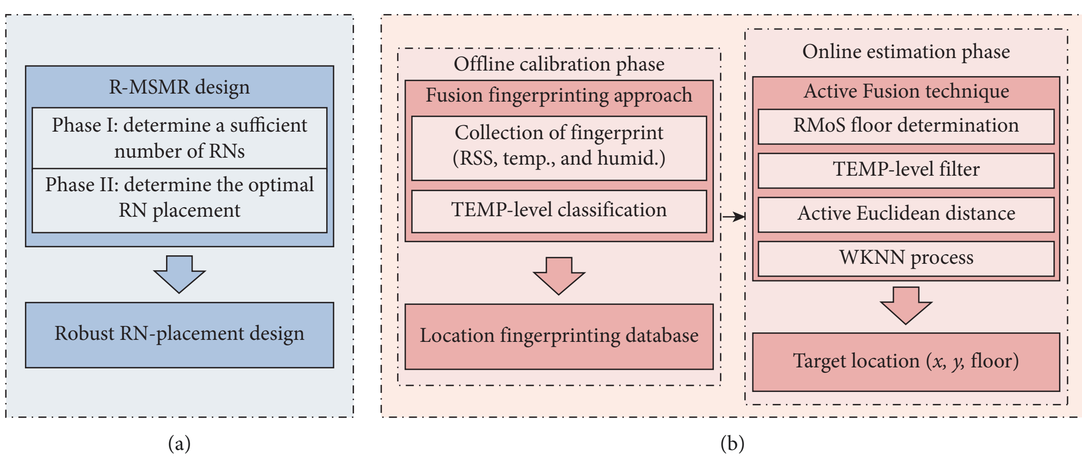

Figure 1: An overview of the RoC framework for the IPSs based on location fingerprinting techniques. (a) System design process. (b) Localization process.

parameters and use this online information to calculate the target location by using four processes of online estimation phase (which will be discussed Section 3.3.2).

3.2. System Design Process. In wireless IPS designs, the insufficient placement of RNs can cause an accuracy performance degradation. Furthermore, the system may achieve less than half of its intended performance levels during the online estimation phase in the event of RN failures [30]. The RoC framework recognizes the reliability requirement of the IPSs and implements a system design method that can sustain situations of signal unavailability due to RN failure. In the first process, the Robust-Maximum Summation of Max RSSI (R-MSMR) developed previously in our mathematical model in [17] is incorporated into the framework. Our system design uses a Binary Integer Linear Programming (BILP) approach, which employs the Simulated Annealing (SA) solution technique, to place a sufficient number of RNs in optimum locations. The design goal of this RN's placement is to achieve a maximizing summation of the maximum RSS at the signal test points (STPs) received from the RNs installed in the service area, as written in equation (1). We will show in Section 5 that our proposed system design can achieve the highest location accuracy during a normal situation and also yields reliable location estimated results under unexpected situations such as RN failures, where S_{ij} refers to a binary $\{0, 1\}$ variable that equals 1 if the STP i is assigned to RN j, P_{ij} refers to the RSS that STP i receives from RN j, T refers to a set of signal test points, and B represents a set of candidate sites.

$$\text{Maximize} \sum_{\forall i \in T} \max_{\forall j \in B} \left(S_{ij} P_{ij} \right). \tag{1}$$

The operation of the R-MSMR design is divided into two phases as shown in Figure 1. Phase I is used to create a good starting solution that defines a sufficient number of RNs to be installed (N_s). In this phase, a set of signal test points (STPs) and a set of candidate sites for installing RNs are assigned as shown in Figure 2(a). An initial number of RNs, which is a minimum starting number of RNs to be installed, is calculated based on the dimension of the service area as shown in Figure 2(b). The initial location of the RNs will be determined by this starting number. Then, the process is repeated until the set of optimization constraints is satisfied. After that, a solution that can provide a sufficient number of RNs is obtained.

In Phase II, the SA approach is used to determine the optimal location of the RNs based on the number of RNs obtained from Phase I. In each iteration, the move operation (in terms of optimization procedure) is used to generate a new possible solution (called a neighbor solution), in which specific attributes of the current solution are modified as shown in Figure 3(a). The cost of each RN-placement solution as the evaluation function for the reliability of the RN-placement structure is calculated in this phase. Then, the process of Phase II continues until a stopping condition is reached. Finally, a robust RN placement solution for the IPSs is attained. Figure 3(b) depicts an example of the RN-placement solution obtained from the proposed R-MSMR design. More details and explanations about the operation of R-MSMR design can be found in [17].

3.3. Localization Process. In the second process, the two main operations of the IPSs based on location fingerprinting techniques are conducted: the offline calibration phase and the online estimation phase. The offline calibration and the online estimation phases are explained in detail as follows.

3.3.1. Offline Calibration Phase. In the offline calibration phase, the fingerprint database is collected by performing a site-survey of the physical environment information inside the service area. In this article, we use the Fusion location fingerprinting approach which has been developed from our previous work [31]. Unlike the traditional location fingerprinting approach, we utilize the combination of three physical environmental parameters to create the information of the fingerprint locations in the database. For each fingerprint location, we record three physical parameters simultaneously, which include the RSS vector, the temperature value, and the relative humidity value. To the best of our knowledge, there is no other research in the literature that utilizes temperature and humidity information in IPSs. After taking those measurements, the TEMP-level classification is conducted, in which the temperature value (in degrees Celsius) and the relative humidity value (in percentage) are used to classify the similar physical environments into subareas as zones. After that, the TEMP level of each fingerprint location is recorded into the database [31]. Note that the information of each fingerprint location consists of the location coordinates (x, y), the floor number (*floor*), the TEMP level, and the RSS vector received from the RNs.

Figure 4 illustrates an example of the proposed Fusion location fingerprinting approach in which information of the temperature and the relative humidity are used to classify each fingerprint location in the database. The different colors of the points on the map represent different TEMP levels that are obtained from the TEMP-level classification process. The TEMP-level classification is a classification algorithm based on behavioral observation information of the temperature and the relative humidity recorded from the actual environment. Therefore, the site-survey of the physical environmental information inside the actual service area needs to be calibrated before starting the offline calibration phase. Note that we define the lost RSS observation only during the offline calibration phase with the lowest sensitivity of the wireless transceiver (i.e., −110 dBm).

3.3.2. Online Estimation Phase. In this phase, the indoor positioning technique is used to estimate the target position inside the building. We present the online estimation technique that uses a distance based approach (i.e., Euclidean distance). The proposed positioning technique is called the Active Fusion technique, in which the procedure consists of four steps: the floor determination process, the TEMP-level filter, the Active Euclidean process, and the WKNN process. The descriptions of each online estimation step are as follows.

(1) Floor Determination Process. The first step of the online estimation phase is to determine the floor number on which the target node is located. We use the robust floor determination algorithm called the Robust Mean of Sum-RSS (RMoS) floor algorithm, which was developed in our previous works [32, 33]. The RMoS floor algorithm can accurately determine the floor on which the target nodes are located and can work under either the fault-free scenario or the RN-failure scenarios. The proposed floor algorithm is based on the mean of the summation of the strongest RSSs obtained. Then, the algorithm selects the floor number that has the highest value of the confidence intervals $(\Phi(\Lambda_f))$ as the floor where the target node is situated. Where Λ_f refers to a set of the summations of the strongest RSSs on the f^{th} floor. This can be written as

$$\text{floor} = \arg\max_{f} \left(\Phi \left(\Lambda_f \right) \right). \tag{2}$$

Figure 5(a) shows an example of the structure of the IPS in a three-story building under the RN-failure scenario. In this figure, one RN on the 1st floor and another RN on the 2nd floor became unavailable. Under this situation, the percentage of correct floor determination of other existing

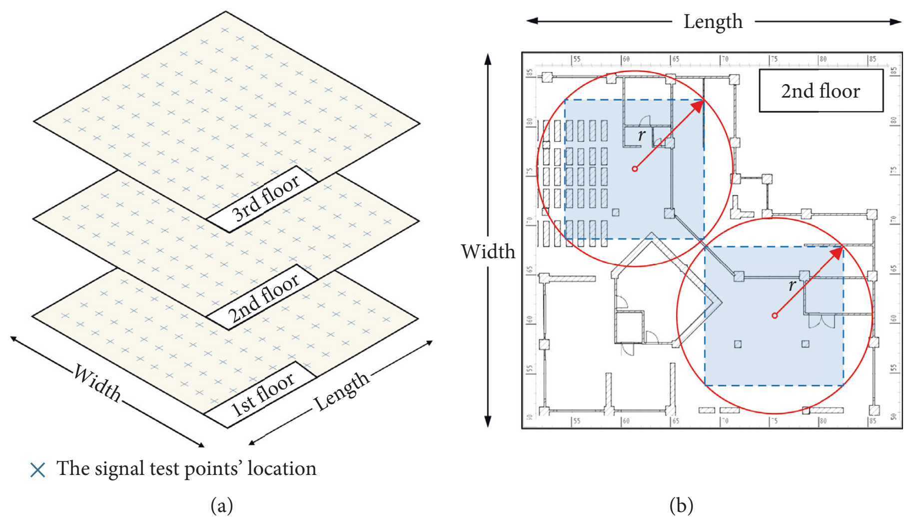

FIGURE 2: An example of R-MSMR design in Phase I. (a) A three-story structure with the location of the assigned STPs. (b) Example of coverage square estimating an RN's coverage area.

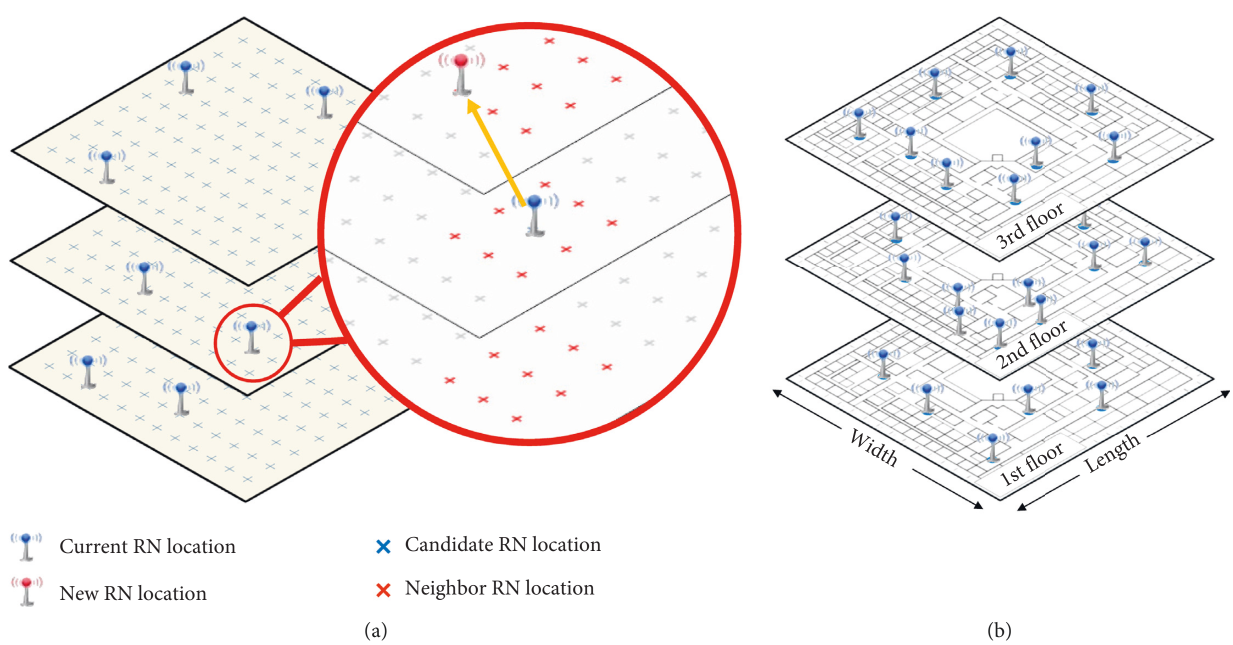

FIGURE 3: An example of R-MSMR design in Phase II. (a) Example of move operation in SA process. (b) An example result of R-MSMR placement design.

floor algorithms could drop from 20% to 50% when two-RNs fail in the system [32]. Unlike other existing floor algorithms, the RMoS floor algorithm can achieve reliable indoor multifloor positioning systems that can provide 100% correct floor determination under such unexpected situations. Figure 5(b) illustrates a 95% confidence interval for the mean of the RSS summations on each floor in a three-story building. It is clear that the confidence interval for the mean of the RSS summations on the actual floor where the target node was located is higher than that of the other floors (i.e., $\Phi(\Lambda_2)$). In this case, the proposed RMoS floor algorithm correctly reports that the target node is on the second floor of the building. Detailed descriptions of the RMoS floor algorithm can be found in [33].

(2) TEMP-Level Filter. The main goal of this second step is to filter the fingerprint locations in the database by using the classification approach. The system will search and select the related fingerprint locations in the database that have the same TEMP level as those on the floor on which the target was located (i.e., the result from previous step). Then, those related fingerprint locations are used to estimate the target location in the next step. This means that the unrelated fingerprint locations are eliminated and are not considered

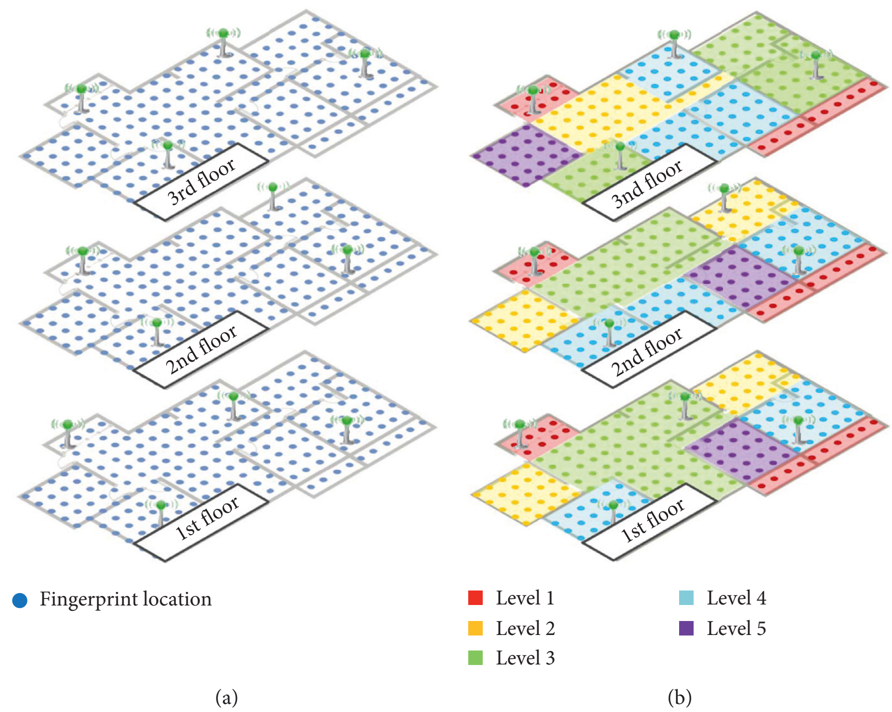

Figure 4: An example of Fusion location fingerprinting process. (a) Traditional location fingerprinting approach. (b) The environment parameter classification.

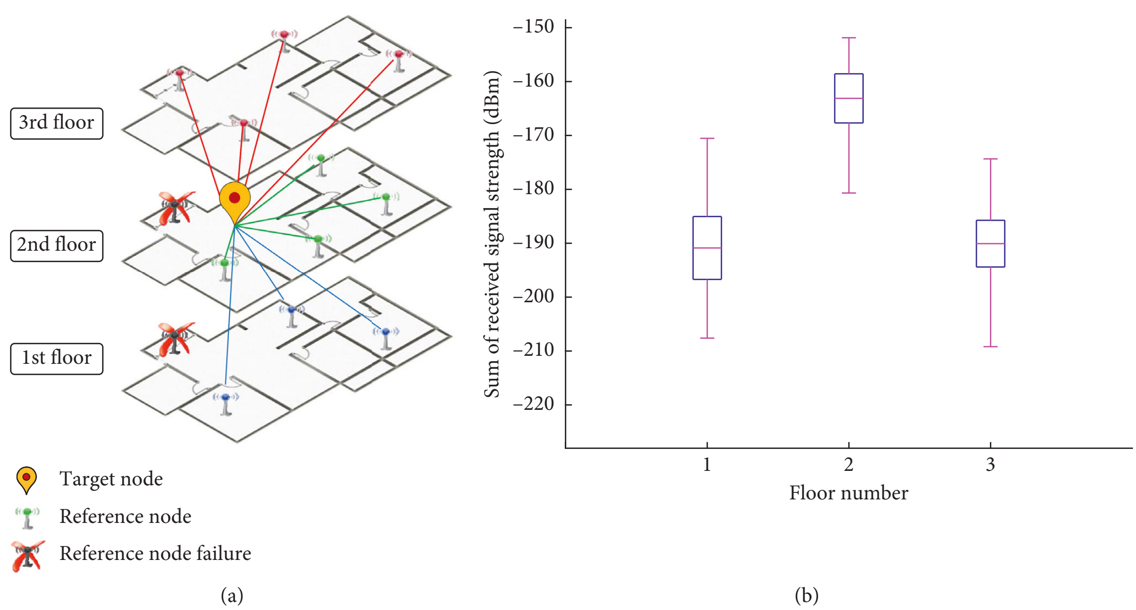

Figure 5: An example of the RMoS floor determination process. (a) Floor determination schematic diagram. (b) An example of the result of the RMoS floor determination algorithm.

in the location estimate. Note that our searching process is based on a binary search algorithm that has the time complexity of $O(\log n)$ [29]. Figure 6 illustrates an example of the TEMP-level filter based on the classification approach. We assume that the TEMP level of the target location is level 3 (i.e., green points) and the target's floor result obtained from the previous process is the second floor. In this case, the fingerprint locations in the database that are located on the second floor with the 3rd TEMP-level are selected, as shown by the green zone in Figure 6. It is clear that the search space of the location estimate is limited. Consequently, the computational time required during the online estimation phase is reduced. Moreover, this can help the IPSs to reduce the error distance in the location estimate [31].

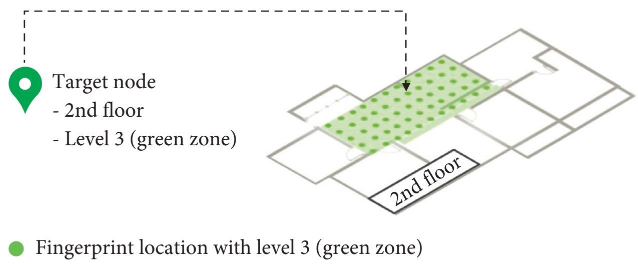

Figure 6: Example of the TEMP-level filter process that considers the fingerprint locations from level 3.

(3) Active Euclidean Process. Next, the third step of the online estimation phase is the distance metric calculation. The correlation of the RSS vector between fingerprint locations and the current location of the target are computed through the distance metric. The coordinate(s) associated with the fingerprint location that provides the smallest distance (e.g., Euclidean distance) is returned as the estimate of the position. In this article, we propose the novel active process for the Euclidean distance algorithm which is called the Active Euclidean distance. This enhanced Euclidean distance algorithm is developed to handle the problem of the online RSS being missing, either as a result of RN failures during the online estimation phase or of being outside a region of RN coverage. Figure 7 illustrates an example of the IPSs in a three-story building under a missing RSS situation. In this figure, one RN on the 1st floor and another RN on the 2nd floor became unavailable. Either hardware failures or software errors could be the reasons for this unavailability. Moreover, the location of the target is outside the RN coverage area, placed on 3rd floor, which is represented by the red dashed line in the figure. In this situation, the target node cannot observe the signal from those three RNs inside the building. Using the traditional Euclidean distance for matching the RSS pattern, the location accuracy of the system could drop by almost half [30]. The major difference between our proposed Active Euclidean distance technique and the traditional Euclidean distance technique is that we consider only the RSS values that are available (i.e., active RNs) when matching the RSS patterns with the location fingerprints in the database. The Active Euclidean distance for the distance metric calculation is written in the following equation:

$$d_i = \sqrt{\sum_{f=1}^{F}\left\{\sum_{n=1}^{N_f}\left(r^i_{fn} - \ddot{s}_{fn}\right)^2\right\}}, \quad i = 1, 2, \ldots, M, \tag{3}$$

where d_i is the Active Euclidean distance between the fingerprint location ith and the target location, note that $i = 1, 2, \ldots, M$, M is the related fingerprint location that has the same TEMP level as the target located on the target's floor, F refers to the total number of floors in the multistory buildings, and N_f is the number of active RNs on the fth floor. The variable r^i_{fn} denotes the average RSS of the fingerprint location ith received from nth active RN on the fth floor. The variable $\ddot{s}_{fn}$ represents the average RSS at the target location received from the nth active RN on the fth floor. According to the example of an IPS in a three-story building as shown in Figure 7, the three, four, and three RNs on the 1st, 2nd, and 3rd floors are found during the online scanning, respectively (i.e. $F = 3$, $N_1 = 3$, $N_2 = 4$, $N_3 = 3$). The example of the Active Euclidean distance equation for the 9th fingerprint location (d_9) can be written as

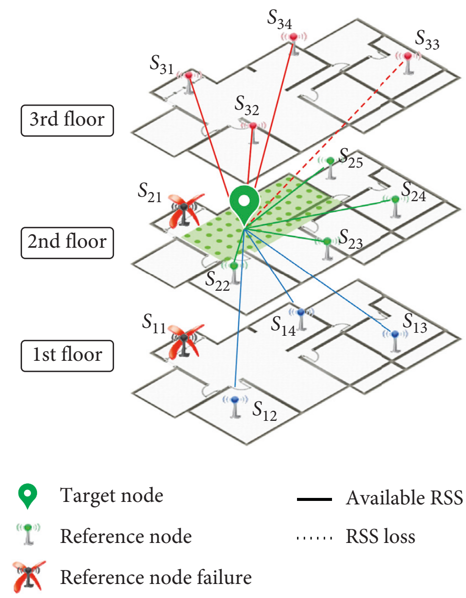

Figure 7: Example of the Active Euclidean distance technique.

$$\begin{aligned}
f &= 1,\ N_1 = 3;\ \left(r^9_{12} - \ddot{s}_{12}\right)^2 + \left(r^9_{13} - \ddot{s}_{13}\right)^2 + \left(r^9_{14} - \ddot{s}_{14}\right)^2, \\
f &= 2,\ N_2 = 4;\ \left(r^9_{22} - \ddot{s}_{22}\right)^2 + \left(r^9_{23} - \ddot{s}_{23}\right)^2 + \left(r^9_{24} - \ddot{s}_{24}\right)^2 \\
&\qquad + \left(r^9_{25} - \ddot{s}_{25}\right)^2, \\
f &= 3,\ N_3 = 3;\ \left(r^9_{31} - \ddot{s}_{31}\right)^2 + \left(r^9_{32} - \ddot{s}_{32}\right)^2 + \left(r^9_{34} - \ddot{s}_{34}\right)^2.
\end{aligned} \tag{4}$$

From this scenario, we do not include the three RNs of $\ddot{s}_{11}$, $\ddot{s}_{21}$, and $\ddot{s}_{33}$ in the calculation, which represents a case of the RN failures and being outside a region of RN coverage. Then, the root squared error of RSS between the 9th fingerprinting location and the target location are computed. Finally, the Active Euclidean distance calculation for the 9th fingerprinting location is obtained.

(4) WKNN Process. The last step of our online estimation phase is the WKNN calculation. The WKNN algorithm is based on using the distance metric between the measured RSS of the target and the RSS of the related fingerprint locations to calculate the target location. In order to determine the coordinates of the target, the first k order of the related fingerprint locations that have the shortest distance metric (i.e., the shortest Active Euclidean distance) are selected. This closeness fingerprint location is called the nearest neighbor location. Then, those restriction distance metrics of the k-nearest neighbor's locations are used to compute the weighting factor [34]. The calculation of the WKNN method is written in the following equations:

$$x_o = \sum_{j=1}^{k} x_j \cdot w_j \quad \forall j \in k, \tag{5}$$

$$y_o = \sum_{j=1}^{k} y_j \cdot w_j \quad \forall j \in k, \tag{6}$$

$$w_j = \frac{\left(1/d_j^2\right)}{\sum_{j'=1}^{k}\left(1/d_{j'}^2\right)}, \tag{7}$$

where d_j is the smallest Active Euclidean distance jth, for $j = 1, 2, 3, \ldots, k$ (i.e., we assign $k = 4$), the coordinate of target (x, y) is estimated by using (5) and (6), while the weighted value for the k-nearest neighbor's coordinates are computed by using (7), where x_o and y_o denote the x- and y-coordinates of location estimation, the variables x_j and y_j refer to the x- and y-coordinates of the nearest neighbor location jth, and w_j refers to the weighted value of the nearest neighbor jth. Finally, we obtain the solution of the target location in three-dimensional space represented by x, y, and *floor*. Figure 8 shows an example of the WKNN process.

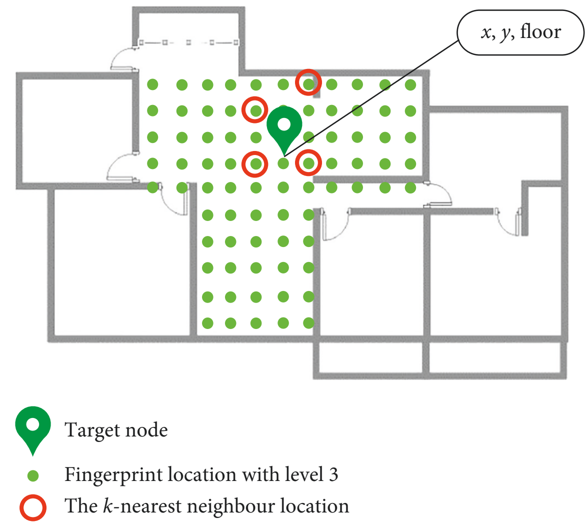

Figure 8: Example of the WKNN calculation.

4. Experimental Setups

To analyze several aspects of indoor positioning performance, we compared the performance results of the proposed IPSs with the traditional IPSs based on the location fingerprinting approach. Three of the essential performance metrics were used to evaluate indoor positioning performance. The three metrics were accuracy, robustness, and computational complexity. The core of this study can be divided into three objectives:

(1) To compare the positioning performance of the IPSs based on the location fingerprinting technique in which the system is employed both using and without using the Active process (which will be discussed in Section 5.1)

(2) To evaluate the performance of the IPSs under a normal situation (accuracy) and the RN-failure situation (robustness) (which will be discussed in Section 5.2)

(3) To analyze the effect of the indoor positioning technique on computational complexity (which will be discussed in Section 5.3)

4.1. Experimental Settings. In our experimental study, two buildings with different floor structures and with different dimension areas are tested. The first building, labelled Building A, is an office building with dimensions of approximately 75 m (width) × 75 m (length). Note that this is the same building used in [17]. The second building, labelled Building B, is a laboratory building with dimensions of approximately 30 m (width) × 44 m (length). Figures 9 and 10 illustrate the floor layouts of Building A and Building B, respectively. The blue dots in the figures represent the RN-placement solution attained from the proposed R-MSMR with $R = 2$, in which 27 and 24 RNs are installed at Building A and Building B, respectively. We assigned the five TEMP levels for the proposed Active Fusion technique which is denoted by red, orange, green, blue, and purple for the 1st to 5th TEMP levels, respectively. Note that the white color area is open space in the building and the 1st TEMP level in the TEMP-level classification is the highest temperature and relative humidity value. We assigned the physical environmental classification inside Building A and Building B with three and five TEMP levels, respectively. Table 3 shows a range of temperature level used in this work. We set the grid spacing of the fingerprint locations at four meters for Building A and two meters for Building B. The number of fingerprint locations for Building A and Building B is 984 locations and 1,755 locations, respectively. A total number of 474 and 384 test points (i.e., target locations) were randomly selected for Building A and Building B, respectively. Note that these numbers of test points were obtained by determining the sample size with confidence intervals [35]. Table 4 provides the setting values of the parameters used in our experiments.

4.2. Experimental Equipment. The main hardware components of the IPSs used in this work are shown in Figure 11. They include the RNs, the target node, and the processing unit. The RNs are wireless transceivers that will send out signals upon request from the target node. Their locations are placed by using the system design approaches (discussed in Section 3.2). The target node will collect the RSS values that are transmitted from the RNs in the service area. It is connected to the SHT15 sensor for measuring the temperature and relative humidity value. This measured information (i.e., RSS and environment information) is passed to the processing unit via a UART-USB interface where the indoor positioning algorithm is carried out. The height of the RN is 2.5 meters, while the target node is 0.8 meters. Figure 12 illustrates the RNs and the target node used in this work. The hardware of both RNs and target node is based on the ZigBee evaluation kit of Freescale (now NXP

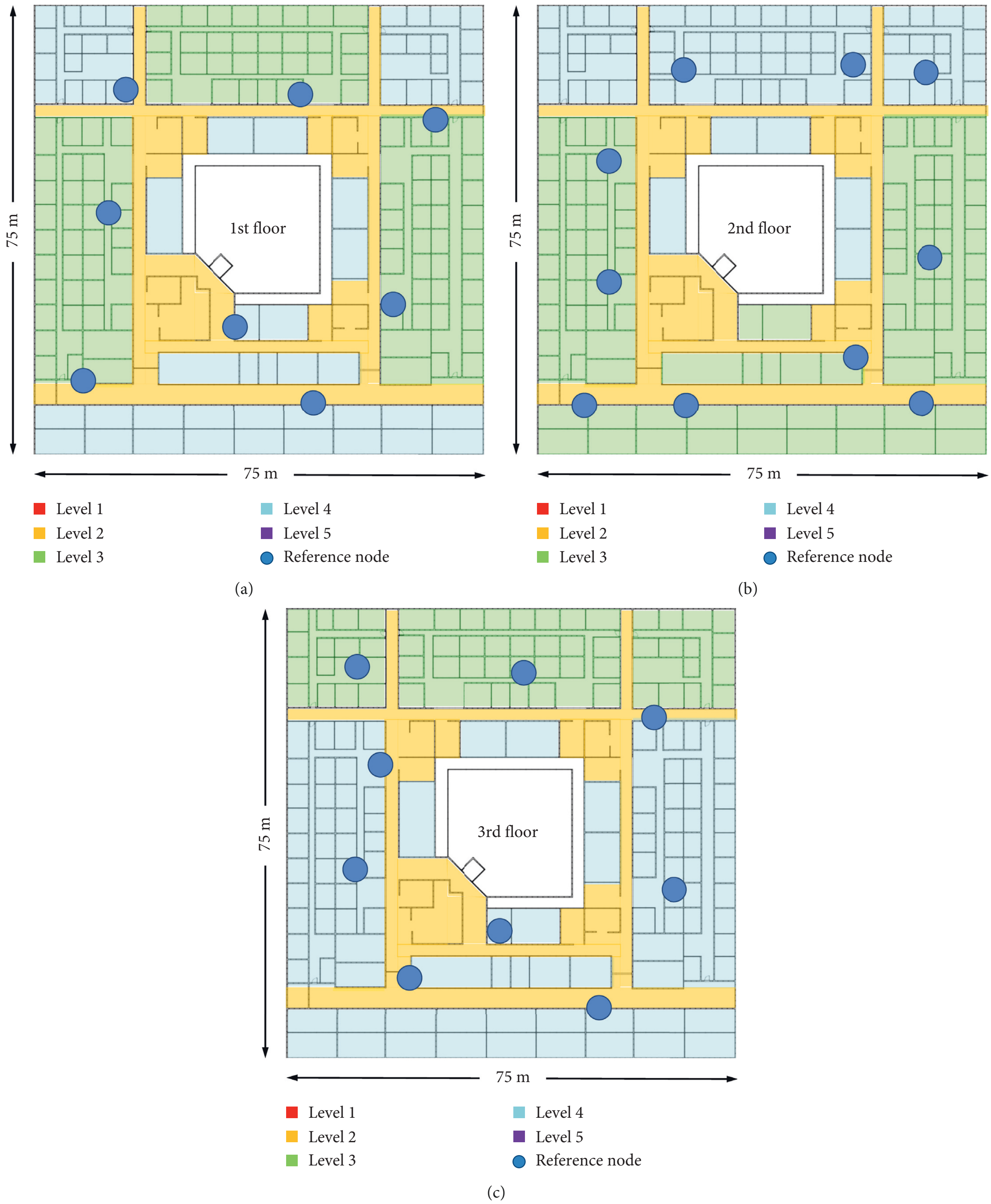

Figure 9: The TEMP-level classification for Building A. (a) 1st floor. (b) 2nd floor. (c) 3rd floor.

Semiconductors) called Freescale ZigBee® 1322xEVK. The kit contains ZigBee devices which are equipped with Freescale MC13224V platform-in-package (PiP) for the 2.4 GHz IEEE 802.15.4 standard. Each MC13224V chip has ARM7TDMI-S which is a 32-bit core microcontroller built in with the ZigBee transceiver. We purposely configured our IEEE 802.15.4 wireless transceivers to operate at 2.480 GHz (i.e., channel 26 according to IEEE standard) [36]. This is to avoid or minimize the interference from Wi-Fi networks inside the buildings. The antennas used in all devices were a mix of the inverted F-shape antennas and external monopole omnidirectional antennas with SMA connectors. The transmit power of all transceivers was set at +3 dBm. Typical receiver's sensitivity of the devices is −95 dBm. With these

FIGURE 10: The TEMP-level classification for Building B. (a) 1st floor. (b) 2nd floor. (c) 3rd floor. (d) 4th floor. (e) 5th floor. (f) 6th floor.

TABLE 3: Range of the temperature level used in this work.

TEMP level	Color	Temperature (°C)	Humidity (%)
1st	Red	≥32	≥80
2nd	Orange	30-31	70–79
3rd	Green	26–29	60–69
4th	Blue	22–25	50–59
5th	Purple	≤21	≤49

setting and specification, the range of these wireless transceivers for indoor with non-line-of-sight is approximately 30 meters. In this work, the wireless transceivers were configured to collect one RSSI sample at every three seconds (a.k.a. sampling rate). The limitation of our experiment is that we only gather the data for stationary node in this study. Table 5 summarizes the hardware specifications of the device used in this study.

5. Results and Discussion

In this section, major aspects of the indoor positioning performance are discussed. First, Section 5.1 provides a comparative performance evaluation of the IPSs using the

Table 4: Values of parameters used in the experiments.

Parameter	Values
Floor dimensions	75 m × 75 m (for 1st to 3rd floor) for Building A 30 m × 44 m (for 1st to 6th floor) for Building B
RN placement	Uniform, MSMR, R-MSMR, $R = 2$, and PhI-Uni (discussed in Section 5.1)
Grid spacing of fingerprint locations	4 m × 4 m for Building A 2 m × 2 m for Building B
Number of test points (i.e., target locations)	474 locations for Building A 384 locations for Building B
Floor determination technique	Group variance floor algorithm [37] RMoS floor algorithm [33]
Positioning technique	Enhanced Euclidean distance (E-Euclidean) Enhanced WKNN (E-WKNN) Active Euclidean distance (Ac-Euclidean) Active WKNN (Ac-WKNN) Active Fusion
TEMP level (for Active Fusion technique)	3 levels for Building A 5 levels for Building B

active process versus those not using the active process. Next, in Section 5.2, the performance of the IPSs under a normal situation and an RN-failure situation is discussed. Finally, in Section 5.3, the computational complexity of different IPSs is analyzed.

5.1. Performance Evaluation on Active Process. In this section, we compare the performance results of the IPSs when using and when not using the active process. The three-story Building A was considered, which employs four different system designs as shown in Figure 13. We compared an average error distance of the proposed RN-placement design (i.e., R-MSMR with $R = 2$) with three different system designs, which include the coverage and uniform placement (Uniform) model, the Maximize-Sum of Maximum RSS (MSMR) model [16], and the PhI-Uni [17]. Note that the designs of these four different RN placements for Building A were originally developed by our previous mathematical model in [17]. However, in our previous work [17], the performance comparison was analyzed between the IPSs under two different RN-failure patterns (i.e., similar and across RN-failure patterns). In this work, we compare the positioning performance of two distance based techniques, which consist of the Active Euclidean distance (i.e., the Euclidean distance technique using an active process) and the traditional Euclidean distance (i.e., the Euclidean distance technique not using an active process). Note that the location coordinates (x, y) and the floor number (*floor*) are computed simultaneously for both cases of the traditional Euclidean distance and Active Euclidean distance. The six cases of the RN-failure per floor situations are considered which consist of zero nodes to five nodes. A total number of 474 random locations were tested as the test points (each floor has 158 locations). The average error distance of each RN-failure situation is calculated from four random patterns of RN failure.

First, we consider the performance results of the IPSs with different system designs. Figure 14 reports an average error distance of the IPSs that deploy four different design structures in the three-story Building A. The solid lines represent the IPSs that use the Active Euclidean distance process, while the dash lines represent the IPSs that use traditional Euclidean distance process. From the results, it is clear that the average error distance of all IPSs increases in line with the increase in the number of RN failures. It is also clear from Figure 14 that the proposed R-MSMR design (the blue line with triangles with $R = 2$_xx legends) can provide greater location accuracy under both the fault-free scenario and the RN-failure scenario than the other system designs. Notice that these results follow the same trend as shown in our previous experiments in [17]. For example, when considering using the Active Euclidean distance process, the proposed R-MSMR with $R = 2$ (the blue solid lines with triangles) has the lowest performance decreasing under the normal situation and the 3RN-failure per floor scenario about 8.4%. On the other hand, the other three different designs have more location accuracy degradation under the same situation. Our results show that they have performance degradation up to 77.3% for the Uniform design, 45.8% for the MSMR design, and 14.9% for the PhI-Uni design. In particular, when we compared the IPSs with R-MSMR with $R = 2$ design and the PhI-Uni design that have same number of RNs installed, we found that the proposed R-MSMR with $R = 2$ can achieve a better 51.2% fault tolerance than the PhI-Uni design under fifteen of the RNs in a three-story building failed. Note that this was 5RN-failure per floor scenario. The main reason is that the signal coverage availability of the proposed R-MSMR is guaranteed by at least the recommended number of signals of the accuracy index and the reliability index which is also one of the optimization constraints as described in [17]. Thus, the RN placement obtained from the proposed system design can effectively handle the problem of online RSS being missing caused by RN failures during the online estimation phase.

Next, we compare the location accuracy of the IPSs with and without using the active process as shown in Figure 14. The results report that the average error distance of the IPSs not using the active process could have very high error distances (i.e., the dashed lines). For example, under the 4RN-failure per floor scenario, the average error distance of the R-MSMR using the active process (the blue solid line with triangles) is 4.83 meters, whereas the R-MSMR not using the active process was over 20 meters (the blue dashed line with triangles). These results indicate that the location accuracy of the R-MSMR under the 4RN-failure per floor scenario could be dropped by almost 80% if the active process is not employed. The reason why the IPSs employing the Active Euclidean distance outperforms the traditional algorithm is that the proposed Active Euclidean distance is developed to handle the problem of online RSS being missing. Unlike the traditional Euclidean distance which includes all RNs in the localization area in its closest pattern matching with the location fingerprints in the database, the proposed Active Euclidean distance only focuses on the RSS values obtained from available RNs for the RSS matching

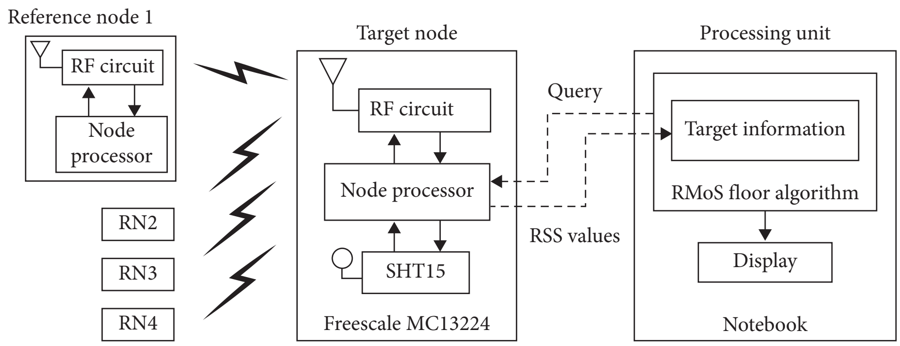

Figure 11: Block diagram of the main hardware components in the indoor positioning systems.

(a) (b)

Figure 12: Experimental equipment used in this work. (a) Reference node (RN). (b) Target node on a cart with laptop PC.

Table 5: Hardware specifications of the IEEE 802.15.4 devices.

Specification	Details
Manufacturer	Freescale (now NXP Semiconductors)
Chipset	MC13224V
Frequency range	2.405 GHz to 2.480 GHz
Operating channel	CH 26 (2.480 GHz) according to IEEE 802.15.4
Rx sensitivity	−95 dBm
Transmit power	+3 dBm
Antenna	Inverted-F antenna or external omnidirectional antenna with SMA connector

calculation. Hence, the lost RSS observation during the online estimation phase, which was caused either by RN failures during the online estimation phase or by being outside a region of RN coverage, is handled. Note that under the fault-free scenario, all IPSs using and not using the active process have an equal average error distance. This means that under a normal situation, the positioning performance of the IPSs using and not using the active process is the same.

Observation from the above result indicates that using the Active Euclidean distance process produces better performance than using the traditional Euclidean distance process, in that the proposed active process can provide greater robustness for the IPSs under the RN-failure situation. Besides the active process, the system design that can satisfy the IPS design requirements for a particular design scenario such as localization that supports rescuers in an earthquake scenario, as the proposed R-MSMR design is also very important for the IPSs that requires system reliability.

5.2. Performance Evaluation under Normal Situation and RN Failure Situation. In this section, we analyze the positioning performance of the IPSs under the fault-free and the RN-

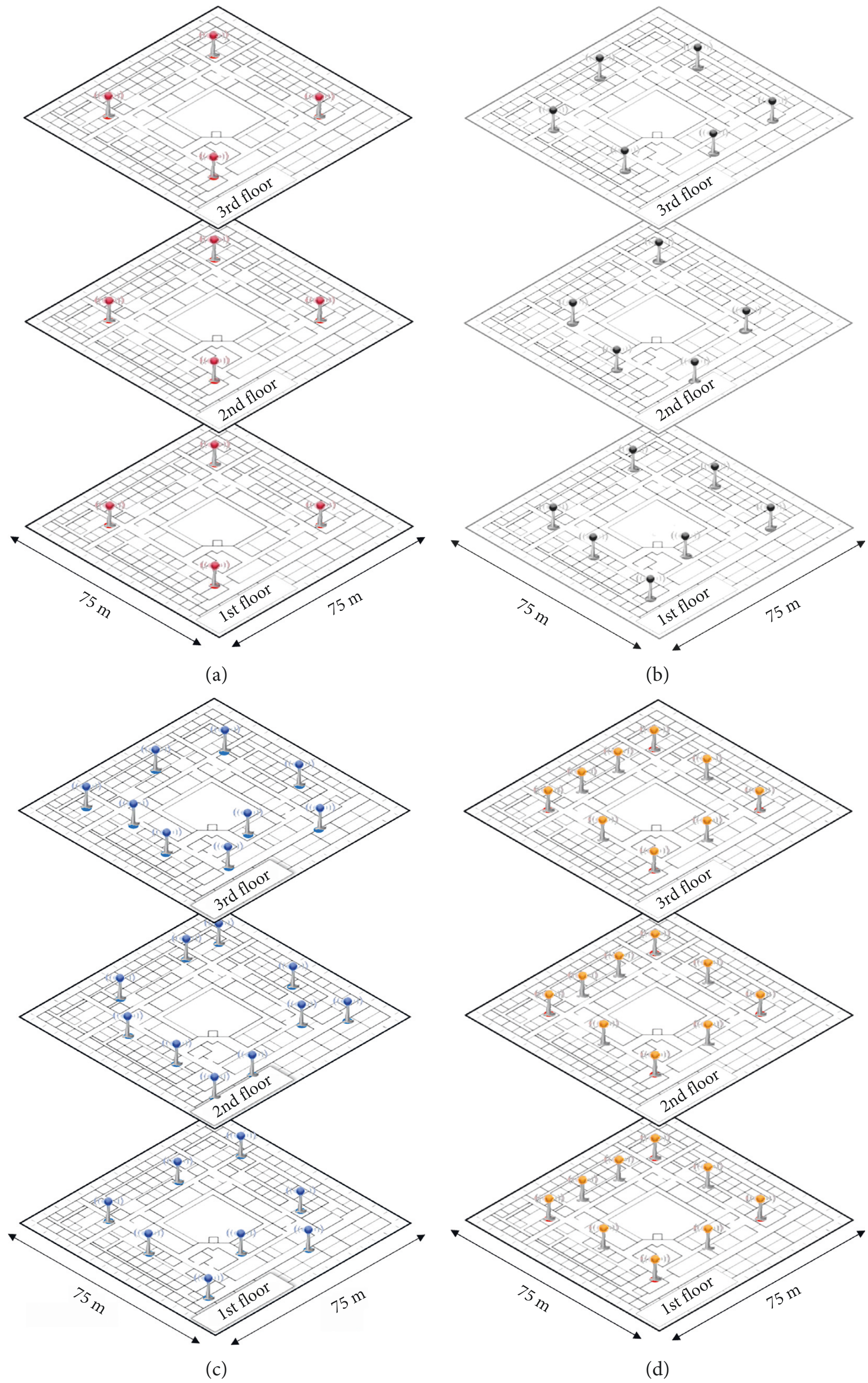

Figure 13: The RN placement designed for a three-floor service area from [17]. (a) Uniform (12 nodes). (b) MSMR (18 nodes). (c) R-MSMR, $R = 2$ (27 nodes). (d) PhI-Uni (27 nodes).

failure scenarios, in which the key performance studies can be divided into two parts: floor determination and location estimation.

5.2.1. Percentage of Correct Floor Determination. In this section, we evaluate the floor determination performance in the three-story Building A. We compare the performance of two different floor determination algorithms without the use of the location fingerprinting database: the Group variance floor algorithm [37] and the proposed RMoS floor algorithm [33]. Two system design structures that have the same number of RNs installed are considered, consisting of the proposed R-MSMR with $R = 2$ and the PhI-Uni as shown in Figures 13(c) and 13(d), respectively. As mentioned in Section 5.1, the six cases of the RN-failure per floor situations and a total number of 474 test points are tested.

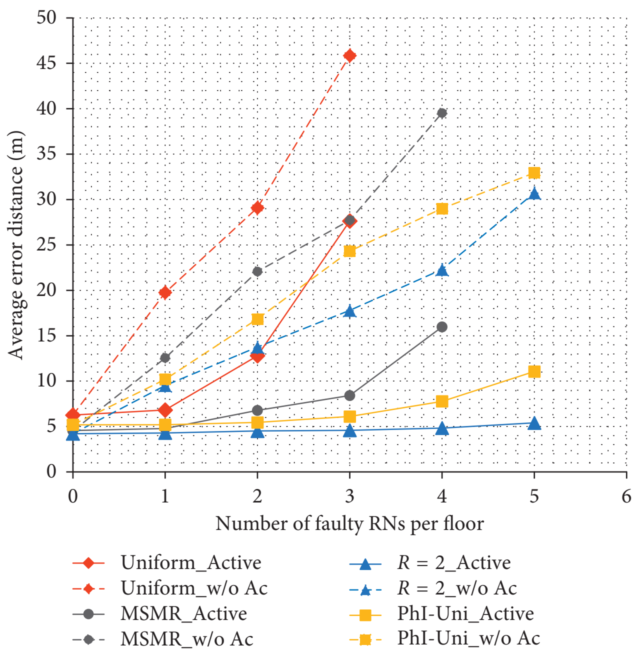

Figure 14: Effect of different numbers of RN-failures per floor on average error distance in Building A.

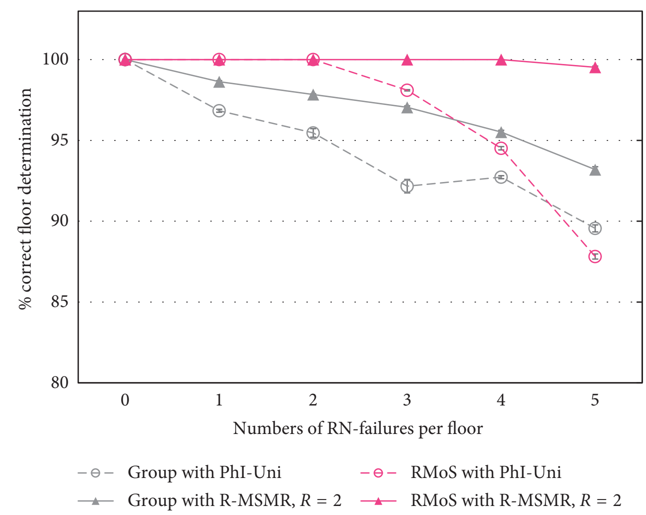

Figure 15: Percentage of correct floor determination in different numbers of RN failures per floor at Building A.

Figure 15 reports the percentage of correct floor determination of the Group variance algorithm and RMoS floor algorithm. We observe that both floor determination algorithms achieve 100% correct floor determination in the fault-free scenario (i.e., all RNs worked properly) for all cases of system designs. However, when some RNs in the system have failed, only the proposed RMoS floor algorithm with the R-MSMR $R = 2$ design (the pink solid line with triangles) can provide fault tolerance that is better than the other IPSs. It yields a 100% correct floor determination performance under a 4RN-failure per floor scenario (i.e., the case of 40% of RN failures in the system). Unlike the proposed combination of the RMoS floor algorithm with the R-MSMR, $R = 2$ design, the other IPSs such as the Group variance algorithm with the R-MSMR $R = 2$ design (the gray solid line with triangles) could not tolerate the RN-failure scenarios. They fail to achieve 100% correct floor determination performance in all RN-failure scenario cases. The reason is that the missing RSS during the online estimation phase could affect the floor point process of the Group variance algorithm. For example, when considering the floor points which were calculated from one of three online statistical parameters as the availability [37], an error of the availability score occurred when some RNs during the online estimation phase have failed. This is the reason why the floor points are incorrect and cause the Group variance algorithm to determine the wrong floor.

Moreover, we observe that the performance of the proposed RMoS algorithm with R-MSMR, $R = 2$ will drop by almost 0.5% when more than 50% of RNs have failed in the service area (i.e., 5RN-failure per floor scenario). The reason is that the RMoS floor algorithm considers only which 50% of RNs on each floor give the strongest RSS values to be suitable for the RSS summations under RN failure [33]. Thus, having more than 50% of the RNs in the building fail may directly affect the RSS summations process of the RMoS algorithm and lead to incorrect floor determination. This is a limitation of the proposed RMoS floor algorithm, that is, it cannot support the worst-case scenarios of RN failure, when more than 50% of the RNs installed in the service area fail.

It is clear from the above discussion that the combination of the RMoS floor algorithm with the R-MSMR, $R = 2$ design outperforms the other IPSs and provides more robust IPS performance, in which the proposed combination algorithm can achieve a 100% correct floor determination performance when the system encountered 40% RN failure in the system. Once again, the structure of the proposed R-MSMR design can achieve higher fault tolerance than other structures that have same number of RNs installed, such as the PhI-Uni. In the next section, to make a clear comparison of several aspects of indoor positioning performance, we will only use the most robust system design as the R-MSMR with $R = 2$ structure for the performance evaluation.

5.2.2. Estimating Location. The performance of the IPS in terms of the accuracy of the location estimation (x, y) under the fault-free scenario and the RN-failure scenarios is evaluated in this section. Building A and Building B are tested, in which the experimental setups of both buildings were described in Section 4.1. Five indoor positioning techniques are used, which include Enhanced Euclidean distance (E-Euclidean), Enhanced WKNN (E-WKNN), Active Euclidean distance (Ac-Euclidean), Active WKNN (Ac-WKNN), and the proposed Active Fusion technique. Note that only in the case of the proposed Active Fusion technique, the floor number was computed by the RMoS floor algorithm, while in the case of the other four positioning techniques, the floor number was computed simultaneously with location coordinates of x, y. A total number of 474 test points and 384 test points were randomly selected for Building A and Building B, respectively. For the case of the RN-failure scenarios, we created four patterns of

RN failure scenarios by randomly turning off 30% of the RNs in the system. Then, the average error distance of these four scenarios were computed.

Figures 16 and 17 report the average error distance of the IPSs that deploy the R-MSMR, $R = 2$ design for Building A and Building B, respectively. The results in the case of a large building, such as Building A, indicate that the five indoor positioning techniques have a similar average accuracy performance under the fault-free scenario of between 3.83 and 4.22 meters. However, under the RN-failure scenarios, in which 30% of the RNs in the system failed, the accuracy performance of the two indoor positioning techniques that did not use the active process dropped by almost 77% (i.e., 76.3% for E-Euclidean and 75.3% for E-WKNN). Unlike the techniques that did not use the active process, the three indoor positioning techniques that did use the active process produced a percentage of difference between their average error distance in the normal situation and the 30% RN-failure scenario of less than 8%. In particular, the proposed RoC framework (i.e., Active Fusion technique) outperformed the other techniques, as the performance of the Active Fusion dropped by less than 4.5%.

Similar results were obtained for the case of the small building (i.e., Building B) as shown in Figure 17. The five indoor positioning techniques had a similar average accuracy performance under the fault-free scenario (i.e., between 3.36 and 3.72 meters). Once again, only the three indoor positioning techniques that used the active process provided fault tolerance under the 30% RN-failure scenario, in which their accuracy performance dropped by less than 5%, while the two techniques that did not use the active process in Building B also reported performance degradation of up to 75% (i.e., 75.1% for E-Euclidean and 74.2% for E-WKNN). It is a major advantage of the proposed active process that it provides a reliable location for the IPSs. It can handle the problem of online RSS being missing caused either by RN failures during the online estimation phase or by being outside a region of RN coverage.

Moreover, we observed that the small building (Building B) produced a higher accuracy performance than the large building (Building A) for all scenarios. The reason is that Building B employs the fingerprinting granularity with 2×2 meters, which has higher resolution of grid spacing than Building A. On the other hand, assigning high fingerprinting granularity for the IPSs based on the location fingerprinting approach can improve the accuracy and precision of the performance [38]. However, the high fingerprinting granularity will be very time-consuming in performing an exhaustive fingerprint collection during the offline calibration phase. This can result in weeks spent on surveying the site and collecting data for a large service area. This is in fact a trade-off between the time consumed and the accuracy of the performance of the IPSs based on the location fingerprinting approach [2].

5.3. Performance Evaluation of Computational Complexity. Based on the experimental results described above, it does not show any tangible difference in those three indoor positioning techniques that used the active process. Thus, in this section, we investigate another essential performance of the IPSs that explains the location processing time during the online estimation phase as computational complexity. We recorded the computational time of those three indoor positioning techniques at Building A and Building B. The number of fingerprint locations for Building A and Building B is 984 locations and 1,755 locations, respectively. A total number of 474 test points and 384 test points were used for Building A and Building B, respectively. For each test point, the location calculation was run twenty times. Their average computational time was computed and reported as a histogram of computational times, as shown in Figures 18 and 19 for Building A and Building B, respectively.

Consider the results shown for Building A in Figure 18. We can see that the proposed Active Fusion resulted in shorter computational times compared to the other techniques. The average computational time of the Active Fusion was 17.8 milliseconds per location, represented by blue bins, while the Ac-Euclidean and the Ac-WKNN were 24.1 and 25.5 milliseconds per location represented by orange bins and purple bins, respectively. Moreover, when we consider Building B, which has a 40% larger number of fingerprint locations than Building A, we found that the computational time of those two techniques that did not use the Fusion location fingerprinting approach (Ac-Euclidean and Ac-WKNN) grew larger as the number of fingerprint locations increased. Their average computational times increased by almost 40% (i.e., 34.7% for Ac-Euclidean and 37.9% for Ac-WKNN, respectively). Unlike the techniques that did not use the Fusion location fingerprinting approach, the proposed Active Fusion requires less computational time than the other two techniques while still maintaining sufficiently accurate performance. In particular, in the 40% larger search space at Building B, the average computational time of the Active Fusion process increased by 2.7%. From the results considered here, it can be concluded that the proposed RoC framework requires a lower computational time than the Ac-Euclidean and the Ac-WKNN by up to 53.8% and 55.1%, respectively. Note that the computational time results of the Euclidean approaches of the Ac-Euclidean and the E-Euclidean were equal. Similar results were obtained for the case of the Ac-WKNN and the E-WKNN.

The reason that the computational time of the Active Fusion not growing as the size of the search space increased is that our proposed technique deploys the Fusion location fingerprinting approach with a TEMP-level filter based on the classification approach to classify the fingerprint locations before the Euclidean distance process is conducted. Instead of computing all of the huge fingerprint locations in the database as is required with the traditional techniques (e.g., Ac-Euclidean and Ac-WKNN), only the related fingerprint locations that have the same TEMP level as the target are considered. This means that the search space of the system (i.e., the fingerprint locations considered in the Euclidean distance process) is limited. This results in a low computational time during the online estimation phase and also reduces the errors in terms of the location estimation. Thus, an increase of 40% in the search space at Building B

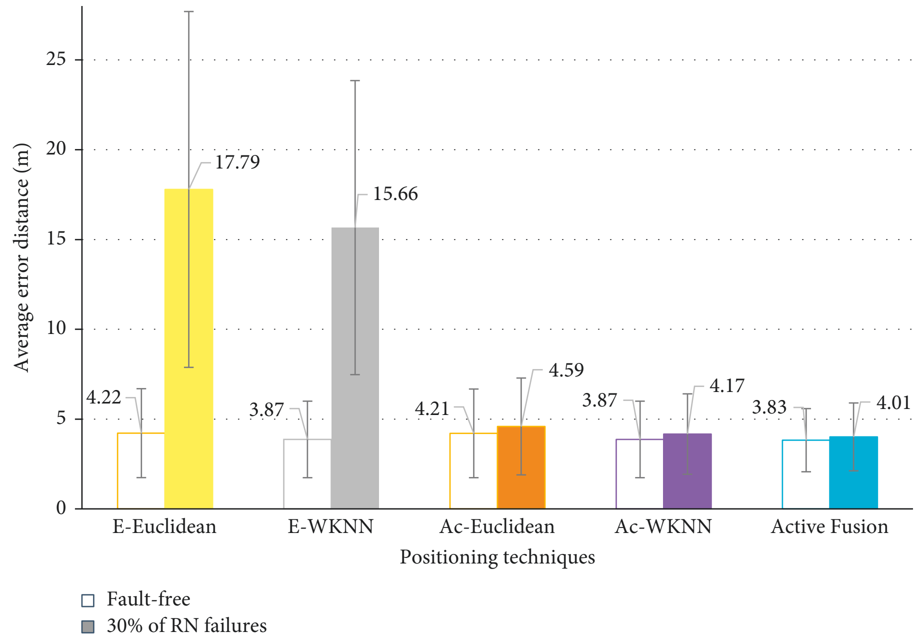

Figure 16: An average error distance of wireless indoor positioning systems that deploy R-MSMR, $R = 2$ at Building A.

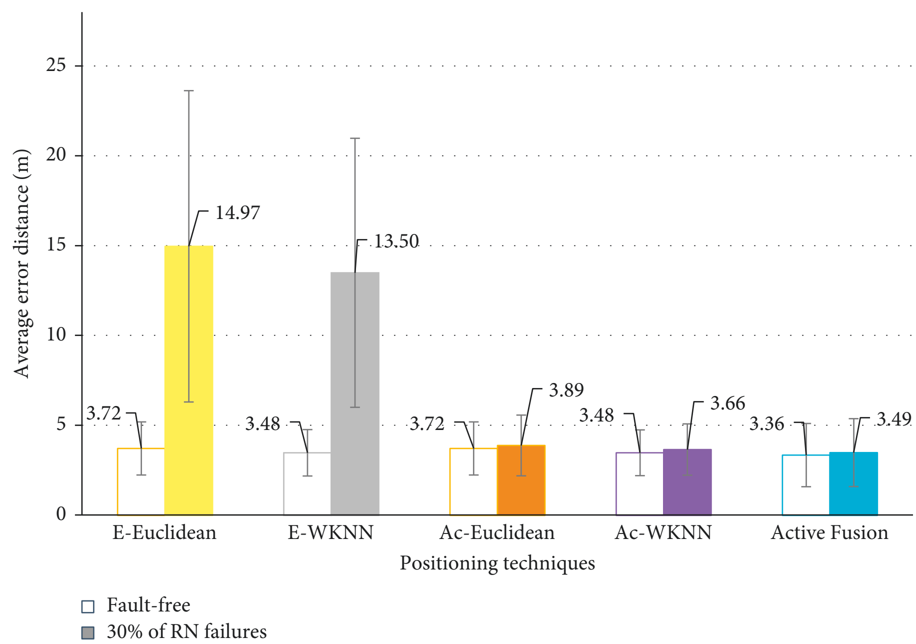

Figure 17: An average error distance of wireless indoor positioning systems that deploy R-MSMR, $R = 2$ at Building B.

does not significantly affect the computational time of the proposed Active Fusion process, in which less than 4% of all those fingerprint locations need to be calculated in the Euclidean distance process (i.e., they are filtered by floor number and the Temp-level).

Moreover, when we consider the evaluating run-time complexity as a Big O notation which is used to predict the upper bound of the growth rate of the algorithm as the input size grows [39], we found that the worst-case complexity of the proposed TEMP-level filter based on a binary search algorithm was lower than other existing classification approaches. Our algorithm has the worst-case complexity of $O(\log n)$ [29], while other existing classification approaches such as the k-means clustering and the FCM have the worst-case complexity of $O(ndc)$ and $O(ndc^2)$ [28], respectively, where n refers to the number of data points, d represents the number of dimensions, and c represents the number of clusters. This evaluation could also explain why an increase in the search space does not significantly affect the online computational time of the matching RSS process of the proposed RoC framework. Thus, we can conclude that the IPSs employing the RoC framework are robust and low-complexity wireless IPSs based on the fingerprinting approach in the RN-failure scenarios considered in our study.

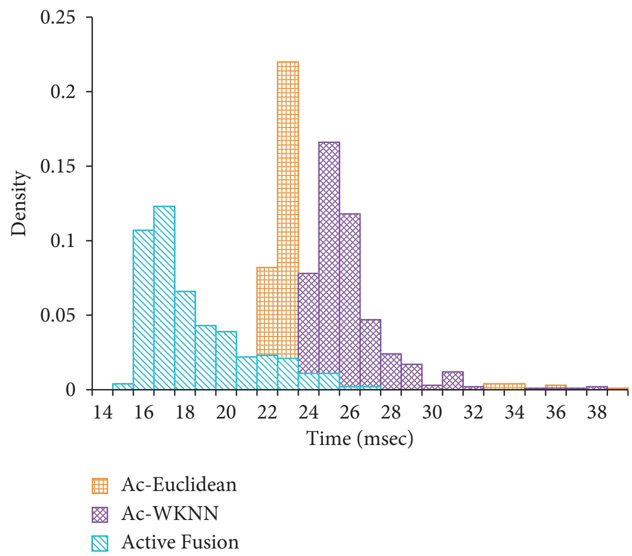

Figure 18: Histogram of the computational time at Building A.

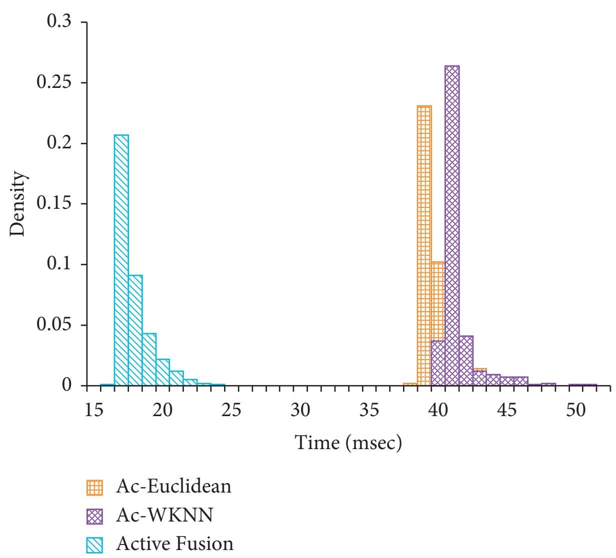

Figure 19: Histogram of the computational time at Building B.

6. Conclusion

In this article, we presented an integrated framework for the wireless IPSs based on location fingerprinting techniques that can be applied to variety of indoor scenarios ranging from single-floor to multiple-floor environments. The proposed framework is called the Robust and low Complexity indoor positioning systems framework (RoC framework). This framework consists of two essential indoor positioning processes: the system design process and the localization process. Experimental results reveal that the RoC framework can achieve robustness in terms of the system design structure, in which it was able to achieve the best positioning performance in either *fault-free* or *RN-failure scenarios*. Moreover, in the online estimation phase, the proposed framework can provide target location reliability in the RN-failure scenarios, in which it was able to attain the highest correct floor determination and the highest location accuracy compared to the other techniques. Furthermore, our proposed RoC framework also yields the lowest computational complexity in online searching time without compromising the positioning accuracy. This can be achieved by exploiting additional environmental information via temperature and relative humidity sensor devices which can help reduce the search space of location fingerprinting. However, this improvement comes at the cost of additional data collection, storage, and filtering process. Specifically, when we compared it to the traditional WKNN under the 30% RN-failure scenario at Building B, the proposed RoC framework demonstrates a better location accuracy than the WKNN by up to 74.1% and yields a lower computational time than the WKNN by about 55.1%.

Our future works will consider system design guidelines which can suggest how and which directions the system designer should take for performance improvement of the Multifloor positioning system. Additionally, the enhanced design framework should still be robust both during the normal situation and when some RNs have failed. These guidelines can also be applied in various other wireless technologies such as Bluetooth Low Energy (BLE) for indoor positioning systems.

Data Availability

The performance comparison results data were used to support the findings of this study are available from the corresponding author upon request.

Disclosure

An earlier version was circulated under the title “Robust and low complexity wireless indoor positioning systems for multi-floor buildings using fingerprinting techniques.” This article was extended from the fourth and fifth chapter of our Ph.D. dissertation.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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