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An Enhanced Floor Estimation Algorithm for Indoor Wireless Localization Systems Using Confidence Interval Approach

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***Abstract*—**Indoor wireless localization systems have played an important role to enhance context-aware services. Determining the position of mobile objects in complex indoor environments, such as those in multi-floor buildings, is very challenging problems. This paper presents an effective floor estimation algorithm, which can accurately determine the floor where mobile objects located. The proposed algorithm is based on the confidence interval of the summation of online Received Signal Strength (RSS) obtained from the IEEE 802.15.4 Wireless Sensor Networks (WSN).We compare the performance of the proposed algorithm with those of other floor estimation algorithms in literature by conducting a real implementation of WSN in our facility. The experimental results and analysis showed that the proposed floor estimation algorithm outperformed the other algorithms and provided highest percentage of floor accuracy up to 100% with 95-percent confidence interval.

***Keywords*—**Floor estimation algorithm, floor determination, multi-floor building, indoor wireless systems.

I. Introduction

THE rapid pace of technological advancement in wireless communications is currently the major driving force of the development of several indoor location services for wide range of applications such as those in commercial, agriculture, medical, and the military uses [1]. Various wireless technologies can be employed for indoor positioning applications. Some systems make use of an existing wireless network infrastructure such as Wi-Fi [2]–[6]. More flexible and efficient systems employ IEEE 802.15.4 Wireless Sensor Networks (WSNs) due to the advantages in term of low power consumption, light weight and low cost [7].

Existing indoor localization systems can be classified into three types based on the structure of service areas. These include the indoor localization systems for two-dimensional service areas, three-dimensional service areas, and multi-story building [1], [8]. Most of existing systems are designed for usages in two-dimensional areas where the position of target object is specified by a coordinate (x, y) [8]. The second type of the indoor positioning system considers a three-dimensional space in a small service area, such as in a room. The state of the object location is derived in the form of coordinate (x, y, z) [9]. Lastly, the positioning systems designed for the indoor multi-story building need to specify not only coordinate (x, y) in two-dimensional plane but also the floor where the object located [2]–[5].

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An important performance of the positioning system for indoor multi-floor building is to accurately determine the floor number. False floor estimation could lead to serious injury or a death. For instance, in emergency situations such as fire, if the system incorrectly estimates the floor where the target located, the victims of fire or the firefighters may be in danger [6].

For this reason, we propose an effective floor estimation algorithm to determine the current target's floor in the environment of the multi-story building. In this work, we focus on floor determination only and use the online RSS collected via IEEE 802.15.4 network interface to estimate the floor number of target. In addition, the proposed floor estimation algorithm is compared with other techniques in literatures.

The remaining sections of this paper are organized into six sections as follows. In Section II, existing floor determination techniques are reviewed. Section III, we explain the proposed floor estimation algorithm. Section IV, the experimental setup of this work is described. Section V provides experimental results and analysis. Finally, Section VI concludes the paper.

II. Existing Technique

In wireless indoor positioning systems for multi-floor buildings, an error location of a target within the two-dimensional plane might mean a false room or error distance in a few meters. On the other hand, the false floor estimation could mean a wrongly detection of the target on a car parking floor instead an office floor. Therefore, the problem of the floor determination is another important issue for positioning problem besides the target's coordinate. It should not be overlooked for the multi-floor positioning systems that require acceptable accuracy. This reason has motivated researchers to develop the floor estimation algorithm to extend the capability of indoor positioning system.

Based on our review, there are three different types of multi-floor positioning techniques. First type, the floor number is estimated in the first step and then the coordinates x and y (target location) is determined later. Second type, the location of target is estimated first and then the floor number is specified later. Third type, the target location and its floor number are defined simultaneously. The authors in [2] presented the positioning algorithm employing WLAN infrastructure. The technique in [2] is the first type of multi-floor positioning techniques which based on fingerprint and Euclidean Distance. At the first stage, the determination of z-value (floor number) is estimated. While the second stage, the estimated x- and y-coordinates are calculated. Likewise the authors in [3] proposed Wi-Fi-based indoor positioning system that combined both characteristics of trilateration and scene analysis method. Their algorithm could estimate a target's floor by using signal strength of access points (APs) from different floors and then the location of the target is determined. The authors in [4] presented multi-floor positioning technique that did not require a time-consuming offline phase in order to build the radio map. In online phase, their positioning algorithm computes the user location and the floor number, respectively. The authors in [5] proposed the fingerprint method uses a previously stored map of the signal strength at several positions and determines the position using similarity functions and majority rules. Thus, their technique could calculate the location and the floor number of the target at the same time.

The authors in [10] proposed new Wi-Fi-based indoor positioning algorithms in order to determine the floor number of target. The two different approaches which used Wi-Fi signal to estimate the target's floor are designed as called the nearest floor algorithm and the group variance algorithm.

A. Nearest Floor Algorithm

This algorithm based on the K-Nearest Neighbor algorithm (KNN algorithm) is called nearest floor algorithm. This technique requires collecting the RSS during offline phase in order to build the database. It does not need to record the signals from all APs. Instead, only the best signal as maximum RSS value for each AP are recoded into the reference database. In the reference database, the information includes reference identification (reference ID), MAC address of APs, the floor number, and the maximum RSS, respectively. Whenever there is a request for a floor determination, the system will compare the strong Wi-Fi signal reading in the online phase with the reference database. Their system will select the closest k APs (k=3). Finally, the best matched floor number from the reference database is selected.

B. Group Variance Algorithm

This algorithm will consider the distribution of the RSS values in each floor. It takes into account three online statistical parameters obtained from each AP, which consists of the range, the variance, and the availability. The algorithm adds weighted values based on their proposed criteria to determine the best score called floor points that use for selecting the floor number. Whenever there is a request for target's floor, all above online statistical parameters were used to calculate the floor points. After comparing the floor points on each floor, the algorithm selects the estimate floor number with the maximum number of floor points.

III. The CIS-RSS Floor Algorithm

In this section, we describe our floor estimation algorithm for the indoor multi-story positioning system. Our proposed algorithm enhances the technique presented in [11]. The algorithm proposed in this paper utilizes the online RSS values received from the reference nodes (RNs) to determine the floor number where the target node is located. The RNs are IEEE 802.15.4 wireless transceivers that are installed on each floor and can respond to a signal inquiry from a target node of which we want to know the position.

Fig. 1 illustrates an example of the structure of the indoor positioning system in the three-story building. In this diagram, four RNs are installed on each floor. Dashed lines represent RSS that the target node receives from all RNs. Our approach does not require time consuming procedure during the offline phase to create the RSS database (i.e. Fingerprint). Instead, only uses the RSS values gathered in real time to perform the floor determination.

The proposed floor estimation algorithm is called the Confidence Interval Sum-RSS (CIS-RSS) floor algorithm. We use the statistical properties of data sets based on the confidence interval of RSS summation which aim to estimate the target's floor. Fig. 2 depicts the flow chart of the CIS-RSS floor algorithm. First, the target node scans RSS vector from RNs installed within the multi-floor building. The RSS vector consists of set of RSS values and the reference node IDs. During the signal inquiry process, the RSS vectors transmitted from each RN are scanned about 20 times. If RSS from any RN cannot be received, it is assumed that the RSS value is equal to -110 dBm.

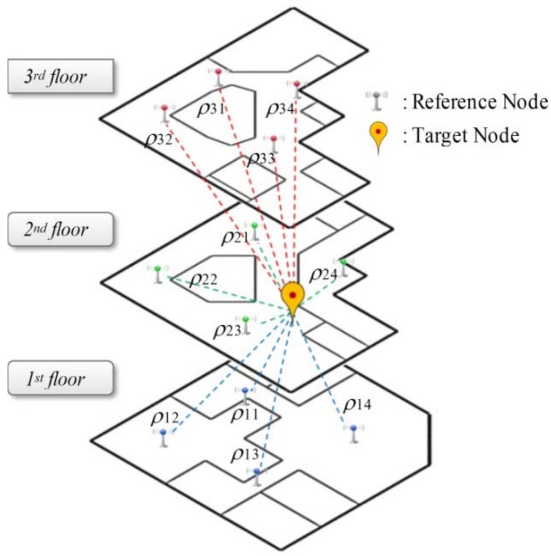

Fig. 1 Floor determination schematic diagram

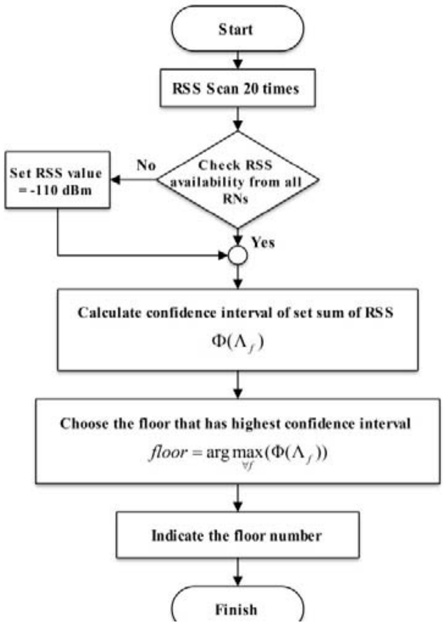

Fig. 2 Flow chart of the CIS-RSS floor algorithm

Next step, the confidence interval of set of RSS summation $\Phi(\Lambda_f)$ is calculated by using (1) where Λ_f is set of RSS summation on floor f^{th} which denote by $\{\gamma^1_f, \gamma^2_f \ldots \gamma^\tau_f \ldots \gamma^\Gamma_f\}$. The summation of RSS γ^τ_f is computed by using (2), where γ^τ_f represents the sum of RSS value which is τ^{th} measurement from all RN on floor f^{th} and ρ^τ_{fn} refers to the RSS value which is τ^{th} measurement from RN n^{th} on floor f^{th}. Using (3) to (5), we calculated the lower limit L_1, the upper limit L_2, and the probability $1-\beta$ that the mean of RSS (μ) will lie between L_1 and L_2. Here, Γ is the number of sampled RSS, ϕ is the number of floors in the multi-story building, N is the number of RNs on each floor, σ^2 is the sample standard deviation and $t_{[P\ ;\ \Gamma]}$ is the (1-(β/2))-quantile of t-distribution with P probability and Γ sample[12]. Note that equal number of the RNs is installed on each floor.

Finally, our floor estimation algorithm selects the floor number that results in the highest confidence interval of RSS summation and reports the floor number where the target node situated. The pseudo code of the CIS-RSS floor algorithm is shown in Table I.

$$P(L_1 \le \mu \le L_2) \approx 1-\beta \tag{1}$$

$$\gamma^\tau_f = \sum_{n=1}^{N} \rho^\tau_{fn} \tag{2}$$

$$L_1 = \eta(\Gamma) - t_{\left[1-\left(\beta/_2\right);\,\Gamma-1\right]}\sqrt{\frac{\sigma^2(\Gamma)}{\Gamma}} \tag{3}$$

$$L_2 = \eta(\Gamma) + t_{\left[1-\left(\beta/_2\right);\,\Gamma-1\right]}\sqrt{\frac{\sigma^2(\Gamma)}{\Gamma}} \tag{4}$$

$$\beta = [(100-\mathcal{C})/100]/2 \tag{5}$$

TABLE I
PSEUDO CODE FOR CIS-RSS FLOOR ALGORITHM

Input:	Online RSS vectors
Output :	Floor number

Select a percent confidence interval $\mathcal{C}$
Select a raw data of target on $f \in \phi$
Repeat
    Repeat
        Repeat
            $\gamma^\tau_f = \Sigma(\rho^\tau_{fn})$ for all $n = N$
        Until $\tau = \Gamma$
        Set $\Lambda_f = \{\gamma^1_f$ to $\gamma^\Gamma_f\}$
    Until $f = \phi$
    Calculate $\Phi(\Lambda_f)$ with %CI = $\mathcal{C}$ for all $f \in \phi$;
    If $\Phi(\Lambda_f)$ of 1st and 2nd is overlap
    then reduce $\mathcal{C}$
    Else $\mathcal{C}$ is the %CI of sum of RSS
Until stopping condition = true
Select f highest $\Phi(\Lambda_f)$ is the floor of target with %CI = $\mathcal{C}$

IV. Experimental Setups

We conducted real implementation and measurement to analyze the accuracy of the proposed floor estimation algorithm, compared with other algorithms in the literature. In particular, we compared our results with those of the nearest floor algorithm and the group variance algorithm [10]. The experiments were setup in the three-story Library building at Suranaree University of Technology. Figs. 3 (a) and (b) show the service environment and the floor's dimension (35m × 35m), respectively. Fifty test points on each floor (i.e. totally 150 test points) were randomly selected to analyze the floor estimation algorithm.

Two different implementations of RNs were considered in our experiments. The first scenario deploys two RNs on each floor whereas the second scenario deploys four RNs on each floor. Fig. 3 (b) shows the cases of using four RNs on each floor of the library buildings (RN1 to RN4). All of RNs are installed at the height of 2m while the mobile node (i.e. target node) is connected to a computer notebook on which the floor estimation algorithm is executed. The height of the wireless transceiver of the target node is 0.8 m. IEEE 802.15.4 wireless transceivers were deployed in this work. They have Free scale MC13224V third generation chipset with built-in ARM7TDMI processor. The antennas of wireless transceivers are the inverted F-shape antennas and operate at 2.480 GHz (i.e. channel 26 of IEEE 802.15.4 standard). Table II shows specifications of the wireless transceivers used in our implementation.

TABLE II
SPECIFICATION OF A WIRELESS TRANSCEIVER

Specification	Detail
Manufacturer	Free scale
Chipset	MC13224V
Frequency range	2.405 GHz – 2.480 GHz
Transmit power	+3 dBm
Sensitivity	-95 dBm
Operating channel	CH 26 (i.e. 2.480 GHz)
Antenna type	Inverted F-antenna

V. Results and Analysis

First, we analyze characteristics of the RSS summation from all RNs installed on different floor. We consider the case that deploys four RNs on each floor. We recorded the RSS at the 77^{th} test point on the second floor of the library building. Fig. 4 shows the Probability Density Function (PDF) of the set of summation of RSS that the test point obtained from all RNs on each floor. We can observe that the sum-RSS obtained from RNs on the second floor (i.e. blue line in Fig. 4) is higher than the sum-RSS obtained from RNs on the other floors. It means that the set of sum-RSS obtained from RNs on the floor where the target node located is stronger than those received from RNs located on the other floors. We use these observed results and characteristics to develop the floor estimation algorithm which can indicate the floor number of test point as described in detail in Section III.

Next, we demonstrate how well the proposed floor estimation algorithm works. We consider the case that deploys four RNs on each floor as shown in Fig. 3. Performance of the proposed algorithm was evaluated by measuring the confidence interval of sum-RSS of signal from different floors. For example, consider the box plot of sum-RSS at the 77^{th} test point of the library building as shown in Fig. 5. The top line and the bottom line of the box represent the upper limit and lower limit of the confidence interval of sum-RSS. The pink line in the middle refers to the average of sum-RSS value. In Fig. 5, the highest box and the other boxes are clearly separated. It means that the floor number of the target node can be accurately determined by using the highest confidence interval of sum-RSS at 95% CI. In this case, the floor that the target node located is the second floor.

Moreover, the accuracy of the proposed floor estimation algorithm, CIS-RSS floor algorithm, was evaluated by comparing the percentage of the correct floor estimation with that of the other techniques in the literature. In particular, we compare with the nearest floor algorithm and the group variance algorithm [10]. We conducted two scenarios of RN deployments (i.e. installing two RNs and four RNs on each floor). For each scenario, we conducted 150 test points (50 test points on each floor).

Table III compares the percentage of the correct floor determination among three algorithms. The results show that the proposed CIS-RSS floor algorithm outperforms the other two algorithms in all scenarios. The CIS-RSS floor algorithm results in the highest percentage of correct floor determination up to 100% in all scenarios whereas the nearest floor and the group variance algorithm yield the correct floor estimation less than those of the CIS-RSS floor algorithm.

(a) Library building (b) 1^{st} floor of Library

Fig. 3 Service environment and the floor layout

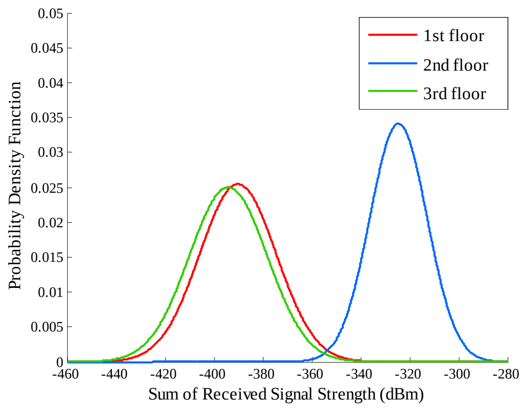

Fig. 4 PDF of sum-RSS value for 77^{th} test point at Library building

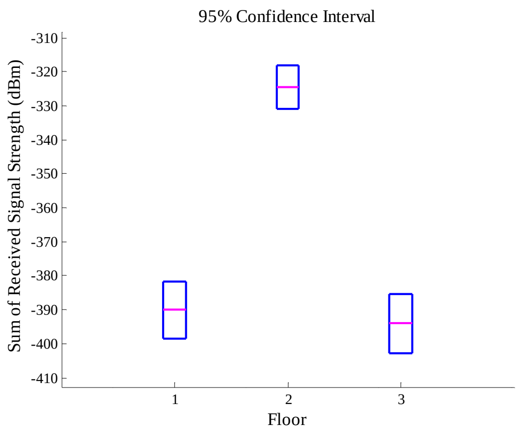

Fig. 5 Confidence interval of 77^{th} test point at Library building

TABLE III
Percentage of the Correct Floor Estimation

Floor estimation algorithm	Number of RNs deployed on each floor	
	2 RNs	4 RNs
CIS-RSS	100%	100%
Nearest Floor	99.3%	96.0%
Group Variance	85.3%	85.3%

VI. Conclusion

In this research, we presented the floor estimation algorithm for the indoor multi-story positioning systems. This algorithm is called CIS-RSS floor algorithm that use the statistical properties of RSS received in online phase to determine the floor number where the target node is located. The proposed algorithm does not require the offline phase to create maps of the radio signal strength. Extensive experiments were conducted to compare the proposed algorithm with the other floor estimation algorithms. The experimental results showed that the CIS-RSS floor algorithm outperformed the other algorithms and could achieve highest percentage of the correct floor estimation up to 100% with 95-percent confidence interval. Besides the accuracy performance of floor algorithm, our floor algorithm could provide the robustness of system; increasing the number RNs do not affect the performance of CIS-RSS floor algorithm.

Our future work will incorporate other parameters of the indoor environments to determine not only the floor number but also the target position in the indoor multi-story building.

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