

A Low-Complexity Floor Determination Method Based on WiFi for Multi-Floor Buildings

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Abstract—Floor determination has become an extremely urgent issue to resolve because many applications require accurate information on floor numbers to provide better localization services. This paper presents a Wi-Fi based, low-complexity floor determination method for multi-floor buildings. In this paper, the Multi-Wall-Floor (MWF) model is used in the simulation and the analysis. Simulation results show that the floor determination accuracy is nearly 100% if the deployment density of Wireless Access Points (WAPs) is sufficiently high on each floor. It is also shown that the proposed method provides a good estimation of floor determination even when only a few WAPs are implemented on each floor. In our scheme, detailed information on the WAP coordinates is not needed, except floor ID and Received Signal Strength (RSS) of each WAP. The novelty of the proposed method is that it can work in extreme conditions, where there are no WAPs on the floor.

Keywords—Indoor positioning; Floor determination; WiFi; Wireless access point; Received signal strength.

I. INTRODUCTION

Determining a user's floor number in multi-floor buildings is still a difficult issue. As urbanization increases, more and more tall buildings will be built in cities. Many applications need accurate floor number information to provide better services. For example, such information could prevent school violence in multi-floor buildings by providing a faster and more efficient response to student alarm signals. Thus, floor determination has become extremely urgent to be resolved.

Outdoor positioning relies for the most part on GPS (Global Positioning System), which has an accuracy ranging from 1 meter to 10 meters. It is widely used in military applications such as surveillance and in civilian sectors such as scientific research, tracking, and navigation as well as e-commerce. However, due to attenuation and scattering, GPS is not suitable for indoors use. Hence, the requirements of indoor positioning systems differ from those of their outdoor counterparts. Many technologies have been proposed for indoor positioning in the last decade. Among these, Wi-Fi has attracted a lot of research effort because it is a mature and relatively low-cost technology. Wi-Fi hot spots are now

becoming commonplace in city buildings. The utilization of these Wi-Fi hot spots' signals offers a feasible solution to floor determination [1-2,12-13].

Nowadays, numerous computing devices such as smart phones and tablet PCs are equipping Wi-Fi modules. Simultaneously, the floor number of each WAP can be known in advance. The following work is to find an effective floor determination method with RSS and ID information of scanned WAPs. To this end, we propose a Wi-Fi based, low-complexity floor determination method for multi-floor buildings. The rest of this paper is organized as follows. Section II summarizes current state-of-art on Wi-Fi based floor determination, and Section III discusses the system model and proposes our method. Simulation results are presented in Section IV to demonstrate the efficacy of the proposed method. The final section presents conclusion and future works.

II. CURRENT STATE-OF-ART OF WiFi-BASED FLOOR DETERMINATION

There are many technology options for floor determination such as time of arrival, angle of arrival, and RSS. This paper focuses on RSS-based choices because of cost and implementation consideration.

Some Wi-Fi based floor determination systems have been proposed [2-6]. Among these systems, fingerprinting-based systems play an important role [2-5]. In particular, Liu et al. [3] have demonstrated a Wi-Fi based indoor positioning system based on fingerprinting. In their research, their floor positioning experimental results showed that the floor determination was highly accurate closed to 100%. However, in common with any fingerprinting systems, the main disadvantage is that a database is usually required to train an accurate localization model. To create a fingerprinting localization model for use in multi-floor buildings, we need a sufficient number of sample points on each floor. This can be time-consuming and expensive. The indoor environment is also very complex, not only due to the presence of walls and floors, but also due to uncertain factors such as human activity and furniture or equipment rearrangements. The effects of such factors are difficult to test and measure with today's technologies. They also hamper the potential utility

of fingerprinting systems in the indoor environment. These systems are also unable to accommodate any changes in the Wi-Fi infrastructure and require a complete recalibration. The need to replace the database is another troublesome issue.

Elsehly et al. [2] have designed two different models for using Wi-Fi signals to determine the floor number in multi-floor buildings. One is called the “nearest floor algorithm.” Essentially, it is a simplified solution of the well-known nearest neighbor classification algorithm used in fingerprinting. Although they used the system to simultaneously update records of Wireless Access Points (WAPs) in the database, the system still cannot overcome the aforementioned disadvantages. Their second model, called the “group variance algorithm” can be divided into three steps. The first step involves grouping the Wi-Fi RSS depending on the floor number. The second step entails calculating the floor parameters (range, variance, availability) for each floor. The last step involves selecting the floor number with the maximum number of points as the estimation result. Their experimental results showed that the group variance algorithm performed worse than the nearest floor algorithm. However, it was more reliable in areas such as washrooms and building edges where the received signal is weak. More importantly, the group variance algorithm does not require the creation of a database in advance. However, the disadvantage of this algorithm will be discussed later in Section IV.

The attenuations of horizontal and vertical signals are significantly different in buildings due to different materials used in the floors and the walls along with their different thicknesses. Generally, the attenuation of the floors is greater than that of the walls. This property may be exploited to estimate the floor number based on the characteristics of the received signals. Actually, floor determination will be easy if the signal attenuation of the floor is much larger up to the user’s device unable to receive a signal or if the received signal is very small from the WAPs on the other floors. Thus, a critical issue that needs to be addressed in those buildings is the moderate loss of the floor penetration value.

Another disadvantage of the conventional systems is that none considers the effect of accidents, e.g., all the WAPs on one floor stopping working, but those on the other floors remaining operational as usual. The existing algorithm would be unable to determine the floor number in such a situation.

III. SYSTEM MODEL AND PROPOSED FLOOR DETERMINATION METHOD

A. System Model

Path loss greatly impacts the localization accuracy of algorithms based on the RSS. It results in varying degrees of loss when the radio signals propagate in different environments. Thus, choosing a suitable path loss model is very important. Research has shown that the Multi-Wall-Floor (MWF) path loss model might be the most precise model when compared to all the other models including the

Motley-Keenan model for both office and commercial indoor topologies [7-11]. The following equation describes the MWF model.

$$L_{MWF} = L_0 + 10n \log(d) + \sum_{l=1}^I \sum_{k=1}^{K_{wl}} L_{wik} + \sum_{j=1}^J \sum_{k=1}^{K_{fl}} L_{fjk} \quad (1)$$

where

L_0 : Pass loss at a distance of 1 meter

n : Power decay index

d : Distance between the transmitter and the receiver

L_{wik} : Attenuation due to wall type i and k^{th} traversed wall

L_{fjk} : Attenuation due to floor type j and k^{th} traversed floor

I : Number of wall types

J : Number of floor types

K_{wi} : Number of traversed walls of category i

K_{fj} : Number of traversed floors of category j

In addition, taking into account the influence of obstruction in indoor environment, we add a normal random variable N with zero-mean and variance of δ^2 to represent shadow noise. Then, the RSSI value from WAP can be written as:

$$L_r = L_{MWF} + N \quad (2)$$

To make the simulation easier, we suppose that all the floors are the same type and all the walls are the same type in our model. We represent the received Wi-Fi signals of the user using the set \mathfrak{R} , which contains the number of signals. The set R_i contains the floor identity and the RSS value of the WAP.

$$\mathfrak{R} = [R_1, R_2, \dots, R_i] \quad (3)$$

$$R_i = [FloorID_i, RSS_i] \quad (4)$$

B. Proposed Feedback Method

In an indoor environment, the thickness of each part of each floor and the thickness of the materials in the floors are nearly equal. In most cases, the thickness of each floor and the thickness of the material are also nearly equal. Based on the signal’s propagation, the floor penetration loss value will fall in a certain range. In our research, we assume that random attenuation value due to the floor follows a constant value which is denoted as L_f . In practical applications, we can measure the attenuation value of each part of each floor of the building, and then average these values as the attenuation due to the floor. Based on the analysis described above, we propose a floor determination algorithm called the “feedback method.”

The following steps describe how the proposed feedback method calculates the floor number during the analysis.

1) *Pre-estimation step:* We conduct a pre-estimation of the user’s floor number. Generally, we choose those floor IDs that have occurred in the set \mathfrak{R} .

2) *Feedback step:* We suppose that the user is on the p^{th} floor which is part of the pre-estimated floor numbers. Based on this assumption, it is simple to determine how many floors the signal penetrated before the user received it. Then, we feedback the attenuation value of the floor to \mathfrak{R} . The feedback value equals to $L_f \times |FloorID_i - p|$.

3) *Estimation step:* We calculate the variance of all the RSS values for each pre-estimation. We then compare the variances of all the pre-estimation steps and select the floor number with the minimum variance value.

If the pre-estimation is correct, the feedback value will eliminate the influence of the floor attenuation. If not, the received RSS values in set \mathfrak{R} will become more confused due to incorrect feedback. Thus, we selected the minimum variance value as the last estimation result. Compared to fingerprinting-based approaches, our proposed scheme does not require frequent updates of the attenuation values after accurate measurement, because the location and make-up of the floor will not usually change after the building has been built, except in exceptional cases. Compared to the group variance method, the proposed feedback method can handle the effects of accidents mentioned above. The group variance algorithm groups the RSS values according to the floor number and the last estimation results from these groups. Thus, this algorithm is unable to determine the number of the floor where the accident occurred. In contrast, our proposed scheme can handle the effects of accidents by selecting all the floor numbers as the pre-estimation.

IV. SIMULATION RESULTS

A. Simulation Environment

The simulations were performed on a multi-floor building model with eight floors. The detailed parameters and settings for the simulations are summarized in Table I.

TABLE I. PARAMETERS OF SIMULATION ENVIRONMENTS

Parameters	Values
Areas of each floor	$36.5 \times 22.7 \text{ m}^2$
Thickness of each floor/wall	40 cm, 30 cm
Height between floors	3 m
Attenuation due to each floor/wall	$L_f = 25 \text{ dB}, L_w = 10 \text{ dB}$
MWF model	$L_0 = 20 \text{ dB}, n = 2.5$ $N \sim (0, \delta^2), \delta = 3$
RSS value	$\geq -110 \text{ dBm}$

Note that, in order to reduce the workload, we used a simple model where the structure of each floor in the building is the same. From the commonly used free space propagation model for path loss at a distance of 1 meter and frequency of 2.4GHz (i.e., Wi-Fi frequency) we set $L_0 = 20\text{dB}$.

B. Analysis of Proposed Feedback Method

The estimated points were chosen at three random positions on the 1st, 5th, and 6th floor, and there were two WAPs on each floor.

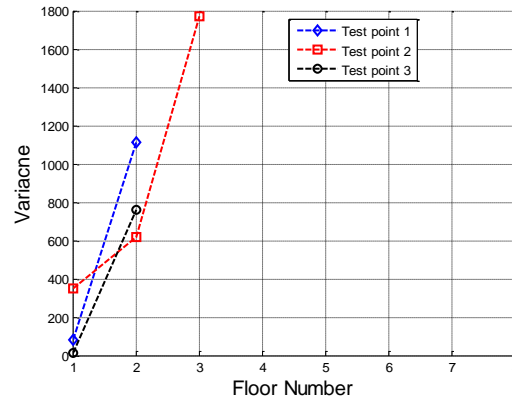


Figure 1. Simulation results for the 1st floor.

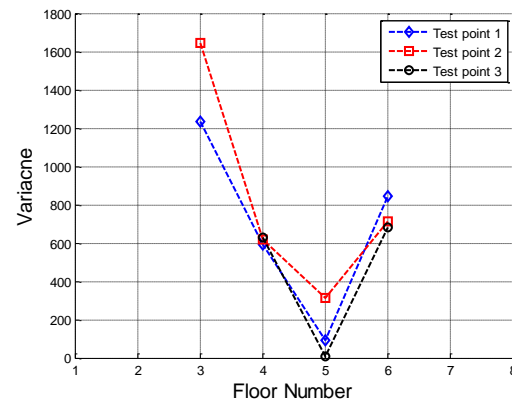


Figure 2. Simulation results for the 5th floor.

Figs. 1 and 2 show the simulation results for pre-estimation floor IDs that occur in the received Wi-Fi signals set. These figures illustrate that the lowest variance occurs when the assumed number from the pre-estimation step equals that of the actual floor number of the user.

In this paper, we also consider a specific case. In that case, all of the WAPs on the floor where an accident happens have stopped working, while WAPs on other floors can still work normally. In this case, we will choose all the floor numbers as the pre-estimation in the simulation as shown in Fig. 3.

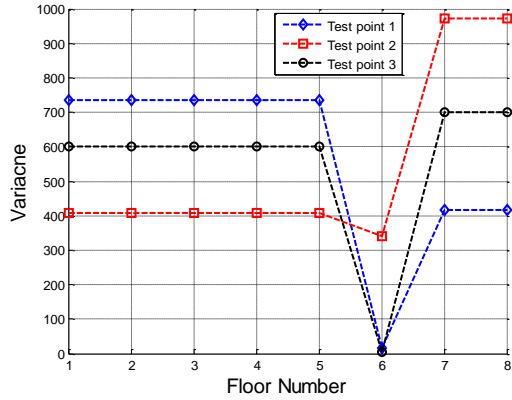


Figure 3. Simulation results for the 6th floor.

In terms of the pre-estimation, the variance maintains the same value for all the floors except the 6th floor. To explain aforementioned phenomena, we present in Table II an example with the received signals set $\mathfrak{R} = [R_1, R_2, R_3]$ on the 6th floor. The table clearly indicates that the variance is the same for the first five floors and the last two floors with an exception of the 6th floor.

TABLE II. EXAMPLE OF THE 6TH FLOOR

Pre-estimation	Feedback			Variance
	$R_1 = [5, R_{ss1}]$	$R_2 = [6, R_{ss2}]$	$R_3 = [7, R_{ss3}]$	
1	$R_{ss1} + 4 \times L_f$	$R_{ss2} + 5 \times L_f$	$R_{ss3} + 6 \times L_f$	V_1
2	$R_{ss1} + 3 \times L_f$	$R_{ss2} + 4 \times L_f$	$R_{ss3} + 5 \times L_f$	V_2
3	$R_{ss1} + 2 \times L_f$	$R_{ss2} + 3 \times L_f$	$R_{ss3} + 4 \times L_f$	V_3
4	$R_{ss1} + L_f$	$R_{ss2} + 2 \times L_f$	$R_{ss3} + 3 \times L_f$	V_4
5	R_{ss1}	$R_{ss2} + L_f$	$R_{ss3} + 2 \times L_f$	V_5
6	$R_{ss1} + L_f$	R_{ss2}	$R_{ss3} + L_f$	V_6
7	$R_{ss1} + 2 \times L_f$	$R_{ss2} + L_f$	R_{ss3}	V_7
8	$R_{ss1} + 3 \times L_f$	$R_{ss2} + 2 \times L_f$	$R_{ss3} + L_f$	V_8

C. Comparison with Group Variance Algorithm

As shown in Figs. 4 and 5, the comparison of the performance of the proposed feedback method with that of the conventional group variance algorithm reveals a significant change according to the number of WAPs on each floor. The simulation results are based on four different cases. Table III shows the detailed parameters.

Cases #1-4 show that the floor determination accuracy gradually deteriorates with the reduction in the number of WAPs on each floor. However, the degree of deterioration in the performance of the two methods is quite different. The proposed feedback method is always able to achieve accuracy of 95% in terms of floor determination especially for Case #1. It shows that the correct determination by the proposed method is significantly close to 100% because the deployment density of the WAPs is relatively high. In

contrast, the performance of the group variance algorithm is worse than the feedback method for each case and the performance of former one decreases rather rapidly. As shown in Case #4, the group variance algorithm can realize accuracy of just 30–40%.

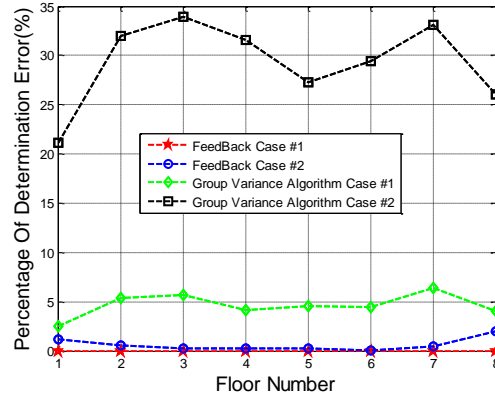


Figure 4. Comparison of the performance (Cases #1 and #2).

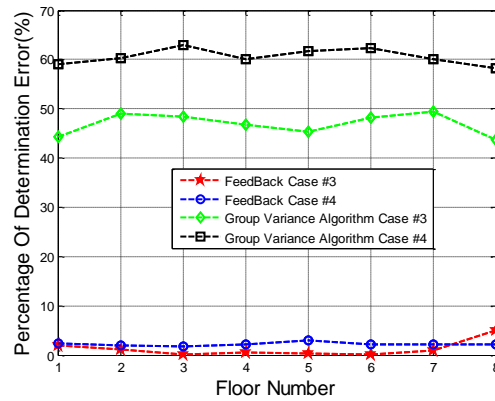


Figure 5. Comparison of the performance (Cases #3 and #4).

TABLE III. COORDINATE INFORMATION

Cases	Positions of WAPs on each floor
Case #1	(5.3 5.3) (5.3 17.4) (15.6 5.3) (15.6 17.4) (25.9 5.3) (25.9 17.4) (33.7 5.3) (33.7 17.4) (15.6 11.4)
Case #2	(10.3 10.3) (20.6 12.4) (30 5) (4 20) (30 20)
Case #3	(10.3 10.3) (20.6 12.4) (30 5)
Case #4	(10.3 10.3) (20.6 12.4)

TABLE IV. COORDINATE INFORMATION

Floor ID	Range	Variance	Availability
F1	0.5	0	0
F2	0.5	0	0
F3	0.5	0	0

The poor performance of the group variance algorithm is due to its inability to distinguish which floor the user is on when the variables shown in Table IV are present. In this

situation, the group variance algorithm cannot make a choice due to the three groups having the same points.

D. Effects of Accidents

We assumed that there are no WAPs on the 1st floor and the 6th floor, and nine WAPs on the other floors. An estimated point was chosen from 1,000 random positions on each floor.

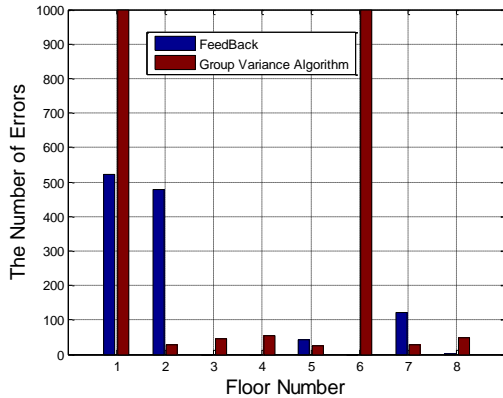


Figure 6. Comparison of the performance under extreme conditions.

Fig. 6 presents the simulation results based on this scenario. The results clearly show that the group variance algorithm was unable to adapt to this case. In contrast, the feedback method was still operational under this extreme condition. In particular, the accuracy of floor determination was high, with the change in the number of WAPs on the 6th floor seemingly causing no influence.

In order to demonstrate it clearly, we divide floor IDs into two types, as shown in Table V, since the received signals are from single direction (up-floor or down-floor), when the user locates on the accident floor which belongs to the edge building. Similarly, the signals will come from double directions (up-floor and down-floor) when the user locates on the accident floor belonging to middle building. Based on that, we can observe that the ability to deal with accidents happening on middle building is stronger than that on edge building.

TABLE V. TYPE OF FLOOR

TYPE	Floor ID
Middle building	2nd ~ 7th floor
Edge building	1st and 8th floor

Meanwhile, the accuracy of the proposed feedback method falls off sharply when the floors are close to those without WAPs (2nd, 5th and 7th floor), because the received signals are from single direction on those floors adjacent to the accident floor.

V. CONCLUSION AND FUTURE WORK

This paper presented a Wi-Fi based floor determination method for multi-floor buildings. Compared to traditional approaches, there are three advantages of the scheme proposed in this paper: robustness, simplicity, and an ability

to deal with accidents. First, the simulation results showed the floor determination accuracy was nearly 100%, if the deployment density of the WAPs is sufficiently high on each floor. They also showed that the proposed method performs well in terms of floor determination, even in the presence of just two WAPs on each floor. Second, there is no need for detailed coordinate information on the WAPs in this scheme. In our research, the floor ID and the RSS value of each WAP are sufficient. Third, the final simulation results showed that this method can work under extreme conditions where there are no WAPs on the floor.

Future work will focus on perfecting the proposed algorithm for the floor determination and developing a mobile application in real environments.

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