Weak multipath effect identification for indoor distance estimation

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***Abstract*—Wireless LANs, especially WiFi, have been pervasively deployed and have fostered myriad wireless communication services and ubiquitous computing applications. Indoor localization is an essential modules of these applications. A primary concern in designing scenario-tailored application is to obtain precise estimated distance combatting with harsh indoor wireless signal propagation issues, particularly multipath effect. The conventional propagation model based on received signal strength indicator(RSSI) is easily affected by temporal and spatial fluctuation due to the multipath effect, which leads to most of the distance estimation errors in current indoor localization systems. Intuitively, these positions in weak multipath effect(WME) conditions, which are slightly affected by multipath effect, perform better under free space propagation model. Therefore, the ability to distinguish weak multipath effect, which is slightly affected by multipath effect is a key enabler for accurate distance estimation. Enabling such capabilities on commercial WiFi infrastructure, however, is difficult due to the coarse multipath resolution with the MAC layer RSSI. In this paper, we propose a universal precise distance estimation scheme based on weak multipath effect identification, leveraging the channel state information(CSI) from the PHY layer. In our distance estimation system, we first select positions which are identified as weak multipath effect conditions. Then we build a free space propagation model with RSSI to estimate distance between the transmitter and the receiver, choosing these selected positions. Experimental results demonstrate that choosing positions in weak multipath effect conditions can effectively improve the accuracy of distance estimation in a variety of typical indoor environments.**

***Keywords*-Indoor localization; channel state information; RSSI; multipath effect;**

I. Introduction

Wireless indoor localization brings about numerous location-based services in many application fields. Such a boom of pervasive computing has sorely urged the need for accurate, robust, and off-the-shelf indoor localization services. Comparing with outdoor positioning, indoor localization is more challenging, since GPS signals are rarely accessible. However, room-level and even submeter precision is often required. Thanks to the ubiquitous deployment of wireless networks and devices in past two decades, we have witnessed extensive wireless indoor localization techniques, such as acoustic signals, ultrasound, FM, infrared, RFID, Bluetooth, cellular, ZigBee, WiFi, UWB [1]. Recently, the Received Signal Strength Indicator (RSSI), which characterizes the attenuation of radio signals during propagation, has been adopted in a large body of indoor localization systems.

According to the propagation loss model, received signal power monotonically decreases when the distance from source is increasing, it is the foundation of the model-based localization [2]. Most of existing radio frequency (RF)-based indoor localization methods are based on the RSSI values [3][4][5][6]. However, utilizing RSSI usually encounters undesirable errors in indoor localization. The reasons are from two respects: First, the RSSI is measured from RF signal at the per packet level, therefore, it is difficult to obtain a precise value; Second, the RSSI is volatile because of the multipath effect. In theory, it is possible to establish a model to estimate the distance using the received power. However, the propagation of RF signal is attenuated by reflection when it hits the surface of an obstacle. As shown in fig 1, in addition to the Line-Of-Sight(LOS) signal, there are possibly multiple Non-Line-Of-Sight(NLOS) signals arriving at the receiver through different paths. Such a multipath effect is even more serious in indoor environment where a ceiling, floor, and walls are present. As a result, it is possible for a closer receiver to obtain a lower RSSI than a further one. And a simple relationship between received power and distance cannot be established. Therefore, the multipath effect causes the main undesirable indoor localization errors. Conventional RSSI-based method to avoid multipath effect are from two respects: First, building a complex model to reduce the error which the multipath effect bring about utilizing various algorithms [7][8][9], thus it spend extra time; Second, improving the accuracy of localization by using fingerprint system [10][11]. However, it needs a lot of labor to collect data and update fingerprint on time. Therefore, we aim to build a universal model based on RSSI without human labor.

We assume that these positions in weak multipath effect(WME) conditions, which are slightly affected by multipath effect, perform better under free space propagation model. Therefore, we argue that a WME identification scheme to improve the accuracy of distance estimation is in need. We strive to select these positions, which are identified as WME conditions, to estimate distance between the transmitter and the receiver. Fortunately, in current widely used orthogonal frequency division multiplexing(OFDM) systems, where data is modulated on multiple subcarriers in different frequencies and transmitted simultaneously, there is a value that estimates the channel in each subcarrier called channel state information(CSI). Different from RSSI, CSI is a fine-grained value from the PHY layer which describes the amplitude and phase on each subcarrier in the frequency domain. There is only one RSSI in a packet, in contrast, we can obtain multiple CSIs at a time. In addition, the CSIs over multi-subcarriers will travel along different fading or scattering paths on account of the multipath effect. It then naturally brings in a capacity to multipath effect identification. Therefore, it is favorable to evaluate multipath effect utilizing the CSI in typical indoor environments. The CSI values are already utilized for LOS identification [12][13] and indoor localization [2][14][15][16]. In conventional distance estimation system, the RSSI values and the CSI values are adopted independently. However, due to the multipath effect, the RSSI values usually fluctuate tempestuously which results in the main distance estimation error in most of RSSI-based indoor localization systems. In contrast, the CSI-based model [2] is environment-related because of its fine-grained reflection for multipath effect. For example, the path loss fading exponent n , which evaluates the degree of signal attenuation in CSI-based model [2], varies very much on different environments.

In this paper, we aim to design a pervasive universal precise distance estimation system based on WME identification in complex indoor scenarios, utilizing RSSI and CSI with commercial WiFi devices. Since the weak and strong multipath effect are mutually exclusive, we harness the hypothsis test framework for statistical weak multipath effect identification. To capture the distinctions between weak and strong multipath effect point with off-the-shelf WiFi infrastructure, we exploit three observations. 1) The PHY layer information on commercial WiFi devices reveals multipath channel characteristics at the granularity of OFDM subcarriers [18], which is much finer-grained than the conventional MAC layer RSSI. 2) The distance estimation error under WME conditions based on free space propagation model is smaller than that under strong multipath effect(SME) conditions. 3) The ratio between the LOS signal strength and NLOS signal strength(LNR) is higher under WME conditions.

We propose a weak multipath effect identification scheme for commodity WiFi infrastructure. The main contributions of this work are summarized as follows

- We exploit PHY layer channel state information to identify the weak multipath effect positions in multipath-dense indoor scenarios. As far as we know, this is the first weak multipath effect identification scheme built upon commercial WiFi infrastructure without hardware modification leveraging CSI, which allows pervasive adoption.
- We build a pervasive universal distance estimation system based on weak multipath effect identification and validate its performance in various indoor office environments.

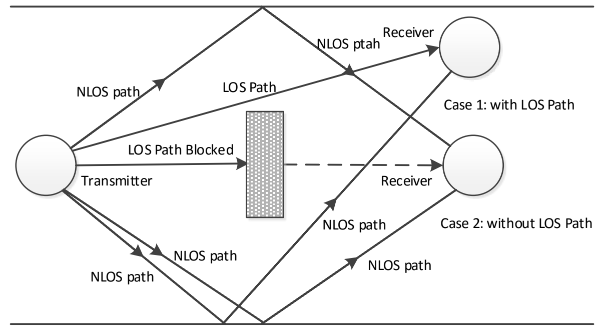


Figure 1. An illustration of multipath propagation and LOS/NLOS conditions.

In summary, the multipath effect can be regarded as a primary characteristic of WiFi channels. We propose a scheme to identify weak and strong multipath effect conditions as an enhancement for current 802.11 standards and future communication protocols, and strive to obtain a precise distance estimation in various indoor office environments for indoor localization.

The rest of this paper is organized as follows. System and implementation are provided in Section II. Then experimental results and analysis is introduced in Section III. Finally conclusion and future work is given in Section IV.

II. System and implementation

In this section, we give an overview of system architecture. Then we describe the implementation details for each part of the propose weak multipath effect identification system.

A. System Architecture

Our system is built based on off-the-shelf WiFi infrastructure. In addition, no modification is needed at the transmitter end(TX-the AP), and only two new components are needed for precise distance estimation which are CSI and RSSI processing at the receiver end(RX-the target mobile device), respectively. Fig 2 shows the detailed design of the distance estimation system architecture.

In our distance estimation system, the CSI values and the RSSI values will be collected simultaneously at the same positions. Then the RSSI values with smaller variations can be obtained through the kalman filter algorithm. Meanwhile, we obtain the revised CSI by normalization and Inverse Fast Fourier Transform(IFFT). Note that, commercial NICs

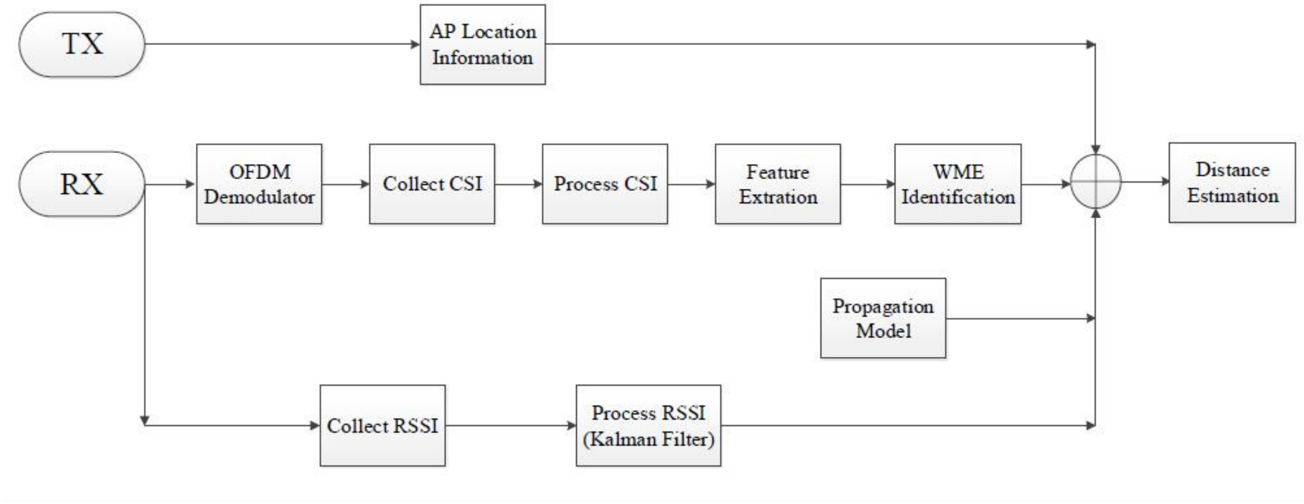


Figure 2. System architecture.

embeds hardware circuts for the FFT and IFFT processing, our algorithm brings ignorable latency to the entire distance estimation procedure [2]. Next, features are extracted from the modified CSI and WME conditions are identified. Finally, these filtered RSSIs, whose collect positions are identified as WME conditions, will be chosen to estimate distance from the TX to the RX. It is handled by a propagation model, which is built on RSSI values off-line. The estimate distance error is calculated by the AP information and the estimated distance.

B. Processing

We collect RSSI and CSI at the receiver end, respectively. To mitigate the temporal fluctuation of RSSI values, we run the Kalman filter algorithm [17] to revise RSSI values. These RSSI values with smaller variations will benefit our distance estimation. We set a sliding window with 10 seconds to filter RSSI values. To design a practical WME identification scheme with commodity WiFi infrastructure, we adopt the recently available PHY layer information. Leveraging the off-the shelf Intel 5300 NIC and a modified driver, a sampled version of Channel Frequency Response(CFR) within WiFi bandwidth is revealed to upper layers in the format of Channel State Information(CSI) [18]. Each CSI depicts the amplitude and phase of a subcarrier:

$$H\left(f_i\right) = \left\|H\left(f_i\right)\right\| e^{j\sin\angle H\left(f_i\right)} \tag{1}$$

Where $H\left(f_i\right)$ is the CSI at the subcarrier with central frequency of f_k, and $\angle H\left(f_i\right)$ denote its phase [12]. Since CFR can be converted into Channel Impulse Response(CIR) via Inverse Fast Fourier Transform(IFFT), an estimation of CIR with time resolution of 1/20MHz=50ns is exposed.

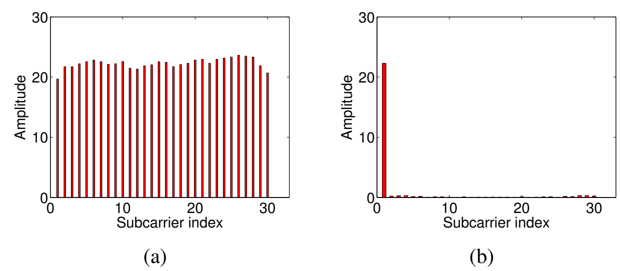


Figure 3. CFR and CIR. (a)CFR in outdoor footballfield. (b) CIR in outdoor footballfield.

we obtain the revised CIR by Inverse Fast Fourier Transform(IFFT). To overcome the drawback of the NIC 5300, we filtered the CFR samples measured at a time through selecting the middle 24 subcarriers.

C. Feature extraction

To guarantee a precise WME identification, we extract suitable features from CSI in frequency domain combining with the LNR in time domain. Here we present primary measured data from a typical office building, and focus on the features for WME identification. We extract features on outdoor football field which can be considered as a WME environment.

1) LNR characteristics of CSI : The rationale for LNR characteristics based WME identification is twofold. (1) For a particular wireless link, signals transmitted via the LOS paths (or direct path) always arrive first. (2) The multipath effect will increase the signal strength on NLOS paths while the signal strength on LOS path (or direct path) keeps normal. Prevalent feature metrics include mean and

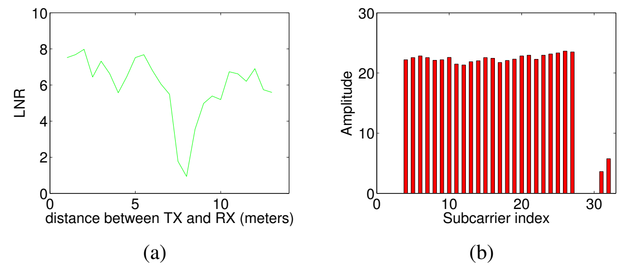


Figure 4. Features for WME identification. (a)LNR in outdoor footballfield. (b)filter CFR, variance and skewness in outdoor footballfield.The prior 24 subcarriers are filtered CFRs in frequency domain, two latter subcarriers are added with ten times variance of filtered CFRs and skewness of filtered CFRs.

variance, which is approximate to the weighted average and fluctuation of the LNR.

We extract CSIs from 5000 packets collected in typical indoor environments, and calculate the corresponding CIRs via IFFT. Fig 3(a) and fig 3(b) show the CFR and CIR, respectively. As fig 3(b) shows, the amplitude of first subcarrier is much larger than other subcarriers. Therefore, we approximatively take the first subcarrier of CIRs as LOS paths(or direct paths) and other NLOS paths. Then the LNR values are calculated through the amplitude of first subcarrier divided by sum amplitude of other subcarriers.

Since CSI on current WiFi fails to estimate precise CIR, the first subcarrier is sometimes mixed with NLOS paths. Therefore, it is insufficient to distinguish WME conditions just through LNR values.

2) Channel Frequency Response of CSI : In order to distinguish WME conditions from SME conditions, we extract features from Channel Frequency Response of CSI. As fig 3(a) shows, due to the drawback of the NIC 5300, there is a small falling in the rising and falling edge of CFR, which is described in the forum at https://github.com/dhalperi/linux-80211n-csitool-supplementary/issues/28. Therefore we just choose 24 subcarriers of the CFR in the middle for feature extraction. Fig 3(a) tells us that the curve of CFR is almost a horizontal line under WME conditions. Hence we extract features which can be a mirror of this phenomenon. After testing many features such as variance, skewness, kurtosis, we choose two candidates, variance and skewness, for our WME identification scheme:

a) Variance: In probability theory and statistics, variance is the expectation of the squared deviation of a random variable from its mean, and it informally measures how far a set of (random) numbers are spread out from their mean. The variance has a central role in statistics. It is used in descriptive statistics, statistical inference, hypothesis testing, goodness of fit, Monte Carlo sampling, amongst many others. As aforementioned, we only extract variance from 24 subcarriers of the CFR in the middle. A small Variance indicates small variation and thus, a high probability of WME conditions.

b) Skewness: Skewness is a general metric which describes the skewed shape of a distribution. Mathematically, skewness s is define as:

$$s = \frac{E\left\{x - u\right\}^3}{\sigma^3} \tag{2}$$

Where x, u and σ denote the measurement, mean, and standard deviation, respectively. A positive(negative) skewness indicates that the measured data spreads out to the right(left) of the sample mean. A small absolute value of skewness indicates a high probability of WME conditions. In summary, both small variance and small absolute value of skewness make sure the curve of CFR close to a horizontal line which is considered as a WME condition.

D. Multipath identification

Twisty corridors, capsule rooms and scattering furniture indoor environment often create a labyrinth for radio signals transmission, where they have to propagate via multiple intricate NLOS paths. As shown in fig 1, it is common for the LOS path to be mixed with multiple aliased NLOS paths (case1), or too harshly attenuated to be perceivable against the noise floor(case 2). In both conditions, there are possibly multiple signals arriving at the receiver through different paths. Hence the weak multipath effect identification problem is to discern these positions where the signal strength is lightly influenced by multipath effect.

In the time domain, the multipath channel is modeled as a temporal linear filter, known as CIR [19] $h\left(\tau\right)$:

$$h\left(\tau\right) = \sum_{i=1}^{N} a_i e^{-j\theta_i} \delta\left(\tau - \tau_i\right) \tag{3}$$

where α_i, θ_i and τ_i are the amplitude, phase and time delay of the i^{th} path, respectively. N is the total number of paths and $\delta\left(\tau\right)$ is the Dirac delta function. Then we can calculate $LNR\left(\tau\right)$:

$$LNR\left(\tau\right) = \frac{\alpha_1 \delta\left(\tau - \tau_1\right)}{\sum_{i=2}^{N} \alpha_i \delta\left(\tau - \tau_i\right)} \tag{4}$$

Various statistics depicting the LNR are then utilized as indicators for WME/SME conditions.

In essence, weak multipath effect identification is aimed to infer the channel state via certain feature metrics of the received signals. Fig 4(a) shows the LNR in outdoor footballfield. And fig 4(b) shows the filtered CFR, variance and skewness in outdoor footballfield. The CSI samples reported from the receiver are filtered to eliminate the impact of transmitting power. The reassembled CFRs are then converted into CIR using IFFT. The two candidate frequency features are extracted from CFRs followed by LNR from CIR. We utilize the LNR to filter most of the SME conditions. Then the identification procedure is formulated

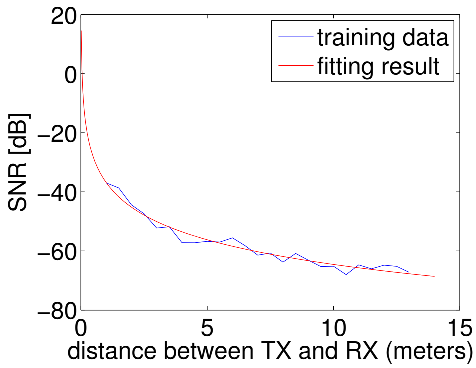


Figure 5. Propagation model.

as a statistical hypothesis test with a pre-calibrated threshold for each of the feature metrics. Given a set of filtered CFR samples from N packets, the variance and skewness s are calculated as introduced. We utilize the LNR to filter most of the SME conditions. Then WME identification is formulated as a classical binary hypothesis test with WME condition H_0 and SME condition H_1. For the variance, the hypothesis test is:

$$\begin{cases} H_0: & V < V_{th} \\ H_1: & V > V_{th} \end{cases} \tag{5}$$

And for skewness based WME identification,

$$\begin{cases} H_0: & S < S_{th} \\ H_1: & S > S_{th} \end{cases} \tag{6}$$

Where V_{th} and S_{th} represent the corresponding identification threshold for Variance and skewness, respectively. The thresholds are pre-calibrated and according to our measurements, a unified threshold for each metric would fit various scenarios including different propagation distance, channel attenuation, and blockage diversity.

E. Propagation model

We use the RSSI values collected on outdoor football field for free space propagation model. As we known, the free space propagation model is an ideal model in which the power loss is only related to distance between the transmitter and the receiver. It means the multipath effect and other interferences in indoor environments are ignored. However, we claim that this outdoor football field is similar to free space propagation model are from two reasons: First, these is almost no obstruction between and around the transmitter end and the receiver end. Second, the artificial grass on this outdoor football field can scatter the reflected multipath, thus mitigating the multipath effect to some extent. Therefore we claim that it is suitable to build a free space propagation model based on the RSSI values which are collected on such a outdoor football field. Fig 5 shows the training data and the fitting result. It is almost a logarithmic decrement which satisfies the conventional power loss of the free space propagation model.

III. Experimental results and analysis

In this section, we present the experiment setup and the methodology, followed by detailed performance evaluation of our distance estimation system in various indoor scenarios.

A. Methodology

We conduct the experiments over two week in typical office environments including corridors, hall and research laboratory. The corridors are enclosed with glass wall and Aluminum alloy plate. The research laboratory are separated by aluminum alloy plate. For the hall, we collect RSSIs and CSIs for LOS and around-corner propagation with a maximum transmitter-receiver distance of 13m every 0.5 meters. Fig 6 shows the floor plan of testing building for corridors and research laboratory, we collect RSSIs and CSIs for LOS and around-corner propagation with a maximum transmitter-receiver distance of 13m , and measured every 0.5 meters. For the research laboratory, we select 5 testing locations. The direct link between a transmitter and a receiver is a clear LOS path, but also may be blocked by aluminum alloy plate and through-wall propagation. We collect 5000 packets for each fair comparison. We also collect RSSIs and CSIs for LOS propagation every 0.5 meters in four directions(i.e,east, west, north and south) on outdoor football filed.

During the experiments, two miniPC equipped with Intel 5300 NIC and modified according to [18] is used as the transmitter and the receiver under a injection-monitor mode as described at https://github.com/dhalperi/linux-80211n-csitool-supplementary/tree/master/injection. A group of 30 CSIs are extracted from each packet and filtered as in Section II-B. A TP-LINK wireless router is employed as the transmitter and a Samsung tablet as the receiver to collect the RSSI.

We mainly focus on the following metrics to evaluate our scheme. (1) mean distance estimation error under each WME condition E_{wme}: the mean distance estimation error under the identified WME conditions in each typical office environments. (2) mean distance estimation error under each SME condition E_{sme}: the mean distance estimation error under the identified SME conditions in each typical office environments. (3) mean distance estimation error under overall WME condition AE_{wme}:the mean distance estimation error under the identified WME conditions in all the typical office environments. (4) mean distance estimation error under overall SME condition AE_{sme}: the mean distance estimation error under the identified SME conditions in all the typical office environments.

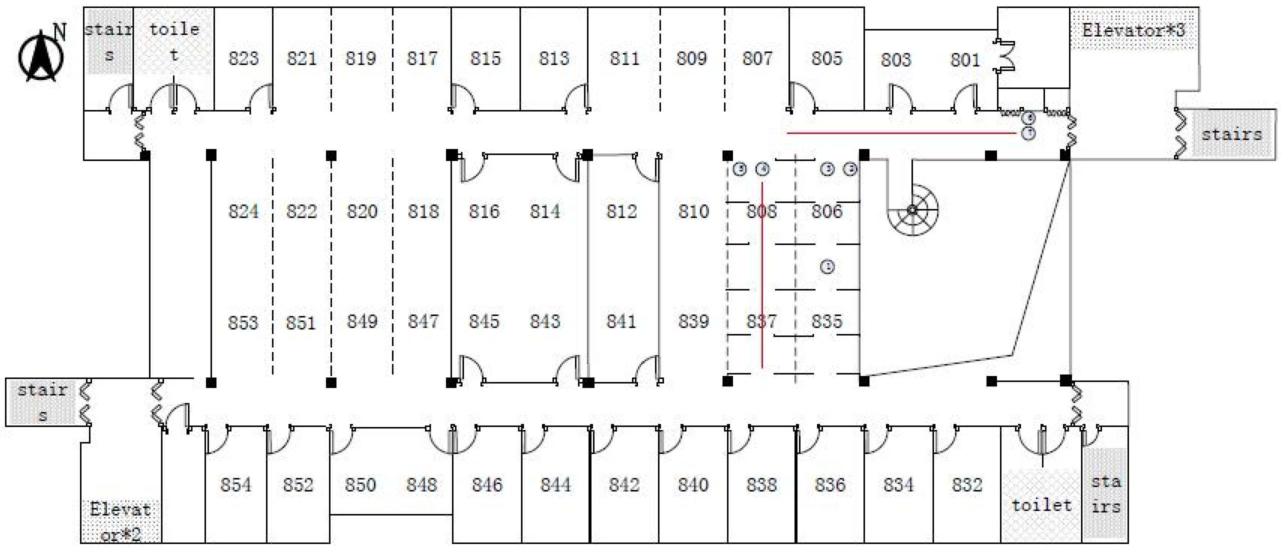
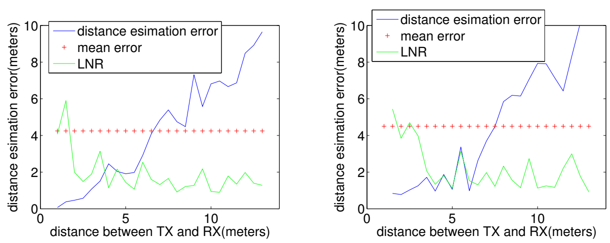
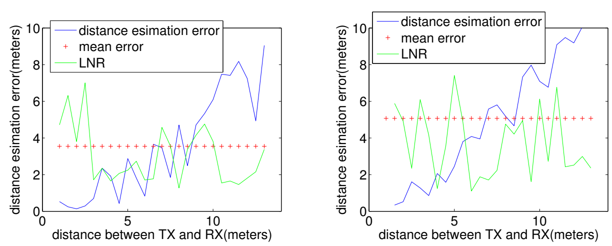


Figure 6. floorplan of the testing building. Serial number from one to seven represent seven testing postions of the TX in corridors and research laboratory. The red line is the track of the RX.



(a) (b)

Figure 8. Impact of APs position under hall conditions. (a)LNR values: TX is placed in the center of the hall, RX moves from center to one side to the other side. (b) LNR values: TX is placed in the corner of the hall, RX moves from one side to the other side.



(a) (b)

Figure 9. Impact of APs position under corridors conditions. (a)LNR values: TX is placed in the center of the corrider, RX moves from center to one side to the other side. (b) LNR values: TX is placed in the corner of the corrider, RX moves from one side to the other side.

B. Overall Performance

1) WME identification Performance: Fig 7 shows the direct link between a transmitter and a receiver which is a clear LOS path, partially blocked by Aluminum alloy plate and through-wall propagation. For all the five conditions, we can make a preliminary classification for WME conditions. These positions such as 6 meters in fig 7(a), 8 meters and 12 meters in fig 7(b), 4.5 meters in fig 7(c) are WME conditions candidates according to a LNR threshold 5. However, the LNR values are insufficient for WME identification in some scenarios such as 10 meters in fig 7(e). To obtain a precise WME identification, we try to extract suitable features from CSI on frequency domain combining with the LNR on time domain. We combine two candidates features, variance and skewness, for further WME identification. For the variance feature, we use the optimal threshold of 1. And a absolute threshold of 0.5 is taken as the ideal value for the skewness feature. These two threshold also demonstrate that they are fit for all the conditions in an indoor environment. These positions are identified as WME conditions where the variance of CFRs is bigger than 1 and the skewness of CFRs is bigger than 0.5. Thus, these positions that 6 meters in fig 7(a), 8 meters in fig 7(b), 4.5 meters in fig 7(c), 3 meters in fig 7(d) and 3 meters in fig 7(e) are identified as WME conditions. We can see that the distance estimations are smaller than the average values in all the conditions.

Fig 8 and fig 9 show the direct link between one transmitter and one receiver which are a clear LOS path and a wall-reflection propagation. These positions that 1.5 meters in fig 8(a), 1.5 meters in fig 8(b), 2.5 meters in fig 9(a) and 3 meters in fig 9(b) are identified as WME conditions. The feature thresholds are the same as aforementioned. It can be seen that the distance estimations are smaller than the average values in both conditions.

2) Distance estimation error under WME/SME conditions: Fig 10 illustrates the mean distance estimation errors un-

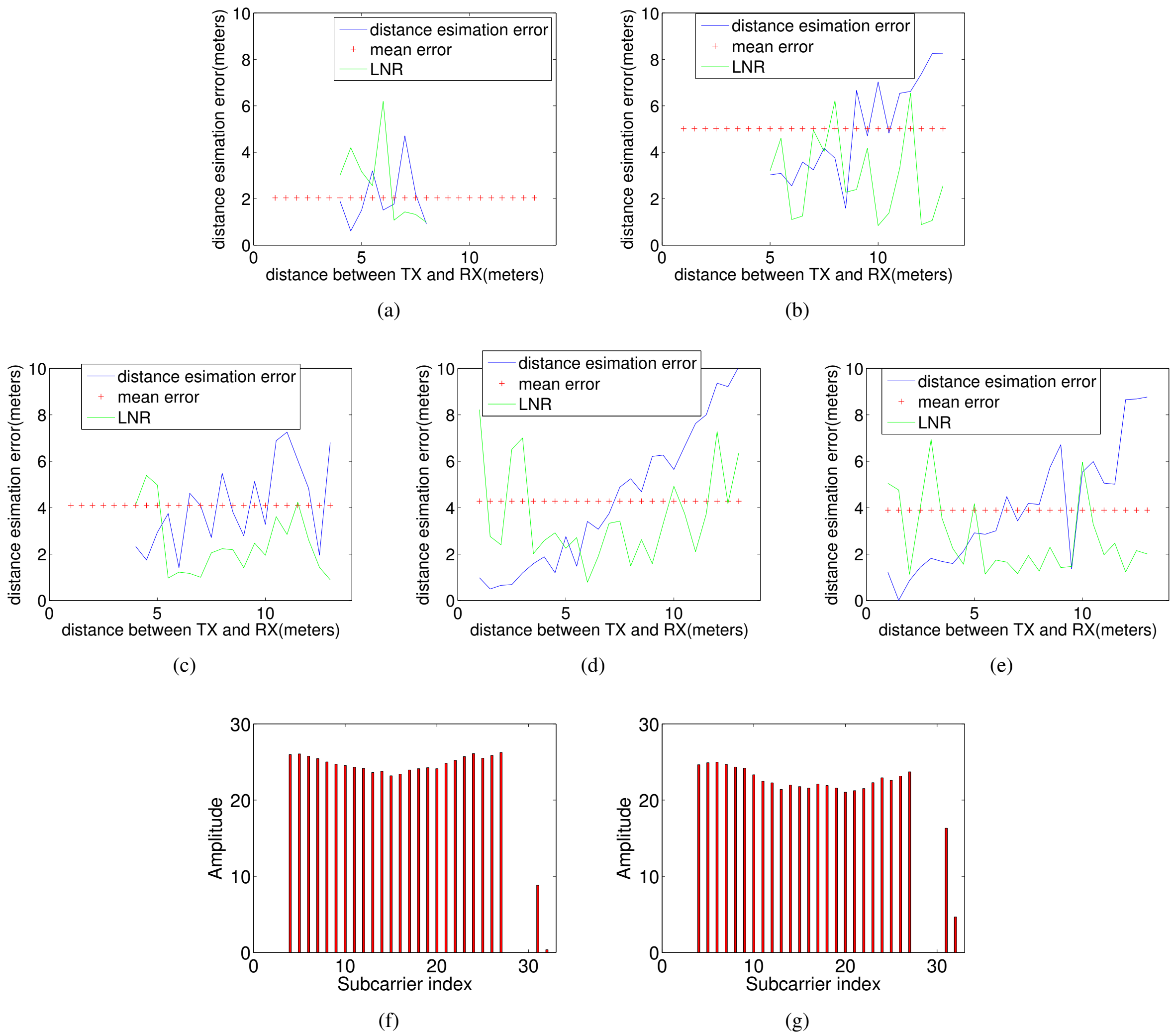


Figure 7. Impact of APs position under research laboratory conditions. As fig 6 shows, the RX travel along the vertical red line. (a)LNR values: TX is placed in position 1. (b) LNR values: TX is placed in position 2. (c) LNR values:TX is placed in position 3. (d) LNR values: TX is placed in position 4. (e) LNR values: TX is placed in position 5. (f) 10 times of the variance and skewness of CFRs at 3 meters in fig 7(e). (g) 10 times of the variance and skewness of CFRs at 10 meters in fig 7(e).

der WME/SME conditions in three different environments. As shown in fig 10, the AE_{wme} is between 1 and 1.5 meters which is much less than the AE_{sme} , larger than 4 meters. It demonstrates that we could obtain a more precise distance estimation through WME identification. The E_{wme} is about 1.8 meters, 0.6 meters and 1.3 meters in there different indoor environments. In contrast, the E_{sme} is about 4.1 meters, 4.5 meters and 4.4 meters in there different indoor environments. It demonstrates that the improvement for distance estimation through WME identification is effective to different indoor environments. In addition, the gap between three E_{wme} is larger it between three E_{sme}. The reason is that the degree of WME in the hall is smaller than it in the corridors and in the research laboratory. In contrast, there is not obvious influence caused by different degree of SME.

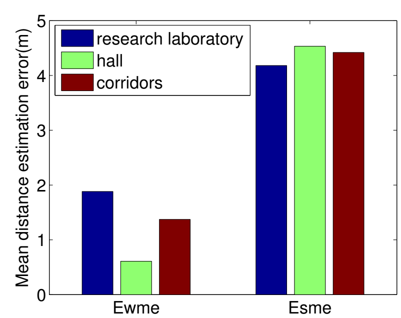


Figure 10. distance estimation error under WME/SME conditions.

3) Impact of AP's position: As fig 7 shows, the WME identification system work well in 5 testing locations and there is not a big gap between the distance estimation error when the AP is placed in different position. It demonstrates that our WME identification system is location-independent to some extent.

IV. Conclusion

In this paper, we conduct the experiments in typical office environments including corridors, hall and research laboratory to illustrate effectiveness of our distance estimation system. The future research in the new and largely open areas of wireless technologies can be carried out along the following directions. First, we can leverage the CSI to quantize the degree of the WME and filter the RSSI values under SME conditions for precise distance estimation. Second, we can build a universal CSI-based model for distance estimation, which is suitable for all the indoor environments.

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