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An Indoor Positioning Method using IEEE 802.11 Channel State Information

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Abstract – In this paper, we propose an indoor positioning system that makes use of the attenuation model for IEEE 802.11 Channel State Information (CSI) in order to determine its distance from an Access Point (AP) at a fixed position. With the use of CSI, we can mitigate the problems present in the use of Received Signal Strength Indicator (RSSI) data and increase the accuracy of the estimated mobile device's location. For the experiments we performed, we made use of the Intel 5300 Series Network Interface Card (NIC) in order to receive the channel frequency response. The Intel 5300 NIC differs from its counterparts in that it can obtain not only the RSSI but also the CSI between an access point and a mobile device. We can obtain the signal strengths and phases from subcarriers of a system which in turn means making use of this data in the estimation of a mobile device's position.

Keywords: Indoor positioning, Channel State Information (CSI), Received Signal Strength Indicator (RSSI)

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1. Introduction

The need for accurate indoor positioning methods, in this time of interconnected societies, is clearly visible. Given the fact that, unlike with GPS technologies, there is no advantage of having a near constant line of sight (LOS) connection between devices; problems like fading, multipath, shadowing, among others are abundant in indoor localization schemes [1,2]. Although modern mobile devices have higher processing power than their predecessors the need for methods low in complexity but highly accurate is still present. In order to accomplish this, the use of Channel State Information (CSI), with its accurate and detailed structure, becomes a viable candidate.

Generally, most indoor localization schemes make use of the Received Signal Strength Indicator (RSSI) in order to determine the position of a mobile device in space [3]. Because using RSSI as a measurement is simple and does not require special hardware several indoor positioning methods make use of it. There are plenty examples such as, Horus which makes use of position estimation by probability including RSSI information [4]. There are two main problems with RSSI based methods. One, RSSI can be unstable and change its value as time passes even when measured in the same position because of multipath in indoor settings. This instability leads to positioning errors that can appear even when measuring from a fixed device. Two, being a coarse value RSSI does not utilize the advantages of using Orthogonal Frequency Division Multiplexing (OFDM) to mitigate the problems that arise from multipath. Given that, with the use of some specific network interface cards, it is now possible to get channel state information which can be processed and used as a reference value for an increase in the performance of indoor positioning compared to other methods [5].

This paper is composed of four sections. Section 1 is the Introduction section. Section 2 describes the theoretical background of CSI. Section 3 describes the system architecture of the proposed method. The experimental results and conclusions are given in Section 4 and 5, respectively.

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2. Theoretical Background

2.1 Channel State Information (CSI)

Because of the capabilities present in IEEE 802.11n and certain network interface cards, we are now able to obtain channel state data instead of just obtaining received signal strength data. This, in turn, means that we can receive and store the CSI of a wireless connection with relative ease. CSI is nothing but a representation of the channel variation that occurs while the signal propagates. When a wireless signal is transmitted several factors can produce variations and errors in its reception, factors such as delay distortion, shadowing, and multipath among others. By using the signal power, we may have an idea of the channel characteristics but this representation is incomplete compared to the one obtainable by utilizing CSI.

If X and Y represent the vectors for a signal that is sent and acquired. Then

$$Y = CSI \cdot X + N \tag{1}$$

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Where the Gaussian noise is represented by vector N and the channel's frequency response, obtainable through estimation from X and Y, is represented by CSI.

The Wireless Local Area Network (WLAN) channel at 2.4GHz could be regarded as a narrowband flat fading channel. Through the Network Interface Card (NIC) we have a system with 48 subcarriers, from these 30 are gathered for channel state information by the NIC's modified firmware. The channel frequency response CSI_i, consists of a value determined by

$$CSI_i = |CSI_i| \exp\{j(\angle CSI_i)\} \tag{2}$$

where the amplitude and the phase of i are represented by $|CSI_i|$ and $\angle CSI_i$ respectively. Given that they can shed light to entirely different properties than RSSI, in this paper, the contemplated scheme is established from these CSI data.

2.2 Hypotheses

First, CSI values can be stable in time at a fixed location, significantly more than RSSI values. If measured at the same location CSI values, which portray channel characteristics in the frequency domain, present significant stability over time.

Second, CSI can build a relationship with distance and a propagation model can be derived from its measurements. CSI values reflect channel frequency responses with abundant multipath components and channel fading. The indoor environment can be viewed as a time varying channel, and therefore CSI may change slightly over time. Our study of channel frequency responses shows that even when these changes might be present a clear relation between the CSI gathered and real distance between AP and mobile device exists. CSI values can be stable in time at a fixed location, significantly more than RSSI values.

Third, the estimated location of a mobile device calculated through the use of CSI data will be more precise than its counterpart calculated by using RSSI. As the premise of indoor localization, we investigated the distance determination accuracy of our method compared with the corresponding RSSI based approach. The primary source of error in indoor localization is multipath propagation caused by multiple reflections that overlap with the direct LOS subcarrier at the receiver. Our proposed scheme takes advantage of the fine-grained properties of CSI to mitigate such multipath effect and exploits the frequency diversity to compensate the frequency selective shading.

3. System Architecture

Our proposed method has been developed and based on Commercial Off-The-Shelf (COTS) components and thus is compatible with the underlying design. In other words, no modifications are necessary at the transmitter end (the AP) while only a new Wireless NIC is necessary, in order to gather CSI data, at the receiver end (the mobile device). Fig. 1 conceptualizes the system architecture design.

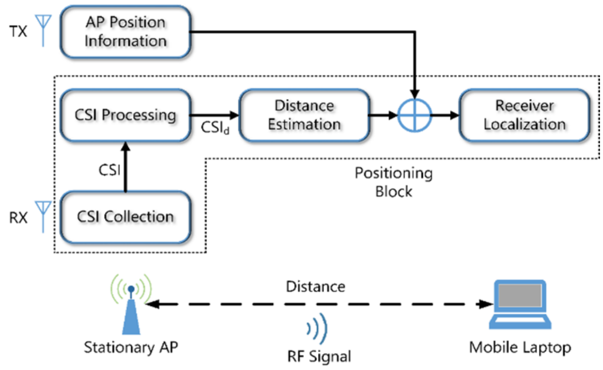

Fig. 1. System Architecture

Usually, when a packet is transmitted, the demodulated signal is only sent, in order to retrieve the message contents, to the decoder. However, one major aspect of our established positioning method is the need for obtaining the CSI data once the demodulation is finished. Given this, we propose a positioning block, pictured above, to gather and process the CSI values.

First, the CSI gathered from the 30 groups of subcarriers are processed in the localization block. Then, the effective CSI will be used to estimate the position of the mobile device. The CSI value is the channel matrix from RX baseband to TX baseband which is needed for channel equalization. Therefore, there is no extra processing overhead when obtaining the CSI data. Nevertheless, RSSI is obtained at the receiver antenna in the 2.4 GHz RF before down converting to the intermediate frequency and baseband. Given this, the free space model built for RSSI-based positioning schemes cannot be directly applied to process the CSI data. We need to refine the radio propagation model according to CSI and compute the distance based on the proposed one.

Finally, as the AP location information is obtained from the network layer while CSI is collected from the physical layer, we then use the simplest trilateration method to obtain the location.

3.1 CSI processing

For wireless communication, attenuation of signal strength through a mobile radio channel is caused by three nearly independent factors: path loss, multipath fading, and shadowing. The path loss refers to the property in which the signal strength decays as the distance between the transmitter and receiver increases, this, in turn, is the foundation of our CSI based localization scheme.

Multipath fading is a rapid fluctuation of the complex envelope of received signal caused by the reception of multiple copies of a transmitted signal through propagation

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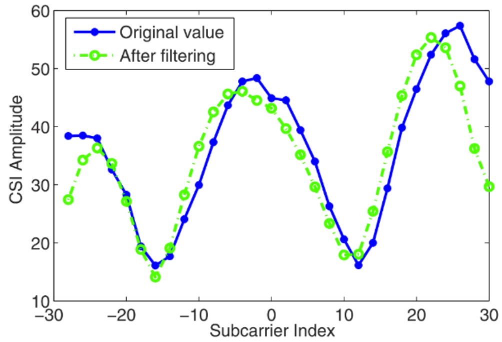

Fig. 2. Time domain channel response

in more than one path, this is caused by physical elements in the propagation environment such as walls and other similar objects. Shadowing represents a slow variation in a received signal strength due to the obstacles in the propagation path. Therefore, before establishing the relationship between CSI and distance, we need to mitigate the estimation error introduced by multipath fading and shadowing.

3.1.1 Time domain multipath mitigation

The 30 groups of CSI represent the channel response in the frequency domain, which is about one group per two subcarriers. With the IFFT processing of the CSI, we can obtain the channel response in the time domain, i.e., *h(t)*. From Fig. 2, we can observe that the LOS signal and multipath reflections come with a different time delay, and generally the LOS signal has higher channel gain, so we can use a trunk window with the first largest channel gain in the center to filter out those reflections. If LOS does not exist, we can identify the shortest path NLOS reflection. According to the Nyquist sampling theorem, wider spectrum leads to higher resolution in the time domain. Due to the bandwidth limitation of WLAN, we cannot distinguish all the reflections but we can use this method to reduce the variance induced by multipath effects. The time duration of the first cluster is determined by setting the truncation threshold as 50 percent of the first peak value. In doing so, we expect to mitigate the estimation error introduced by multipath reflections.

3.1.2 Frequency domain fading compensation

Moreover, since CSI represents the channel responses of multiple subcarriers, a combination scheme is also introduced to process the CSI value in our system for compensation of the fading of received signals in the frequency domain to enhance the location accuracy.

In general, when the space between two subcarriers is larger than the coherence bandwidth, they are fading independently.

Since the channel bandwidth of the 802.11n system is larger than the coherence bandwidth in a typical indoor environment, the fading across all subcarriers are frequency selective. To combat this frequency selectively fading of wireless signals, multiple uncorrelated fading sub channels (multiple frequency subcarriers), that is 30 groups of CSI values are combined at the receiver. The motivation for leveraging the frequency diversity stems from the fact that the probability of simultaneous deep fading occurring on multiple uncorrelated fading envelopes (in our case, resulting from frequency diversity) is much lower than the probability of a deep fade occurring on a single frequency system. Thus, exploiting the wide bandwidth of WLAN that assures sufficiently uncorrelated subcarriers will reduce the variance in CSIs owing to small-scale factors, which appears to be one of the major sources of location determination error. In our proposed system, we weighted average the 30 groups of CSIs in the frequency domain in order to obtain the effective CSI, which exploits the frequency diversity to compensate the small scale fading effect.

Given a packet with 30 groups of subcarriers, the effective CSI of this packet is calculated as

$$CSI_d = \frac{1}{K}\sum_{k=1}^{K}\frac{f_k}{f_0}\times|H_k|,\quad k\in(-15,15) \tag{3}$$

where f_0 is the central frequency, f_k is the frequency of the k^{th} subcarrier, and $|H_k|$ is the amplitude of the k^{th} subcarrier's CSI.

Note that selection of weighting factors are based on the fact that the radio propagation is frequency related. According to the free space model, the received signal strength is related to the frequency the signal is transmitted. So, by this weighting method, we transfer the channel gain from multiple subcarriers to a single subcarrier, i.e., the central one. Next, we will establish the relationship between the CSI_d and distance.

3.2 Calibration

Given that, the CSI data is gathered from the baseband on the receiver side, the propagation model used with RSSI is no longer applicable to our scheme. Therefore, a new indoor propagation model is developed in order to showcase the relationship that CSI_d and distance possess. This is done by amending the free space propagation model, as shown here

$$d = \frac{1}{4\pi}\left[\left(\frac{c}{f_0\times|CSI_d|}\right)^2\times\sigma\right]^{\frac{1}{n}} \tag{4}$$

where c stands for the wave speed, σ stands for the environment factor, and n stands for the path loss fading exponent. Both parameters, σ and n, vary within different

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indoor environments. The environment factor σ represents the gain of the baseband to the RF band at the transmitter side, on the other side, the gain of RF band to baseband at the receiver, and the antenna gains as well. Moreover, for NLOS, σ also includes the power loss due to wall penetration or shadowing. The path loss fading exponent n changes according to the environment. For example, when the signal propagates along a corridor, i.e. free space, n will take a value around 2. In a scenario where the indoor environment is highly complex in structure, such as a crowded office, n could take a value above 4. In an indoor radio channel with clutter in the medium, where often the LOS path is augmented by the multipath NLOS at the receiver, signal power decreases with a path loss fading exponent higher than 2 and is typically in the order of 2 to 4 [6].

A supervised training algorithm is introduced in order to gather the parameters with three APs. The underlying flow of the supervised algorithm is shown in Fig. 3, as can be seen, it consists of two main stages. First, CSI data from several packets are gathered at two APs in order to train the environment factor σ and the path loss fading exponent n for the refined indoor propagation model. Second, CSI data gathered at the third AP are utilized to supervise the efficiency of the parameter estimation. The two steps run side to side until there is a match.

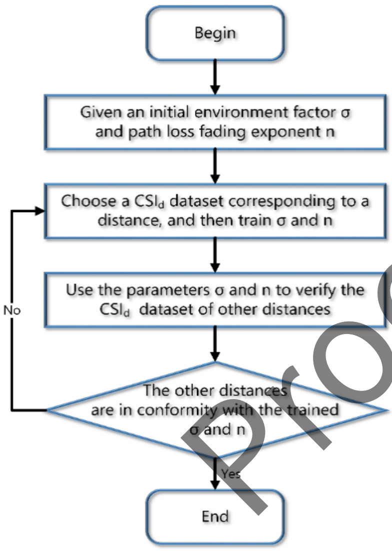

Fig. 3. Supervised training algorithm

3.3 Location determination

Finally, we must calculate the distance between the mobile device and the APs based on the refined indoor propagation model and obtain its position. Summarizing, the receiver aggregates the CSI_d values from the physical layer to triangulate the location of the mobile device.

The coordinates of each AP are determined and gathered for posterior use in the location estimation. BecauseAs implementing APs nowadays is quite simple, we can easily gather multiple AP's coordinates simultaneously.

According to the aforementioned distance calculation procedure, we can leverage the effective CSI values and the refined radio propagation model to obtain the distance between AP and mobile device pairs. With this complete, we make use of the trilateration method as in [7], which is a simple but highly effective approach, to locate the device. Finally, we can obtain the unique coordinates of the device as the center of the three references range intersection.

4. Experimental Results

4.1 Experimental setup

Our experiment testbed is comprised of two major components, the access point, which is an iPTime wireless router, and the mobile terminal, which is a Samsung laptop equipped with the Intel 5300 NIC, both of them placed in the hallway of the IT-1 Building's 3rd floor shown in Fig. 4. At the mobile device, the Intel 5300 NIC receives wireless signals from the access point, and then stores raw CSI values from the firmware. In order to read CSI values from the NIC driver, we install Ubuntu at a kernel level.

In our experiment, mobile terminal (Intel 5300 NIC)

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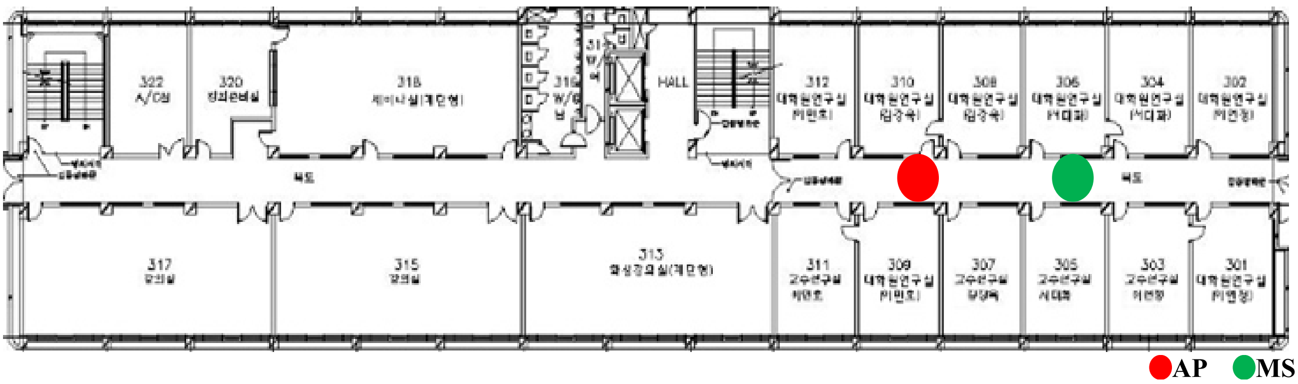

Fig. 4. IT Building 1's 3rd-floor plan

receives a packet, and stores the calculated CSI value in the form of CSI per packet reception. With this mobile terminal, we can collect calculated CSI data from 30 different subcarriers which are all used for determining the terminal's position.

4.2 Reliability of the proposed method

In order to evaluate the performance of the proposed method, we considers two factors such as temporal stability and positioning performance, from reliability point of view.

4.2.1 Temporal stability

One highly important aspect in the evaluation of CSI data is the fact that it possesses great temporal stability when compared to RSSI data. It has been shown previously in several types of research that RSSI is a coarse packet level estimation that varies easily due to the effects of multipath. In Fig. 5 we can clearly observe that as time passes RSSI values do not follow a stable pattern and are scattered between a large range of values. As can be seen, if extreme outliers are filtered, there is a difference between measurements of up to 15 dBm in a period of no more than 60 seconds.

On the other hand, since CSI is fine grained PHY layer data that provides detail at the subcarrier level, it is highly important to figure out if it remains stable as time passes in a practical environment. Fig. 6 portrays this temporal stability, where it can be observed that differences of up to only 3 dBm are to be expected in a real environment, such

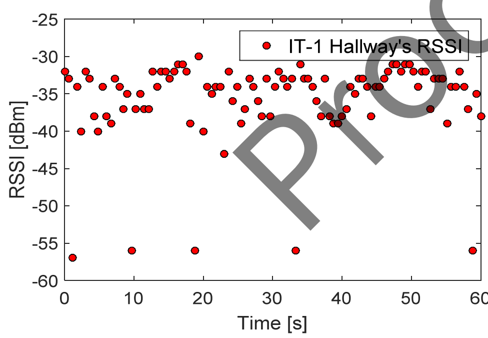

Fig. 5 Temporal instability of RSSI

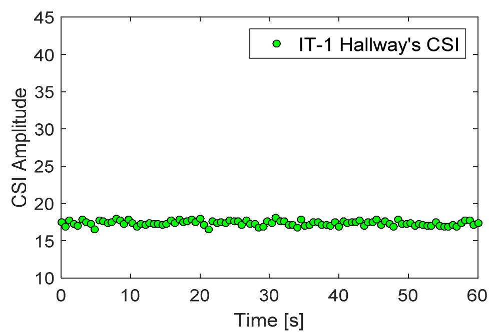

Fig. 6 Temporal stability of CSI

as the hallway in which the measurements were made. Following this, we can conclude that, compared to RSSI, CSI's temporal stability is substantially greater, which in turn means that the performance of the proposed method over time will be maintained.

4.3 Positioning performance

In order to compare our results, we made use of two different scheme's results, including Horus [5], and Max. Likelihood (MaxL) [8]. In order to obtain a fair comparison, these schemes use a similarly measured dataset.

The performance metric for the comparison of localization algorithms is the mean sum error ε. Assume the estimated location of an unknown user i is $(\hat{x}_i,\ \hat{y}_i)$ and the actual position of the user is $(x_i,\ y_i)$. The error of the distance estimation is then calculated as

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2} \tag{5}$$

We evaluate the performance of the proposed method in a representative scenario. The mean and standard deviation of the location errors are presented in the table that follows. In the hallway experiment, the mean distance error is about 1.24 meter for the proposed method. The proposed scheme outperforms Horus in this scenario, Horus has a mean error of 1.54 m. Which in turn means that the proposed method achieves a 20% improvement over Horus and a 40% improvement over MaxL, by exploiting the fine-grained properties of CSI subcarriers.

Fig. 7 shows the cumulative distribution function (CDF) of distance errors by the three schemes including the proposed one in the same environment(IT-1 Hallway).

As shown in Fig. 7, the proposed scheme(blue line) guarantees that calculated errors are limited within 2m. On the other hand, Horus(green line) and MaxL(red line) schemes (using RSSI measurements) produces distance errors upto 2.7m and 3.7m, respectively.

This means that the proposed scheme can enhance the reliability of the ranging information by 25% to 60%,

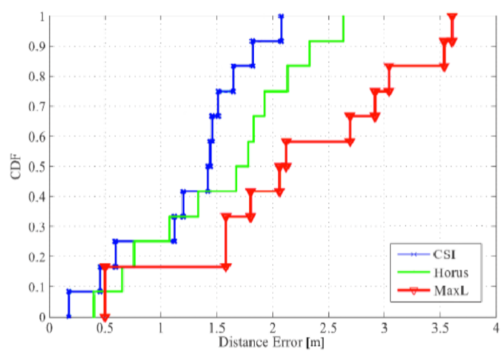

Fig. 7 CDF of distance errors

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Table 1. Mean errors for the proposed and existing methods

Method	Mean Error [m]	Standard Deviation [m]
CSI Ranging	1.24	0.57
Horus	1.54	0.70
MaxL	2.16	1.04

5. Conclusion

We proposed an effective and reliable ranging scheme for indoor localization in this paper. Our scheme can be categorized as CSI based approach which uses a modified propagation model from reference AP for precise ranging (resulting in precise location).

In our scheme, CSI data for 30 subcarriers from the Intel 5300 WLAN Card are collected and used for precise and reliable ranging. Experimental results shows that the performance of proposed scheme can be enhanced by 25% to 60%. This results can be understood that the proposed scheme can extend ranging coverage using same radio signals.

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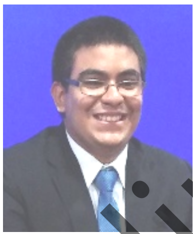

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