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Wi-Fi based Indoor Localization using Channel State Information

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ABSTRACT

Indoor positioning systems are becoming increasingly popular because they enable location-based services in indoor environments. GPS is not effective for indoor positioning because its performance degrades in urban areas, around walls and buildings, and indoors. The strength of the GPS signal is very low in indoors, making it ineffective. Wi-Fi technology has emerged as a cost-effective and widely available solution for indoor positioning due to its ubiquity. This research paper presents Wi-Fi-based indoor localization method that leverage Channel State Information (CSI) for enhanced accuracy and reliability. We explore the theoretical foundations, practical implementation, and experimental results of using CSI for indoor localization. The proposed methodology demonstrates promising results in real-world indoor environments.

Keywords : RSSI, CSI, Localization, Indoor, Wi-Fi.

I. INTRODUCTION

Indoor localization is essential for facilitating location-aware applications in indoor environments such as malls, hospitals, airports, and smart buildings. While Global Positioning System (GPS) is the solution of choice for outdoor positioning, signal attenuation and multipath effects make it ineffective indoors[1]–[3]. Wi-Fi-based indoor localization techniques have acquired popularity because they utilize existing infrastructure and offer more precise and cost-effective solutions.

A. Wi-Fi Based Indoor localization

Although there are numerous advancements that can be used for indoor localization, a Wi-Fi network already installed within a building can serve as a platform for implementing indoor localization at no additional cost[4]–[6]. Wi-Fi based indoor positioning has been appealing due to its free accessibility and low-cost characteristics[7]. A typical Wi-Fi-based indoor localization system employs a received signal strength indicator for estimation. However, the distance assumption based on the received signal strength indicator (RSSI) is readily affected by the temporal and spatial variation caused by the multipath environment.[8]. These modifications account for the majority of estimation errors in the current localization system. [9] This work investigates the frequency diversity of subcarriers in orthogonal frequency division multiplexing systems and proposes an alternative method for position detection that employs subcarrier-level information. Each subcarrier's channel state information (CSI) is used to construct a propagation model[10]. I'm utilizing off-the-shelf 802.11 NICs to realize the indoor localization system, and the entire system has been implemented and analysed for efficacy in indoor scenario. The primary observation demonstrates that the precision and latency of position calculation can be vastly enhanced by employing the CSI value as opposed to the typical RSSI[11].

II. BACKGROUND

A. Types of Wi-Fi-based indoor localization techniques

Wi-Fi-based indoor localization techniques can be broadly classified into three categories: fingerprinting-based methods, trilateration and triangulation, and proximity-based approaches[6].

1) Fingerprinting-based methods

Fingerprinting is a method where location attributes are collected and stored in a database during the training phase. During the online phase, new attributes are extracted and compared to previously stored data. This method is cost-effective and can be designed entirely in software, making it a better alternative to time-based or angulation-based positioning systems[12]. The process is divided into two phases: offline, which involves collecting maps manually or using propagation models, and online, where mobile stations measure signal attributes at test locations and compare them to the database[13].

2) Trilateration and Triangulation based methods

Trilateration and triangulation are based on the principle of measuring the distance between the device to be localized and at least three reference points. To localize a device using trilateration, the device measures its distance to at least three reference points. The reference points can be Wi-Fi APs, other devices, or known locations. Once the device has measured its distance to the reference points, it can use the trilateration algorithm to calculate its absolute position.

To localize a device using triangulation, the device measures its angle of arrival to at least three reference points. The reference points can be Wi-Fi APs, other devices, or known locations. Once the device has measured its angle of arrival to the reference points, it can use the triangulation algorithm to calculate its relative position.

Trilateration and triangulation can achieve high accuracy, but they require the distance or angle of arrival to be measured to at least three reference points. This can be challenging in indoor environments due to multipath propagation and interference.[14], [6].

3) Proximity-based methods

Proximity-based approaches detect the presence of Wi-Fi APs near a device, allowing it to infer its location based on known locations. These methods are simple but less accurate than fingerprinting-based methods and trilateration and triangulation. Common approaches include using the number of visible APs, which indicates density or remoteness, or using received signal strength (RSS), which measures the strength of the signal received from an AP. However, RSS is not a reliable measure of distance due to environmental factors like multipath propagation and interference, making proximity-based approaches less accurate than fingerprinting-based methods[15].

B. Channel State Information (CSI)

Channel state information (CSI) in Wi-Fi is a set of data that describes the characteristics of the wireless channel between a transmitter and receiver. CSI includes information such as the amplitude, phase of the signal at subcarrier level. CSI is used for advanced applications, including beamforming, MIMO (Multiple Input, Multiple Output) techniques, channel equalization, and interference cancellation [16], [17], [18]. Figure-1 shows the MIMO OFDM system and channel response for each Tx-Rx antenna pair.

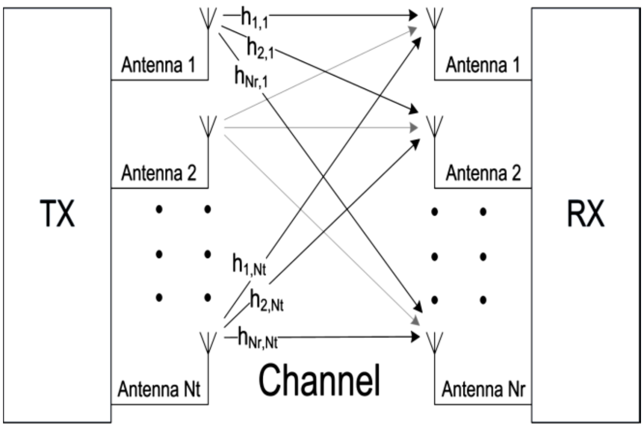

Figure 1 MIMO-OFDM system

In MIMO system, in the time domain, the received signal r(t) is the convolution of transmitted signal s(t) and channel impulse response h(t).

$$r(t) = s(t) * h(t)$$

It indicates that the received signal is generated from the transmitted signal after it has propagated through a multipath channel. In frequency domain it is presented by

$$R(f) = S(f)H(f)$$

The sampled version of *H(f)* are called channel state response of each subcarriers and can be presented by.

$$H(f_k) = |H(f_k)|e^{j\angle H}$$

where $H(f_k)$ is a channel state information sampled at the k^{th} subcarrier. It represents a complex number with magnitude and phase angle of every subcarrier[16], [17].

III. METHODOLOGY

A. CSI data collection

To collect the real-world CSI data, Linux based 802.11n CSI Tool is used. The Linux 802.11n CSI Tool is based on the Intel Wi-Fi Wireless Link 5300 802.11n MIMO radios as shown in Figure-2 and uses custom firmware and open-source Linux wireless drivers. The tool contains all the necessary software and programs for reading and parsing channel measurements[10], [19].

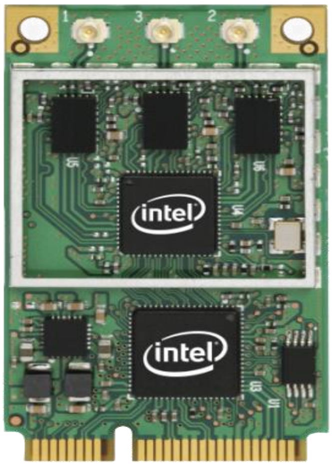

Figure 2 Intel 5300 NIC

For use with the Linux 802.11n CSI Tool, a computer with an Intel Wi-Fi Wireless Link 5300 radio and the Linux operating system are required. Additionally, you must install CSI Tool and compile the modified firmware. After installing the tool, one can start accumulating CSI measurements as displayed in below commands[20].

```
cd ~/netlink
sudo ./log_to_file L1AP1.dat
ping 172.16.1.110
```

This command will start recording CSI measurements into L1AP1.dat file. The Ping command generate traffic between AP and Computer through Wi-Fi channel.

```
csi_trace = read_bf_file('L1AP1.dat');
```

Above command run the script that extract important CSI data from the *.dat* and generate *csi_trace* file. Following matlab script and command display the CSI data value and generate the CSI Vs. Subcarrier plot for recorded trace file.

```
>> csi_entry = csi_trace{1}

csi_entry =

timestamp_low: 1.6277e+09
bfee_count: 1564
Nrx: 3
Ntx: 2
rssi_a: 38
rssi_b: 30
rssi_c: 39
noise: -88
agc: 22
perm: [3 1 2]
rate: 8463
csi: [2x3x30 double]

>> csi = get_scaled_csi(csi_entry);
>> plot
(db(abs(squeeze(csi(1,:,:)).')))

>> legend ('RX Antenna A', 'RX
Antenna B', 'RX Antenna C',
'Location','SouthEast’);

>> xlabel('Subcarrier index');
>> ylabel('SNR [dB]');
```

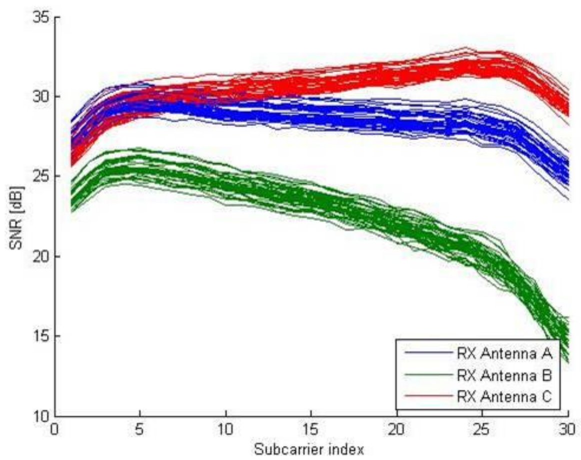

Figure 3 SNR Vs Subcarrier index

B. Test-Bed Environment for CSI data collection

To accurately evaluate the system, the chosen test environment must correspond to a real-world scenario. Consequently, we can say that the test environment is a generic representation of comparable real-world settings. For our test environment, we selected a laboratory chamber. The total area of the testing space is divided into 1x1 meter locations. And observations are considered for each square meter.

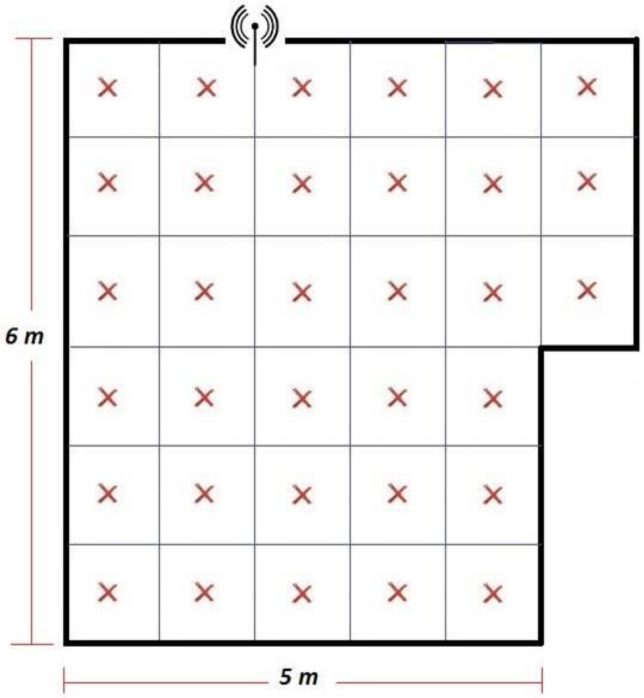

Figure 4 Test-Bed Environment

The access point is located on the front wall at a height of 2 meters for collecting readings and conducting tests. Figure-4 present the Test-Bed area.

Signals received at any indoor location will be multipath signals by definition. varied locations will receive multipath signals with varied magnitude and phase characteristics. When collected for a long enough period of time, the received channel response for each subcarrier contains valuable information for fingerprinting that location. According to the accumulation of multiple multipath signals at a given location, it has been observed that location-specific multipath signals maintain stable patterns. These consistent patterns for each location can be used to implement localisation at the meter scale level. Figure-3 represent SNR Vs Subcarrier plot for a location. The shape of the plot and the number of magnitude clusters are unique and location-dependent. Consequently, they maximize the likelihood of discovering or extracting the characteristics of each location and construct the fingerprint database. Most of the locations have single cluster of values while fee having two or three magnitude clusters. Figure 5 shows the graphical representation of magnitude cluster in terms of mean and variance.

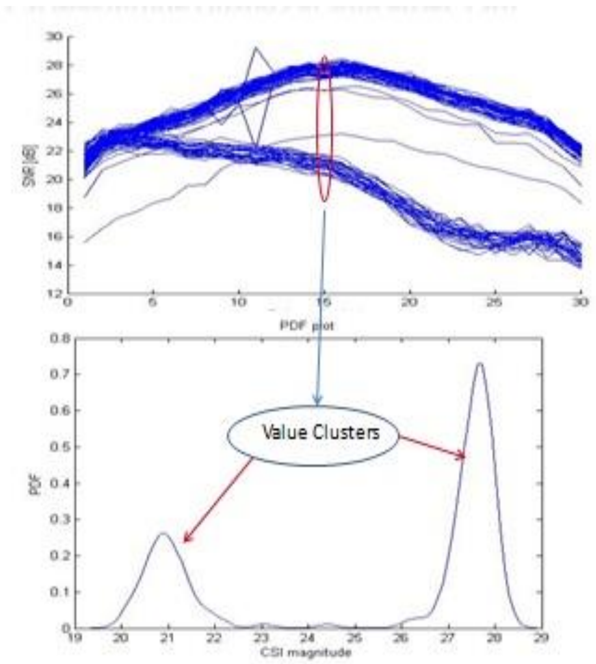

Figure 5 CSI magnitude cluster for single subcarrier

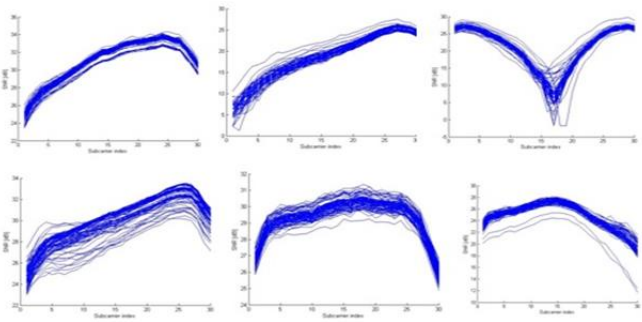

Figure 6 CSI plot for Different Locations

Figure-6 depicts the consistent pattern of CSI magnitude across multiple test locations.

C. Fingerprinting-based localization

The process of fingerprint-based localization can be divided into two distinct parts. The first phase, known as the offline phase, involves the generation of a dataset. The second phase, referred to as the online phase, is when the actual localization takes place.

1) Training Phase

The offline phase, also known as the training phase or calibration phase, involves the collection of fingerprinting maps. During this stage, it is necessary to record radio maps for the designated site where the positioning system is intended to operate. In essence, a radio map can be defined as a compilation of attributes that are distinct to certain locations. The CSI value, as well as the mean and deviation, and phase information, collectively contribute to the construction of the fingerprint identification associated with a particular location. Each individual fingerprint is rigorously gathered and thereafter stored within the database.

Figure-4 shows different CSI magnitude plots of different locations. It is visible that every location has its own pattern and data clusters. In any given scenario, the quantity of magnitude clusters seen for a single antenna does not exceed three clusters. This insight helps the clustering process and enables the application of algorithms that are efficient in terms of running time. The K-means method was employed in our study. The K-means clustering algorithm is utilized to divide a given dataset into a predetermined number of clusters. The clusters are derived by calculating their nearest mean value.

2) Localization phase

The online phase refers to the stage of localization. During the online phase, the mobile station collects data on signal quality at the designated test location. Subsequently, the present measured signal values are compared in order to identify the most suitable match within a database.

3) Classification Algorithm

A classification module estimates the minimum distance between the fingerprint database and the currently set CSI values. Based on the given information, the system will determine the potential candidate locations. Subsequently, determine the most probable geographical position as the intended location.

Let's consider the data set of mean value and variance for different locations, which are stored as **M = {M**^{1}**, M**^{2}**, …. M**^{i}**}** and for variance as **V = {V**^{1,}**, V**^{2}**, ….V**^{i}**}.**

Here, the M and V values for every location include all subcarrier values. Now let us consider the test location to be identified from its mean and variance values. The given equation compares T's value with the fingerprint dataset and identifies the most probable location.

$$d(T, M^i) = \sum_{f=1}^{30} \log V_f^i + \sum_{f=1}^{f} \left(\frac{\left| T_f - {M_f}^i \right|^2}{{V_f}^{i\,2}} \right)$$

Figure 7 shows the fingerprint-based localization system architecture.

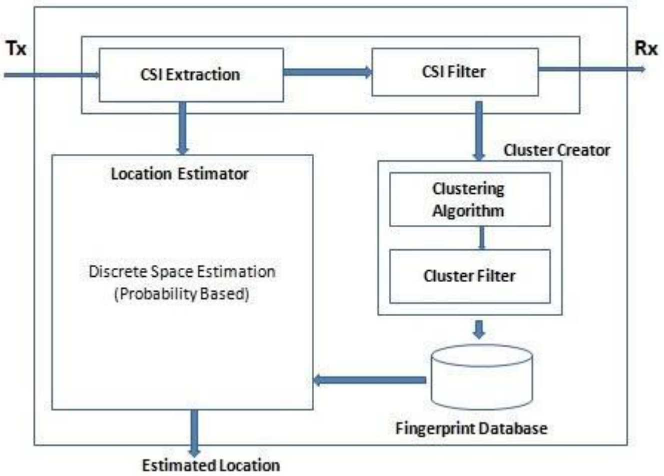

Figure 7 Clustering Architecture

IV. RESULTS AND DISCUSSION

For evaluating the performance of the proposed system, we selected a test location as shown in Figure 4. All the CSI traces for the 33 locations shown were recorded during the offline phase. In the online phase, we randomly gather CSI traces with different settings, as mentioned below, and evaluate the robustness and accuracy of the proposed system.

- The receiver has three receiving antennas, and the optimal antenna for retrieving a single trace is chosen using permutation data. Tests indicate that the choice of antenna has a significant impact on the achievable accuracy.

- The extent of recording windows will increase measurement latency while simultaneously improving precision. Consequently, there is a trade-off between measurement windows and intended precision.

- It is not mandatory to utilize all the subcarrier values for localizing the target. As the number of subcarriers increases from a minimum of five to thirty, measurement precision progressively improves.

The following table presents a comparative analysis of performance metrics based on the selection of various subcarriers and the corresponding number of received packets. The database was compiled for a total of 33 sites, after which the online data was entered using various configurations across 10 distinct testing times.

Parameter		Accuracy
No. of subcarriers	5	65%
	10	82%
	15	91%
No. of received packets (window size)	1	55%
	5	73%
	30	85%

The test setting chosen for our study was two-dimensional space. In order to locate the target in a practical setting, it will be necessary to engage in three-dimensional reading. The process of collecting 3D data will take a long time because fingerprint-based positioning is extremely complex. Modifications to the interior environment, particularly alterations in the metallic structure, might induce changes in the pattern of multipath channel state information (CSI) traces. Regular intervals are necessary for the revision of the CSI database.

V. CONCLUSION

Localization is one of the most appealing applications, and it is becoming more prevalent in our daily lives. The significance of indoor localization and the limitations of GPS are emphasized. A literature survey shows that Wi-Fi-based localization techniques have minimal overhead costs, are adaptable, and have appropriate speed and accuracy. RSSI is environment-dependent, device-specific, and creates significant temporal fluctuations. Hence, RSSI induces errors in localization. A new approach is described that uses channel response at the sub-carrier level to retrieve relevant features for localization. This location-specific signal clustering is used to accomplish indoor positioning at the meter level. Location detection is implemented here by employing magnitude values for various subcarriers. As a future enhancement, the phase information can also be integrated to improve accuracy and efficiency.

VI. REFERENCES

[1] C. Di Flora, M. Ficco, S. Russo, and V. Vecchio, "Indoor and outdoor location based services for portable wireless devices," in *25th IEEE International Conference on Distributed Computing Systems Workshops*, 2005, pp. 244–250.

[2] D. Zhang, F. Xia, Z. Yang, L. Yao, and W. Zhao, "Localization technologies for indoor human tracking," in *2010 5th international conference on future information technology*, 2010, pp. 1–6.

[3] H. Koyuncu and S. H. Yang, "A survey of indoor positioning and object locating systems," *IJCSNS Int. J. Comput. Sci. Netw. Secur.*, vol. 10, no. 5, pp. 121–128, 2010.

[4] V. Honkavirta, T. Perala, S. Ali-Loytty, and R. Piché, "A comparative survey of WLAN location fingerprinting methods," in *2009 6th workshop on positioning, navigation and communication*, 2009, pp. 243–251.

[5] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Commun. Surv. \& tutorials*, vol. 11, no. 1, pp. 13–32, 2009.

[6] Z. Farid, R. Nordin, M. Ismail, and others, "Recent advances in wireless indoor localization techniques and system," *J. Comput. Networks Commun.*, vol. 2013, 2013.

[7] A. Banerjee, D. Maas, M. Bocca, N. Patwari, and S. Kasera, "Through Wall People Localization Exploiting Radio Windows," *arXiv Prepr. arXiv1307.7233*, 2013.

[8] Y. Liu, Z. Yang, and X. Wang, "Location, localization, and localizability," *J. Comput. Sci. Technol.*, vol. 25, no. 2, pp. 247–297, 2010.

[9] J. Liu, Y. Zhang, and F. Zhao, "Robust distributed node localization with error management," in *Proceedings of the 7th ACM international symposium on Mobile ad hoc networking and computing*, 2006, pp. 250–261.

[10] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Tool release: Gathering 802.11 n traces with channel state information," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 41, no. 1, p. 53, 2011.

[11] K. Heurtefeux and F. Valois, "Is RSSI a good choice for localization in wireless sensor network?," in *2012 IEEE 26th international conference on advanced information networking*

and applications, 2012, pp. 732–739.

[12] S.-H. Fang, T.-N. Lin, and K.-C. Lee, "A novel algorithm for multipath fingerprinting in indoor WLAN environments," *IEEE Trans. Wirel. Commun.*, vol. 7, no. 9, pp. 3579–3588, 2008.

[13] C. Beder and M. Klepal, "Fingerprinting based localisation revisited: A rigorous approach for comparing RSSI measurements coping with missed access points and differing antenna attenuations," in *2012 international conference on indoor positioning and indoor navigation (IPIN)*, 2012, pp. 1–7.

[14]A. Siddig, A. Makki, and C. Bleakley, "Lighthouse: Precise 802.11-based localization," in *International Conference on Indoor Positioning and Indoor Navigation*, 2013, pp. 1–6.

[15] M. Youssef and A. Agrawala, "The Horus WLAN location determination system," in *Proceedings of the 3rd international conference on Mobile systems, applications, and services*, 2005, pp. 205–218.

[16] L. Hanzo, Y. Akhtman, L. Wang, and M. Jiang, *MIMO-OFDM for LTE, WiFi and WiMAX: Coherent versus non-coherent and cooperative turbo transceivers*, vol. 9. John Wiley \& Sons, 2010.

[17] M. Jiang and L. Hanzo, "Multiuser MIMO-OFDM for next-generation wireless systems," *Proc. IEEE*, vol. 95, no. 7, pp. 1430–1469, 2007.

[18] D. Tse, *Fundamentals of Wireless Communication12*. 2004.

[19] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Predictable 802.11 packet delivery from wireless channel measurements," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 40, no. 4, pp. 159–170, 2010.

[20] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "802.11 with multiple antennas for dummies," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 40, no. 1, pp. 19–25, 2010.