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Channel Matters: Exploring LoS/NLoS Channel Effects on WiFi Sensing Performance

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***Abstract*—WiFi sensing has recently emerged as a non-invasive and privacy-preserving solution and has been extensively studied across various application domains. This approach leverages the channel state information (CSI) of ambient WiFi signals, combined with deep neural network techniques, to recognize unique CSI fingerprints associated with different human activities or environmental movements. It has been shown that the performance of WiFi sensing systems is sensitive to environmental changes and deployment-related factors such as the placement of transmitters and receivers, sampling rates, and the presence of obstacles (e.g., walls). However, the impact of different WiFi channels on the performance of WiFi sensing systems has received limited attention. In this study, we investigate this effect using two transceiver (TX-RX) pairs operating in Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) scenarios. Through our experiments, we demonstrate that the choice of WiFi channels for transceiver devices significantly influences system accuracy. Depending on the selected channels for LoS and NLoS devices, WiFi sensing performance can be either positively or negatively affected.**

***Index Terms*—WiFi signals, CSI, OFDM, LoS, NLoS.**

I. Introduction

We have recently witnessed a growing number of research studies on WiFi sensing that aim to enable non-invasive smart sensing solutions using Internet of Things (IoT) devices. By leveraging ubiquitous WiFi devices and signals and recently developed tools [1]–[3] that facilitate access to Channel State Information (CSI), researchers have utilized signal propagation characteristics embedded in CSI data to develop various applications. These include authentication of people [4], recognizing their movements [5], and even distinguishing people from pets [6] or other individuals [7].

WiFi sensing relies on fine-grained analysis of variations in the received radio signals. This is usually obtained from CSI data (and associated amplitude and phase information) across WiFi subcarriers. The multi-path effects during the signal propagation when people perform different movements generate distinct CSI patterns which are then learned usually through deep neural network (DNN) models to recognize these activities.

A. Motivation

Most of the current WiFi sensing studies focus on developing new applications or enhancing sensing performance through complex DNN models [8]. While there are some studies [9] that investigate the capabilities and limitations of CSI based WiFi sensing, there is more exploration needed to deepen our understanding of its fundamentals.

Most of the existing WiFi devices operate in the 2.4 GHz, 5.0 GHz or 6.0 GHz bands. There are also some specialized devices that can support uncommon higher bands, such as 60 GHz, for specific applications, but they are not common. The choice of frequency band affects WiFi sensing performance; for example, higher bands can capture finer movements but at the cost of reduced sensing range. Within each WiFi frequency band, there are also different channels. While for a single transmitter (TX) and receiver (RX) based WiFi sensing system using different channels may not exhibit a clearly distinguishable impact, when multiple device pairs are used the effect on the sensing performance can be more pronounced, due to the interference among them.

Understanding the impact of channel selection on WiFi sensing performance is crucial, particularly for applications that require accurate and time-sensitive sensing, such as security alerts [10] and health monitoring [11]. Additionally, strategic channel selection can enhance the resilience of WiFi sensing systems against cyber threats by dynamically adjusting channels to mitigate potential attacks and maintain system security.

B. Contributions

In this study, we aim to explore the effect of selected WiFi channels on the performance of WiFi sensing studies. In particular, we consider a Line-of-Sight (LoS) and a Non-Line-of-Sight (NLoS) link with the same and non-overlapping channels and perform experiments in different combinations to analyze their effect on each other and on the performance of the WiFi sensing system. We perform extensive experiments under various conditions to analyze and compare the WiFi sensing performance with both single and two pairs. Our experimental results show that NLoS link accuracy is affected negatively by the LoS link if they run in the same channel, which is not surprising due to the co-channel interference. However, we also observe that the NLoS link is positively affected when it uses a non-overlapping channel that is different from the LoS link. Different channel NLoS link performance is even better than in the NLoS-only scenario. While there is no interference expected between these non-overlapping channels, we observe increased variance in amplitude values across subcarriers, which then yields higher sensing accuracy.

The rest of the paper is structured as follows. In Section II, we provide an overview of related studies in the literature followed by some preliminaries in Section III. We then present the details of our system and experimental setup in Section IV. In Section V, we provide our experimental results. Finally, we conclude the study and discuss future directions in Section VI.

II. Related Work

With the release of the tools enabling access to CSI data and recent advances in deep learning methods, CSI-based WiFi sensing solutions have recently grown [12]. Besides the popular applications such as human activity or gesture recognition [5], and occupancy counting [13], it is used for distinguishing human and non-human movements [14], and for robot-assisted rehabilitation tracking [15].

WiFi sensing performance is highly affected by different parameters during deployment. For example, [16] examines the impact of different TX and RX device positions on system performance. Several studies [17]–[19] have also aimed to mitigate environment- and subject-specific effects to enhance model generalization and robustness. Similar concerns regarding noise and interference affecting wireless signals have been observed in other domains, such as CSI feedback in MIMO systems [20]. Additionally, the effect of obstacles in the environment (e.g., wall) has been studied in [21] highlighting the importance of TX and RX locations relative to the obstacles.

As a deeper understanding of channel state information is essential in developing accurate WiFi sensing systems, in recent studies, we see thorough investigations into it. For example, a comprehensive analysis of the capabilities and limitations of CSI-based Wi-Fi sensing using 802.11ax (Wi-Fi 6) signals is presented in [9]. In [22], the non-uniformity of channel state information is explored. In another study [23], experimental evaluation of 2.4 GHz and 5 GHz based WiFi sensing systems is performed, demonstrating the slightly superior performance of the 5 GHz band.

To the best of our knowledge, only a few studies have looked at the effects of channel selection in WiFi sensing. For example, [24] introduces a hopping mechanism to select optimal channels by leveraging wideband channel diversity. While that study focuses on feature separability using channel hopping and deep learning, we explore the impact of signal variance across subcarriers under different channel conditions for LoS and NLoS TX-RX pairs. Similarly, [25] analyzes the effect of channel selection on the interference and sampling rate of WiFi sensing systems; however, it does not provide results on how this impacts system accuracy. Unlike these studies, we specifically explore the effect of channel selection in LoS and NLoS links on WiFi sensing performance.

III. Preliminaries

A. WiFi Channel State Information

Channel state information provides insight into how the signal propagates between a transmitter and a receiver. This includes reflections and scattering from the environment and surrounding objects over multiple paths. The channel can be represented as:

$$\mathbf{y} = \mathcal{H}\mathbf{x} + \boldsymbol{\eta}, \tag{1}$$

where $\mathbf{y}$ and $\mathbf{x}$ denote the received and transmitted signal vectors, respectively, $\mathcal{H}$ represents the CSI matrix, and $\boldsymbol{\eta}$ is the noise vector in the channel.

CSI captures the combined effect of both LoS and NLoS propagation paths. The LoS path represents direct signal transmission between TX and RX, while NLoS paths arise from reflections off surrounding objects, introducing additional signal components. The channel frequency response (CFR) is often modeled as:

$$\mathcal{H}(f,t) = e^{-j2\pi\Delta f t}\left[\mathcal{H}_{\text{static}}(f) + \sum_{n=1}^{N_d} b_n(f,t)e^{-j2\pi f\theta_n(t)}\right],$$

Where $\mathcal{H}_{\text{static}}(f)$ represents the static contribution of the channel, which consists of signals traveling through the LoS path and reflections from stationary objects, the term $\sum_{n=1}^{N_d} b_n(f,t)e^{-j2\pi f\theta_n(t)}$ captures the dynamic contributions introduced by NLoS paths with time-varying characteristics. Here, N_d denotes the number of dynamic paths, $b_n(f,t)$ represents the amplitude attenuation for the n-th dynamic path, and $\theta_n(t)$ corresponds to the time delay of the n-th path.

The term Δf represents the subcarrier spacing in an OFDM-based WiFi system, which determines the frequency separation between consecutive subcarriers in the CSI measurements. The impact of these paths on CSI is highly dependent on the surrounding environment. For instance, movement along a LoS path can introduce variations in the dynamic components, while stationary objects in a NLoS scenario contribute to the static components.

In this study, we collect the CSI frames using ESP32 microcontrollers and the ESP32-based CSI extraction tool [3]. Out of the total 64 subcarriers, only 52 of them contain actual CSI data that is not static or zero, and thus we use only the data of these subcarriers.

B. Variance of Amplitude

Variance measures the spread of values around the mean. A high variance in amplitude across subcarriers indicates greater diversity in amplitude values. Since subcarriers capture different transmitted signal paths and interactions, higher variance suggests that subcarriers experience different levels of attenuation, reflection, and scattering across multiple paths, enriching the feature set for analysis. Conversely, if the variance were low, the signal patterns across subcarriers would be too similar, reducing the ability to differentiate activities.

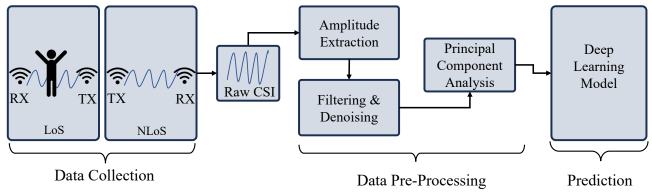


Fig. 1: System Overview

Let $X_{i,j}$ denote the amplitude value of the j-th subcarrier at the i-th time step, N denote the total number of subcarriers and μ_i represent the mean amplitude across all subcarriers at the i-th time step. The variance across subcarriers at the i-th time step is computed as,

$$\sigma_i^2 = \frac{1}{N}\sum_{j=1}^{N}\left(X_{i,j} - \mu_i\right)^2, \tag{2}$$

where,

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} X_{i,j} \tag{3}$$

IV. Experiment Setup

In this section, we describe the system used for our experiments, and then talk about the data collection and model development process.

A. System Overview

The overall system is illustrated in Fig. 1 and consists of three major stages. In the first stage, we collect data in LoS and NLoS simultaneously to ensure a fair comparison. The collected raw CSI data is then processed in the next stage, where we extract the amplitude and apply various denoising techniques. Specifically, we remove null subcarriers and apply Hampel filter to eliminate outliers. We also use moving average filter to smooth the amplitudes and perform Principal Component Analysis (PCA) to find the most significant components of the data. In the final stage, we feed the processed data into a prediction model constructed using 1D convolutional and dense layers, to train and classify the activities accurately.

B. Data Collection

We designed the experiments to collect WiFi CSI in a controlled environment, with a focus on sensing a set of human activities through signal variations in LoS and NLoS settings.

The hardware used during experimental setups include four ESP32 microcontrollers and one Raspberry Pi, model 4B with 2GB RAM. We used the ESP32-CSI-Toolkit [3], [26] to collect CSI using one or two pairs of ESP32 WiFi-enabled microcontrollers, with one ESP32 serving as TX and the other as RX in each pair, respectively. In this study, we used WiFi Channel 1 (2.412 GHz) and Channel 11 (2.462 GHz) for LoS and NLoS transceivers. The ESP32 devices captured CSI data from WiFi signals transmitted over either of these channels at a packet rate of 100 Hz. To ensure precise time synchronization and continuous logging of both CSI, the ESP32 devices were connected to a Raspberry Pi. Note that, one TX-RX pair was located at the LoS and the other one at the NLoS, and we considered different setup combinations by changing their channels to 1 or 11, or turning them off.

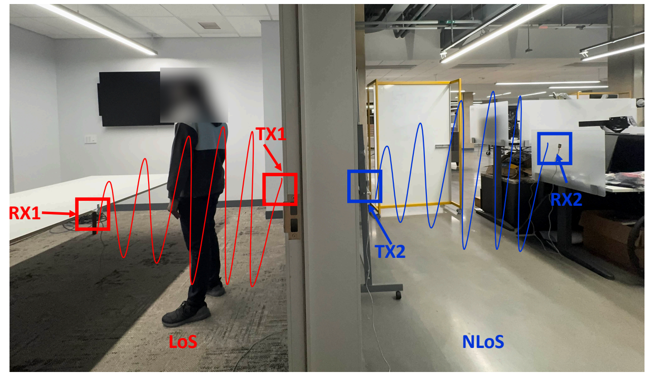


Fig. 2: Experimental setup for LoS and NLoS scenarios

Scenario	LoS Setup	NLoS Setup
1	LoS using Channel X	NLoS is using Channel X
2	LoS using Channel X	NLoS using Channel Y
3	LoS turned OFF	NLoS Using Channel X
4	LoS turned OFF	NLoS Using Channel Y

TABLE I: Experiment Scenarios

Table I presents the different experimental scenarios, detailing the WiFi channel assignments for LoS and NLoS pairs. Here, X refers to either Channel 1 or 11 and Y is the other one, i.e., if X is Channel 1 then we consider Y as Channel 11 and vice-versa. The experiments were conducted in a 5 m x 4.5 m indoor environment, where the TX and RX were placed 70 cm above the ground. As it is shown in Fig. 2, a glass-wall partition separated the LoS and NLoS areas and the distance between the TX and RX pairs of both scenarios were 160 cm,

For data collection, we conducted experiments involving three whole-body activities, each performed 10 times by a volunteer in a round-robin manner. The activities were (i) walking, (ii) moving hands up and down, and (iii) moving legs right and left. While splitting the dataset for the deep learning model, we used eight repetitions of each activity for the training set and the remaining two for the test set.

C. Model Development and Training

We designed a deep learning model for our activity classification task using Tensorflow/Keras framework. The model follows a sequential architecture incorporating a one dimensional convolutional layer and dense layers, along with dropout and batch normalization.

Experiment	Channel		Accuracy	
	LoS	NLoS	LoS	NLoS
1	1	1	70%	68%
	1	11	74%	89%
		1		80%
		11		79%
2	1	1	97%	86%
	1	11	96%	91%
3	1	1	90%	71%
	1	11	91%	92%
		1		78%
4	1	1	89%	73%
	1	11	84%	90%
		1		75%
5	1	1	83%	73%
	1	11	83%	76%
		1		73%

TABLE II: Accuracy in different scenarios and experiments.

We begin by reshaping the input data into a three-dimensional tensor of size $(52, 1)$, adding a channel dimension for compatibility with the one-dimensional convolutional layer. The output from the convolutional layer is then flattened to transition from feature extraction to fully connected layers. Next, we stack four dense layers with neuron counts decreasing from 192 to 32. Each dense layer employs ReLU activation and is followed by batch normalization to ensure stable gradient flow and faster convergence.

Dropout layers are applied progressively to prevent overfitting as the network becomes deeper. The final layer is a dense layer with three neurons and uses the softmax activation function to generate probability distributions for each of the target classes. The model is compiled using the Adam optimizer, with categorical cross-entropy as the loss function and accuracy as the evaluation metric. We then use this model to obtain classification on three performed human activities.

V. Experimental Results

In this section, we present the results of our experiments, conducted under different scenarios outlined in Table I. In Table II, we provide a summary of these results for both LoS and NLoS links across all experiments. Note that in every experiment, the volunteer performs the activities in the LoS link area. Next, we begin with discussing the results in the first experiment in detail, followed by an analysis of the remaining experiments.

In the first experiment, we considered all four scenarios together. We first analyze the use of same and different channels (Scenario 1 and 2) in both LoS and NLoS pairs. As shown in Table II, using different channels for LoS and NLoS results in higher NLoS accuracy (89%) compared to using the same channel (68%). Even the LoS OFF cases (Scenario 3 and 4) achieve better performance (80% and 79%, respectively) than the same channel scenario (Scenario 1).

Fig. 3 further illustrates the model's performance through confusion matrices. We see that the model achieves high to moderate classification accuracy for *Walking* class as it is the most distinctive among these three activities. For most of the cases, *Leg Right Left* class provides most of the misclassification by getting confused with *Walking* class, which is reasonable considering the involvement of legs in both of these activities. Additionally, activities performed at different speeds (e.g., slow arm movement or quick steps) introduce variations that may not be captured consistently across all samples; leading to occasional misclassifications.

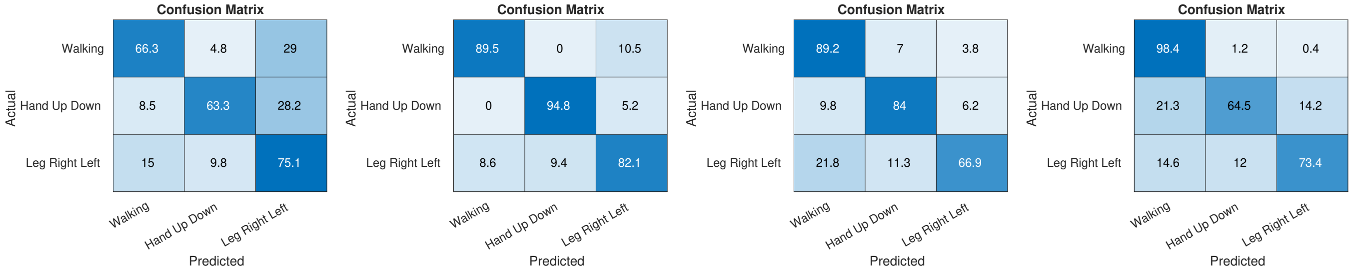
Activity	NLoS 1, LoS 1	NLoS 11, LoS 1	NLoS 1, LoS OFF	NLoS 11, LoS OFF
Walking	3.43	17.25	3.63	5.46
Hand Up/Down	3.61	16.46	3.83	5.38
Leg Right/Left	3.64	16.98	4.01	5.40

TABLE III: Mean amplitude variance values for different NLoS scenarios and activities.

To investigate the performance difference across different scenarios under various LoS and NLoS configurations further, we calculate the variance of amplitude across subcarriers. From the results in Table III, it is evident that variance is significantly higher in the NLoS channel 11 with LoS channel 1 scenario compared to the other three configurations. Fig. 4 suggests that non-overlapping channels introduce greater diversity in the signal, leading to a richer feature space for classification. When using the same channel, the co-channel interference between the LoS and NLoS signals reduces the signal diversity. On top of that, even the LoS OFF scenarios show slightly higher variance than the same channel LoS-NLoS scenario. As shown in Fig. 5, the amplitude values for Scenario 2 range from approximately 4 to 18, whereas in the other three scenarios, the range is roughly between 10 and 18.

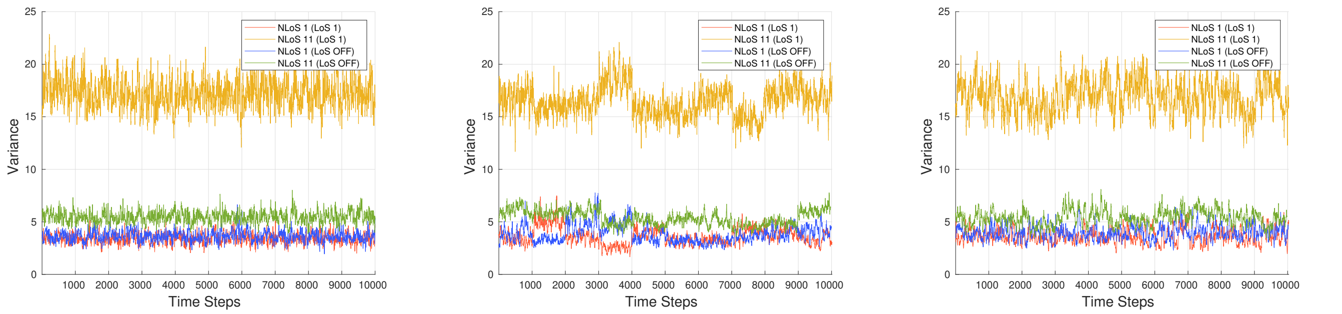
These results show that same channel interference is destructive for sensing performance in NLoS scenarios, thus removing the same channel LoS pair can increase the performance. While this was expected, we observed an unexpected result in the different channel LoS-NLoS scenario. Our initial expectation was to observe similar performance in NLoS link when there is a LoS pair running in non-overlapping channel or when LoS pair is turned off. However, our results show that using a non-overlapping channel in the LoS pair can improve the NLoS performance compared to NLoS only scenario (i.e., LoS OFF). Further analysis revealed that this improvement is due to the higher variance in amplitude distribution across subcarriers, which enhances the model's ability to differentiate between activities.

In non-overlapping channels, the signals from LoS and NLoS operate at different frequencies, minimizing destructive interference and allowing independent propagation paths to dominate. This leads to higher variance in the signal, which enhances feature diversity for classification. Therefore, allocating non-overlapping channels to different TX-RX pairs, particularly for LoS and NLoS links, can directly improve the performance of WiFi sensing applications.



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3 (d) Scenario 4

Fig. 3: Confusion matrix of each NLoS scenario of experiment 1



(a) Walking (b) Moving Hands Up and Down (c) Moving Leg Right and Left

Fig. 4: Variance of amplitude across subcarriers during all repetitions of each activity for NLoS pairs of Experiment 1.

In order to verify if our observations are consistent, we performed additional experiments, with results presented in Table II for experiments 2 through 5. These results confirm that the performance comparison across different scenarios remains consistent. It is important to note that the accuracy of the system for LoS and NLoS links varies across experiments, likely due to differences introduced by the student volunteer while performing the activities. However, within each experiment, we consistently see that we have better NLoS accuracy in different channel cases (i.e., Scenario 2) than in the same channel case (i.e., Scenario 1). Moreover, the same channel case has worse (in experiment 5, it was similar) sensing accuracy compared to NLoS only case, and the different channel case has a better performance than NLoS only case. Since data for each scenario was collected separately within the same experiment, there was also some variation across these scenarios. However, relatively similar LoS performance across different scenarios of each experiment shows a proper and consistent data collection process.

VI. Conclusion

In this work, we investigated the impact of using same or different channels in LoS and NLoS pairs on WiFi sensing performance. We employed deep learning models to recognize human activities in both LoS and NLoS environments while the activity occurred in the LoS region. Our results show that the highest NLoS accuracy is achieved when LoS and NLoS pairs transmit on different channels. Additionally, we observed that using the same channel degrades NLoS recognition performance, performing worse than having no LoS pair at all. Through a deeper analysis, we have shown that the variance of amplitude across subcarriers provides a valuable insight into this performance difference.

In our future work, we will explore scenarios with additional TX-RX pairs and diverse channel combinations across various settings. By strategically allocating channels, we can help maximize sensing performance in such multiple TX-RX deployments. Our findings can also have potential applications in security, as users can dynamically adjust their channels to evade attackers and minimize potential threats.

References

[1] Linux 802.11n CSI Tool, 2025. [Online]. Available: https://dhalperi.github.io/linux-80211n-csitool/.

[2] Nexmon: The c-based firmware patching framework, 2025. [Online]. Available: https://nexmon.org.

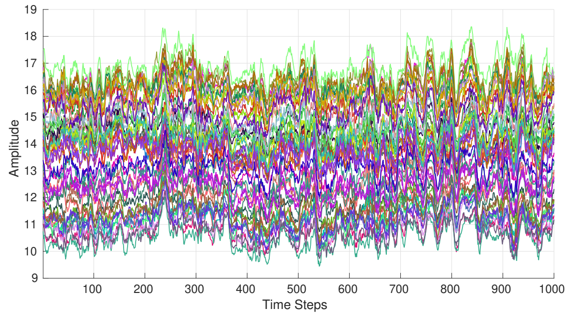
[3] S. M. Hernandez, "ESP32 CSI Tool," 2025. [Online]. Available: https://stevenmhernandez.github.io/ESP32-CSI-Tool/

[4] C. Shi, J. Liu, H. Liu, and Y. Chen, "WiFi-enabled user authentication through deep learning in daily activities," *ACM Transactions on Internet of Things*, vol. 2, no. 2, pp. 1–25, 2021.

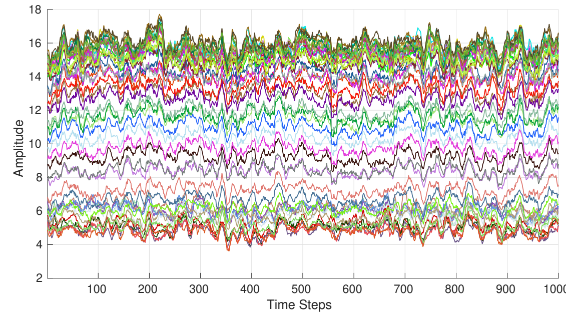
[5] D. Wu, Y. Zeng, R. Gao, S. Li, Y. Li, R. C. Shah, H. Lu, and D. Zhang, "WiTraj: Robust indoor motion tracking with WiFi signals," *IEEE Trans. on Mobile Computing*, vol. 22, no. 5, pp. 3062–3078, 2021.

[6] Y. Lin, Y. Gao, B. Li, and W. Dong, "Revisiting indoor intrusion detection with wifi signals: Do not panic over a pet!" *IEEE Internet of Things Journal*, vol. 7, no. 10, pp. 10 437–10 449, 2020.

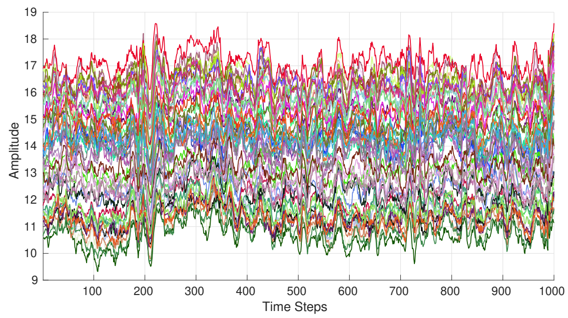
[7] J. Hu, T. Zheng, Z. Chen, H. Wang, and J. Luo, "MUSE-Fi: Contactless muti-person sensing exploiting near-field Wi-Fi channel variation," in *Proceedings of the 29th Annual International Conference on Mobile Computing and Networking (Mobicom)*, 2023, pp. 1–15.



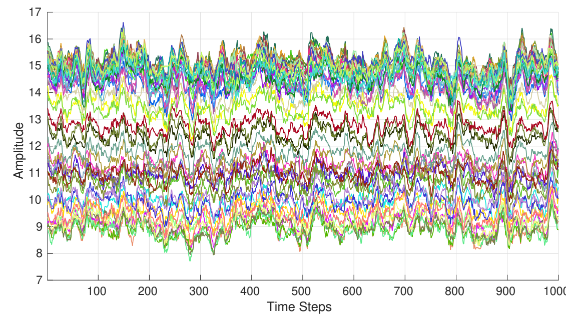
(a) Scenario 1



(b) Scenario 2



(c) Scenario 3



(d) Scenario 4

Fig. 5: Amplitude values in NLoS pair for each subcarrier across different scenarios in Experiment 1

[8] Y. Ma, G. Zhou, and S. Wang, “WiFi sensing with channel state information: A survey,” *ACM Computing Surveys (CSUR)*, vol. 52, no. 3, pp. 1–36, 2019.

[9] M. Cominelli, F. Gringoli, and F. Restuccia, “Exposing the CSI: A systematic investigation of CSI-based Wi-Fi sensing capabilities and limitations,” in *IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2023, pp. 81–90.

[10] M. McDonough, T. Moomaw, M. Touhiduzzaman, and E. Bulut, “Wi-Alert: WiFi Sensing for Real-time Package Theft Alerts at Residential Doorsteps,” in *Proceedings of the Twenty-fourth International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing*, 2023, pp. 424–429.

[11] M. Touhiduzzaman, S. M. Hernandez, P. E. Pidcoe, and E. Bulut, “Wi-PT-Hand: Wireless Sensing based Low-cost Physical Rehabilitation Tracking for Hand Movements,” *ACM Transactions on Computing for Healthcare*, vol. 6, no. 1, pp. 1–25, 2025.

[12] S. M. Hernandez and E. Bulut, “WiFi Sensing on the Edge: Signal Processing Techniques and Challenges for Real-World Systems,” *IEEE Commun. Surv. Tutorials*, vol. 25, no. 1, pp. 46–76, 2023.

[13] S. Depatla and Y. Mostofi, “Crowd counting through walls using WiFi,” in *IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2018, pp. 1–10.

[14] G. Zhu, Y. Hu, B. Wang, C. Wu, X. Zeng, and K. R. Liu, “Wi-MoID: Human and Nonhuman Motion Discrimination Using WiFi With Edge Computing,” *IEEE Internet of Things Journal*, vol. 11, no. 8, pp. 13 900–13 912, 2023.

[15] W. Akpabio and E. Bulut, “PhysiFi: WiFi Sensing for Monitoring Therapeutic Robotic Systems,” in *Proceedings of 23rd International Conference on Pervasive Computing and Communications (Percom) Workshops - 2nd International Workshop on Pervasive Wireless Sensing and Edge Computing (WiSense), Washington D.C., USA*, 2025.

[16] X. Wang, K. Niu, J. Xiong, B. Qian, Z. Yao, T. Lou, and D. Zhang, “Placement matters: Understanding the effects of device placement for WiFi sensing,” *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 6, no. 1, pp. 1–25, 2022.

[17] Z. Shi, Q. Cheng, J. A. Zhang, and R. Y. Da Xu, “Environment-robust WiFi-based human activity recognition using enhanced CSI and deep learning,” *IEEE Internet of Things Journal*, vol. 9, no. 24, pp. 24 643–24 654, 2022.

[18] C. Chen, G. Zhou, and Y. Lin, “Cross-Domain WiFi Sensing with Channel State Information: A Survey,” *ACM Computing Surveys*, vol. 55, no. 11, pp. 1–37, 2023.

[19] S. M. Hernandez and E. Bulut, “WiFederated: Scalable WiFi sensing using edge-based federated learning,” *IEEE Internet of Things Journal*, vol. 9, no. 14, pp. 12 628–12 640, 2021.

[20] S. Samiul Alam, A. Chakma, A. Imran, and Y. Min Jang, “DCsiNet: Effective Handling of Noisy CSI in FDD Massive MIMO System,” *IEEE Wireless Commun. Letters*, vol. 13, no. 9, pp. 2556–2560, 2024.

[21] B. Xie, M. Cui, D. Ganesan, and J. Xiong, “Wall Matters: Rethinking the Effect of Wall for Wireless Sensing,” *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 7, no. 4, pp. 1–22, 2024.

[22] A. Sharma, D. Mishra, S. Jha, and A. Seneviratne, “An Investigation into the Non-Uniformity of Channel State Information in WiFi Sensing Systems,” in *IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 2024, pp. 1–6.

[23] H. Guan, A. Sharma, D. Mishra, and A. Seneviratne, “Experimental accuracy comparison for 2.4 GHz and 5GHz WiFi sensing systems,” in *IEEE International Conference on Communications (ICC)*, 2023, pp. 4755–4760.

[24] F. Wang, W. Gong, J. Liu, and K. Wu, “Channel selective activity recognition with WiFi: A deep learning approach exploring wideband information,” *IEEE Transactions on Network Science and Engineering*, vol. 7, no. 1, pp. 181–192, 2018.

[25] A. Sharma, D. Mishra, T. Zia, and A. Seneviratne, “A novel approach to channel profiling using the frequency selectiveness of WiFi CSI samples,” in *IEEE Globecom Conference*, 2020, pp. 1–6.

[26] S. M. Hernandez and E. Bulut, “Lightweight and Standalone IoT based WiFi Sensing for Active Repositioning and Mobility,” in *21st International Symposium on ”A World of Wireless, Mobile and Multimedia Networks” (WoWMoM)*, Cork, Ireland, Jun. 2020.