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Exploiting channel state information of WiFi signal for human activity detection: an experimental study

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ABSTRACT

Ubiquitous computing aims to seamlessly integrate computing into our daily lives, and requires reliable information on human activities and state for various applications. In this paper, we propose a device-free human activity recognition system that leverages the rich information behind WiFi signals to detect human activities in indoor environments, including walking, sitting, and standing. The key idea of our system is to use the dynamic features of activities, which we carefully examine and analyze through the characteristics of channel state information. We evaluate the impact of location changes on WiFi signal distribution for different activities and design an activity detection system that employs signal processing techniques to extract discriminative features from wireless signals in the frequency and temporal domains. We implement our system on a single off-the-shelf WiFi device connecting to a commercial wireless access point and evaluate it in laboratory and conference room environments. Our experiments demonstrate the feasibility of using WiFi signals for device-free human activity recognition, which could provide a practical and non-intrusive solution for indoor monitoring and ubiquitous computing applications.

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1. INTRODUCTION

Human activity recognition (HAR) is a key challenge in context-aware computing and has important applications in various fields, including healthcare, security, and home automation. HAR involves identifying and classifying human activities based on sensor data collected from the environment. The goal of HAR is to provide automated monitoring and analysis of human behavior, which could be used for improving life quality, enhancing safety and security, and providing personalized services to individuals [1]–[5]. HAR can be performed through contact-based or contactless methods. While contact-based methods require wearable sensors, contactless methods are non-intrusive and can provide long-term monitoring. Contactless methods include video, ultrasound, and RF-based techniques such as ultra wideband, continuous wave radar, ZigBee, and WiFi [6]–[9].

WiFi-based contactless HAR has emerged as a promising solution due to the extensive adoption of commercial WiFi hardware in indoor settings, the affordability of WiFi equipment, and the rich information provided by the channel state information (CSI) and received signal strength indicator (RSSI). In WiFi-based HAR, the WiFi signal between a transmitter and a receiver can be used to detect human activity on the basis of signal strength, amplitude as well as phase, all of which are impacted by human movement. Previous investigations [10]–[12] have shown that CSI performs better than RSSI for detecting human activity.

However, WiFi-based HAR faces several challenges, including changes in location, environmental noise, and the need for accurate and efficient algorithms for activity recognition. To address these challenges, this article proposed a device-less human activity detection system that exploits the rich information contained in WiFi signals to monitor indoor environments and recognize different activities. The system is designed to be low-cost, easy to deploy and non-intrusive, which makes it suitable for long-term monitoring. The main contributions of this article are:

- We propose a device-free human activity recognition system that leverages the dynamic features of activities, which we carefully examine and analyze through the characteristics of channel state information.
- We design an activity detection system that uses discriminative characteristics of wireless signals in the frequency and temporal domains for recognition, and evaluate the impact of location changes on WiFi signal distribution for different activities, resulting in an effective system that can detect sitting, standing, and walking activities.
- We implement our proposed system on a single off-the-shelf WiFi device connecting to a commercial wireless access point and evaluate its performance in laboratory and conference room environments. Our experiments demonstrate the feasibility of using WiFi signals for device-free human activity recognition and present a practical solution for indoor monitoring and ubiquitous computing applications.

The rest of this paper is structured as follows: we first provide some preliminaries on WiFi detection and technical details in section 2, providing the background knowledge necessary for understanding our approach. In section 3, we provide design details as well as an overview of the system architecture, giving an overall view of the proposed system. In section 4, we describe the experimental environment, hardware/software configuration, implementation and evaluation, providing an in-depth analysis of our approach and results. Finally, we conclude the article and provide directions for future research in section 5.

2. PRELIMINARIES

For WiFi device-free sensing technologies, objects, such as the dynamic human activities explored in this research, exert an influence on transmitted signals, resulting in the superposition of multipath signals at the receiver. This phenomenon presents opportunities for signal identification and exploitation. The characterization of this impact on the communication link between the transmitter and the receiver is achieved through the use of CSI, which offers a higher degree of precision compared to the RSSI [13]–[15].

The majority of WiFi routers support IEEE WLAN standards, including 802.11 a/g/b/n/ac/ax. Versions from 802.11n onward incorporate advanced technologies like multiple-input multiple-output (MIMO) and orthogonal frequency division multiplexing (OFDM), which have the potential to enhance data throughput [16], [17]. Consequently, we have the capability to collect CSI data from a variety of communication channels. This CSI data is utilized for the detection of human activity. In the context of OFDM subcarriers, the CSI information captures both amplitude and phase, allowing for the representation of the received signal:

$$y = H \times x + n \tag{1}$$

Where y is the received signal, x is the transmitted signal, n stands for channel noise, and H refers to the CSI, a complex matrix representing the channel's frequency response (CFR) for each subcarrier in every spatial stream.

As a result, the CSI can be represented as an $m \times n \times w$ matrix, where m stands for the number of transmitter antennas, n represents the number of reception antennas, and w denotes the number of subcarriers, encompassing all subcarriers and specialized streams. This finely detailed matrix serves as an accurate depiction of the temporal and spectral characteristics of the channel, including the impact of small-scale multipath effects. The components H of the received packets, assuming the presence of m transmitters and n receivers in the MIMO system, are structured:

$$H = \begin{bmatrix} H_{1,1} & \cdots & H_{1,n} \\ \vdots & \ddots & \vdots \\ H_{m,1} & \cdots & H_{m,n} \end{bmatrix} \tag{2}$$

Every element of the matrix $h_{\mathrm{i,j}} = (h_1, h_2, \dots, h_w)$, is a vector that contains the channel state h_{k} for every transmitting (i) and receiving (j) antenna pair's for every k-th subcarrier. It is possible to describe the value h_{k} as follows, where $|h_k|$denotes the amplitude and θ denotes the phase, and it gives information on the amplitude as well as phase of the relevant subcarrier [12]:

$$h_k = |h_k| e^{jsin\theta} \quad (3)$$

To estimate the CSI, the transmitter transmits long training symbols (LTS) within the packet preamble, containing predefined information (symbols) for each subcarrier. When the LTS is received, the WiFi receiver computes the CSI by analyzing the received signal in conjunction with the original LTS. However, it's essential to emphasize that real-world CSI is subject to various factors such as multi-channel effects, receiver/transmitter processing, hardware and software errors, and other environmental influences [18]. Figure 1 illustrates the phenomenon of multipath effects in the propagation of a WiFi signal.

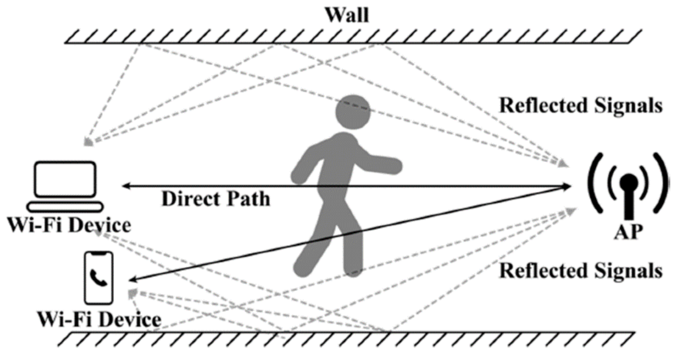


Figure 1. Illustrates the phenomenon of multipath effects in the propagation of a WiFi signal

Multipath phenomena are inherent to wireless transmission systems due to signals often taking indirect paths before reaching the receiving antenna. The multipath effect results from the combination of several outside factors:
- Reflection: phase change when the signal reflects.
- Scattering: variation of the path affecting the shape of the signal.
- Attenuation: reduction of the observed amplitude.

Static environmental elements exert a consistent influence on multipath effects, whereas dynamic objects, such as the human body, introduce variability into these effects. Human actions are the source of this multipath variability, encompassing both passive movements like breathing and active movements like walking [19], [20]. By analyzing alterations in both signal amplitude and phase between transmission and reception, we can discern whether human activities have affected the signal and deduce the specific activity performed by the individual. This article will primarily focus on the utilization of amplitude analysis.

3. MATERIALS AND METHODS

In this section, our primary goal is giving a thorough insight into our system's architecture. To achieve this, we start by providing a comprehensive overview of the entire system, highlighting its essential features and functions. Subsequently, we explore the specific roles and interactions of each individual component.

3.1. System overview

We propose a system for detecting human activity using CSI data collected via commercial WiFi devices. The overall process is illustrated in Figure 2 and consists of three primary modules: data collection, preprocessing, and human activity detection. In the data collection module, original CSI data is collected from commercial WiFi devices using a WiFi router for transmission and a desktop computer for receiving the data packets. The raw CSI is extracted from the received packets, and its variation is analyzed to identify the existence of objects and motions within the environment. The acquired information is then preprocessed to eliminate any inaccuracies and interference, followed by feature extraction to identify meaningful patterns.

3.2. Data collection

According to (1), CSI estimation involves transmitting a pilot signal from a transmitter (Tx) to a receiver (Rx), followed by computing the CSI at the receiver. Typically, this is done by sending a ping packet from Tx to Rx for CSI estimation. We used the Linux 802.11n CSI tool with the Intel 5300 network interface card (NIC) [21]. Figure 3 shows the data collection device configuration. In this setup, both Tx and Rx continuously transmit signals, allowing the receiver to estimate CSI from incoming packets.

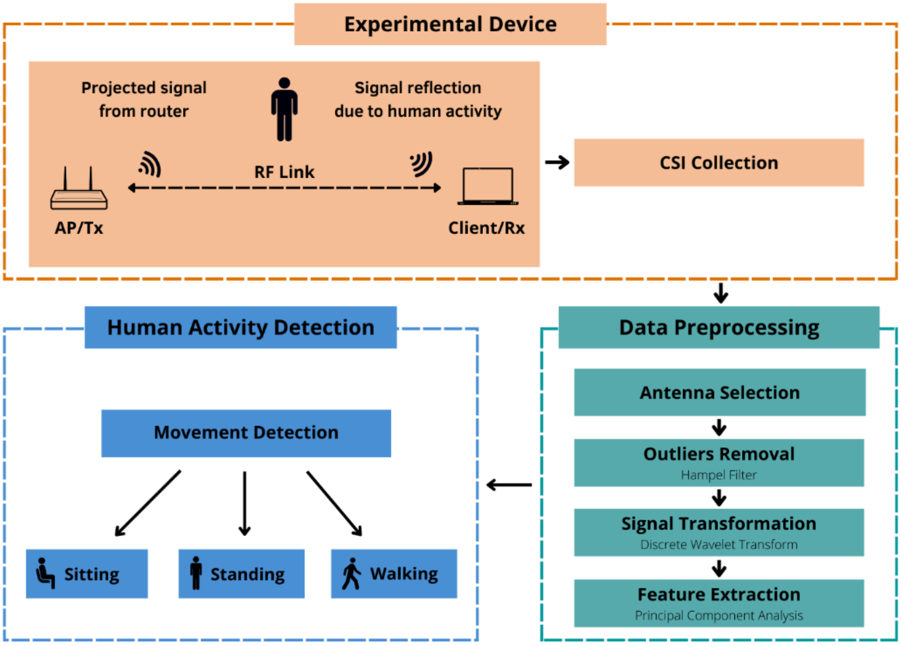


Figure 2. System architecture overview

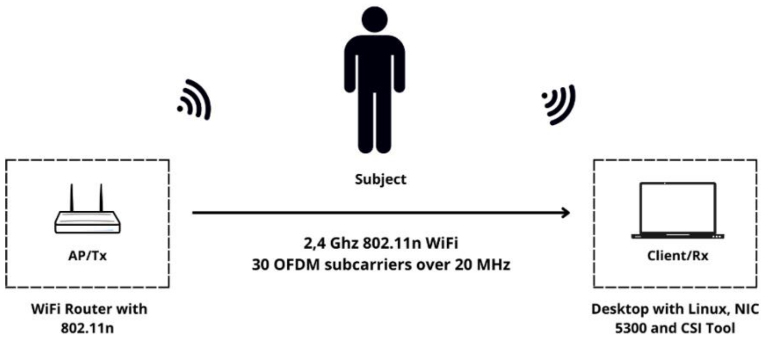


Figure 3. Illustration of CSI collection

3.3. Data preprocessing

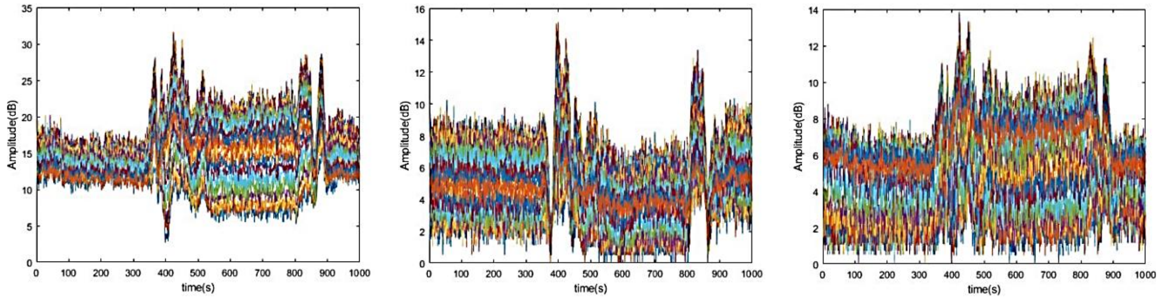
To ensure the quality of the CSI measurements, data preprocessing is a crucial step in our system. This process becomes necessary due to hardware imperfections and surrounding noise, which can introduce corruption in the collected data. The following steps outline the data preprocessing procedures implemented to mitigate these issues effectively.

3.3.1. Antenna selection

After collecting data using the Intel 5300 network card and storing it in a .data file, we imported the data into MATLAB [22] and conducted a comparative analysis of three different antennas during various activities: sitting, standing, and walking. One antenna consistently exhibited dynamic responses, while another remained predominantly static. We excluded data from the least sensitive antenna and identified the most sensitive antenna as the reception reference [23]. The second antenna displayed distinct fluctuations over time, making it ideal for capturing activity variations. Figure 4 illustrates CSI amplitude variation over time across 30 subcarriers for the three antennas, where Figure 4(a) for antenna 1, Figure 4(b) for antenna 2, and Figure 4(c) for antenna 3.

3.3.2. Outliers removal with Hampel filter

The amplitudes and phases of the CSI may contain noise due to internal factors like power transmission, rate adaptations, and thermal noise in devices, which can interfere with the signal and lead to incorrect values unrelated to human presence. To address this, the initial step after importing the raw data involves noise reduction. Numerous techniques are available for this purpose, such as employing a combination of filters to extract desired time or frequency domain information. We utilize the widely-used Hampel outlier filter to remove prominent outliers [24]. The denoising results, illustrated in Figure 5, demonstrate a smoother CSI waveform with reduced local disturbances compared to the original waveform.



(a) (b) (c)

Figure 4. Illustrates the CSI amplitude on 30 subcarriers of three antennas; (a) antenna 1, (b) antenna 2, and (c) antenna 3

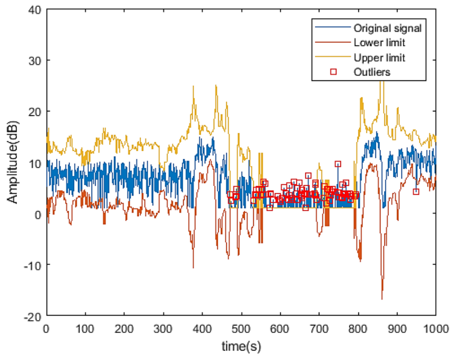


Figure 5. Illustrates denoising the amplitude of the second subcarrier for the second antenna

3.3.3. Signal transformation using discrete wavelet transform

To improve accuracy of CSI values in time series, a noise reduction technique such as discrete wavelet transform (DWT) can be applied to eliminate high-frequency noise unrelated to the targeted activity and caused by changes in transmission speeds or variations in the external environment. DWT is particularly useful for this purpose, as it allows optimum time/frequency resolution and multi-scale analysis of the data. The effectiveness of noise reduction using DWT is demonstrated in Figure 6. Figure 6(a) illustrates the original CSI, while Figure 6(b) depicts the denoised CSI achieved through DWT. Additionally, because wavelet denoising has linear time complexity and does not require assumptions about signal continuity, it is computationally efficient. In DWT, the components of a closely related low-pass scaling filter and a high-pass mother wavelet filter are convolved to create the wavelet basis vectors. From a single base wavelet $\psi(x)$, wavelet $\psi_{s,t}(x)$ is produced [25]:

$$\psi_{s,t}(x) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{s-t}{s}\right) \qquad (s \neq 0) \tag{4}$$

Where the translation parameter is represented by t, and the scaling parameter by s. When $t = n(n = \cdots, -1,0,1 \ldots)$ and $s = 2^m(m = 0,1,2, \ldots)$, where m is the scale index and n is the translation index, respectively, we get the result:

$$\psi_{m,n}(x) = 2^{-\frac{m}{2}}\psi(2^{-m}(x-n)) \tag{5}$$

The 1-D function $f(x)$ can be represented by the projection of the function $f(x)$ onto the wavelet set $\psi_{m,n}(x)$ using the DWT $W(m,n)$:

$$W(m,n) = \int_{-\infty}^{+\infty} dx \overline{\psi_{m,n}(x)} f(x) \tag{6}$$

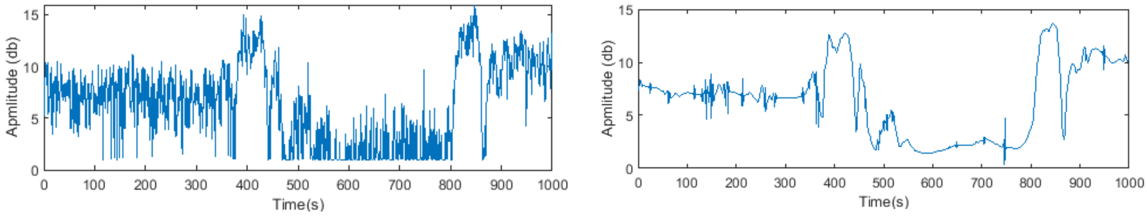


Figure 6. Displays the CSI amplitude of the second subcarrier for the first antenna; (a) before DWT and (b) after DWT

3.3.4. Signal extraction via principal component analysis (PCA)

The CSI signal obtained through the utilization of the 802.11n protocol's CSI tool encompasses amplitude and phase details for each of the 30 available sampling subcarriers. To efficiently manage this substantial volume of CSI data collected within a brief time frame, we employ PCA [26]. PCA is an algorithm that effectively extracts data components containing the most information, significantly reducing the data while preserving essential environmental information. By utilizing variance as a measure of the informational content in the signal, PCA transforms the matrix into a set of linearly uncorrelated principal components. This method finds widespread application in blind signal separation and feature extraction for pattern recognition tasks [18]. Figure 7 provides an illustration of employing PCA for the purpose of dimensionality reduction in the CSI signal.

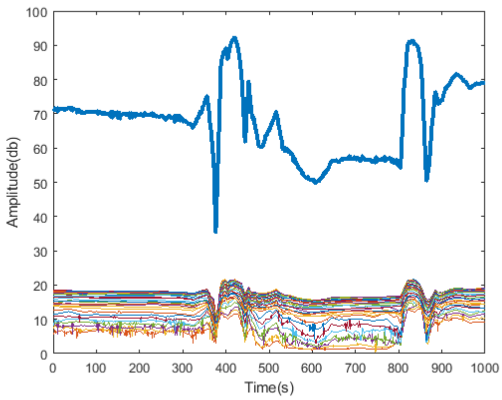


Figure 7. Illustrate the PCA for CSI dimension reduction

4. EXPRIMENT AND ANALYSIS

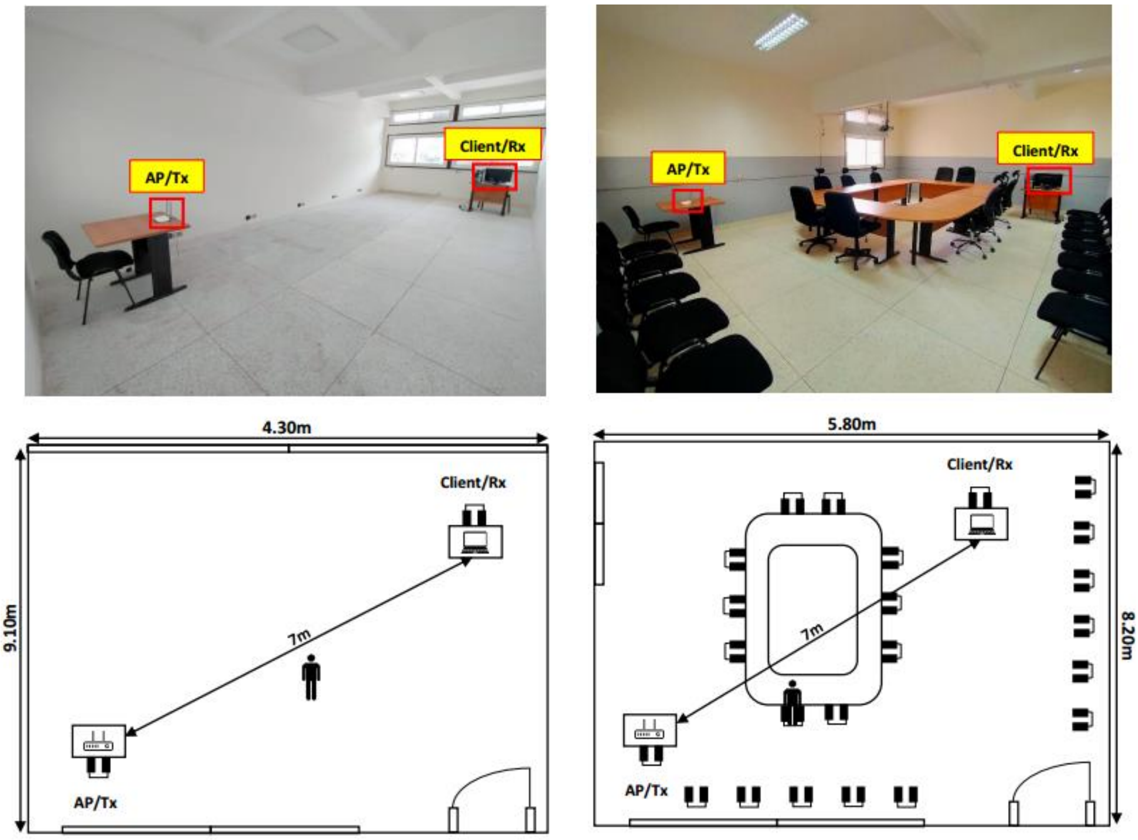
In this section, we describe the experimental environments, hardware, and software setup. We present the obtained results from the proposed approach. We then conduct a comprehensive performance analysis to evaluate its effectiveness.

4.1. Expriment environnment

The experiments were carried out in two distinct environments: a laboratory and a conference room to evaluate the effectiveness of our system. The dimensions and parameters are detailed in Table 1. We employed two devices in this setup: one as the Tx, functioning as an access point (AP) transmitter, and the other as the Rx, representing the desktop computer. Both devices were consistently positioned at a fixed height of 0.75 meters to ensure an uninterrupted signal path. The physical layout of the environments, including tables, desks, computers, and various pieces of wooden and metallic equipment, remained unaltered throughout the experiment. The experimenter maintained a constant position and orientation during signal capture, ensuring reliable and consistent signal measurements. Figure 8 provides visual representations of these experimental environments, with Figure 8(a) illustrating the laboratory and Figure 8(b) depicting the conference room.

Table 1. Presents a summary of the experiment parameters

Characteristics and parameters	Environment	
	Laboratory	Conference room
Dimensions	9.10 m * 4.30 m	8.20 m * 5.80 m
Occupancy	1 Person	1 Person
Bandwidth	20 MHz	20 MHz
Channel	11 (2462 MHz)	11 (2462 MHz)
Frequency	2.417 GHz	2.417 GHz
Antennas	3 Rx * 2 Tx	3 Rx * 2 Tx
Spatial streams	MIMO	MIMO
Subcarriers	30	30



(a) (b)

Figure 8. Experimental environments; (a) laboratory and (b) conference room

4.2. Expriment setup

We conducted an experimental study in a standard 2.4 GHz 802.11n WiFi network. We used an HP 290 G1 MT business computer as the transmitter, connected to a TP-LINK TD-W8961N commercial wireless access point, which acted as a dual-antenna transmitter. The desktop ran Ubuntu 14.04.4 LTS with the 4.2.0-27 kernel and featured an Intel WiFi Link 5300 card with three antennas for reception. MATLAB was installed on the same desktop for offline data processing related to human activity. The transmission rate was set at 100 packets per second, and we extracted CSI data from received packets, covering 30 subcarrier groups within a 20 MHz channel bandwidth, using a customized version of an open-source wireless driver [21]. A CSI matrix of size 2×3×30 can be extracted from each packet, which represents complex CSI values of subcarriers that are received from each of three antennas of a network card. Table 2 lists the hardware and software used in the experiment.

Table 2. Hardware and software used in the experiment

Device name	Role	Hardware/software	Specification and use
Laptop	Rx	HP 290 G1 MT Business PC	Receiving WiFi packets
Access point	Tx	TP-LINK TD-W8961N	Transmitting WiFi packets
Network interface card	Intel 5300	Intel 5300 Mini Wireless Network Card, 450 Mbps, 3 antennas 6 dbi, INTEL5300AGN	Receive CSI data
Software	MATLAB platform	MATLAB R2018b	Constructing system

Figure 9 illustrates the experimental hardware employed in the study, including Figure 9(a) Intel WiFi 5300, Figure 9(b) the desktop computer, and Figure 9(c) the access point. The combination of these components facilitated the seamless execution of the experiment. The hardware setup, with its integral components, played a crucial role in gathering accurate data and achieving reliable results.

(a) (b) (c)

Figure 9. Illustrate the experimental hardware; (a) Intel WiFi 5300, (b) descktop computer, and (c) acces point

4.3. Expriments and results

We conducted the experiments in two distinct environments: a laboratory and a conference room, with a distance of 7m between the transmitter and reception antennas. The laboratory environment had a clear line-of-sight (LOS) reception, while the conference room had obstructed LOS pathways due to metal tables and chairs, resulting in high multipath effects, depicted in Figures 8(a) and (b). The volunteer performed sitting, standing, and walking activities in both environments, and the activities were performed by only one person. Table 3 provides a description of the activities used in the experiments.

Table 3. Describe the activities used in the experiments

Activity	Description
Sitting	Sitting on a chair
Standing	Standing up
Walking	Walking from receivers towards the transmitter

The objective of this research was to assess the influence of diverse human actions on the transmission characteristics of wireless communication channels. The collected indirect wireless data was analyzed for patterns. The experiments revealed that human activities result in significant fluctuations in the CSI amplitude. Figures 10(a) and (b) display the CSI amplitudes of all subcarriers and the second antenna relative to a human subject who was sitting, standing, and walking between the WiFi transmitter and receiver in the laboratory and conference room environments, respectively. The results show that the CSI amplitudes remained unchanged while the individual was stationary in both environments, but they began to fluctuate when the subject started moving. However, the magnitude and patterns of the CSI amplitude fluctuations were notably different between the laboratory and conference room environments. In the conference room, the CSI amplitude fluctuations were more significant due to the high multipath effects caused by the obstructed LOS pathways. This indicates the environment significantly influences the wireless propagation channel and the resulting CSI measurements.

Figures 11(a) and (b) display the results of a PCA performed on CSI data collected during experiments in laboratory and conference room environments, respectively. Volunteers performed sitting, standing, and walking activities in both environments. Each figure includes three subplots, illustrating the PCA results for each activity in the corresponding environment. he analysis demonstrates how human activities affect the distribution of WiFi signals and confirms the capability of the proposed WiFi-based system to identify human activities. Furthermore, the experiments highlight how changes in location impact the wireless propagation channel. The results also suggest that the proposed system is effective in detecting human activities, regardless of the environment.

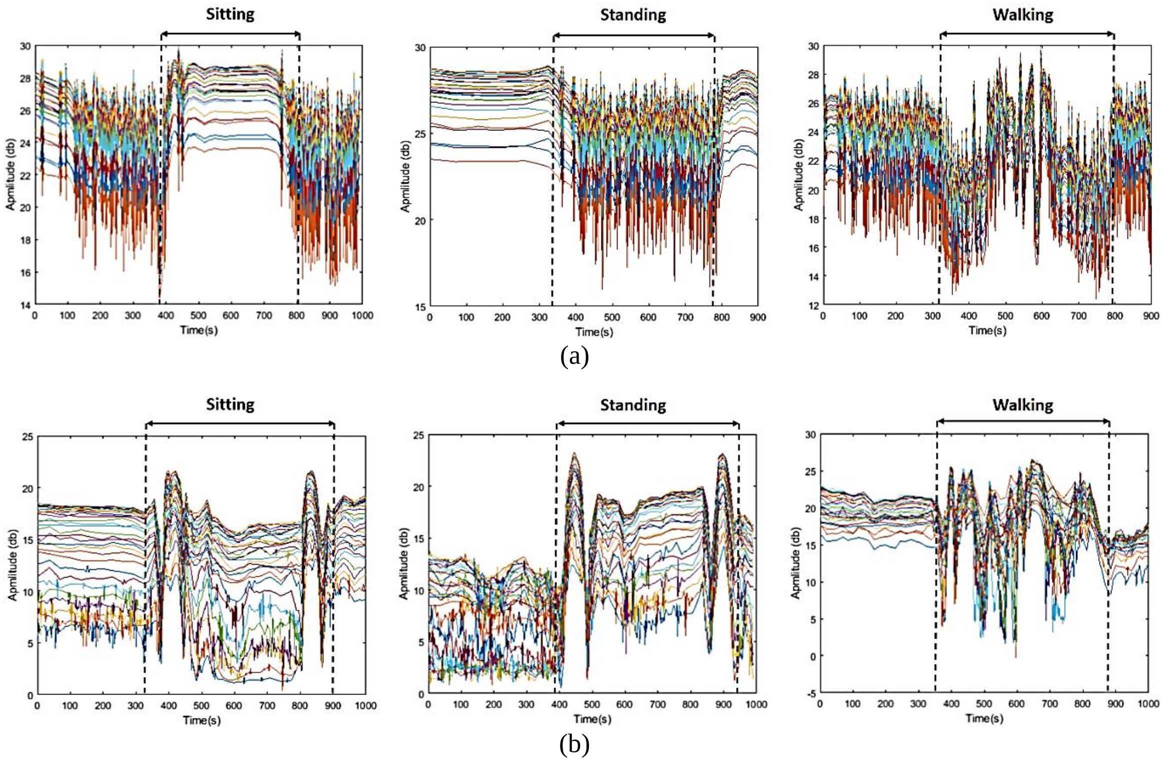


Figure 10. CSI amplitude recorded during different activities: sitting, standing, and walking in various environmentts respectively; (a) laboratory and (b) conference room

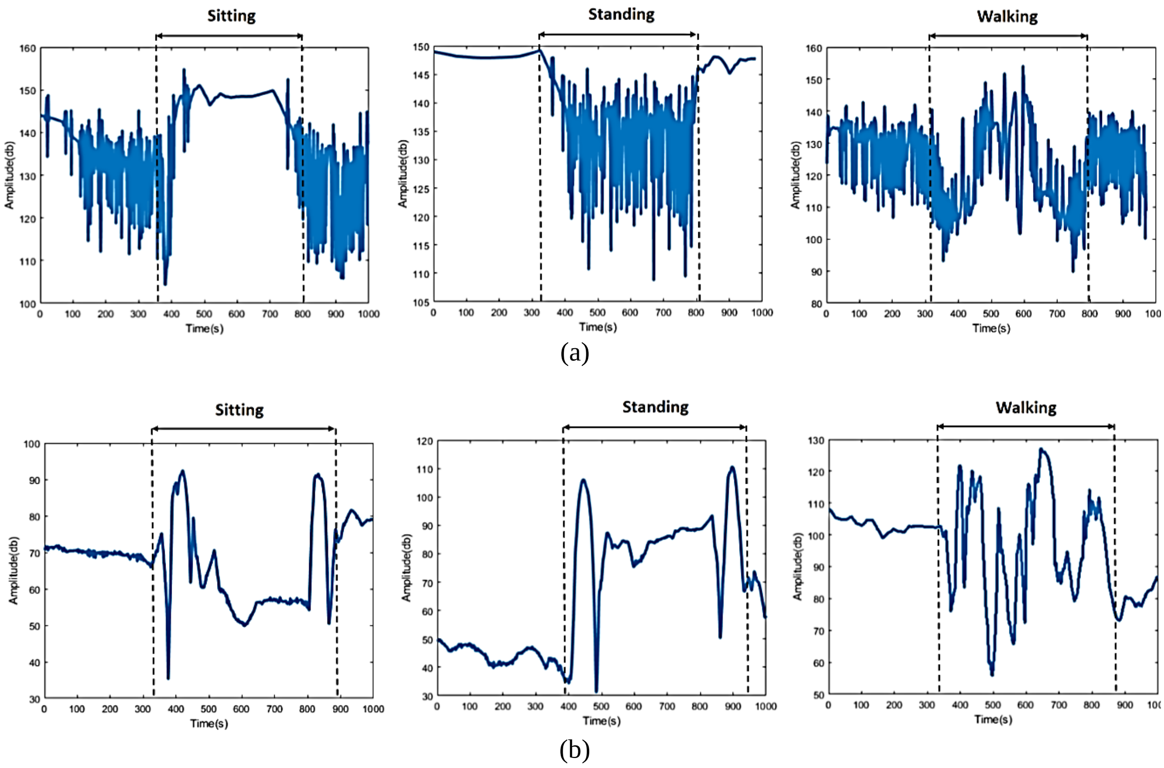


Figure 11. Illustrates CSI amplitude of the first PCA for antenna 2 over 30 subcarriers after filtering of various activities: sitting, standing, and walking in different environments, respectively; (a) laboratory and (b) conference room

4.4. Discussion
We investigated how human activities affect wireless signal propagation within two different environments: a laboratory with clear line-of-sight reception and a conference room with obstructed LOS pathways resulting in high multipath effects. Our results show that human activities cause significant variations in the amplitude of CSI for wireless signals. The fluctuations were more significant in the conference room environment due to the high multipath effects. To detect these activities, we proposed a WiFi-based system that was effective in both environments. Specifically, our system successfully detected sitting, standing, and walking activities based on the fluctuations in the CSI amplitude of wireless signals. Our study highlights the importance of considering the environment when designing wireless communication systems, as the impact of the environment on the resulting CSI measurements underscores the need for careful calibration and testing, especially in indoor environments where multipath effects can be pronounced. Moreover, our results suggest that wireless signals could be utilized for device-free recognition of human activity, opening up possibilities for various applications. Therefore, our study demonstrates the potential of WiFi signals for indoor monitoring and ubiquitous computing applications, providing a practical solution for device-free human activity recognition.

5. CONCLUSION AND FUTURE WORK
In this paper, we conducted experiments to investigate the influence of human activity and the surrounding environment on CSI, and demonstrated how CSI can be collected and analyzed to detect specific movements without compromising user privacy. The results showed that human activity has a significant impact on the wireless propagation channel, and the proposed WiFi-based system is effective in detecting these activities. Our study provides a specific understanding of utilizing CSI data for human activity recognition and the necessary steps to build a robust model. For future research, we aim to expand our analysis to recognize more diverse activities, including those involving objects. We also plan to investigate the impact of different environments and wireless frequency bands on the accuracy of human activity recognition. As 802.11ad utilizes the 60 GHz band, it affords larger bandwidth than the combined 2.4 GHz and 5 GHz bands, potentially resulting in more accurate human activity detection. These studies will help improve the robustness and accuracy of the proposed system, making it useful for a wider range of applications.

REFERENCES

[1] Y. Zheng, L. Capra, O. Wolfson, and H. Yang, “Urban Computing: Concepts, Methodologies, and Applications,” *ACM Transactions on Intelligent Systems and Technology*, vol. 5, no. 3, pp. 1–55, Oct. 2014, doi: 10.1145/2629592.

[2] J. Ma, H. Wang, D. Zhang, Y. Wang, and Y. Wang, “A Survey on Wi-Fi Based Contactless Activity Recognition,” in *2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld)*, Toulouse: IEEE, Jul. 2016, pp. 1086–1091, doi: 10.1109/UIC-ATC-ScalCom-CBDCom-IoP-SmartWorld.2016.0170.

[3] H. Boudlal, M. Serrhini, and A. Tahiri, “Human activity monitoring system with commodity WiFi infrastructure using channel state information,” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 31, no. 2, p. 763, Aug. 2023, doi: 10.11591/ijeecs.v31.i2.pp763-776.

[4] H. Boudlal, M. Serrhini, and A. Tahiri, “A Monitoring System for Elderly People Using WiFi Sensing with Channel State Information,” *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 17, no. 12, pp. 112–131, Jun. 2023, doi: 10.3991/ijim.v17i12.36613.

[5] H. Boudlal, M. Serrhini, and A. Tahiri, “An Intelligent Monitoring Approach Based on WiFi Sensing for Smart Hospital,” in *Artificial Intelligence and Smart Environment*, Cham: Springer International Publishing, 2023, vol. 635, pp. 212–223, doi: 10.1007/978-3-031-26254-8_30.

[6] M. H. Arshad, M. Bilal, and A. Gani, “Human Activity Recognition: Review, Taxonomy and Open Challenges,” *Sensors*, vol. 22, no. 17, p. 6463, Aug. 2022, doi: 10.3390/s22176463.

[7] Z. Hussain, Q. Z. Sheng, and W. E. Zhang, “A review and categorization of techniques on device-free human activity recognition,” *Journal of Network and Computer Applications*, vol. 167, p. 102738, Oct. 2020, doi: 10.1016/j.jnca.2020.102738.

[8] Z. Wang *et al.*, “A Survey on Human Behavior Recognition Using Channel State Information,” *IEEE Access*, vol. 7, pp. 155986–156024, 2019, doi: 10.1109/ACCESS.2019.2949123.

[9] H. Boudlal, M. Serrhini, and A. Tahiri, “A comprehensive review of wifi sensing technologies: Tools, challenges and future research directions,” presented at *the International Conference on Advances in Communication Technology And Computer Engineering*, Meknes, Morocco, 2023, p. 030004, doi: 10.1063/5.0148509.

[10] N. Damodaran and J. Schafer, “Device Free Human Activity Recognition using WiFi Channel State Information,” in *2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, Leicester, United Kingdom: IEEE, Aug. 2019, pp. 1069–1074, doi: 10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00205.

[11] J. Liu, H. Liu, Y. Chen, Y. Wang, and C. Wang, “Wireless Sensing for Human Activity: A Survey,” *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 1629–1645, 2020, doi: 10.1109/COMST.2019.2934489.

[12] C. Wang, S. Chen, Y. Yang, F. Hu, F. Liu, and J. Wu, “Literature review on wireless sensing-Wi-Fi signal-based recognition of human activities,” *Tsinghua Science and Technology*, vol. 23, no. 2, pp. 203–222, Apr. 2018, doi: 10.26599/TST.2018.9010080.

[13] X. Ding, T. Jiang, Y. Zhong, S. Wu, J. Yang, and J. Zeng, "Wi-Fi-Based Location-Independent Human Activity Recognition with Attention Mechanism Enhanced Method," *Electronics*, vol. 11, no. 4, p. 642, Feb. 2022, doi: 10.3390/electronics11040642.
[14] J. Wang and J. G. Park, "A Novel Indoor Ranging Algorithm Based on a Received Signal Strength Indicator and Channel State Information Using an Extended Kalman Filter," *Applied Sciences*, vol. 10, no. 11, p. 3687, May 2020, doi: 10.3390/app10113687.
[15] Z. Wang *et al.*, "A Survey on CSI-Based Human Behavior Recognition in Through-the-Wall Scenario," *IEEE Access*, vol. 7, pp. 78772–78793, 2019, doi: 10.1109/ACCESS.2019.2922244.
[16] Y. Chapre, A. Ignjatovic, A. Seneviratne, and S. Jha, "CSI-MIMO: An efficient Wi-Fi fingerprinting using Channel State Information with MIMO," *Pervasive and Mobile Computing*, vol. 23, pp. 89–103, Oct. 2015, doi: 10.1016/j.pmcj.2015.07.002.
[17] G. Zhang, M. De Leenheer, A. Morea, and B. Mukherjee, "A Survey on OFDM-Based Elastic Core Optical Networking," *IEEE Commun. Surv. Tutorials*, vol. 15, no. 1, pp. 65–87, 2013, doi: 10.1109/SURV.2012.010912.00123.
[18] Y. Ma, G. Zhou, and S. Wang, "WiFi Sensing with Channel State Information: A Survey," *ACM Computing Surveys*, vol. 52, no. 3, pp. 1–36, May 2020, doi: 10.1145/3310194.
[19] L. Guo, L. Wang, J. Liu, and W. Zhou, "A Survey on Motion Detection Using WiFi Signals," in *2016 12th International Conference on Mobile Ad-Hoc and Sensor Networks (MSN)*, Hefei, China: IEEE, Dec. 2016, pp. 202–206, doi: 10.1109/MSN.2016.040.
[20] H. Li, X. He, X. Chen, Y. Fang, and Q. Fang, "Wi-Motion: A Robust Human Activity Recognition Using WiFi Signals," *IEEE Access*, vol. 7, pp. 153287–153299, 2019, doi: 10.1109/ACCESS.2019.2948102.
[21] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Tool release: gathering 802.11n traces with channel state information," *ACM SIGCOMM Computer Communication Review*, vol. 41, no. 1, pp. 53–53, Jan. 2011, doi: 10.1145/1925861.1925870.
[22] "MATLAB - MathWorks - MATLAB & Simulink." Accessed: May 18, 2023. [Online]. Available: https://www.mathworks.com/products/matlab.html
[23] L. Guo, Z. Lu, S. Zhou, X. Wen, and Z. He, "When Healthcare Meets Off-the-Shelf WiFi: A Non-Wearable and Low-Costs Approach for In-Home Monitoring," *arXiv*, 2020, doi: 10.48550/ARXIV.2009.09715.
[24] T. Z. Chowdhury, "Using Wi-Fi channel state information (CSI) for human activity recognition and fall detection," M.S. thesis, Electrical and Computer Engineering, University of British Columbia, Canada, USA, 2018, doi: 10.14288/1.0365967.
[25] D. Zhu, N. Pang, G. Li, and S. Liu, "WiseFi: Activity Localization and Recognition on Commodity Off-the-Shelf WiFi Devices," in *2016 IEEE 18th International Conference on High Performance Computing and Communications; IEEE 14th International Conference on Smart City; IEEE 2nd International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, Sydney, Australia: IEEE, Dec. 2016, pp. 562–569, doi: 10.1109/HPCC-SmartCity-DSS.2016.0085.
[26] W. Li *et al.*, "A Taxonomy of WiFi Sensing: CSI vs Passive WiFi Radar," in *2020 IEEE Globecom Workshops (GC Wkshps*, Taipei, Taiwan: IEEE, Dec. 2020, pp. 1–6, doi: 10.1109/GCWkshps50303.2020.9367546.

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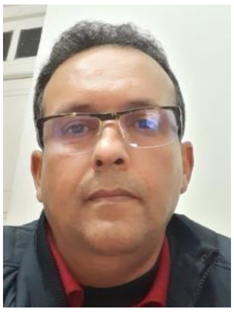

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