A Monitoring System for Elderly People Using WiFi Sensing with Channel State Information

https://doi.org/10.3991/ijim.v17i12.36613

Hicham Boudlal[1](✉), Mohammed Serrhini[2], Ahmed Tahiri[1]
[1] Laboratory of ACSA, Mohammed First University, Oujda, Morocco
[2] Laboratory of LaRI, Mohammed First University, Oujda, Morocco
boudlal_hicham1718@ump.ac.ma

Abstract—Healthcare professionals, industry, and academics have all recently expressed a strong interest towards WiFi sensing. These techniques could be used to identify critical occurrences that sensitive persons may suffer, such as falls, sleep abnormalities, wandering behavior, respiratory illnesses, and irregular heart activity. In this paper, we propose a low-cost, non-intrusive method to remotely monitor elderly people without deploying devices on their bodies in a given space, using channel state information (CSI) from passive WiFi detection. Specifically, we monitored variables such as sitting and standing activity, and experimental validation in practical situations with variable occupants, various environmental settings, and interference from other WiFi devices demonstrates robustness and scalability. Our results suggest that the proposed method can be put into practical-real use to detect activity and alert emergency personnel immediately, providing rapid medical assistance, saving lives, minimizing damage, and reducing anxiety for elderly people residing alone.

Keywords—WiFi sensing, CSI, off-the-shelf WiFi device, elderly people monitoring, multi-environment

1 Introduction

Modern society is increasingly concerned about an aging population, higher rates of obesity, cardiovascular disease, depression and mental health problems, and increasing healthcare needs. As a result, there are currently serious financial and resource limitations on the provision of healthcare around the world [1]. The proportion of people aged 65 years old to the general population will increase, reaching 35% in 2030. In 2030, there will be one billion people aged 65 in the entire world [2]. The vast majority of elderly people practice self-care mostly in their own homes. Every year, one in three elderly people will fall. This can lead to injuries, a worse quality of life, and, sadly, it is one of the main causes of mortality in this age group [2], [3].

In healthcare applications, sensing and monitoring systems could provide people the ability to identify long-term daily activities as well as vital sign changes, all within the intimacy of their homes. Simple, long-term, continuous health monitoring in the daily home environment allows for the recording of disease symptoms as well as physiologic decline which cannot be identified in a brief formal clinical visit. Such systems of monitoring could be utilized for behavioral monitoring, involving mental health as well as emotional states, and they can be integrated with deep learning. Smart homes can use this information to facilitate daily lives [4], [5].

802.11 (WiFi)-based activity sensing is one of the sensing technology utilized in modeling human activity that is receiving significant attention from researchers due to the practical benefits provided through its ubiquitous nature as well as its robust signal coverage in homes and urban environments more broadly. In addition, the technology's unobtrusiveness and inability to generate an image of a person are advantages when it comes to privacy, which is a major issue for numerous users [6], [7].

The properties of the communication channel are impacted by a person's (static or moving) presence inside the WiFi signal environment, such as by expanding propagation pathways, attenuating the signal, causing a frequency shift, etc. This results in time-varying characteristics that correspond to body movements or physical gestures in real time. Channel Status Information (CSI) are widely used for describing the propagation characteristics of the signal, including distortion brought by human activity. This has inspired research into the use of CSI data obtained from common network cards or specialized systems to analyze various forms of human behavior by understanding the patterns of wireless signals [8], [9].

Recent research has explored various sensing technologies for monitoring the activities of elderly individuals. While these studies have made significant contributions to the field, they have certain limitations such as the need for wearable devices or expensive smart home platforms. In this study, we propose a WiFi sensing-based approach that overcomes these limitations and offers a low-cost and unobtrusive means of monitoring elderly individuals in their homes.

With this motivation, in this paper, a WiFi sensing based approach to monitor the activities of elderly people is proposed. In accordance to theoretical analysis and observation of CSI through multiple experiments in various environments and conditions (LOS/NLOS), CSI features are used to identifying activity of elderly people. The main contributions of this paper are as follows:

- We are investigating the potential of using passive Wi-Fi sensing with a low-cost commercial WiFi card (Intel 5300) to monitor the elderly without a device.
- The design of a unique WiFi-based system for monitoring elderly people is proposed.
- We study wireless signal characteristics impacted by elderly people.
- The proposed approach is implemented as a prototype system.
- Experiments are conducted for validating performance of proposed approach in different environments and in LOS and NLOS conditions.

The structure of this paper is outlined as follows: Section II presents the background information and describes technical details. Section III presents the design details, general system architecture and methodologies. Section IV describes the experimental environment, hardware/software configuration, implementation and evaluation. Finally, conclusions and future work are given in Section V.

2 Background

In this section, the necessary background information is presented to provide context for their research. Each subsequent subsection offers valuable insights that contribute to a comprehensive understanding of the study.

2.1 Channel State Information (CSI)

In wireless communication, channel state information (CSI) is an estimation of a communication link's channel characteristics. CSI describes the physical environment's impact on wireless signal propagation, including reflections, diffractions, and scattering [10]. Modern WiFi devices follow to the IEEE 802.11n/ac standard and use Orthogonal Frequency Division Multiplexing (OFDM) [11] at the physical layer, which allows for numerous transit and receive antennas for MIMO communication. The channel is divided into many subcarriers using OFDM, and data is conveyed over the subcarriers using the same modulation and coding technique. This division of the channel into subcarriers enables OFDM to resist the frequency selective fading brought on by multipath. Each subcarrier experiences separate flat fading as a result of being smaller than the coherence bandwidth. In this manner, the impact of multipath on various subcarriers can be considered of as mostly uncorrelated.

For OFDM subcarriers, the CSI information is used to represent both signal strength and phase data. The received signal can be mathematically expressed as:

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

Where y denotes the received signal, x is the transmitted signal, n is the channel noise, and H represents the CSI, which is a complex number matrix indicating the channel frequency response (CFR) for each subcarrier in each spatial stream.

Accurately estimating the CSI is crucial for reliable wireless communication. However, estimating the CSI is a challenging task due to various factors such as noise, interference, and hardware/software faults. Channel estimation algorithms play a vital role in estimating the CSI by extracting meaningful information from the received signal. These algorithms use techniques such as least-squares estimation and maximum likelihood estimation to estimate the channel response. Inaccurate CSI estimation can lead to errors in signal transmission, which can result in poor communication performance. Therefore, the development of robust and efficient channel estimation algorithms is essential for improving the reliability and performance of wireless communication systems [12], [13].

Recent advancements in OFDM technology include the use of multi-user MIMO (MU-MIMO) and beamforming techniques. MU-MIMO allows multiple users to simultaneously transmit and receive data over the same frequency band, increasing the system's overall throughput. Beamforming techniques enable the system to focus the transmitted signal on a specific user or group of users, reducing interference and improving signal quality. These advancements are being incorporated into the latest IEEE

802.11ax (WiFi 6) and IEEE 802.11be (WiFi 7) standards, which offer improved performance and efficiency over previous standards. However, the accurate estimation of CSI remains crucial for the reliable operation of these technologies [14], [15], [16], [17].

The subcarrier level signal spectrum is captured by the OFDM receiver and includes amplitude attenuation and phase shift using complex numbers. These estimates can be illustrated as follows:

$$H_i = |H_i| e^{j \angle H_i} \tag{2}$$

Where the amplitude and phase information of the i^{th} subcarrier are represented by $|H_i|$ and $\angle H_i$, respectively. The transmitter delivers Long Training Symbols (LTS), which include pre-defined information (symbols) for each subcarrier in the packet preamble, in order to measure the CSI. Where LTS are received, the WiFi receiver calculates the CSI using the received signal and the original LTS. However, the CSI in real-world systems is impacted by multi-channel, receiver/transmitter processing, hardware as well as software faults [18].

By providing information on the channel characteristics of a wireless communication link, including signal strength and phase data for each subcarrier within each spatial stream, the Channel State Information (CSI) allows the communication system to adapt to the current channel conditions. This adaptation ensures high reliability and high data rates in multi-antenna systems, as it enables the system to account for physical spatial environments, such as objects or human bodies, that can impact wireless signal propagation and communication performance. The CSI Value ensures high reliability and high rate communication in multi-antenna systems by allowing the communication system to adapt to the current channel conditions. The size of the matrix is built in three dimensions using N transmitter antennas, M receiver antennas, and K subcarriers for MIMO and OFDM technologies. According to Figure 1, the CSI packet was transmitted as $N \times M \times K$ with packet index t. Wireless signal propagation performance will reveal the physical spatial environment, which includes any object or human body, by both the direct path as well as the multiple reflection paths.

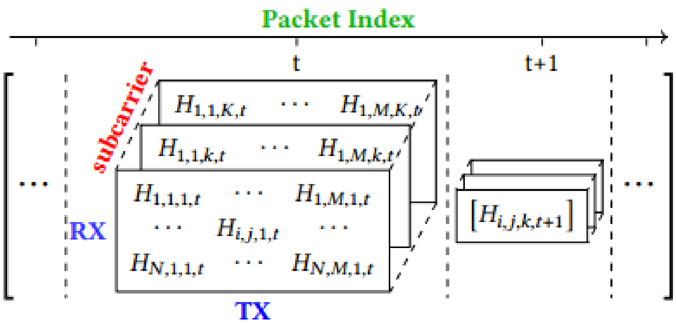


Fig. 1. CSI matrices of MIMO-OFDM channels [18]

In addition to IEEE 802.11n/ac, a new wireless standard, IEEE 802.11bf, is currently under development and utilizes WiFi sensing for WLAN detection. IEEE 802.11bf leverages the Channel State Information (CSI) to detect the presence of people, objects, and movements by exploiting the Doppler shifts in wireless signals [19]. While our research focuses on the use of CSI for elderly monitoring using existing IEEE 802.11n technology, the insights gained from our study can be applied to the future implementation of IEEE 802.11bf for improved wireless sensing in smart environments. The use of CSI in IEEE 802.11bf will be crucial for the implementation of advanced signal processing techniques such as precoding and interference cancellation, which can enhance the system's overall performance. Challenges remain in using CSI for these applications, including dealing with noise and interference that affect the CSI measurements and developing effective signal processing algorithms to extract meaningful information from the CSI data. The future implementation of IEEE 802.11bf for WLAN detection using CSI has the potential to revolutionize the way we use wireless networks for smart environments and the Internet of Things (IoT) [20], [21].

2.2 Identification of LOS and NLOS in real time

Line-of-sight (LOS) propagation, which is a property of electromagnetic radiation or acoustic wave propagation, describes waves that travel in a straight line from the source to the receiver. Straight-line light emissions are also transmitted electromagnetically. The atmosphere and physical impediments may diffract, refract, reflect, or absorb the rays or waves, which means they normally cannot cross the horizon or pass through solid obstructions.

The wireless signal is received after scattering, diffraction, and reflection when the transmitter and receiver have no obvious path to one another because of objects like furniture, walls, and other obstructions. Time delays, phases, and amplitudes vary according on the chosen route. This is known as NLOS (Non-line-of-sight). It refers to radio transmissions over a partially obstructed path, often by a physical object in the innermost Fresnel zone. [22]. As illustrated in Figure 2, there are many NLOS paths mixed in with the LOS path between transmitter and receiver1 and obstructions between transmitter and receiver2.

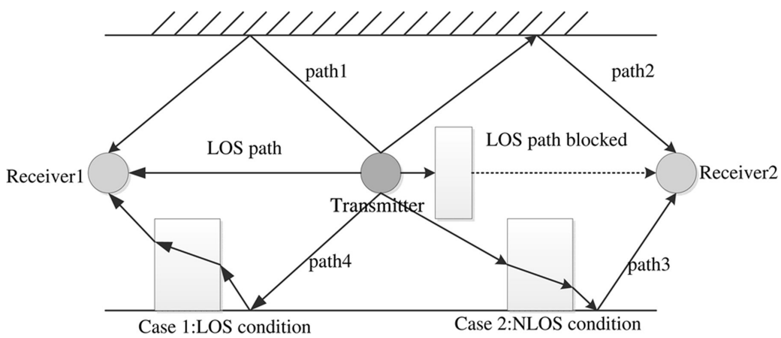


Fig. 2. Shows an illustration of LOS/NLOS conditions and multipath [22]

3 System design and methodology

In this section, the economic study is described, an overview of our system design is presented, and then each component of the system is detailed as well as the processing methodology.

3.1 Costs WiFi device platform

Most homes and hospitals have WiFi infrastructure in place to allow the collection of CSI data. Although it may be easily implemented in a hospital or home without WiFi infrastructure using two COTS WiFi device, as a laptop with Intel WiFi Link 5300 (IWL 5300) 802.11n network cards. While WiFi range extensions as well as supplemental WiFi devices can be used depending on size of the hospital or residence, the cost is still relatively low. For example, if we needed to install 6 pairs of WiFi device for covering all the hospital or residence, cost would be less than $300 when taking into account the cost of a receiver (Intel 5300 card), which costs $10, and a WiFi access point transmitter, which costs about $40. As opposed to this, wearable monitoring technologies require each individual to wear their own sensor, which costs $200 apiece and may require a monthly subscription. If 10 sensors are required, the cost will be $2,000, significantly higher as compared to our designed system.

3.2 System overview

With the use of variations in the correlation between CSI sequence frames that are influenced by human movement, our system aims to monitor elderly people. When there are periods of greater fluctuation, it may be determined that the subject's movements have an effect on the RF environment. It is possible to monitoring elderly people by measuring this.

As illustrated in Figure 3, the system can be divided into three main sections. The first section involves collecting data using the CSI hardware and either delivering it to the system as a batch or buffering it on a real-time system. The second section includes pre-processing the data to remove errors and noise, while the third section involves feature extraction to retrieve appropriate patterns from the pre-processed data.

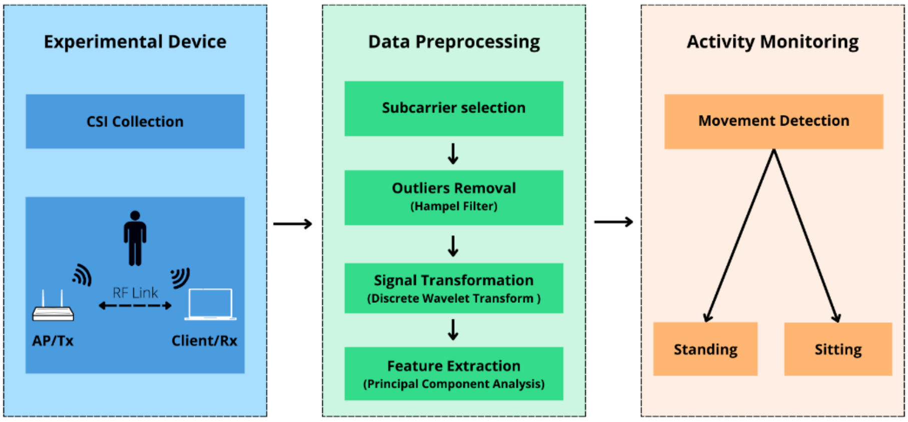


Fig. 3. Overview of system design

3.3 CSI collection

Device architecture. According to equation (1), to estimate the CSI, a transmitter (Tx) must send a pilot signal to a receiver (Rx), and the CSI must then be calculated. The receiver estimates CSI using a signal which is often a ping packet that is sent from Tx to Rx. The Linux 802.11n CSI tool [23] based on the Intel 5300 network interface card (NIC) is a tool available for this collecting. Figure 4 shows the configuration of device used for data collection.

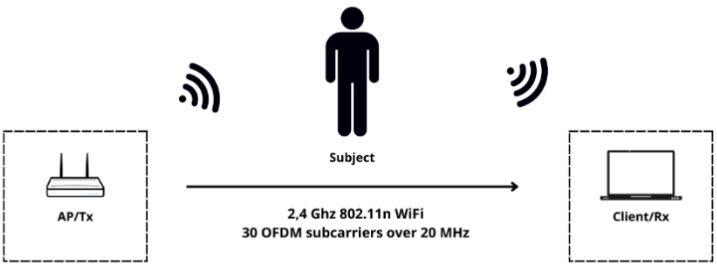


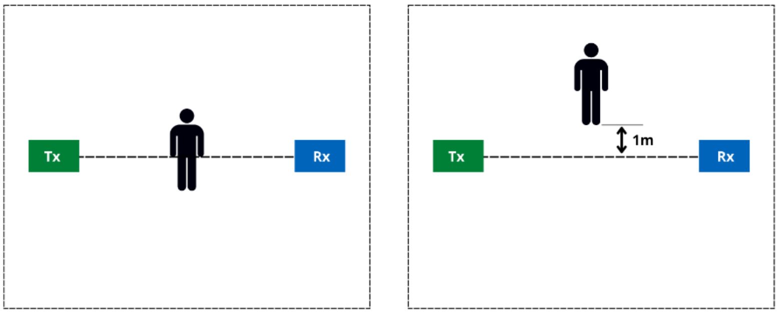
Fig. 4. CSI collection illustration

In this architecture, Tx and Rx have dedicated continuous transmission, and Rx will estimate CSI over incoming packets. This reduces hardware, computational as well as power costs. In COVID 19 pandemic context, a low installation cost solution is desired.

Comparison of the LOS and NLOS modes. The effects of various human positions on performance of the system is studied as described below:

- LOS mode: this mode, the person is in a straight line between Tx and Rx, as shown in Figure 5(a).

- NLOS mode: In this mode, the person is not on a straight line but rather somewhere between Tx and Rx. The predicted distance between a person's body and the line that connects the antenna and the receiver is 1 m, as shown in Figure 5(b). We chose a distance of 1 meter for the NLOS scenarios, which is a commonly used distance in literature for typical indoor environments (e.g., [24]).



(a) Light of sight (b) Non light of sight

Fig. 5. Illustration of LOS and NLOS mode. (a) Light of sight, (b) Non light of sight

3.4 Preprocessing of WiFi CSI data

Despite using the best possible equipment and configuration to collect CSI data, it can contain a significant amount of noise and raw information that cannot be utilized directly. This noise is caused by both environmental factors and reflected radio waves, as well as potential hardware and software errors. Therefore, data preprocessing is a crucial step in building a stable and accurate model for recognizing human activity based on WiFi CSI data.

Subcarrier selection. To collect the data, we used an Intel 5300 network card, and the data was stored in a .data file. The connection diagram used for the collection of the subcarrier data is shown in Figure 6. During the process of establishing the connection, the receiver (Rx) sent Internet Control Message Protocol (ICMP) echo request packets to the transmitter (Tx). Once the connection was established, the receiver received ICMP echo reply packets.

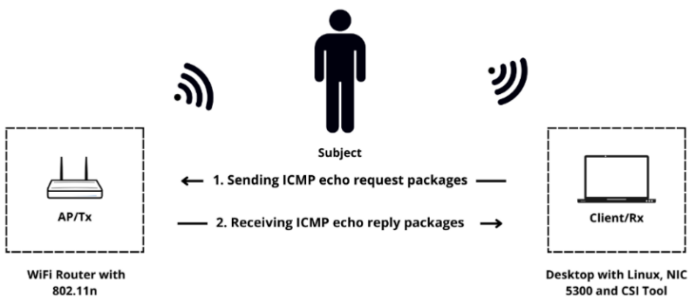


Fig. 6. Connection diagram used for the collection of subcarrier data

We import the data into MATLAB [25]. Further details are given in the next section (3.5). We compare the changes of three different antennas in standing and sitting activities of the elderly. We can see that the second antenna has clear fluctuations over time, i.e., it can better reflect standing and sitting activities. Figure 7 shows an example of the variation of the amplitude of the Channel State Information (CSI) on 30 subcarriers of the three antennas over time.

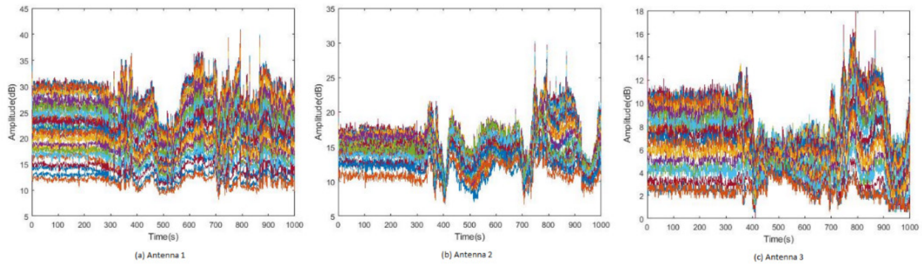


Fig. 7. Shows CSI amplitude on 30 subcarrier of the three antennas. (a) Antenna 1, (b) Antenna 2, (c) Antenna 3

In addition, the subcarriers of a certain sequence number of the three antennas can be compared. Figure 8 shows an example of CSI amplitude over time for the third subcarrier of the three antennas. We observe that the amplitude of the third subcarrier for the three antenna has a different sensitivity caused by the activity due to frequency diversity. Furthermore, we can select a certain antenna and subcarrier for observation, Figure 9 shows an example of the CSI amplitude over time for the second antenna and the third subcarrier.

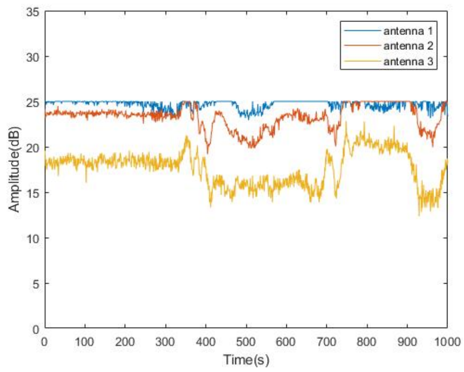


Fig. 8. Shows CSI amplitude for the third subcarrier of the three antennas

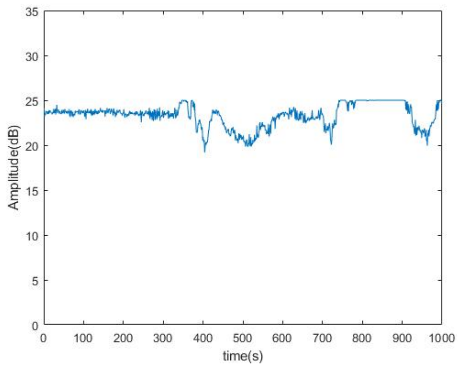


Fig. 9. Illustration of CSI amplitude for the second antenna and third subcarrier

Outliers removal technique. Amplitudes and phases of the CSI contain noise produced by internal state changes, including power transmission, rate adaptations, thermal noise in devices, etc. It changes the signal and contains erroneous values which are not caused by human presence. Denoising the data is therefore the following step after importing the original data. There are several different noise reduction techniques, which include combining different filters to extract the desired time domain or frequency domain information. The most obvious outliers should be eliminated first. We apply the most commonly used Hampel outlier filter to address this issue [26]. We can observe from the denoising results in Figure 10 that the CSI waveform is smoother after filtering than the original waveform. Additionally, there are less local burrs.

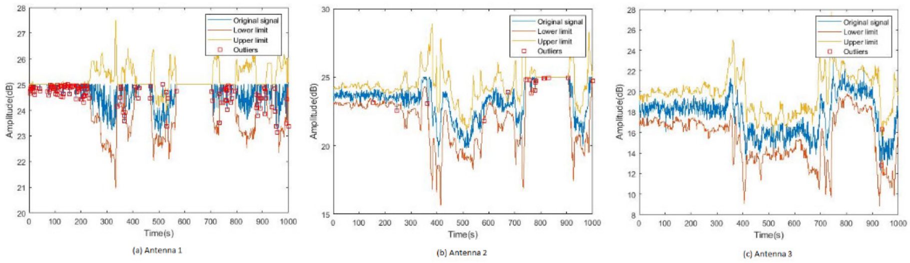


Fig. 10. Illustration of denoising amplitude of the third subcarrier for all antennas. (a) Antenna 1, (b) Antenna 2, (c) Antenna 3

After removing the outliers, we then use various high-performance filters and time-frequency transformation methods to filter out the high-frequency noise.

Noise reduction based on Discrete Wavelet Transform. In order to enhance the reliability of CSI values within time series, we apply noise reduction to reduce the impact of external factors such as frequent changes in transmission speeds or changes in the external environment. To achieve this, we use the discrete wavelet transform (DWT) to remove high-frequency noise that is not related to the target activity. The DWT is a signal processing technique that provides optimal time/frequency resolutions and multi-scale analysis of the data.

Specifically, the DWT decomposes a signal into different frequency bands using wavelet analysis and represents the decomposition using a tree structure. By removing the high-frequency noise using DWT, we can ensure that the remaining CSI values are more accurate and reliable. Figure 11 illustrates the efficiency of noise reduction by DWT. Notably, wavelet denoising is computationally efficient because it is linear in time complexity and does not assume signal continuities [24].

Dimensions reduction with Principal Component Analysis. The CSI signal obtained by the CSI tool within the 802.11n protocol contains both amplitude and phase information of each sampling subcarrier, totaling 30 subcarriers of sampling. However, processing raw CSI measurements can be computationally intensive, and we are required to compress the obtained large amount of CSI information in a short period of time.

To address this issue, we use Principal Component Analysis (PCA) to perform dimension reduction. PCA is an algorithm that combines and compresses the variance in the data, allowing us to extract the data components that are rich in information. Specifically, PCA utilizes orthogonal transformation to transform a matrix into a group of principal components. These principal components are a collection of variables that are linearly uncorrelated, while the input is a group of variables that may be correlated [18]. The variance of the principal components is used to measure the informational content of the data. By using PCA to compress the data, we can greatly decrease the amount of data without sacrificing important information.

In our case, we are dealing with a pattern recognition problem, and we aim to keep as much environmental information in the CSI as possible. However, we cannot simply select some carrier signals for judging, as the environmental information weights reflected by various carriers in different environments are diverse and dynamically changing. The fading of some carriers can also make the abrupt changes in environmental information that other carriers respond to less noticeable. Thus, simply superimposing all the carrier signals or averaging them is not a feasible solution.

To address this challenge, we use PCA to extract the most informative components of the CSI signal, which are then used for pattern recognition. Figure 12 illustrates the principal component analysis (PCA) for CSI dimension reduction.

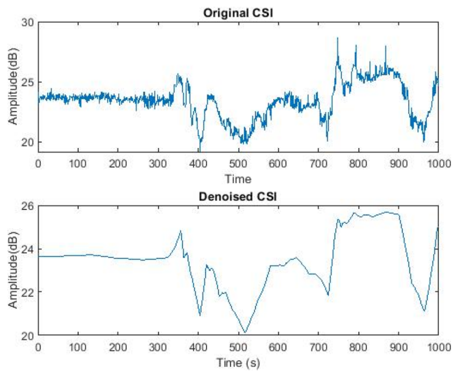


Fig. 11. Illustration of CSI amplitude of subcarrier three and antenna 2. (a) Original CSI, (b) Denoised CSI with DWT

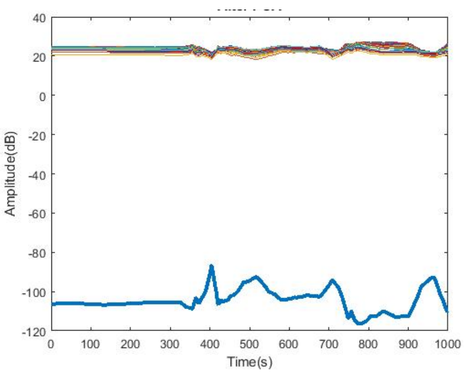


Fig. 12. Illustrates the principal component analysis (PCA) for CSI dimension reduction

3.5 Processing techniques

Before using the CSI values included in the .dat files, the data had to be preprocessed following the procedures described on the CSI Tool website [27]. The preprocessing of the CSI data is performed according to the following procedures:

Import data into MATLAB. The CSI data is imported in MATLAB cells for analysis using a toolkit named linux-80211n-csitool-supplementary supplied by the WiFi CSI tool.

CSI inspecting and normalizing. To extract channel state matrices stored in a .dat file, we utilized the read_bf_file function provided by the linux-80211n-csitool-supplementary. The code used was as follows: "*csi_trace = read_bf_file('file.dat')*", which returns a 1x1000 cell array consisting of 1000 structs, each containing CSI information for a received packet (as depicted in Figure 13 (a)). To access a particular CSI entry, we used the code "*csi_entry = csi_trace{1}*", which yielded a structured array with multiple entries (Figure 13 (b)). The channel state matrix for the current frame was stored in the "*csi*" label. However, the CSI values in the matrix were normalized to Intel's internal reference and required conversion to absolute units. This conversion was performed using the get_scaled_csi function, also included in the linux-80211n-csitool-supplementary package. Specifically, the code "*csi = get_scaled_csi(csi_entry)*" was used, which resulted in the normalized CSI values being converted to absolute units (Figure 13 (c)).

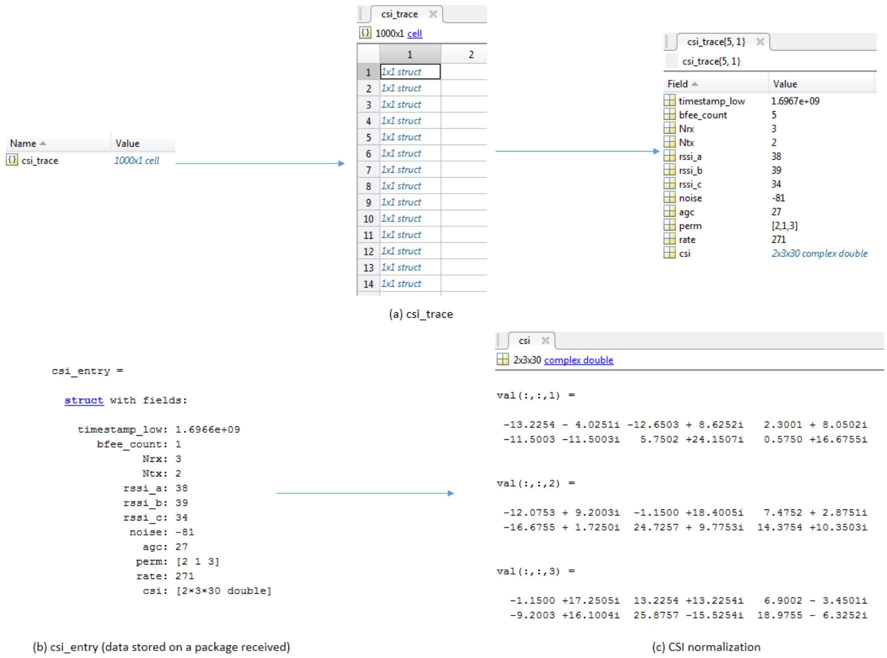


Fig. 13. Processing technique. (a) csi_trace, (b) csi_entry (data stored on a package received), (c) CSI normalization

The CSI variable obtained by this method was a 3 × 2 × 30 matrix with positive values that reflected the MIMO channel state for this frame. These CSI matrices values were utilized to determine the features.

Defining filters. We need reduce the noise in the raw CSI data because it is extremely high. The techniques we discussed above will be used to minimize the noise.

4 Experiment and analysis

In this section, we describe the environment in which the experiment is performed, the details of the hardware and software configuration and the experimental results, following by a detailed performance evaluation of the proposed approach.

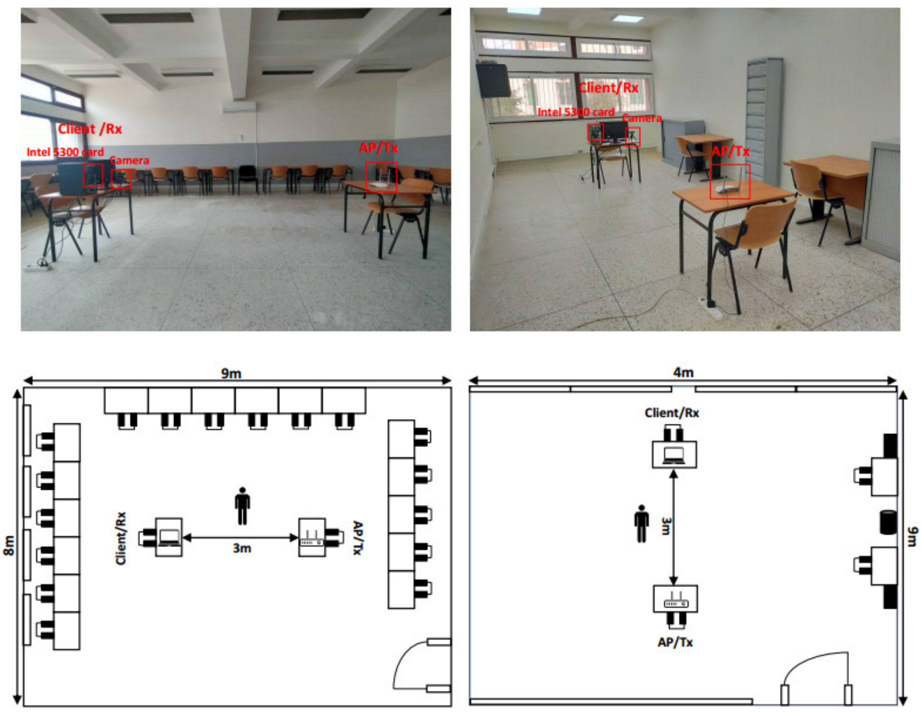
4.1 Experimental environment

The experiments are conducted in two different environments and their dimensions and parameters, as shown in Table 1:

Table 1. Summary of experiment parameters [28]

Characteristics and parameters	Environment	
	Laboratory	***Office***
Dimensions	8m * 9m	4m * 9m
Occupancy	1 Person	1 Person
Bandwidth	20MHz	20MHz
Channel	11 (2462MHz)	11 (2462MHz)
Frequency	2.417GHz	2.417GHz
Antennas	3Rx * 2Tx	3Rx * 2Tx
Subcarriers	30	30

Two devices that serve as transmitter (Tx) and receiver (Rx) were used to instrument the two test environments, where Tx and Rx represent the access point (AP) transmitter and the receiver laptop respectively. The height of the WiFi device is 75 cm, there is no change in the physical environment of the laboratory or office during the experiment. The office and laboratory rooms are furnished with tables, desks, computers and other furniture made of wood or metal. In both test scenarios, the experimenter's position and direction remained unchanged during data collection and estimation. Figure 14 illustrate the two experimental environment.



(a) The laboratory (b) The office

Fig. 14. Experimental environments. (a) The laboratory, (b) The office

4.2 Experimental setup

We conducted an experiment in a Wi-Fi network 802.11n at 2.4 GHz using a single off the shelf Wi-Fi device (i.e., HP 290 G1 MT business computer) connecting with a commercial wireless access point (AP) (i.e., TP-LINK TD -W8961N) which acts as a double antenna transmitter. The laptops are running Ubuntu 14.0.4.4 LTS with kernel 4.2.0-27 and is equipped with Intel WiFi Link 5300 card with 3 antennas that act as a receiver. On the same laptop, a Matlab script that processes offline data collection and provides information about the activities of elderly people. Most of the interesting activities occur within a few seconds. For capturing the signal impacted by these short-term activity, the laptop communicates with the WiFi access point by sending ICMP echo request packets every 10 ms and receiving ICMP echo reply packets, the sampling rate is 100 Hz. We extract CSI data from the received packets for 30 subcarrier groups of 20 MHz channel bandwidth using a modified version of an open source wireless driver [23]. Additionally, we used a camera (EKACOM Webcam 1080P with Microphone, Full HD) to automatically capture pictures and provide additional context to the recorded data. The purpose of using the camera was to validate the accuracy of the system's activity recognition results. Table 2 provides a list of the hardware and software utilized for the experience.

Table 2. Lists of experimental hardware and software

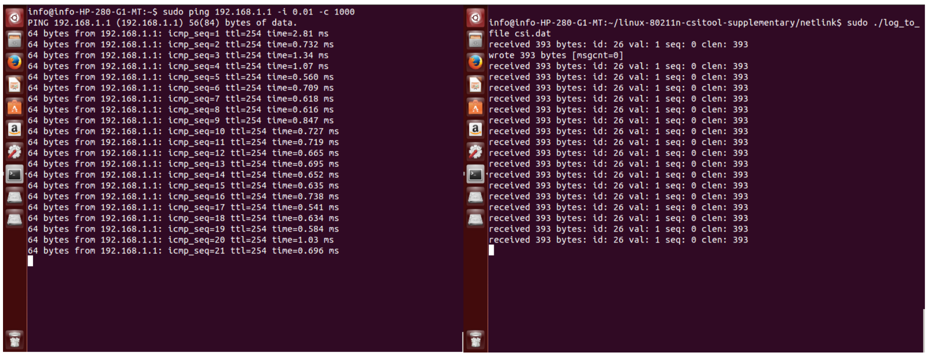
Device name	Role	Hardware / Software	Specification and use
Laptop	Rx	HP 290 G1 MT Business PC	Receiving WiFi packets
Access Point	Tx	TP-LINK TD-W8961N	Transmitting WiFi packets
Network interface Card	Intel 5300	Intel 5300 Mini Wireless Network Card, 450Mbps, 3 antennas 6dbi, INTEL5300AGN	Receive CSI data
Software	MATLAB platform	MATLAB R2018b	Constructing system
Camera	Take pictures automatically	EKACOM Webcam 1080P with Microphone, Full HD	Capturing images to validate the accuracy of the system's results

Figure 15 illustrate the experimental hardware.

Fig. 15. Illustrate the experimental hardware

4.3 Experimental results

We conducted real experiments in both laboratory and office environments, as illustrated in Figure 13, where the furnishings and the placement of the AP transmitter and receiving laptop were set at a distance of 3 meters. Throughout the one-hour duration, a volunteer performed continuous sitting and standing activities in each scenario, namely Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) environments, as shown in Figure 5. To ensure the proper collection and storage of CSI data for future reference, a consistent and reliable WiFi signal between the router and receivers was maintained while the volunteer carried out the activities. Figures 16(a) and 16(b) depict the operation interface of the transmitter and receiver, respectively. During the experiment, we transmitted a total of 1000 packets, each with a size of 393 bytes. The receiver's laptop was responsible for signal reception and logging.



(a) Transmitter interface (b) Receiver interface

Fig. 16. Shows operating interface of the transmitter and receiver. (a) Transmitter interface, (b) Receiver interface

The indirect wireless data that is impacted by human actions is the only data we can collect for our work. Determining the influence that various human activities will have on the wireless propagation channel is therefore the first step. To this end, we conducted experiments in the lab and the office at LOS and NLOS locations, with Figure 17 depicting the results. Specifically, we focused on the activities of sitting and standing due to the limited space available in the testing environments.

Although the CSI amplitude may vary with transmission power, it is often a trustworthy measurement for feature extraction, and burst noise can be decreased by employing filtering techniques. As a result of the movement of the human and objects, the estimated channel will have a varied amplitude and phase, changing the multipath characteristic of the wireless channel. Figure 17 shows the CSI amplitude of all subcarriers and the second antenna in relation to a human subject standing and sitting between a WiFi transmitter and receiver. For the first 400 packets, the person stays motionless before beginning to stand or sit. As shown, all subcarriers' and the second antenna's CSI amplitudes are relatively stable when the subject is not moving, but when activity starts, the amplitudes of the CSIs begin to fluctuate dramatically, confirming our model analysis.

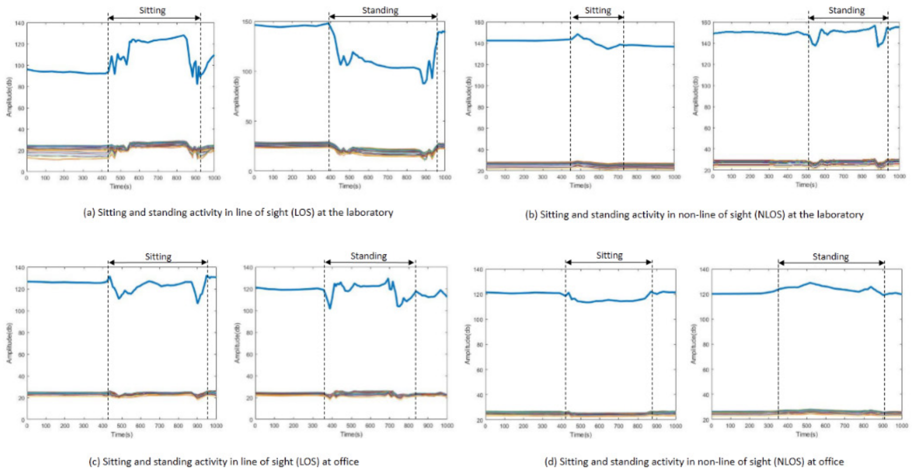


Fig. 17. CSI amplitude measured on a certain duration of different scenarios. (a) Sitting and standing activity in line of sight (LOS) at the laboratory, (b) Sitting and standing activity in non-line of sight (NLOS) at the laboratory, (c) Sitting and standing activity in line of sight (LOS) at office, (d) Sitting and standing activity in non-line of sight (NLOS) at office

We deployed a camera to capture activity [29]. Evidently, the high accuracy of activity recognition indicate strong performance of the activity recognition system. Figure 18 shows the current CSI package ID attached to the photo taken by the camera. These results demonstrate that we can accurately monitor the activities of elderly people.

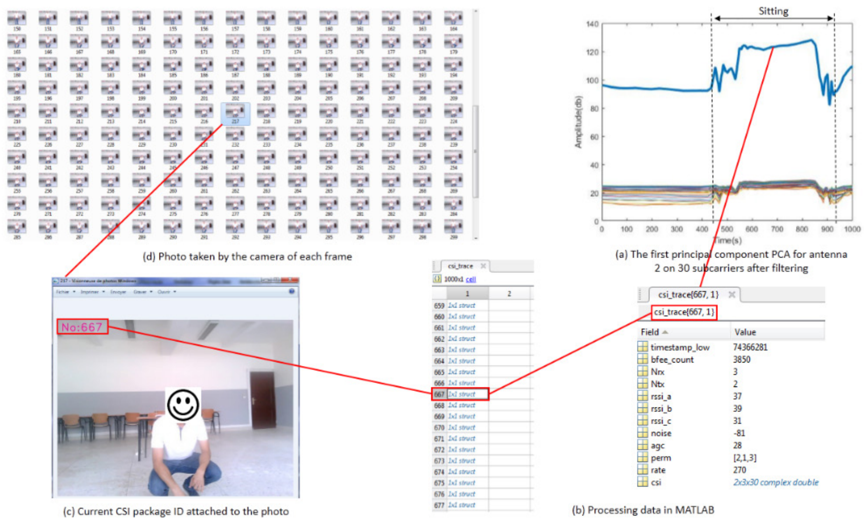


Fig. 18. Shows the current CSI package ID attached to the photo taken by the camera

5 Conclusion and future work

The use of intelligent sensing technology in healthcare monitoring has gained significant attention, with the potential to advance rapidly due to the widespread availability and affordability of commercial WiFi devices. Unlike currently available wearable sensors and systems that require direct contact, WiFi sensing can provide a high-accuracy contactless monitoring solution. In this paper, we have demonstrated how a WiFi network can be utilized to monitor elderly people using a single access point and a single WiFi device. Our proposed system utilizes fine-grained channel state information provided by standard WiFi devices to detect motion patterns related to the activities of elderly people. Our extensive experiments conducted in both laboratory and office environments demonstrate that our proposed approach utilizing the existing WiFi network can achieve equivalent or better accuracy than the current sensor-based approach. This WiFi-based approach provides a novel opportunity to implement free and low-cost devices for monitoring elderly people in non-clinical environments. For future work, we plan to investigate the use of directional antennas to reduce the effect of surrounding obstacles and moved objects, thus improving accuracy. Additionally, we will analyze the effects of WiFi transmitter and receiver position and posture on the deployment of the system.

6 References

[1] B. Tan, Q. Chen, K. Chetty, K. Woodbridge, W. Li, and R. Piechocki, 'Exploiting WiFi Channel State Information for Residential Healthcare Informatics'. arXiv, Dec. 09, 2017. Accessed: Aug. 08, 2022. [Online]. Available: http://arxiv.org/abs/1712.03401

[2] A. Khalili, A. Soliman, M. Asaduzzaman, and A. Griffiths, 'Wi-Fi sensing: applications and challenges', J. Eng., vol. 2020, no. 3, pp. 87–97, Mar. 2020. https://doi.org/10.1049/joe.2019.0790

[3] M. G. Amin, Y. D. Zhang, F. Ahmad, and K. C. D. Ho, 'Radar Signal Processing for Elderly Fall Detection: The future for in-home monitoring', IEEE Signal Process. Mag., vol. 33, no. 2, pp. 71–80, Mar. 2016. https://doi.org/10.1109/MSP.2015.2502784

[4] Y. Ge et al., 'Contactless WiFi Sensing and Monitoring for Future Healthcare - Emerging Trends, Challenges and Opportunities', IEEE Rev. Biomed. Eng., pp. 1–1, 2022. https://doi.org/10.1109/RBME.2022.3156810

[5] H. Jiang, C. Cai, X. Ma, Y. Yang, and J. Liu, 'Smart Home Based on WiFi Sensing: A Survey', IEEE Access, vol. 6, pp. 13317–13325, 2018. https://doi.org/10.1109/ACCESS.2018.2812887

[6] Zimu Zhou, Chenshu Wu, Zheng Yang, and Yunhao Liu, 'Sensorless sensing with WiFi', Tsinghua Sci. Technol., vol. 20, no. 1, pp. 1–6, Feb. 2015. https://doi.org/10.1109/TST.2015.7040509

[7] J. Liu, H. Liu, Y. Chen, Y. Wang, and C. Wang, 'Wireless Sensing for Human Activity: A Survey', IEEE Commun. Surv. Tutor., vol. 22, no. 3, pp. 1629–1645, 2020. https://doi.org/10.1109/COMST.2019.2934489

[8] S. Yousefi, H. Narui, S. Dayal, S. Ermon, and S. Valaee, 'A Survey on Behavior Recognition Using WiFi Channel State Information', IEEE Commun. Mag., vol. 55, no. 10, pp. 98–104, Oct. 2017. https://doi.org/10.1109/MCOM.2017.1700082

[9] M. S. Aljumaily and G. A. Al-Suhail, 'Towards ubiquitous human gestures recognition using wireless networks', Int. J. Pervasive Comput. Commun., vol. 13, no. 4, pp. 408–418, Nov. 2017. https://doi.org/10.1108/IJPCC-D-17-00005
[10] Z. Yang, Z. Zhou, and Y. Liu, 'From RSSI to CSI: Indoor localization via channel response', ACM Comput. Surv., vol. 46, no. 2, pp. 1–32, Nov. 2013. https://doi.org/10.1145/2543581.2543592
[11] 'What is OFDM: Orthogonal Frequency Division Multiplexing » Electronics Notes'. https://www.electronics-notes.com/articles/radio/multicarrier-modulation/ofdm-orthogonal-frequency-division-multiplexing-what-is-tutorial-basics.php (accessed Aug. 25, 2022).
[12] R. S. Ganesh and D. J. J. Kumari, 'A Survey on Channel Estimation Techniques in MIMO-OFDM Mobile Communication Systems', vol. 4, no. 5, 2013.
[13] S. M. Aldossari and K.-C. Chen, 'Machine Learning for Wireless Communication Channel Modeling: An Overview', Wirel. Pers. Commun., vol. 106, no. 1, pp. 41–70, May 2019. https://doi.org/10.1007/s11277-019-06275-4
[14] E. Mozaffariahrar, F. Theoleyre, and M. Menth, 'A Survey of Wi-Fi 6: Technologies, Advances, and Challenges', Future Internet, vol. 14, no. 10, p. 293, Oct. 2022. https://doi.org/10.3390/fi14100293
[15] C. Deng et al., 'IEEE 802.11be-Wi-Fi 7: New Challenges and Opportunities'. arXiv, Aug. 03, 2020. Accessed: Mar. 03, 2023. [Online]. Available: http://arxiv.org/abs/2007.13401
[16] Z. Lv and Y. Li, 'Compressive Sensing Based Channel Estimation for High-order MIMO Systems', Int. J. Online Eng. IJOE, vol. 14, no. 07, p. 30, Jul. 2018. https://doi.org/10.3991/ijoe.v14i07.8218
[17] H. TH. Alrikabi, A. H. M. Alaidi, A. S. Abdalrada, and F. T. Abed, 'Analysis the Efficient Energy Prediction for 5G Wireless Communication Technologies', Int. J. Emerg. Technol. Learn. IJET, vol. 14, no. 08, p. 23, Apr. 2019. https://doi.org/10.3991/ijet.v14i08.10485
[18] Y. Ma, G. Zhou, and S. Wang, 'WiFi Sensing with Channel State Information: A Survey', ACM Comput. Surv., vol. 52, no. 3, pp. 1–36, May 2020. https://doi.org/10.1145/3310194
[19] R. Du et al., 'An Overview on IEEE 802.11bf: WLAN Sensing'. arXiv, Jul. 11, 2022. Accessed: Feb. 28, 2023. [Online]. Available: http://arxiv.org/abs/2207.04859
[20] F. Restuccia, 'IEEE 802.11bf: Toward Ubiquitous Wi-Fi Sensing'. arXiv, Mar. 27, 2021. Accessed: Feb. 28, 2023. [Online]. Available: http://arxiv.org/abs/2103.14918
[21] N. Cavus, S. E. Mrwebi, I. Ibrahim, T. Modupeola, and A. Y. Reeves, 'Internet of Things and Its Applications to Smart Campus: A Systematic Literature Review', Int. J. Interact. Mob. Technol. IJIM, vol. 16, no. 23, pp. 17–35, Dec. 2022. https://doi.org/10.3991/ijim.v16i23.36215
[22] X. Li, X. Cai, Y. Hei, and R. Yuan, 'NLOS identification and mitigation based on channel state information for indoor WiFi localisation', IET Commun., vol. 11, no. 4, pp. 531–537, Mar. 2017. https://doi.org/10.1049/iet-com.2016.0562
[23] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, 'Tool release: gathering 802.11n traces with channel state information', ACM SIGCOMM Comput. Commun. Rev., vol. 41, no. 1, pp. 53–53, Jan. 2011. https://doi.org/10.1145/1925861.1925870
[24] 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, Dec. 2016, pp. 562–569. https://doi.org/10.1109/HPCC-SmartCity-DSS.2016.0085
[25] 'MATLAB - MathWorks - MATLAB & Simulink'. https://www.mathworks.com/products/matlab.html (accessed Jan. 19, 2023).

[26] T. Z. Chowdhury, 'Using Wi-Fi Channel State Information (CSI) for Human Activity Recognition and Fall Detection', p. 139.

[27] 'Linux 802.11n CSI Tool — Installation Instructions'. https://dhalperi.github.io/linux-80211n-csitool/installation.html (accessed Aug. 11, 2022).

[28] A. Sharma, J. Li, D. Mishra, G. Batista, and A. Seneviratne, 'Passive WiFi CSI Sensing Based Machine Learning Framework for COVID-Safe Occupancy Monitoring', in 2021 IEEE International Conference on Communications Workshops (ICC Workshops), Montreal, QC, Canada, Jun. 2021, pp. 1–6. https://doi.org/10.1109/ICCWorkshops50388.2021.9473673

[29] 'CSI-Tool-Camera-Shooting/csi_fun.h at master · qiyinghua/CSI-Tool-Camera-Shooting', GitHub. https://github.com/qiyinghua/CSI-Tool-Camera-Shooting (accessed Aug. 26, 2022).

7 Authors

Hicham Boudlal has obtained his engineering degree in networks and telecommunications from ENSA Oujda in 2017. In 2021, he joined the ACSA laboratory at the Faculty of Sciences, Mohammed First University, Oujda, Morocco. His main research interests include network architecture, network security, channel state information, and wifi sensing (Email: boudlal_hicham1718@ump.ac.ma).

Mohammed Serrhini is professor with the department of computer science at Faculty of Sciences, Mohamed First University, Oujda, Morocco, his research interests are in the areas of computer vision, image processing, brain computer interface in education, and security (Email: serrhini@gmail.com).

Ahmed Tahiri received PhD in numerical analysis at the free university of brussels (ULB). He is a professor at the department of computer science, Faculty of Sciences at the University Mohammed First, Morocco. His research interests include issues related to numerical approximations and their optimal implementations. Recently, he is interested in intelligent systems (Email: tahiriahmed02@yahoo.fr).

Article submitted 2022-11-04. Resubmitted 2023-03-15. Final acceptance 2023-04-06. Final version published as submitted by the authors.