Room occupancy analysis using Wi-Fi channel state information

NICU CEZAR VINTEA, University of Twente, The Netherlands

1 ABSTRACT

This research shows that using the Wi-Fi CSI for occupancy analysis purposes proves that it can accurately be used to estimate the occupied rooms after gaining training data from the environment. This is done by training an FNN model to recognize different scenarios of room occupancy by collecting channel state information from all the possible occupancy combinations. Additionally, the paper highlights and analyses the parameters that influence the accuracy of the scanning like room count, and people count, and proves that distance does not have a big impact on the efficiency of the model. Even though the approach requires extended research with the implication of more people and the usage of bigger spaces, the system proved accurate enough to be used as an alternative to current detection methods.

1.1 Keywords

WiFi sensing, channel state information, activity recognition, human identification, localization, human counting, WiFi imaging

2 INTRODUCTION

Nowadays, the importance of the ability to accurately monitor environmental parameters is increasing across various domains, including healthcare, security, and daily life. Effective monitoring systems can maximize patient care, improve security, and simplify everyday activities. However, trivial sensing methods such as video and audio monitoring have significant downsides. Video monitoring systems are often highly ineffective when there is not enough light and also raise privacy concerns. Audio monitoring can be useful and efficient in certain scenarios, however, it can become ineffective in case it is polluted by noise. Moreover, many modern sensing solutions require the use of wearable devices, which can be uncomfortable for long-term usage and contribute to electronic waste. Radar technology does not have the downsides of the systems described above and also is considered to be highly accurate, however, it is far too expensive for daily use and also requires extensive calibration for proper functioning. Wi-Fi Channel State Information, on the other side, could become a usable alternative. Wi-Fi CSI uses devices that are capable of transmitting and receiving Wi-Fi signals and does not require additional hardware. Currently, these kinds of devices such as routers and PCs are present in every household, so it is already more convenient than any system that requires installations and hardware costs. Unlike video systems, Wi-Fi CSI is not affected by lighting conditions, providing consistent performance regardless of environmental light. It also eliminates the need for wearable devices, which makes the usage of the technology more comfortable and appealing for the users. Unlike radar technology, Wi-Fi CSI systems are cost-effective, easy to set up, and accessible, as they utilize existing Wi-Fi devices present in most modern buildings. These advantages make Wi-Fi CSI a powerful detection tool across multiple applications, from healthcare to security and more.

2.1 Motivation

Room occupancy analysis and accurate people locating in a set of multiple rooms or through multiple obstacles could be an improvement on energy consumption in big buildings since it could potentially sense human activity over big areas and regulate the energy output, usage of utilities, and heating. Another area that this technology can improve is security. Since Wi-Fi CSI does not depend on lighting it can be very efficient in intruder detection. Moreover, it does not look like a method of detection since any router or PC can be the emitter and receiver. The safety of the workers is usually a big concern in industrial buildings and factories. Production facilities usually contain big, heavy, and dangerous equipment, so Wi-Fi CSI can be another measure that prevents possible accidents. Additionally, Wi-Fi CSI could also be used as an improvement in efficiency and cost in the process of production by scanning over bigger areas and controlling the process.

2.2 Specific problem

There are multiple studies that are using Wi-Fi CSI for a range of different scopes like monitoring human parameters and vital signs[4, 9], recognition of human gestures and poses[1, 7, 13], people identification by face[2, 11] and even locating people on a bigger surface. However, there is not enough research on people's location on an extended surface with multiple obstacles in between. This research will focus on assessing how accurate can Wi-Fi CSI sensing be in a set of sequential rooms and also analysis of the parameters that influence the accuracy of the scanning.

2.3 Research question

How effective is the usage of Wi-Fi channel state information (CSI) for human localization across multiple rooms with multiple participants?

- How does room count influence the accuracy of the sensing?
- How does the distance between devices influence the accuracy of the scanning?
- How does the number of people influence the accuracy of the scanning?

3 RELATED WORK

Wi-Fi Channel State Information became a promising alternative for existing sensing methods in various sensing domains, including human activity recognition, gesture recognition, and vital sign monitoring. Researchers have explored its potential in the mentioned areas and used Wi-FI CSI scanning in different scenarios. Researchers implemented the usage of deep learning in the context

TScIT 37, July 8, 2022, Enschede, The Netherlands

of human activity recognition, thus improving the knowledge base of techniques that can potentially be used in similar scenarios [1, 6]. Systems resilient to environmental changes have demonstrated robustness in activity recognition scenarios [6]. Some studies focused on identifying individuals through walls using Wi-Fi signals, showing the possibility and effectiveness of using WI-FI CSI in closed environments [11]. Gesture recognition has also been explored using Wi-Fi CSI, with the systems requiring minimal interaction with the hardware and providing accurate results [10, 13]. In healthcare, Wi-Fi CSI has shown good performance in monitoring heart and breathing rates by analyzing the CSI phase[9]. The potential of Wi-Fi sensing for healthcare applications has been reviewed, highlighting emerging trends, challenges in the industry, and potential usages[4]. However, there still exists a gap in research focused on room occupancy detection through walls using Wi-Fi CSI. Existing studies have explored the tracking of human poses, human gestures, vital signs, and even movement analysis through walls, but lack in providing focused research for efficient and reliable room occupancy detection in indoor environments on a bigger surface divided into rooms[3, 7].

During this research some works did provide useful insights into the exploration of Wi-Fi CSI as a sensing method and also some parameters for the process itself that proved efficient. [12] gives a comprehensive review of the signal processing techniques, algorithms, applications, and performance results of Wi-Fi sensing with CSI. Moreover, it explains in detail the structure of data later used in training starting from the physical layer in order to provide a full overview of the system that is used. Some of the papers gave a perspective on the parameters used in the research such as the frequency of scanning that is considered efficient for this purpose[5, 6].

4 MEASUREMENT TOOLS

4.1 CSI sensing tools

For this research 2 mini-PCs (ASRock BOX-1220P) were used on Linux Ubuntu and for the purpose of CSI sensing the PCs were equipped with AX211 Wi-Fi chips. Each device has 2 antennas. The transmitting device uses 2 antennas to transmit, while the receiving device uses only one antenna to listen to the incoming signal. The scripts used to analyze and extract data from the scanning results are built onto PicoScenes middleware.

4.2 Data analysis tools

For the purpose of data analysis, Python 3.12 language on PyCharm was used. In order to process data multiple Python libraries were used. For processing raw data from CSI files, the CSIread library was used. For data structuring and visualization of performance were pandas and matplotlib libraries. Finally, for model training and testing sklearn library was the choice.

5 MEASUREMENT ENVIRONMENT

5.1 Scenario 1

For the purpose of this research 2 different scenarios were used. In the first experiment, 4 sequential rooms were used. The rooms used in both scenarios were not completely empty. Every room contained a table with 6 chairs on average that were placed relatively identically in each room. The first device was placed in room number 1, while device number 2 was placed in room number 4 so there were 2 different rooms, 3 walls, and approximately 10 meters between them. The participants would occupy one of the 2 rooms in between.[*Figure 1*]

5.2 Scenario 2

In the second environment, the devices were placed even further from each other (approximately 14 meters), but in the same room. In this environment, the participants could occupy even the rooms in which the devices are placed. The parameters of the scanning remain the same.[*Figure 2*]

6 METHODOLOGY

6.1 Data Extraction

Wireless signal propagation is significantly influenced by environmental factors, leading to phenomena such as reflections, diffraction, refraction, and scattering. Each channel between two antennas can follow a distinct path, encountering varying numbers of obstacles and environmental influences. The state of these channels can be recorded in a channel state information matrix $\boldsymbol{H}$. This matrix has the dimensions of $\boldsymbol{N_T} \times \boldsymbol{N_R}$ (number of transmitting and receiving antennas, respectively), where each element $\boldsymbol{H_{ij}}$ is defined by the amplitude and phase of the signal received between any transmitting (T) and receiving (R) antenna. This relationship is expressed as $\boldsymbol{H_{ij}} = \| \boldsymbol{H_{ij}} \| \; e^{j \angle \boldsymbol{H_{ij}}}$ where $\boldsymbol{H_{ij}}$ represents the received amplitude and $\angle \boldsymbol{H_{ij}}$ represents the received phase, given as $\boldsymbol{a+bj}$. This information is extracted via PicoScenes into a set of packets received together with some information about the system used and the raw data in the format of the $\boldsymbol{H}$ matrix. For both scenarios, a specific number of rooms will be used. Each room can either be empty or contain a person. The participants will stand in only one place in the room on every scanning session. When the combination requires any of the rooms to be empty the participant assigned to that specific room leaves the room and gets out of the scanning range. This way every room has 2 different possibilities:

- True(When there is a person inside)
- False(When the room is empty)

To be able to collect all the necessary combinations of occupancy, n participants are required where n is the number of rooms and the count of scanning sessions is $2^{\boldsymbol{n}}$ for every possible combination. For the first scenario only 2 rooms that can contain people will be used, thus there are 4 possible combinations that look like this:

- (False, False)
- (False, True)
- (True, False)
- (True, True)

For the second scenario, the procedure is similar. However, in this instance, 4 rooms are used for sensing, so it requires 16 different scanning sessions. For each combination, there is a separate scanning session taken at a 40s transmission time and 30 Hz transmission rate. The given parameters were chosen because the 30 Hz transmission rate aligns with the practices observed in recent research[5, 8]

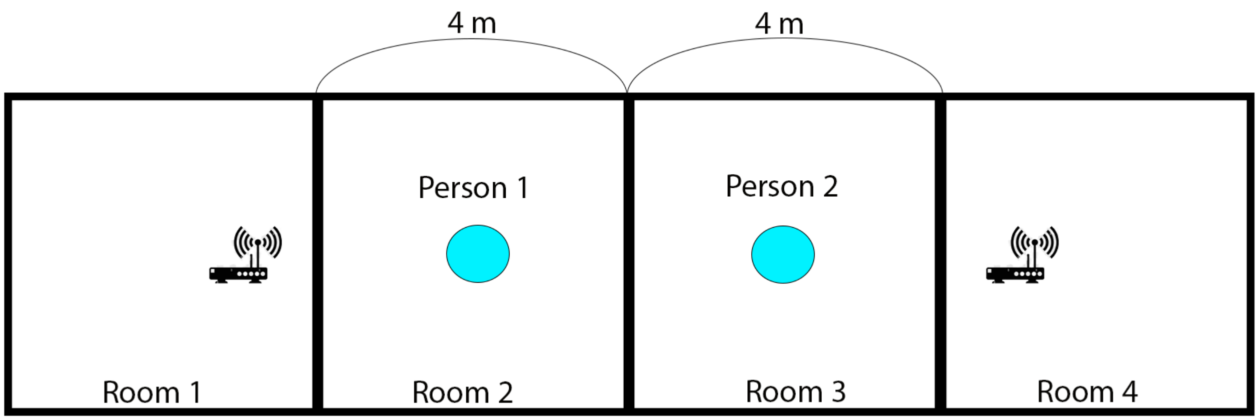


Fig. 1. Diagram of scenario 1

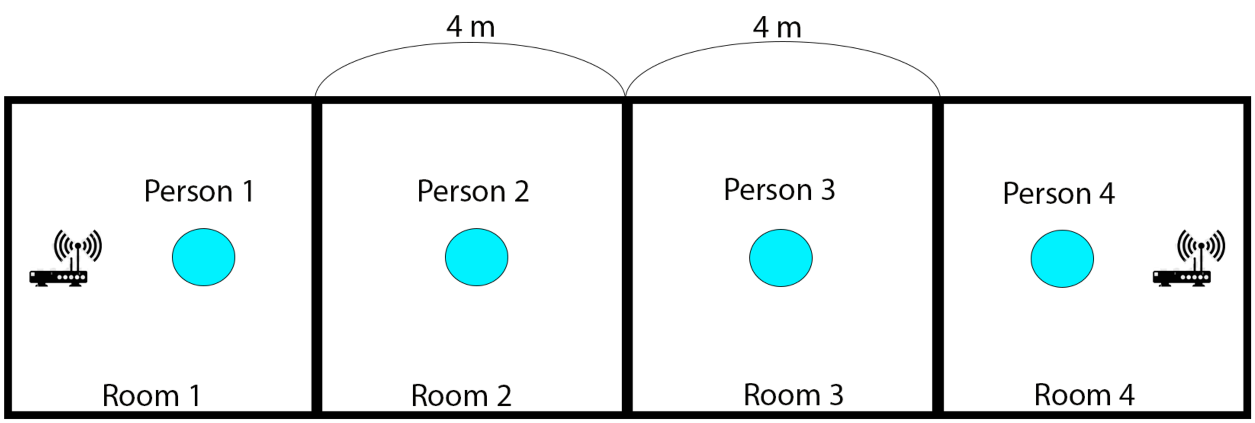
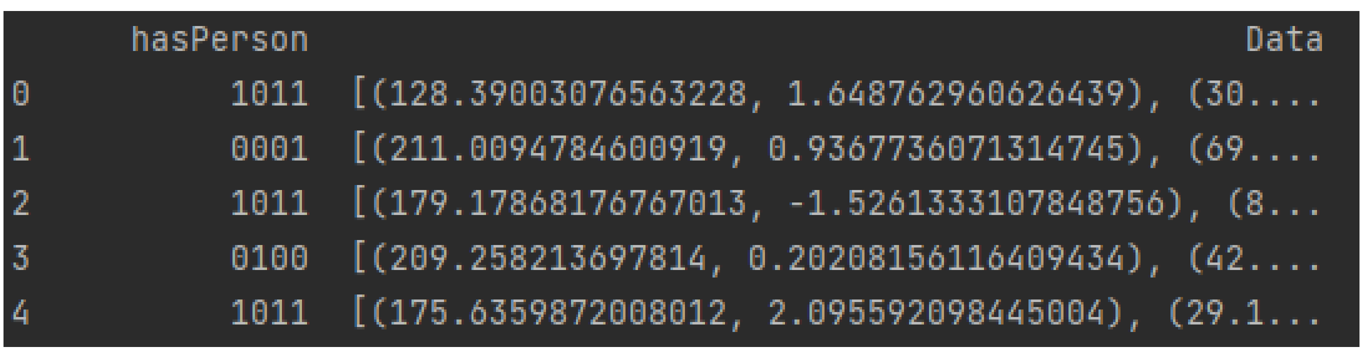


Fig. 2. Diagram of scenario 2



	hasPerson	Data
0	1011	[(128.39003076563228, 1.648762960626439), (30....
1	0001	[(211.0094784600919, 0.9367736071314745), (69....
2	1011	[(179.17868176767013, -1.5261333107848756), (8...
3	0100	[(209.258213697814, 0.20208156116409434), (42....
4	1011	[(175.6359872008012, 2.095592098445004), (29.1...

Fig. 3. Structure of the training dataset

and applications of Wi-Fi CSI for sensing and monitoring. Studies have demonstrated that a 30 Hz rate strikes a balance between capturing sufficient detail for accurate monitoring and maintaining manageable data volumes[6]. Moreover, a lower transmission rate helps in minimizing network congestion. By opting for 30 Hz, the system avoids overwhelming the network while still providing reliable sensing capabilities. Together with 40s transmission time, 30 Hz provides enough data to train the model properly, but does not overflow the memory with excessive material. From each combination of True/False the file that contains data from one sensing session is renamed to its binary equivalent, so:

- (False, True) - 01
- (False, True, False, True) - 0101

This way the CSI files that resulted from the scanning can be renamed based on the combination of people in the rooms and later used to create categorical variables that the model can train on.

6.2 Data Transformation

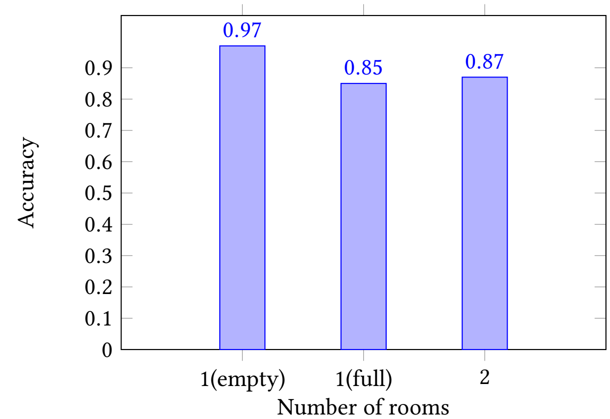
After the data was extracted into raw CSI files via PicoScenes. Each CSI file is read by the read() method from the CSIread library. The result of reading is a dataset with each received packet, their details, and the matrix of complex numbers corresponding to it that reflects the channel state information at the time the specific packet traveled and arrived. From this dataset, each packet's matrix is extracted. For each complex number, a tuple is created from the calculated phase and amplitude and added to a list. For each packet, the list of tuples together with the discrete result taken from the CSI file name is added to a new dataset which will be used in training. This procedure is followed by every CSI file. When every file is processed and transformed to the template shown above, all the entries from all the files are randomly combined into a general dataset that is further used for training.[*Figure 3*]

6.3 Training

For the purpose of training a FeedForward Neural Network was used. The model has 3 layers: Input layer(32 neurons), Hidden layer(32 neurons), and Output layer(number of neurons equal to the number of classes in the target variable.) After data transformation, the newly created dataset of 4000 CSI packets from the first scenario is fed to the model for training and testing. The dataset is split into 30% test data and 70% training data. After the split, the training data is used to train to fit the model with an epoch number of 50 and a batch size of 150 while the percentage of entries used for validation is 20% on the data gained from the first scenario. For the second scenario, the batch size was increased to 250. The full combined training dataset from the scenario included 17000 packets, so in order to prevent over-fitting a bigger number than the first case was chosen.

7 RESULTS

7.1 Scenario 1



This chart shows the accuracy obtained from the sensing in the first scenario. The general accuracy of the model when all 4 possible combinations are involved in training and there are 4 categorical variables to choose between, the model got an accuracy of 0.87. When trained on only 2 datasets for each room individually with categorical variables:

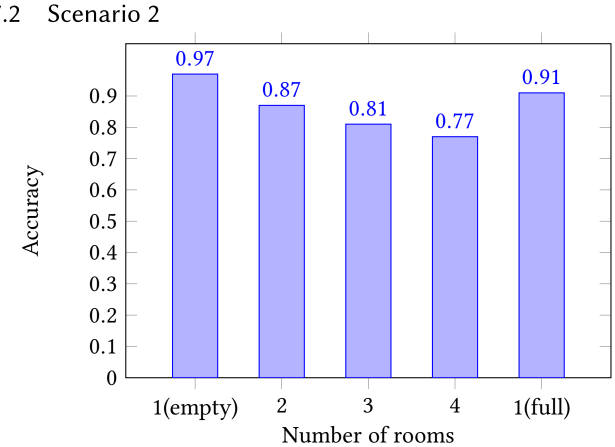
- 10 and 00(only first room is used in training and testing while the second room is empty)
- 01 and 00(only second room is used in training and testing while the first room is empty)

The average accuracy is 0.97. However, when trained in the same scenario, but with categorical variables:

- 11 and 01(only first room is used in training and testing while the second room is full in both cases)
- 11 and 10(only second room is used in training and testing while the first room is full in both cases)

The average accuracy is 0.85. From these results, it is clear that the number of rooms used in sensing is inversely proportional to the accuracy of the scanning, and also in the case of training on individual rooms the results prove that the presence of an extra person in the other room negatively influences the sensing accuracy.

7.2 Scenario 2



This chart shows the accuracy obtained from the sensing in the second scenario. The results of this scenario further prove the impact of the number of rooms on the accuracy and also support the observation from the first experiment that individual scanning when the other rooms are empty is more accurate than when the other rooms are full. This proves that the number of people is proportional to the noise induced by the scanning, thus influencing the sensing accuracy. Moreover, from both experiments, it is clear that, although the distance is different in both scenarios, it did not have any influence on the accuracy.

7.3 Discussion

After the 2 experiments were performed, the results highlighted some of the factors that influenced the accuracy of CSI sensing. The parameter that influences the accuracy of the scanning the most is the number of rooms. Since every added room increases the possible combination count it creates more categorical variables that the model has to decide on. As can be observed from the results the number of rooms used in model training is inverse-proportional to the accuracy of the scanning. The second factor that causes an impact on the accuracy is the number of people. Judging by the individual accuracy(full and empty) of rooms in both experiments the model performs better when there are fewer people. Distance, however, did not prove to be a crucial factor in the performance of the model, since the same number of rooms in both experiments obtained the same accuracy, although the distance was different in both experiments. Based on the results obtained from the experiments it is safe to say that Wi-Fi CSI can be accurately used in estimating room occupancy over multiple rooms with a minimum accuracy in this paper of 0.77 over 4 rooms and an accuracy of 0.87 over 2 rooms. However, the method used in this research cannot be considered scalable. For the training of the model, it is necessary to train the model on every possible combination that can occur in the rooms that would use Wi-Fi CSI which requires extended time and n people for n number of rooms. As presented in this research, for the first experiment with 2 rooms it required 4 different scans, while for 4 rooms the number of combinations exponentially increased to 16 which is highly inefficient. Moreover, the scenario and the objects present in the rooms and their location can drastically influence the results obtained by the receiver. Based on these factors, Wi-Fi CSI can be considered an accurate method to estimate room occupancy, but requires more research on the training process and its optimization.

8 CONCLUSION

8.1 General

In conclusion, it is appropriate to say that even if the experiments have proven that Wi-Fi CSI is accurate enough to be used to estimate occupancy in an indoor environment, it requires a lot of training data and it is not currently scalable, since with every room that the devices cover will add to the complexity of training and to the data collection time. However, during these experiments, some of the factors that influence the scanning process and the accuracy of the system in general were identified and analyzed. These findings could serve as a base for further development in similar scenarios and the start of a new generation of sensing technology. Despite these challenges, this research has proven successful in highlighting the potential and current limitations of Wi-Fi CSI for occupancy detection.

9 LIMITATIONS

9.1 Space limitations

In this research, the Wi-FI CSI accuracy could be analyzed only on 4 sequential rooms due to the limitations of the space that was used and the lack of bigger accessible spaces to perform the experiments. For further development and research of the CSI in a similar use case, an extended space would be required.

9.2 Environment limitations

For completely accurate results the space used for sensing should be free of any external noise provoked by objects that are not related to the experiment. Unfortunately, the experiments were performed in one of the buildings of UT campus which do have chairs and tables. These objects can interfere with the sensing process and influence the results of the scanning.

9.3 Human factor limitation

For the performed experiments multiple people were used and for the second scenario, there were 16 different scanning sessions to be performed. Because every scanning session takes approximately 40 seconds and it also takes time to arrange the participants in a specific combination, participants spend a substantial amount of time on this experiment.

9.4 Further work

Wi-Fi CSI can incontestably be used as a method to assess room occupancy since its accuracy proved to be at a decent level. However, it does require more research in terms of scaling the training process from 2^n to a more realistic complexity. Moreover, this research did not focus on experiments with more participants in one room at the same time, which could potentially bring new challenges to the topic. Besides that, the environment that the devices are used on is has a big impact on the accuracy, thus rooms with multiple big objects and frequent layout changes can become a problem for the model. That is why for the successful development of a usable approach extended research has to be conducted.

10 ACKNOWLEDGMENTS

The author would like to thank all the participants who generously contributed their time and participated in this study. Special thanks to Jeroen K. Brinke and H. Yanqiu for their guidance and support throughout the research process, providing creative solutions to design challenges.

A USAGE OF AI

A.1 Appendix A.1

During the preparation of this work, the author(s) used [Grammarly] in order to check the spelling of words and paraphrase the incorrectly written parts of the text. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the work.

A.2 Appendix A.2

During the preparation of this work the author(s) used [ChatGPT] in order to find references, paraphrase already written text, searching information. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the work.

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