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Experiments on Detecting and Counting People via Ambient Wi-Fi

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***Abstract*—This paper investigates how well the presence and number of people in an indoor space can be detected using channel state information from ambient Wi-Fi signals using off-the-shelf hardware. Experiments show that well-known machine learning algorithms like k-nearest neighbors, neural networks, and support vector machines can be trained to detect human presence almost perfectly. In addition, the number of people (up to six) can be estimated with moderate success. Potential applications include smart homes as well as industrial and commercial environments.**

***Index Terms*—Wi-Fi sensing, channel state information (CSI), occupancy detection, people counting.**

I. Introduction

The widespread success of wireless local area networks based on the IEEE 802.11 standard — commonly known as Wi-Fi — has sparked interest in expanding the capabilities of this technology beyond its original purpose of wireless connectivity. Companies and researchers are developing Wi-Fi solutions for wireless *sensing*, which aim to infer about the surrounding environment from measured channel conditions. Of key importance is the temporal dynamics of the channel caused by movement of people and objects; motion inside a room can be detected as it changes the multipath propagation constellation. Wi-Fi sensing opens up a wide range of applications in fields like home automation, security and safety, and health monitoring [1]. In response to these prospects, the IEEE has established Task Group 802.11bf to develop an amendment to the Wi-Fi standard that enables wireless sensing [2], [3].

In this context, we explore how to detect the presence of people in an indoor area and count their number by interpreting ambient radio signals transmitted from existing Wi-Fi infrastructure [4]. A vital aspect is that the people themselves do not need to carry any devices; sensing is performed in a passive and device-free manner. This is a crucial advantage over active or device-based sensing, where specialized sensors and equipment (motion sensors, acoustic sensors, or cameras) are required. In addition, when it comes to sensing of humans, wireless technologies offer advantages over cameras, including better privacy as well as lower costs and rapid scalability due to existing infrastructure.

Our work explores the following questions: How accurately can we detect and count people in a room using today's technology without modifying hardware or software? Specifically, how well can we accomplish this task using commercial off-the-shelf (COTS) transceivers based on the IEEE 802.11ac standard (Wi-Fi 5), along with standard algorithms that estimate the number of people via analyzing channel conditions?

This paper studies these questions using machine learning algorithms, which are trained with data on the channel conditions and then classify such data sets to make a guess on the number of people. Occupancy detection is implemented as a special case of people counting, distinguishing whether nobody or at least one person is present. Like other wireless sensing approaches, we obtain the required channel conditions from the channel state information (CSI), which is offered on each subcarrier. Our goal is to explore the performance of off-the-shelf hardware and software in its standard state.

The contributions and insights are as follows:

- *Proof-of-concept for occupancy detection*: We demonstrate by experiments that today's Wi-Fi and standard algorithms are sufficient to detect the presence of people inside a room with almost perfect accuracy.
- *Performance of people counting:* We analyze the accuracy of learning algorithms to count the number of people in a room by analyzing and classifying CSI data. Experimental results with up to six people show that k-nearest neighbors, neural networks, and support vector machines achieve reasonable accuracies, both for each class individually (worst class is 80 %) and overall (up to 90 %).

The paper is structured as follows: Section II provides a literature review that summarizes and compares research on Wi-Fi-based occupancy detection and people counting. Section III discusses the basics of how CSI can be used for Wi-Fi sensing. Section IV is the main part of the paper: it presents a case study that compares different machine learning algorithms for Wi-Fi-based occupancy detection and people counting. Finally, Section V concludes.

II. Literature Review

General Classification: There is a variety of commercial solutions for occupancy detection and person counting in local areas, including methods based on images, worn devices, and radio signals [5]. Image-based solutions [6] are probably the most common approach to count people in crowds; they offer high accuracy with a passive approach but require additional infrastructure and raise privacy concerns as individuals can be identified. Device-based methods are also used but their feasibility is limited to people who carry mobile phones or wear other devices like smart watches [7]. In the domain of radio-based sensing [4], radar technology is used to detect and analyze the echo reflected from an object. Small commercial radars are available but cannot accurately detect minor movements of people and objects [5].

Wi-Fi Sensing with CSI: Wi-Fi sensing, as a radio-based method, is the most immature method of all technologies mentioned. Initially, researchers used the received signal strength indicator (RSSI) for sensing applications. However, due to unpredictable fluctuations of the RSSI in multipath environments, researchers have shifted to CSI as a more reliable signal for human sensing and detection [1]. Table I provides an overview and a comparison of literature on Wi-Fi-based occupancy detection and people counting using CSI. It lists the main work, hardware platform, tool for CSI extraction, algorithms, and performance results.

III. Basics of Channel State Information

The channel conditions in Wi-Fi systems are described by the CSI between transmitter and receiver on a given carrier frequency f at time t. Systems based on orthogonal frequency division multiplexing (OFDM) measure the CSI for each of the subcarriers. Each CSI contains both amplitude and phase information and basically constitutes the channel frequency response $H(f,t) = \sum_i p_i(t)\, e^{-2\pi f \tau_i(t)}$ with amplitude attenuation factor p_i and propagation delay τ_i of the ith path [1].

The CSI is determined as follows: The transmitter sends a predefined sequence of training symbols x on each subcarrier. The receiver receives this sequence in modified form $y = H\,x + n$ with noise n. The receiver compares the sequence y and the known training sequence x to estimate the channel response for each subcarrier, forming a CSI matrix $\boldsymbol{H}$ [1].

The CSI characterizes the environment. Certain characteristics can be found using mathematical tools and machine learning. Although CSI extraction methods exist in the IEEE 802.11 standard, the CSI is not readily available at the user level but is kept hidden by transceiver chips. To extract CSI, different tools have been developed for commercial hardware [8].

IV. Experimental Case Study

Our case study illustrates how well Wi-Fi channel conditions in combination with established classification methods can be used for detecting and counting people. Our experiments show that standard supervised machine learning algorithms applied to CSI data can (a) reliably identify human presence in a room, achieving a nearly perfect detection rate and (b) estimate the number of up to six people in the room with medium to high rate. In the following, we describe the experimental setup, data preprocessing and feature extraction, classification algorithms, and performance metrics, before presenting and discussing the results.

A. Experimental Setup

The experiment takes place in an office room of size 22 m^2. It is furnished with wooden tables, cupboards, and sideboards (see Figure 1). Two computers (equipped with Intel AX200 NICs) are used as transmitter (TX) and receiver (RX), respectively. They are placed in a way that the received signals are not dominated by the line-of-sight path but contain multipath components. This is done to capture many potential human locations in the room. We focus on sub-7 GHz sensing using 802.11ac in the 5 GHz band. Both transmitter and receiver use two antennas each (2×2 MIMO). The Picoscenes tool is used to capture and collect the CSI [18].

Fig. 1: Office room with experimental setup for Wi-Fi-based people detection and counting

Wireless transmissions between the two computers are performed while there are zero to six people in the room. These people are standing and walking to different locations from time to time. A CSI value is captured for each transmission and all values are collected to yield a dataset of seven occupancy scenarios. Each scenario is measured for five minutes; the overall experiment takes about 40 minutes, capturing 40,000 CSI measurements. There are 245 OFDM subcarriers per wireless transmission stream, yielding a total of 980 subcarriers for the four 2×2 MIMO transmissions. The CSI dataset is labeled with the respective class of occupancy ($N = 0$ to 6 people) before training different machine learning algorithms in MATLAB. Two thirds of the CSI data is used for training, the rest for performance evaluation (testing and validation).

B. Preprocessing

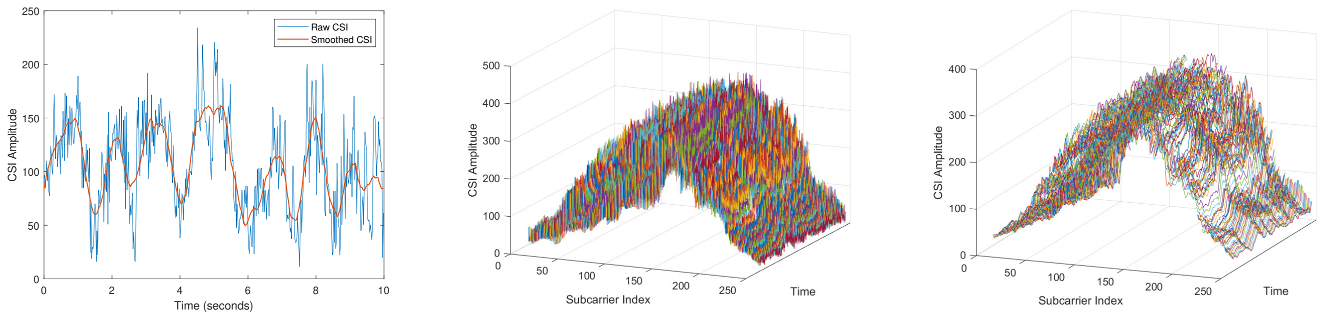
A preprocessing of the raw CSI data is performed in the following steps. First, missing pilot subcarriers are interpolated and cyclic shift delay on the phase is removed using the Picoscenes MATLAB parser. Second, outliers and noise caused by commodity hardware and environmental factors are removed. This is done via a Hampel filter to eliminate spike noise and a Savitzky-Golay filter to remove white noise [19]. Figure 2 shows the amplitude before filtering and after filtering (smoothed).

C. Feature Extraction

Next, the preprocessed CSI data undergoes a feature extraction. The CSI data comprises four streams of 245 subcarriers each. Instead of extracting features from each individual subcarrier (forming a high-dimensional feature set),

TABLE I: Summary and comparison of different Wi-Fi sensing based occupancy detection and people counting applications

Reference	Main Work	Hardware Platform	CSI Collection Tool	Algorithms	Performance	Wi-Fi Frequency
[9]	System to count people and estimate their speed up to 5 people	Intel 5300 Wi-Fi NIC	Linux 802.11n CSI Tool	No data training-Predeveloped sample database	Moderately accurate speed estimation; high accuracy in static environments	2.4 GHz
[10]	Deep learning (DL) to count crowds up to 5 people	Intel 5300 Wi-Fi NIC	Linux 802.11n CSI Tool	Convolutional Neural Networks (CNNs)	Accuracy: 86.4%; 90% with activity recognition model	5 GHz
[11]	A DL system for people counting in indoor environments up to 4 people	Celeno 802.11ac Doppler radar	- - -	A novel 3D-Convolutional Neural Network (3D-CNN)	Accuracy: 89%	5 GHz
[12]	Device-free crowd counting system using commodity Wi-Fi devices up to 7 people	COTS Wi-Fi routers	Upgraded Atheros CSI Tool for OpenWrt based firmware	Information theory based tansfer learning algorithm	Overall 91.97% accuracy; 81.8% for 7 people case	5 GHz
[5]	A real-time Passenger Counting system deployed inside the vehicle (car and subway)	X310 SDR	- - -	Model based on the queuing theory. A mathematical inference method with a priori probability	Accuracy in car: 93.8%, Accuracy in subway: 92.6%”	2.4 GHz
[13]	Passenger counting in mobile environments using multiple transceivers up to 20 people	Raspberry Pi	Nexmon CSI Tool	SVM, Random Forest (RF), KNN	Accuracy: 90.83%	5 GHz
[14]	Crowd counting in quasi-static scenarios by track ing the breathing rates of multiple users up to 4 people	COTS Wi-Fi devices	- - -	Markov chain model for breathing signals; Employed an iterative dynamic programming algorithm to continuously track multiple breathing traces	Accuracy: 86%	5 GHz
[15]	A system for through-the-wall crowd counting using ambient Wi-Fi signals up to 5 person	Intel 5300 Wi-Fi NIC	Linux 802.11n CSI Tool	Backpropagation (BP) neural networks for the features and combines with weighting and threshold judgment to realize the through-the-wall crowd counting detection	Accuracy: 90%	5 GHz
[16]	Crowd counting with localization; A system to detect people presence and location up to 10 people	ESP32 WiFi nodes	ESP32 CSI Tool	Deep Learning	Accuracy: 91%	2.4 GHz
[17]	A passing people counting and direction system using commodity Wi-Fi devices up to 4 people	Intel 5300 Wi-Fi NIC	Linux 802.11n CSI Tool	A model for detecting the bi-directional motion based on the phase difference; source separation techniques for counting the multiple persons	Direction accuracy: 95%, Counting accuracy: 92%	2.4 GHz



(a) Unfiltered and smoothed CSI of one subcarrier (b) Unfiltered CSI data (c) Smoothed CSI data

Fig. 2: CSI data smoothing.

TABLE II: Performance results of different algorithms on detecting and counting people

	Accuracy A_N in %								A
Algorithm / Class: $N =$	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**>1**	**Overall**
Support vector machine (cubic)	100	95.2	87.0	83.0	87.0	85.3	89.0	97.0	89.3
k-Nearest neighbors (fine)	100	99.2	99.0	97.5	97.0	96.4	97.1	99.0	98.0
Neural network (wide)	100	96	91.0	88	92.0	91.3	91.4	97.0	92.6

we extract aggregated features from each stream [20]. After comparing various features and their combinations, we select six statistical features and one transformation-based feature. The statistical features include mean, standard deviation, entropy, skewness, second order moment, and correlation. The transformation-based feature relates to the coefficients from the discrete wavelet transform. We apply feature extraction on each stream separately and then combine them to obtain the final feature matrix.

D. Algorithms

The number of people is estimated by supervised machine learning algorithms trained on CSI data. The estimation is made in a way that the algorithms perform a classification task based on the features extracted from the CSI. A classification decision is correct if the algorithm's output is "N people" when there are indeed N people in the room ($N = 0, \dots, 6$). The following three algorithm categories are utilized:

- support vector machines (SVM),
- k-nearest neighbors (KNN), and
- neural networks (NN).

Different variants are tested in each category, but only the results of the best-performing variant from each category are presented. For instance, SVMs are used with different kernel functions including linear, quadratic, cubic, fine Gaussian, medium Gaussian, and coarse Gaussian, but only results of the cubic kernel are presented, as it outperformed all other kernels.

E. Performance Metrics

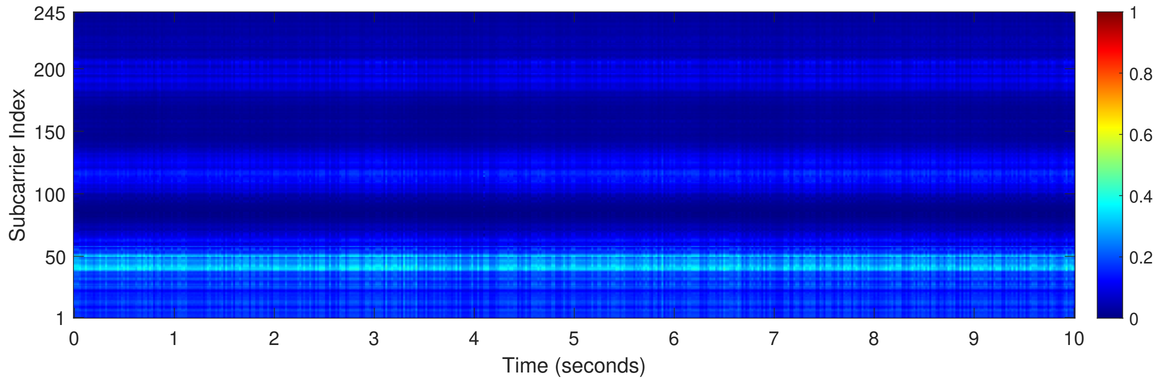
In order to assess how well a certain algorithm estimates the number of people, we count the algorithm's correct and incorrect classifications for each of the seven classes ($N = 0, \dots, 6$ people). From these numbers, we compute two types of fractions that serve as performance metrics:

- *Class-specific accuracies:* For each class N, the *accuracy* A_N is defined as the fraction of correctly classified cases relative to the total number of cases in that class. For example, an accuracy of $A_1 = 90\,\%$ means: if there is a single person in the room, the algorithm guesses this number correctly in $90\,\%$ of the cases.
- *Overall accuracy:* In addition, the *overall accuracy* A is defined as the fraction of correct classifications across all N classes.

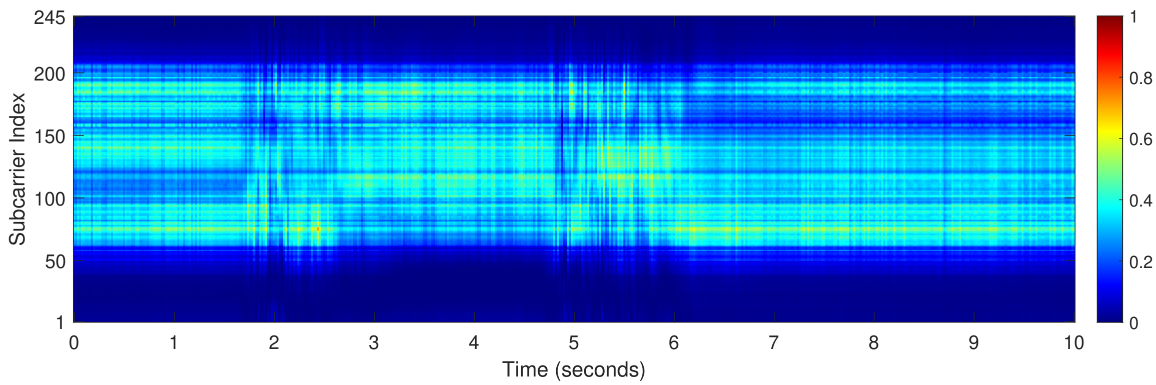
F. Results and Discussion

Occupancy detection: We are first interested in whether the room is empty ($N = 0$) or occupied by at least one person ($N > 0$). Our experiments show that all three algorithms achieve near-perfect accuracy in distinguishing between these two cases. This high accuracy is achieved because the movement of people causes significant fluctuations of the CSI compared to an empty room as shown by the power response of CSI [21] in Figure 3.

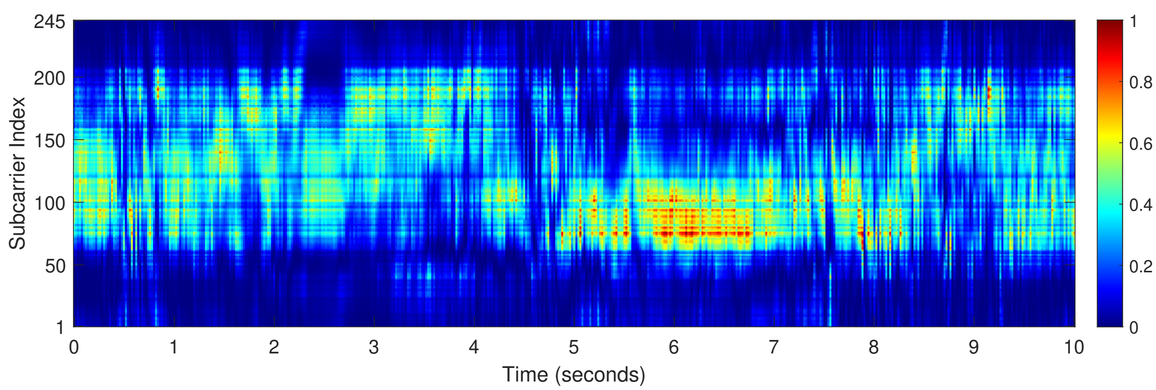
Counting people: Next, we would like to know the exact number of people in the room. Table II shows the class-specific and overall accuracies of the three algorithms. The results can be interpreted as follows: The KNN yields the best performance in our experimental setup. It is able to detect the exact number of people N with an accuracy consistently above $90\,\%$ for each N, achieving an overall accuracy of $98\,\%$. For illustration, Figure 4 shows the test confusion matrix obtained for the KNN. The entries show the number of correct and incorrect classifications made by the algorithm. A similar performance is achieved by NN and SVM, both in terms of



(a) Empty room.



(b) One person in room.



(c) Three persons in room.

Fig. 3: Power response of CSI for all subcarriers over time.

class-specific accuracy (again always above 80 % for each N) and overall accuracy (93 % and 89 % respectively).

Single or multiple occupancy: Finally, we distinguish between zero people ($N=0$), one person ($N=1$), and multiple people ($N > 1$). If there is more than one person in the room, the KNN is able to classify this situation correctly in 99 % of all cases. Together with the results for zero or one person, this means that each of the three scenarios can be detected with an accuracy of at least 99 %. The neural network achieves a similar accuracy of 97 % for multiple people and a worst-case accuracy of about 96 %.

V. Conclusions and Outlook

Our experiments demonstrate that the presence of people in a typical office room can be detected with high reliability by analyzing the channel state of signals from off-the-shelf Wi-Fi transceivers using standard classification algorithms. Beyond this, not only the mere presence but also the actual number of people can be estimated with an accuracy of at least 96 % using k-nearest neighbors classification with up to six people.

Based on this proof of concept, our ongoing work focuses on developing a demonstrator for real-time occupancy detection and people counting. Additional efforts are needed to

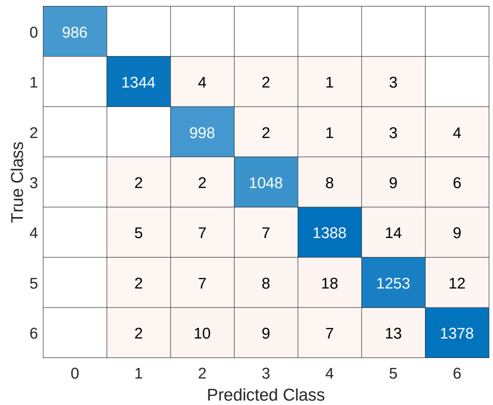


Fig. 4: Test confusion matrix for counting people with KNN: Each entry gives the number of classifications for a given class (number of people N). Entries with blue (orange) background represent correct (incorrect) classifications.

make the system more robust against changes in the environment, extend its applicability to larger rooms, and improve the accuracy of estimating the exact number of people.

Potential applications of this technology include human activity sensing for health monitoring, assisted living, and intrusion detection in smart homes and other environments. In commercial and industrial settings, it can contribute to analyzing customer behavior in retail and detecting human presence in hazardous areas to enhance workplace safety. Additionally, occupancy detection can support emergency response and rescue operations within buildings and in public transport systems such as trains and subways.

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