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Wi-Fi Sensing for Occupancy Detection in Aircraft Cabins

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***Abstract*—We present a proof of concept for real-time occupancy detection in aircraft cabins using onboard Wi-Fi infrastructure for wireless sensing. A Doppler-based approach is used to extract features from channel state information; they are employed to train an ensemble model to estimate the number of occupants. Experiments in a small cabin mockup achieve a classification accuracy of 98 %. Such a system could serve as a valuable component in evacuations.**

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

I. Introduction

The task of occupancy detection is to determine the presence and number of people inside a space using sensors and signals. This capability is essential in smart buildings, industrial facilities, and transportation systems to support automation and safety. A compelling application can be found in the aviation domain, specifically in monitoring of aircraft cabins. Estimating of the number of passengers and crew members is essential for maintaining operational efficiency and ensuring safety, especially in emergency situations where rapid and coordinated evacuation is required. Camera systems are often impractical in this context due to visibility constraints, high deployment and maintenance costs, and privacy issues. These limitations demonstrate the need for more robust, inexpensive, and privacy-preserving alternatives for cabin monitoring. A promising candidate for this purpose is Wi-Fi-based sensing [1]–[3]. It uses the cabin's existing wireless infrastructure, thus enabling rapid deployment without additional hardware.

Building on this motivation, we develop a Wi-Fi-based system for occupancy detection and people counting in aircraft cabins. This paper represents the first feasibility study of such a system. The contributions are as follows:

- *System development and implementation.* We present a lab prototype for real-time passive people detection and counting in indoor environments using Doppler features extracted from Wi-Fi channel state information (CSI).
- *Novel application.* We propose to employ Wi-Fi-based sensing as a viable solution for passenger and crew detection in aircraft cabins, representing a novel and scalable approach to privacy-preserving monitoring.
- *Experimental analysis and proof-of-concept.* We assess the system performance in a small cabin mockup (Fig. 1), demonstrating excellent accuracy for occupancy detection and reasonable accuracy for people counting, providing a first proof-of-concept for the intended application.

The primary use case motivating the development of this system is the real-time verification that a cabin has been fully cleared upon an evacuation. It focuses on the final phase of deboarding, highlighting the role of cabin crew, who oversee the process and are typically the last to leave the aircraft.

Section II covers related work. Section III provides the basics of Doppler-based sensing. Section IV introduces the experimental setup. Section V outlines our detection and counting technique. Section VI assesses the performance via experiments. Section VII concludes and outlines next steps.

II. Related Work

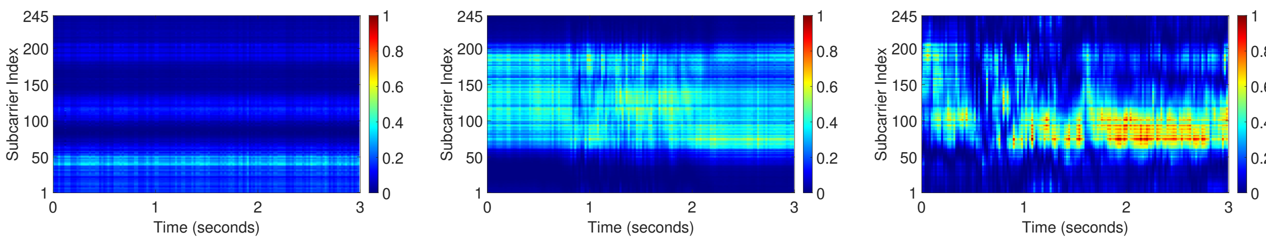
Several works have investigated occupancy detection in indoor environments using Wi-Fi-based sensing (see [4]). Most prototypes rely on CSI to exploit fine-grained characteristics of the channel [5]. Recent methods interpret CSI characteristics using deep learning-based feature extraction or statistical feature analysis. For example, a convolution neural network can be employed to extract features from CSI data, which are then fed to a long-short-term-memory model to count people [6]. One can also use phase differences between two antennas to extract features in time and frequency domains, which are then used by a neural network for through-the-wall people counting [7]. Similarly, statistical feature extraction based on CSI data can be used for people counting [8].

Moreover, Doppler-based approaches, especially range-Doppler mapping and micro-Doppler analysis, have been explored for capturing dynamic motion patterns that indicate human presence. Range-Doppler maps generated through Wi-Fi pulse Doppler radar are employed to estimate the number of people by analyzing Doppler signatures using a 3D convolutional neural network [9]. Another approach is to apply millimeter-wave Wi-Fi in combination with a convolutional neural network, utilizing range-Doppler analysis to extract motion-related features [10]. Wi-Fi sensing is also explored inside vehicles to count and localize passengers. A model for passenger counting based on queuing theory was developed for cars and subway carriages [11]. Similarly, an artificial neural network-based system was designed to localize passengers in an aircraft cabin using Wi-Fi and the wireless avionics intra-communication (WAIC) system [12].

III. Concept of Doppler-Based Sensing

Radio waves from a transmitter to a receiver are subject to attenuation, blockage, and multipath effects. These effects

Fig. 1: Aircraft (A330) cabin mockup.



(a) Empty cabin.

(b) One person in the cabin.

(c) Three people in the cabin.

Fig. 2: Power response of CSI for all subcarriers in one stream over time.

occur because waves are absorbed, reflected, diffracted, and scattered at objects in the environment. Changes in the environment, like human movement, can modify the propagation paths over time. The Doppler effect leads to frequency shifts due to mobility, which results in a frequency spread at the receiver due to multipath propagation. The concept of Doppler-based occupancy detection suggests that the Doppler spectrum observed at the receiver varies with the number of people present [13]: the spectrum typically exhibits a wider spread as the number of people increases.

These effects are visible when analyzing the CSI, a measured parameter that describes the channel. In Wi-Fi systems, CSI contains amplitude and phase information for each subcarrier, essentially representing the channel frequency response. As shown by the power response of CSI over time [14] in Figure 2, the presence and movement of people causes CSI changes and variations compared to an empty cabin. The Doppler spectrum is derived by applying the Fast Fourier Transform (FFT) to the CSI, from which discriminative features can be extracted for occupancy detection.

IV. Experimental Setup

Our experiments are made in a small cabin mockup (see Fig. 1), which features a metallic foil behind the lining to obtain a fuselage-type electromagnetic environment similar to a real aircraft. Two computers equipped with COTS Intel AX200 network interface cards (NICs) are used as the transmitter (TX) and receiver (RX), respectively. They are placed as close as possible to the cabin's roof to mimic the Wi-Fi transceiver placement in real aircraft. Both use two antennas each with a 2×2 MIMO configuration. We focus on sub-7 GHz sensing using 802.11ac in the 5 GHz band with an 80 MHz channel bandwidth. The tool Picoscenes is used to extract CSI from the NICs [15].

The cabin is occupied by N people (ranging from 0 to 4), who sometimes stand up and walk around while transmissions between the TX and RX capture CSI data to construct a dataset for five occupancy scenarios. We get $2 \times 2 = 4$ streams of CSI data each with 245 subcarriers. The collected dataset is labeled with the respective occupancy class N before training a machine learning model. The robustness in real-time detection and counting is tested on completely new data.

V. Passenger Estimation Technique

The processing pipeline is as follows (see Fig. 3): The raw data is preprocessed and filtered. Next, relevant features are extracted and fed into a trained ensemble learning model, which estimates the number of people.

Preprocessing: Outliers and noise generated by commodity hardware and environmental influences are eliminated through the use of a Hampel filter to remove spike noise and a Savitzky-Golay filter to remove white noise [8].

Feature extraction: Feature extraction follows a Doppler spectrum-based approach [13]. Denoting $h^{s}_{i,j}$ the CSI magni-

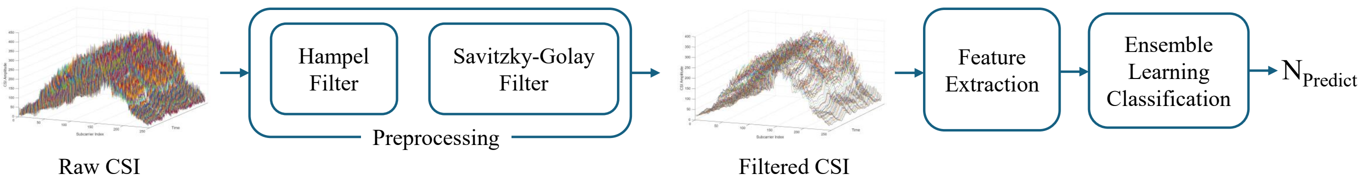


Fig. 3: Process steps.

tude for packet $i = 1, \dots, I$ on subcarrier $j = 1, \dots, J$ for stream $s = 1, \dots, S$, the CSI matrix for stream s is

$$\mathbf{H}^s = \left[h^s_{i,j}\right]_{I \times J} . \tag{1}$$

Next, the FFT is computed over a sliding window of length L for each column of $\mathbf{H}^s$, obtaining the matrix

$$\mathbf{H}^s_k = \left[H^s_{l,j}\right]_{L \times J} , \tag{2}$$

where $H^s_{l,j}$ is the magnitude of the l-th spectral component ($l = 1, \dots, L$) for subcarrier j. Each column of $\mathbf{H}^s_k$ contains the Doppler spectrum of subcarrier j for the k-th window.

Next, we take the mean over all subcarriers to obtain the mean Doppler spectrum of each window and remove the DC component. The resulting mean Doppler spectrum can be characterized by different spectral descriptors [13]. After evaluating various such descriptors and their combinations, we select five ones as our features: kurtosis (`kurt`), entropy (`ent`), spread (`sp`, the second central moment of the log-frequency spectrum), standard deviation (`std`), and skewness (`sk`). We compute these features for each stream and use the combined feature matrix as input to train a machine learning algorithm. A feature vector extracted from window k of stream s can be denoted as

$$\boldsymbol{f}^s_k = \left[\texttt{kurt}^s_k \quad \texttt{ent}^s_k \quad \texttt{sp}^s_k \quad \texttt{std}^s_k \quad \texttt{sk}^s_k\right] , \tag{3}$$

the feature matrix for stream s is

$$\mathbf{F^s} = \begin{bmatrix} \texttt{kurt}^s_1 & \texttt{ent}^s_1 & \texttt{sp}^s_1 & \texttt{std}^s_1 & \texttt{sk}^s_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \texttt{kurt}^s_K & \texttt{ent}^s_K & \texttt{sp}^s_K & \texttt{std}^s_K & \texttt{sk}^s_K \end{bmatrix} , \tag{4}$$

and the overall feature matrix is $\mathbf{F} = \left[\mathbf{F^1} \quad \mathbf{F^2} \quad \dots \quad \mathbf{F^S}\right]$.

Ensemble Learning Classification: As the system should provide estimations in real-time, we target simple classification learners instead of deep learning. We analyze different classification models and choose Ensemble Learning with subspace discriminant for training as it gives the best and consistent performance. The feature matrix $\mathbf{F}$ is used to train the system. After training, the real-time performance and robustness is assessed on completely new test data. The test confusion matrices for different window lengths L are given in Figure 4.

VI. Experimental Results and Discussion

To validate the ability of the system to detect occupancy and estimate the number of people in the cabin, we count the correct and incorrect classifications for each of the five occupancy classes ($N = 0, \dots, 4$ people). The performance is analyzed using two metrics: overall accuracy (percentage of correct classifications across all classes) and class-specific accuracy (percentage of correctly classified cases compared to the total number of cases in that class).

Occupancy detection: The task of occupancy detection is to estimate whether the cabin is empty ($N = 0$) or occupied by at least one person ($N > 0$). Figure 4 shows that our prototype is able to distinguish between these two cases with almost perfect accuracy. This high accuracy is attained even with small window lengths L, as the movement of people results in notable CSI changes visible in the Doppler spectrum, which can be observed by the power responses for different occupancy scenarios shown in Figure 2.

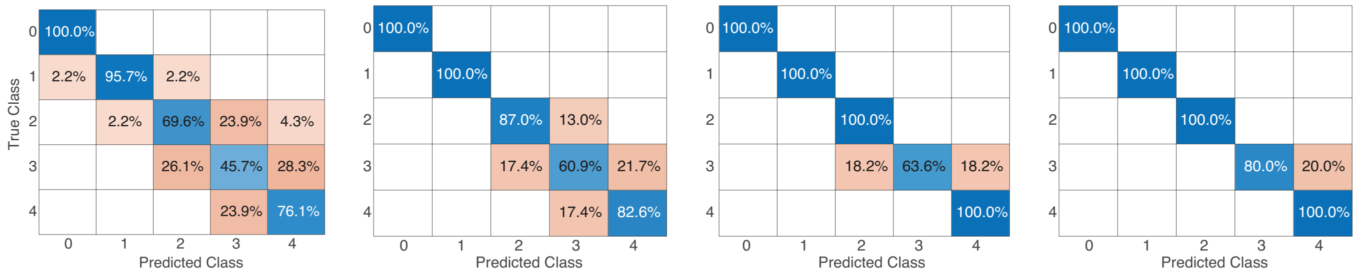
Counting people: The task of people counting is to estimate the exact number of individuals inside the cabin. Figure 4 shows the confusion matrix giving class-specific accuracies for different window lengths. For $L = 128$, 256, 512, and 1024, the overall test accuracies are 77.4 %, 86.1 %, 92.7 %, and 96.0 %, respectively.

Accuracy-delay tradeoff: The model's classification accuracy increases with increasing window length. This is because a longer window enables the model to get a better average of the Doppler spectrum and thus extract more stable features. However, there is a tradeoff between accuracy and delay. A quick rough estimate can be achieved for $L = 128$ while $L = 1024$ yields a very accurate estimation but takes longer.

Operational use case analysis: The system can support aircraft deboarding by estimating whether all passengers and crew have left the cabin. A key question is the accuracy and speed of this estimation. Table I shows the accuracy achieved for different window lengths, along with the corresponding time required to capture the CSI data. An appropriate window length can be chosen based on the requirements of the specific use case. For example, regular deboarding and emergency evacuations may require different capture times and accuracies. For standard de-boarding, a large L can be used, leading to a very accurate estimation. In contrast, emergency evacuations require rapid decision-making. Here, a small L enables fast estimates at the cost of reduced accuracy.

TABLE I: Accuracy of occupancy detection

Window length L	128	256	512	1024	2048
Accuracy	77 %	86 %	93 %	96 %	98 %
Time to capture CSI	7 s	13 s	26 s	52 s	103 s



(a) $L = 128$ (b) $L = 256$ (c) $L = 512$ (d) $L = 1024$

Fig. 4: Test confusion matrix for counting people with Ensemble Learning for varying FFT window length L.

VII. Conclusions and Outlook

This feasibility study demonstrated that Wi-Fi-based sensing systems might be employed for passive passenger occupancy detection and counting in small aircraft cabins. This has the potential to improve operational efficiency and safety without additional infrastructure while maintaining privacy. Occupancy detection is especially crucial in evacuation scenarios, where Wi-Fi-based systems may serve as redundant complements to existing solutions or replace them to reduce costs. Our approach was to train an ensemble learning model using FFT-based features extracted from CSI. The FFT window length characterizes the accuracy-delay tradeoff. A proof-of-concept was deonstrated in an Airbus A330 cabin mockup.

As future work, we plan to extend our system to quasi-static passengers and enhance its adaptability across various cabin environments. The main challenge is that Doppler shift captures people's motion, so stationary people are hard to distinguish from the background [16]. Still, detecting stationary passengers may be possible using higher frequencies such as millimeter waves [16], along with breathing-pattern analysis [17] and micro-Doppler traces. We thus plan to extend our system to detect nearly motionless seated passengers, including those who may be asleep or unconscious.

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