Low Cost Parking Spot Occupancy Detection Using Wireless Sensing

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***Abstract*—This paper presents a novel, low-cost approach to accurately detecting empty parking slots using wireless sensing techniques and channel state information (CSI) data. Existing solutions either rely on dedicated sensors for each parking spot, which increases deployment costs, or estimate the total number of available spaces without pinpointing their exact locations. In contrast, our approach leverages CSI-based wireless sensing to achieve accurate, real-time detection of individual empty parking slots while maintaining cost efficiency. By utilizing CSI data, our method enables robust and reliable parking slot detection even in dynamic environments. This scalable and easily deployable solution aims to improve smart parking systems, optimizing urban mobility and parking efficiency.**

***Index Terms*—wireless sensing, channel state information, parking slot detection, smart parking, parking space accounting, smart cities**

I. Introduction

The rapid urbanization and increase in vehicle ownership have intensified challenges associated with parking management. The average American spends 17 hours per year searching for parking, resulting in an estimated $73 billion in wasted time and fuel [1]. Efficient detection of empty parking slots not only alleviates traffic congestion and reduces environmental impact but also enhances driver satisfaction as well as increasing the revenue of parking facilities [2]. Traditional parking management systems have evolved from manual ticketing to sophisticated sensor-based networks. However, many parking facilities lack such systems due to their high cost and intrusive deployment requirements.

Existing solutions for parking occupancy detection often rely on deploying dedicated sensors in each parking spot, such as magnetic or ultrasonic sensors. While these methods can provide accurate occupancy information, they significantly increase deployment and maintenance costs, making large-scale implementation economically unfeasible [3]. Alternatively, some systems estimate the total number of available parking spaces without identifying the specific locations of empty slots, which limits their practicality for drivers seeking immediate parking.

Wireless sensing has emerged as a promising technology that utilizes existing wireless signals, such as Wi-Fi, to detect and interpret physical phenomena without requiring additional hardware or line-of-sight visibility. By analyzing fine-grained wireless features such as Channel State Information (CSI), wireless sensing enables applications in diverse domains. For instance, it has been used in healthcare to monitor hand movements during physical therapy exercises [4], in smart buildings to perform real-time occupancy detection for energy-efficient automation [5], and in activity recognition systems capable of classifying physical gestures and movements [6]. These studies demonstrate the versatility and robustness of wireless sensing techniques in dynamic, real-world environments. Our work builds on these principles and adapts them for the problem of detecting empty parking slots in a low-cost, non-intrusive manner.

Recent research has explored the use of wireless sensing techniques for vehicle detection as well. Most of these studies focus moving vehicles, such as those in traffic monitoring [7], rather than stationary vehicles in parking lots. There are few notable studies for parking occupancy detection as well, particularly those leveraging Wi-Fi Channel State Information (CSI). For instance, WiParkFind utilizes off-the-shelf Wi-Fi devices to monitor parking occupancy by analyzing CSI data [8]. This approach reduces the need for dedicated sensors and lowers deployment costs. However, WiParkFind focuses on estimating the number of available parking slots without pinpointing their exact locations, which can be less helpful for drivers searching for parking in real-time.

Our research addresses these gaps by proposing a low-cost, non-intrusive system that utilizes wireless sensing techniques and CSI data to accurately detect and identify individual empty parking slots. Unlike existing solutions that either require sensors for each spot or only provide aggregate occupancy counts, our approach leverages CSI-based wireless sensing to pinpoint the exact locations of vacant parking spaces. This easily accesible and deployable solution aims to improve smart parking systems, thereby optimizing urban mobility and parking efficiency.

The rest of the paper is organized as follows. We discuss the related work in Section II. In Section III, we provide the system model and provide the steps of the proposed solution and related experiments to evaluate the performance of the proposed solution. In Section IV, we provide the details of the experimental setup, including the hardware and software components used in our experiments, followed by Section V, where we provide and describe the results of our experiments. Finally, we conclude and discuss future work in Section VI.

TABLE I: Comparison of proposed parking occupancy detection solutions.

Method/References	Coverage	Low-cost?	Non-Intrusive?	Accuracy	Other Issues and Drawbacks
IR Sensors [9], [10]	Per-spot	✗	✗	High	Susceptible to weather and heat from sources other than vehicles
Ultrasonic Sensors [11]	Per-spot	✗	✗	High	Potential inaccuracies with soft or angled surfaces, as well as susceptibility to acoustic noise
Ground Wi-Fi Sensors [12]	Per-spot	✓	✗	High	Highly impractical due to the box placed on the ground at each parking spot
LoRa & RFID Sensors [13]	Per-spot	✓	✗	High	Potential for false positives, limitations in diverse environments and challenges with robustness
Vision Based [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]	Multi-spot	✓	✗	Medium	Requires high computational resources, potential privacy issues, susceptible to weather and low light
Ultra-wide-band Radar [25]	Multi-spot	✗	✓	Medium	Study does not provide experimental results for cases where multiple vehicles are present
Crowd-sourcing [26], [27], [28]	Multi-spot	✓	✓	Low	Effectiveness heavily depends on user participation
WiParkFind [8]	Multi-spot	✓	✓	Low	Only provides vacancy count rather than pinpointing individual spots
Our work	Multi-spot	✓	✓	High	

II. Related Work

In this section, we provide an overview of related studies in the literature. There are two main approaches for parking space accounting. While some aim to detect the presence of vehicles in individual parking spots, others focus on estimating the total number of available parking spaces. In order to achieve the former, dedicated sensors are typically deployed in each parking spot, such as magnetic or ultrasonic sensors. Studies in this area have focused on improving the accuracy of these sensors, reducing their cost, or enhancing their energy efficiency. For the latter, the method is usually based on counting the number of vehicles entering and leaving the parking lot. Since this approach is less accurate than the former, as it does not provide information about the specific locations of empty parking spaces, while being much cheaper, most of the studies in this area focus on making the individual sensor technologies more cost-effective. In order to achieve this, some studies have proposed using different sensor technologies to detect the presence of vehicles in parking spaces. Others have explored the feasibility of using fewer sensors and mitigating the need for dedicated sensors for each parking spot. For this reason, we will first review the studies that focus on individual sensor technologies for parking space accounting, and then we will review the studies that focus on using fewer sensors that can be used for multiple parking spots.

A. Per-Spot Sensor Occupancy Detection

Most of the current solutions for parking occupancy detection rely on deploying dedicated sensors in each parking spot. For example, magnetic sensors are widely used to detect the presence of vehicles in parking spaces. These sensors can be embedded in the pavement and are capable of detecting changes in the magnetic field caused by the presence of a vehicle. They are relatively inexpensive and easy to install, but they may not work well in all weather conditions or with certain types of vehicles. There are also ultrasonic sensors that use sound waves to detect the presence of vehicles. These sensors can provide accurate occupancy information, but they are more expensive and require more maintenance than magnetic sensors.

Some studies have explored other sensor technologies for individual parking spaces. Some studies propose using infrared sensors to detect the presence of vehicles [9], [10]. These sensors can be used to detect the heat emitted by vehicles, making them suitable for outdoor environments. However, they may not work well in all weather conditions and can be affected by other heat sources in the vicinity.

One study has proposed using a combination of different sensor technologies [11]. This approach combines magnetic sensors with ultrasonic sensors to improve the accuracy of parking occupancy detection and increase the battery life of the sensors.

Another approach is to use wireless signals to detect the occupancy of parking spots. For example, a study has proposed using Wi-Fi signals to detect the presence of vehicles in parking spaces [12]. The sensor used in the study can provide accurate occupancy information and is relatively inexpensive. However, this approach requires a box to be installed on the ground of each parking spot, which can be intrusive and costly. There are studies that also focus on other wireless technologies, such as LoRa and RFID [13], still requiring dedicated sensors for each parking spot.

B. Multi-Spot Occupancy Detection

With the improvements in artificial intelligence and machine learning, some studies have proposed using vision-based systems for parking occupancy detection. These systems can cover multiple parking spots [2], process the images captured by the cameras, and detect the presence of vehicles in individual parking spaces. Most of these studies rely on deep learning algorithms to analyze the images and detect the presence of vehicles [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], while others use traditional computer vision techniques [24]. In addition to the high cost and computational requirements of these systems, they also have some environmental limitations. For example, they may not work well in low-light conditions or in different weather conditions if the parking lot is not covered.

One study experimentally evaluated the performance of a ulta wide-band (UWB) radar system for parking occupancy detection [25]. The study found that the UWB radar system can accurately detect the presence of vehicles in parking spaces. However, it failed to provide results for cases where multiple vehicles are present.

There have also been studies for parking spot accounting that do not require a phsical detection of vehicles. Rather, they rely on crowd-sourced data to estimate the number of available parking spaces [26], [27], [28]. These proposed solutions heavily rely on user participation and thus tend to be less accurate than the other methods.

The closest work to our study is WiParkFind, which was briefly introduced earlier. This system uses off-the-shelf Wi-Fi devices to monitor parking occupancy by analyzing channel state information (CSI) data using machine learning [8]. They used Intel 5300 Wi-Fi cards connected to two laptops to collect CSI data. The experiments were conducted in a parking lot with 10 spots. The researchers were able to predict the number of available parking slots with an accuracy of 78.2%. However, WiParkFind focuses on estimating the total number of available parking slots without pinpointing their exact locations, which our study aims to address.

III. System Model

A. Assumptions

We assume that parking spaces in question are located in a parking lot with a known layout which consists of multiple adjacently placed parking spots and vehicles are expected to be parked in a vertical manner. While the proposed system can be used in both indoor and outdoor parking lots, parallel parking is not supported since it introduces additional challenges in distinguishing between parked vehicles and other objects as well as changing the parking lot layout. However, the proposed system can be extended to support parallel parking in the future, possibly by training the model with additional data from parallel parking scenarios.

B. Problem Statement

In the proposed scenario, the objective is to detect the presence of a vehicle in a parking space using wireless signals. The system is designed to operate in a parking lot with multiple adjacent parking spaces, where each space can either be occupied by a vehicle or remain empty. The goal is to accurately identify the occupancy status of each parking space based on the received wireless signals, without requiring dedicated sensors for each spot.

C. System Overview

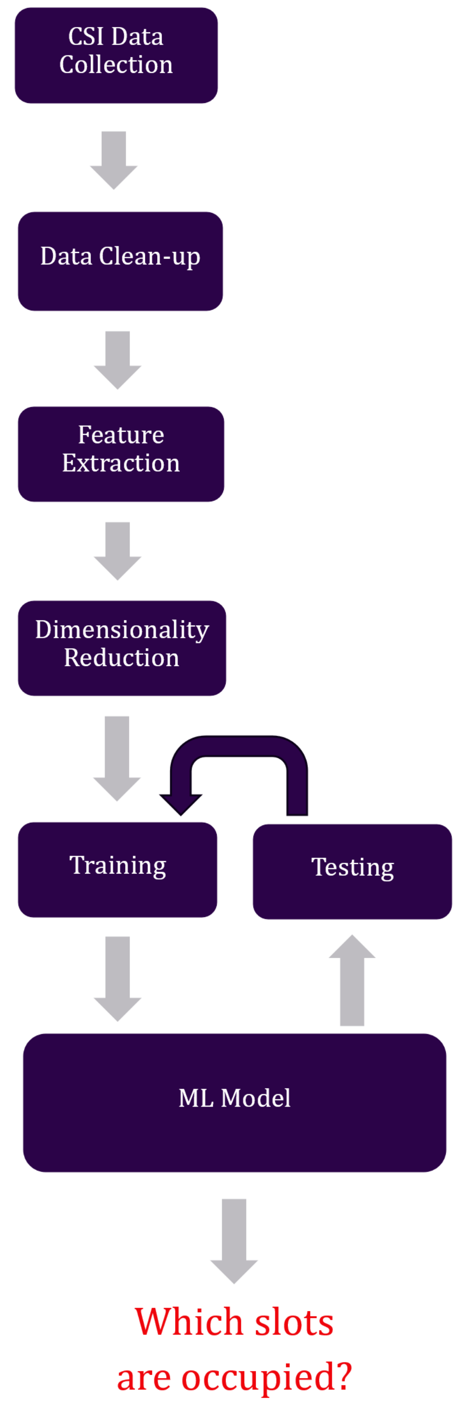

Fig. 1: The architecture of the proposed system

The proposed system follows a multi-stage process as illustrated in Figure 1. Each stage plays a crucial role in transforming raw wireless signals into accurate parking occupancy information.

1) CSI Data Collection: The first step involves collecting Channel State Information (CSI) in various parking scenarios. This data captures the multipath propagation characteristics of Wi-Fi signals, which are affected by the presence and absence of vehicles.

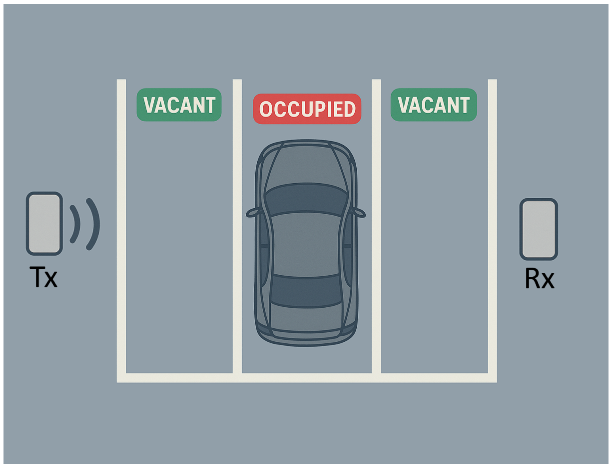

Fig. 2: Data collection setup

The data collection setup is shown in Figure 2. The system consists of a transmitter (Tx) and a receiver (Rx), where the transmitter sends Wi-Fi signals to the receiver. The receiver captures the CSI data, which includes information about the amplitude and phase of the received signals. This data is collected over time to create a comprehensive dataset that reflects different parking scenarios, including different combinations of occupancy states across multiple parking spaces between the transmitter and receiver.

2) Data Cleaning: The raw CSI data collected often contains noise and outliers due to environmental factors and hardware imperfections. Therefore, a data cleaning phase is essential. This involves removing any irrelevant or corrupted data points, filtering out noise, and normalizing the data to ensure consistency. Techniques such as median filtering, moving average smoothing, and outlier detection algorithms can be employed to enhance the quality of the CSI data.

3) Feature Extraction: Next, relevant features are extracted from the cleaned CSI data. CSI provides information about the channel frequency response (CFR) across multiple orthogonal frequency-division multiplexing (OFDM) subcarriers. For each packet received at time t, the CSI for the k-th subcarrier, $H(f_k, t)$, can be represented as a complex number:

$$H(f_k, t) = |H(f_k, t)|e^{j\angle H(f_k,t)} = a + jb$$

where $H^*(f_k, t)$ is the complex conjugate of $H(f_k, t)$, a and b are the real and imaginary parts of the CSI, respectively. The amplitude and phase of the CSI can be expressed as:

$$\text{Amplitude}(f_k, t) = |H(f_k, t)| = \sqrt{a^2 + b^2} \quad (1)$$

$$\text{Phase}(f_k, t) = \angle H(f_k, t) = \tan^{-1}\left(\frac{b}{a}\right) \quad (2)$$

This extraction process provides a an amplitude and phase value for each subcarrier at each time instance.

4) Dimensionality Reduction: To reduce the dimensionality of the extracted features and improve computational efficiency, dimensionality reduction techniques such as Principal Component Analysis (PCA) or t-Distributed Stochastic Neighbor Embedding (t-SNE) can be employed. These techniques help to retain the most significant features while discarding redundant or irrelevant information. The reduced feature set is then used for training the machine learning model.

5) Model Training and Testing: Subsequently, a machine learning model is trained using the extracted features and corresponding ground truth labels which consists of the occupancy state of the parking spaces. For example, if the parking lot has 10 parking spaces, the occupancy state can be represented as a binary vector of length 10, where each element indicates whether the corresponding parking space is occupied (1) or empty (0). While the proposed system can be trained with any machine learning model, neural networks are particularly effective due to their ability to capture complex patterns in the data as well as their suitability for time-series data based on signal processing. Additionally, the model is tested using a separate validation dataset to evaluate its performance and generalization capabilities.

IV. Experimental Setup

In this section, we provide the details of the experimental setup, including the hardware and software components used in our experiments. We also describe the data collection process, the data cleaning and preprocessing steps, and the feature extraction techniques employed to prepare the data for model training and testing.

A. Hardware Setup

Due to time and budget constraints, we used a scaled-down version of the proposed system. Model vehicles were used to simulate the parked vehicles in a parking lot. Preliminary experiments were conducted to evaluate the feasibility of using other types of objects, such as cardboard boxes, to represent parked vehicles. However, these objects did not yield satisfactory results, as they did not produce the same level of multipath propagation as real vehicles. Therefore, we decided to use model vehicles for our experiments. Furthermore, the material of the model vehicles was chosen to be similar to that of real vehicles, as this would help in achieving better results. The model vehicles used in our experiments were 1:12 scale models of real vehicles that were made of a relatively realistic combination of plastic and metal. The model vehicles were placed on a table, and the transmitter and receiver were positioned at a fixed distance from each other on the sides of the row of parking spots. Since the the number of classes to be classified is equal to two to the power of the number of parking spots, we used three parking spots and three model vehicles to create a total of eight classes. As transmitter and receiver, we used two ESP32 microcontrollers, which are low-cost, low-power microcontrollers with built-in Wi-Fi capabilities. The

ESP32 microcontrollers were programmed to send and receive Wi-Fi signals, allowing us to collect Channel State Information (CSI) data from the wireless signals.

Fig. 3: Experimental setup for data collection

As shown in Figure 3, the transmitter was placed on one side of the parking spots, while the receiver was placed on the other side. The transmitter was connected only to an off the shelf portable power bank, which emphasizes the low-cost and low-power nature of our system. The receiver was connected to a Raspberry Pi, which was used to store the collected data. For each parking combination, the CSI data was collected for 10 seconds, and this process was repeated 20 times.

B. Software Setup

The ESP32 microcontrollers were flashed with a custom firmware that enabled them to send and receive Wi-Fi signals. The firmware was based on a previous work that provided a framework for collecting CSI data from ESP32 devices [29]. The resulting CSI data in a CSV format was then transferred to another computer for further processing. The data was cleaned by removing null values followed by a preprocessing step using a moving average filter to smooth out noise and fluctuations in the signal. In order to extract features from the raw CSI data, amplitude and phase values were calculated for each subcarrier at each time instance. The amplitude and phase values were then used to create a feature vector for each data point. The data was then split into training and testing sets, with 80% of the data used for training and 20% for testing. The training set was used to train a machine learning model, while the testing set was used to evaluate the performance of the model. A Convolutional Neural Network (CNN) with 9 layers was used for the model training and testing. The CNN model was implemented using TensorFlow and Keras libraries in Python. The model was trained using the training set, and the performance of the model was evaluated using the testing set. A sliding window method was used to create the training and testing sets, where a window of size 50 was used to create overlapping segments of the data.

V. Experimental Results

In this section, we present the experimental results of our proposed system. The evaluation of the system is based on the data collected from the experimental setup described in Section IV.

The main performance metric used to evaluate the system is the classification accuracy on the test dataset, which is defined as the ratio of the number of correctly classified instances to the total number of instances. We will present the confusion matrix to illustrate the classification results in detail.

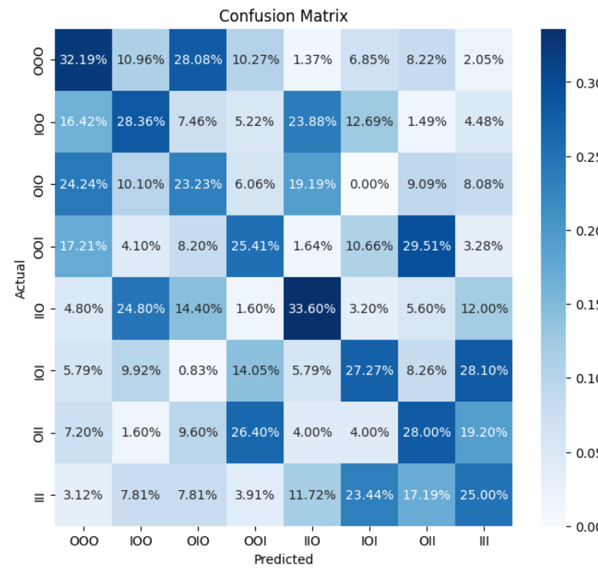

Fig. 4: Confusion matrix illustrating classification results

The confusion matrix shown in Figure 4 provides a detailed view of the classification results. The overall accuracy on the test dataset is **56%**. As it can be seen from the confusion matrix, the model performs well in classifying the class where all parking spots are empty (OOO) and the class where all parking spots are occupied (III). It is also noteworthy that the model performs well in classifying the class where only one parking spot is occupied (OOI, OIO, and IOO). However, the model confuses the classes where the states of two parking spots are the same and the third one is different. It also struggles to detect the occupancy of the middle parking spot and it confuses IOI with III. We suspected that this could be due to the placement of the Tx and Rx devices, which were placed on the sides of the row of parking spots. Different placement of the Tx and Rx devices were tested to evaluate their impact on the classification performance. However, the results were not significantly different from the ones presented here. While these results are not conclusive and the performance is not high enough for practical applications, they provide a good starting point for further research in this area. When compared to the results of WiParkFind that achieved an accuracy of 76% when predicting only the number of vehicles in a row of parking spots, our system shows potential for improvement in future iterations.

VI. Conclusion

In this paper, we have investigated the feasibility of using wireless sensing for parking spot occupancy detection in a low-cost and non-intrusive manner by detecting multiple parking spots simultaneously. We proposed a system that leverages off-the-shelf Wi-Fi devices to collect Channel State Information (CSI) data and employs machine learning techniques for classification. Our experimental results demonstrate that the proposed system can achieve an overall classification accuracy of 56% in detecting parking spot occupancy states. The results indicate that the system performs well in identifying the states where all parking spots are either empty or occupied, as well as when only one parking spot is occupied. However, the system struggles with cases where two parking spots have the same state and the third one is different, particularly when the middle parking spot is involved. The overall accuracy we achieved is lower than expected, which we attribute to the quality of the CSI data collected and the limited number of classes. We believe that further improvements can be made by optimizing the placement of the transmitter and receiver devices, as well as by experimenting with real vehicles instead of model vehicles. When compared to the existing systems, our system is significantly cheaper and easier to deploy. With the promising results we obtained, we believe that our system can be further improved and optimized for practical applications in parking management systems.

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