Sensing Objects Using WiFi Signal Communications

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***Abstract*- How does WiFi signal communication sense objects? Prior research has been conducted about wireless signal communication, specifically focusing on the potential for extracting valuable information about objects present within certain areas by developing data obtained from WiFi signals. The most analyzed types of data in Wifi signal communication are the Received Signal Strength (RSS) and Channel State Information (CSI). These analyzing types of communications have been shown to offer important details into a range of factors, such as the location, speed, direction, and movement of the objects. The main objective of this paper is to examine the complex method of object detection using the RSS and CSI of WiFi signals. It will provide a comprehensive examination of the processes involved in the emission and reception of these signals, thereby enlightening the various intricacies that play a significant role in determining their effectiveness as a means of detecting objects. In addition, this paper aims to explore the specific procedures that must be followed to capture the RSS and CSI of WiFi signals. As well as the ways various types of data can be applied to the task of object detection. By examining the nature of WiFi signal communications, and specifically, the role played by the RSS and CSI data in the detection of objects, this paper seeks to significantly improve the understanding of the subject matter. This paper will also explore the multiple applications and implications of how the findings with the detection of RSS and CSI of WiFi signals can be useful and what it means for the overall understanding of the subject. It is important to consider the larger context in which these technologies are presented to provide a thorough understanding of the relationship between WiFi signal communications and object-sensing capabilities. When conducting future studies of the various processes, procedures, and applications that come with WiFi signal communication, the information that is presented will help as a valuable resource for anyone who wished to educate themselves further on the topic. As well as those who are seeking to develop new and innovative approaches to object detection using WiFi signal communications.**

Keywords — WiFi signal communications, RSS, RSS-based sensing, CSI, CSI-based sensing

I. Introduction

In the present day of advanced technology, signals are everywhere. WiFi signals are by far the most widely utilized signals for internet connectivity and communication throughout the world. However, WiFi is not only a tool for connecting with others and streaming shows. It also has the potential to be used for sensing objects. The communication technology of WiFi signals has been widely studied and used in various applications such as the localization and tracking of WiFi-enabled devices. The Received Signal Strength (RSS) and Channel State Information (CSI) are two of the most commonly used parameters in WiFi signal communications. RSS is a proxy for channel quality and can be used for estimating the distance between devices. CSI, on the other hand, provides richer channel information in the frequency domain [1]. With proper processing, RSS can be used to accurately estimate the location of a user using WiFi signals, and a database of labeled RSS fingerprints [2]. While CSI can exhibit site-specific patterns in different environments while retaining a stable overall structure in the same environment [1]. This makes RSS and CSI excellent candidates for sensing objects using WiFi signals. To add, the overview of using WiFi signals sensing objects, including the use of RSS and CSI, their strengths and limitations, and the potential applications of WiFi-based sensing can explain the relationships between WiFi signal communications and sensing objects.

II. Received Signal Strength (RSS)

Received Signal Strength (RSS) is a measure of the strength of the signal received by a wireless device from an access point. It is a commonly used technology in wireless communication such as RFID, GSM, WiFi, and Bluetooth. RSS acts as a proxy for channel quality and can be used to measure environmental information such as propagation distances [1].

A. Received Signal Strength–Based Sensing

The process of capturing RSS involves measuring the power level of the signal received by a wireless device, such as a smartphone or WiFi access point. This measurement can be done using a variety of methods, including signal strength indicators on the device or software tools that capture RSS data from WiFi access points [2]. Sensing objects with RSS involves using the captured RSS data. This is mainly done by fingerprinting, where a set of RSS values from multiple access points is used to identify and locate a specific device or individual [1]. Other techniques include using RSS to estimate propagation distance, measuring human motion from RSS fluctuations, or detecting the presence of objects in the environment. By leveraging RSS, it is possible to achieve a highly accurate and calibration-free WiFi localization approach. This method specifically aims to minimize the impact of RSS fluctuations, which may arise from varying environmental conditions and heterogeneous hardware configurations. This is accomplished by constructing a supporting set (SS) and applying an advanced expectation maximization (EM) algorithm to intelligently estimate the user's label [2]. Figure 1 shows the general overview of the approach. Instead of direct matching, this approach constructs a supporting set (SS) in the online phase, which is a subset of the label set, selected by the similarity between the online RSS sample and offline database. SS is a latent space that likely includes the true label (location) of the user. Optimal Size Selection (OSS) is an important component of the approach for RSS-based WiFi localization. The OSS algorithm uses Bayesian Information Criterion (BIC) to adaptively determine a suitable size for the supporting set (SS). The OSS algorithm helps to ensure that the SS is not too large or too small, which can improve the accuracy of the location estimation. The algorithm balances the complexity of the model with its goodness of fit to the data to determine the optimal SS size. With the OSS algorithm, the approach can effectively mitigate the impacts of changing environments and heterogeneous hardware without the need for fingerprint or hardware calibration [2]. By incorporating fingerprint quality into the estimation of the true label using an expectation maximization (EM) algorithm, the true location of the user can be accurately estimated. The proposed EM algorithm consists of two steps: the expectation step (E-step) and the maximization step (M-step). The E-step evaluates the fingerprint quality in the SS to estimate the true label y, while the M-step maximizes the objective function to refine the estimation. By adaptively mitigating the impacts of changing environments and heterogeneous hardware simultaneously without fingerprint and hardware calibrations, this method is highly attractive in practical applications [2]. One advantage of RSS-based sensing is its low cost and easy administrations, only requiring WiFi-enabled devices and access points. Additionally, RSS-based sensing can be done in a privacy-preserving manner since it does not require wearable sensors or cameras. However, RSS-based sensing also has several limitations and disadvantages. One limitation is that RSS is single-valued and does not depict multipath propagation accurately, making it less reliable and robust in environments with dense multipath propagation. This can lead to unpredictable RSS fluctuations and limit the ranging accuracy [1]. Another disadvantage is that commercial WiFi hardware often lacks the sophistication needed for advanced radar signal processing, making it challenging to capture and process RSS data with sufficient time resolution and accuracy for certain applications [2]. However, RSS-based sensing remains a promising area of research, and various approaches have been proposed to overcome its limitations. For instance, researchers have explored using multiple-input multiple-output (MIMO) technology to harness multipath propagation and achieve higher accuracy in through-wall sensing of objects [1].

III. Channel State Information (CSI)

Channel State Information (CSI) is a critical element of wireless communication systems that describes the channel properties of any wireless communication link. It reveals detailed measurements of each subcarrier compared to the Received Signal Strength (RSS) of the entire WiFi channel. CSI conveys channel information that is invisible in the medium access control (MAC) layer, which provides richer channel information in the frequency domain [1]. CSI is captured from the WiFi signal by estimating the amplitude and phase of each subcarrier, using Orthogonal Frequency Division Multiplexing (OFDM) technology as shown in Figure 2. Each OFDM subcarrier is separated by CSI, which can manage to resolve multipath effects at the subcarrier level. By leveraging the proliferation of WiFi devices and networks, the reuse of WiFi infrastructures can enable ubiquitous sensing and large-scale deployments of sensorless sensing with WiFi [1].

A. Channel State Information–Based Sensing

CSI-based sensing is a novel approach in wireless sensing that has gained massive attention in recent years. Unlike traditional wireless sensing methods that rely on Received Signal Strength (RSS), CSI-based sensing uses the channel information invisible in the MAC layer and conveys richer channel information in the frequency domain [1]. CSI-based sensing involves capturing and processing the amplitude and phase of each subcarrier in the OFDM signal to identify site-specific patterns in different environments and retain stable overall structure in the same environment. The process of CSI-based sensing is complex and involves several stages. The first stage involves capturing the CSI data from the WiFi signal by estimating the amplitude and phase of each subcarrier using OFDM technology. The raw CSI data is then denoised and smoothed using the Discrete Wavelet Transformation (DWT) technique to filter out high-frequency components and burst noises while retaining the signal's quality. The filtered data is then passed through a set of high-pass and low-pass filters at each level, providing detailed and approximation coefficients, respectively. These detailed coefficients contain information about the noise and the abrupt changes caused by human activity. The next stage involves dimension reduction to reduce the overall computational complexity of the system, followed by spectrogram generation to capture the changes in the wireless signal caused by moving personnel and convert these into Doppler spectrograms in Figure 3 [3]. Figure 3 illustrates how the setup of the WiFi system impacts its ability to detect movement. People walked back and forth while their movements were recorded, and different WiFi layouts produced different results in the recordings. There are numerous applications that utilize both Received Signal Strength (RSS)-based sensing and Channel State Information (CSI)-based sensing techniques. On the other hand, CSI has been effectively utilized to develop a discreet, cost-effective, and easily implementable real-time motion detection and classification system. Previous research has extensively explored the practical use of CSI for human activity recognition, encompassing various applications such as motion localization, presence detection, crowd counting, and even keystroke detection. CSI is often favored over RSS for these specific applications because it can capture the authentic changes in the signal that are attributed to a person's movement. This is achieved by revealing the underlying channel properties of the wireless communication link [4]. To implement CSI-based sensing, a WiFi NIC is used to continuously monitor variations in the wireless channel using CSI. The NIC captures CSI values at each of the 30 subcarriers and stores them as a matrix, where its size is the total number of antennas used to receive the packet and represents the number of space/time streams transmitted. The amplitude and phase information in the CSI data can be used to extract features for motion detection and classification. One important aspect of implementing CSI-based sensing is developing a real-time processing system to collect and process the CSI data. This involves addressing four main tasks: ingesting incoming packets received from the router, parsing the packets into meaningful data, storing the data for future recall purposes, and plotting the CSI amplitude and variance in a time series. To accomplish this, the implementation may use Python's multiprocessing module to allow for the simultaneous execution of multiple processes. Another important aspect of implementing CSI-based sensing is selecting appropriate machine-learning techniques for motion classification. This may involve selecting features from the CSI data using techniques such as Discrete Wavelet Transform (DWT) [3]. Machine-learning algorithms such as Decision Trees, Naive Bayes, and Long Short-Term Memory (LSTM) can be used for object classifying detection based on the analyzed features. Each individually selected machine-learning algorithm depends on a certain specific application, such as the desired accuracy and the size and complexity of the dataset. The CSI system had strong signals across all frequencies, with higher frequencies indicating faster torso movements and lower frequencies indicating limb movements. In other activities, CSI had lower frequencies because the movements were slower. CSI-based sensing has several advantages, including its ability to pinpoint the availability of the line of sight (LOS) path in multipath environments, detect micro-body part motions and offer more information [1]. However, CSI-based sensing has some limitations, including its inability to distinguish between different types of human motions and the extent of motion granularity and variety that CSI is capable of distinguishing in practice. Furthermore, the system layout has a significant impact on the WiFi sensing performance, and the CSI system's size is too large to be directly used as input to a machine-learning algorithm for classification [3].

IV. IEEE 802.11bf

In terms of standardization and regulatory compliance, the IEEE 802.11bf standard incorporates essential features for power management and interference avoidance. CSI-based sensing and RSS-based sensing are two different methods of utilizing WiFi signals for sensing purposes. CSI-based sensing involves analyzing changes in the Channel State Information (CSI) of WiFi signals, which can provide information about the presence and movement of people or objects in the environment. CSI-based sensing extracts information from the MIMO transmissions between the access point (AP) and the client device, including the amplitude, phase, and angle of the signal. The presented information can be used to detect the movement, identify, and track people or an object’s location within an indoor environment. However, RSS-based sensing analyzes changes in the Received Signal Strength (RSS) of WiFi signals, which can also provide details about the presence and movement of objects within the signal area. RSS-based sensing can be used to detect the presence of objects, measure their distance, and track their movement within the environment. RSS-based sensing is a simpler method than the CSI-based sensing because it only requires measuring the power of the received signal [5]. The IEEE 802.11bf standard is designed to incorporate both CSI-based and RSS-based sensing. It provides a common framework for sensing applications, including standardized interfaces, data formats, and communication protocols. The standard also includes essential features for power management and interference avoidance, such as low-power modes and channel selection mechanisms. However, there are concerns about the collection and utilization of both CSI and RSS data information related to data privacy and security. To address these concerns, there must be standards and regulations that protect user privacy and ensure that data is collected and used in an ethical and responsible manner as possible. Regardless of these challenges, the potential benefits of WLAN sensing are substantial. One main benefit that it provides is that can be used for a wide range of applications, including smart homes, healthcare, and industrial automation. For example, in healthcare, WLAN sensing can be used to monitor patients and detect falls or other incidents. In industrial automation, WLAN sensing can be used to track the movement of goods within a warehouse or factory. Another example, in smart homes, WLAN sensing can be used to detect the presence and location of people or objects, adjust lighting and temperature settings, and track the movement of pets or children [5].

V. Conclusion

WiFi signal communications hold significant potential for sensing objects through the use of Received Signal Strength (RSS) and Channel State Information (CSI), both of which offer unique advantages and disadvantages depending on the specific application. Utilizing RSS-based sensing provides a cost-effective and easily implementable approach for a variety of applications, including localization, human motion sensing, and object detection. This method relies on measuring the power of the received signal to infer information about the surrounding environment, making it a versatile and accessible option for many users. On the other hand, CSI-based sensing leverages the abundant channel information available in the frequency domain to capture site-specific patterns in diverse environments while maintaining a stable overall structure within the same environment. This data offers the potential for higher accuracy and more detailed information about the environment it is located in. However, it is noted to not only observe the power of the received signal but also the phase and amplitude of the individual subcarriers that make up the signal. Both RSS-based and CSI-based sensing methods present their own unique strengths and limitations. With their effectiveness influenced by factors such as the layout of the WiFi system, the types of motions being detected, and the presence of interference from other signals or objects. WLAN sensing has the potential to transform the way individuals sense and interact with their surrounding environments despite the challenges it faces. By integrating communication technologies with sensing capabilities, users can gain a more extensive understanding of their environment. While they can also take advantage of this information in various applications. The continuation of the research and development in this field will be critical to fully utilize the potential of WLAN sensing and to address concerns related to privacy and security. As the technology evolves, it will be key to find a balance between maximizing the benefits of WLAN sensing. Furthermore, it also protects the privacy of individuals and the security of sensitive information. In summary, the relationship between WiFi signal communications and RSS-based and CSI-based sensing of objects showcases the numerous possibilities of integrating communication technologies with sensing capabilities. By leveraging the unique advantages of both methodologies and addressing the challenges associated with each, WLAN sensing has the potential to revolutionize the way interactions with and understand our surrounding environments. As research and development continue to advance in this field, it will be exciting to see the new applications and innovations that emerge from the integration of WiFi signal communications and object sensing.

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APPENDIX

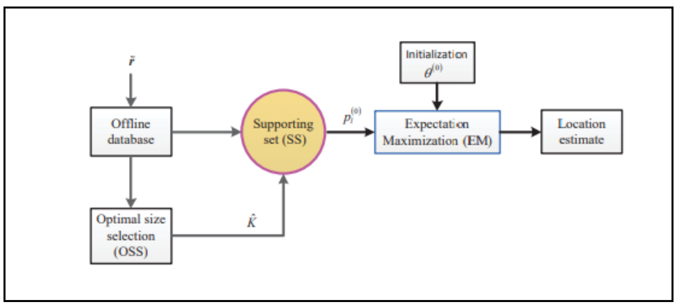

Fig. 1. Overveiw of the An Accurate and Calibration-free Approach for RSS-based WiFi Localization [2]

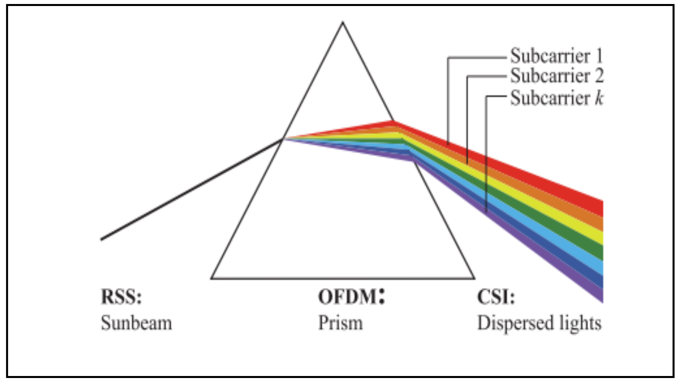

Fig. 2. Analogous illustration of RSS and CSI [1]

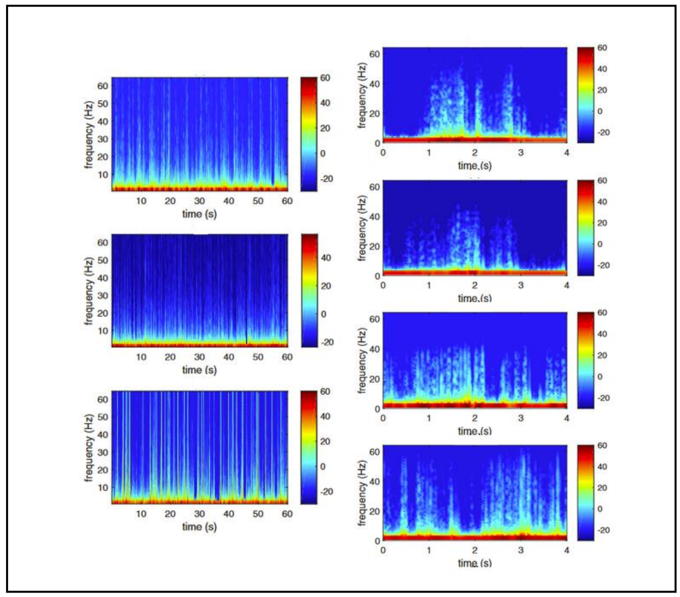

Fig. 3. Walking spectrogram from CSI (left) and slower movement spectrogram from CSI (right) [3]