Current State of Hardware and Algorithms in WiFi Radars

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***Abstract*—Recent advances in wireless sensing demonstrate the ability of commodity WiFi waves to detect human activity. Using IEEE 802.11 WiFi instead of cameras, wearable sensors and LiDARs can be a widely available and cost-effective solution to the human surveillance and detection problem. It can play a crucial role in applications, such as healthcare, intrusion detection systems and smart homes.**

WiFi sensing schemes rely on using the fine granularity of the physical layer CSI made possible by the OFDM modulation technique. This paper introduces the necessary theoretical background to cover wireless sensing. The most relevant state of the art is analyzed to determine the performance of WiFi based on different metrics and scenarios. Recent works are able to accurately estimate human pose using deep learning approaches. WiFi-based human recognition proves to be a reliable detection mechanism using off-the-shelf and low-cost hardware.

***Index Terms*—wifi, ofdm, csi, human detection**

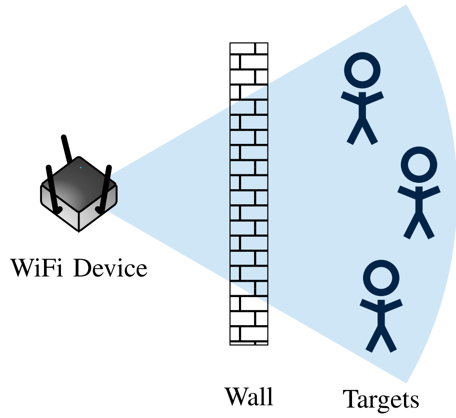

Figure 1: Environment for through-wall detection of human activity using WiFi signals.

1. Introduction

Human activity detection and sensing has been analyzed for various surveillance and monitoring applications for years. Such solutions are widely applicable in domains such as intrusion detection systems [1], healthcare [2], smart home [3], monitoring of children and elderly [1] or even augmented reality [3] and gaming [4].

When considering approaches for the estimation of human positioning, there are mainly three solutions. The first option relies on approaches based on visualization [5], such as 3D cameras. In this case, the cameras are used to capture images of humans to then recognize and match their activities [3]. However, the performance of this approach can be altered by physical factors, e.g., lighting conditions or angles blocked by objects [3]. A second solution to the detection problem is the use of wearable sensors [5], such as LiDAR and radar sensors [6]. Nonetheless, such devices have to be attached to the targets of the detection, which is not always feasible. Both of these approaches are characterized by high costs, power and energy consumption, and may sometimes be out of reach for daily use. This work focuses on another detection method which uses 1D sensors, more specifically, commodity WiFi signals for sensing.

The use of wireless signals for activity recognition has been receiving attention due to its cost-efficiency and high availability. Initial research has used the received signal strength indicator (RSSI) for indoor localization [7]. However, using the physical (PHY) layer for *channel state information (CSI)* proves to be more accurate for indoor localization than RSSI [7]. This is due to CSI's ability to have multipath characteristics, which offers a more accurate representation of the environment [7]. Multiple detection approaches use the PHY layer CSI provided by WiFi. The accuracy of this solution relies on the fine granularity of channel information offered by the *orthogonal-frequency-division-multiplexing (OFDM)* modulation, which is the standard for IEEE 802.11 a/g/n WiFi standards [7], [8]. For this approach, any activity in the environment is detected using the amplitude and phase information of the OFDM sub-carriers. The use of WiFi for indoor detection can be more effective than its counterparts since it is not prone to errors caused by illumination, dead angles and it also offers an off-the-shelf solution [6]. When comparing it to wearable sensors, it is also "non-invasive", since it is not required that the targets wear any additional equipment [1]. Thus, using commodity WiFi signals to detect human activity through walls can be a cost-effective, widely available and more private approach.

Figure 1 displays a typical system for through-the-wall detection using standard IEEE 802.11 WiFi. The blue highlighted area represents the sent WiFi signals coming from the transmitter antennas. Note that in this case, the WiFi device stands for both transmitter and receiver. The radio frequency (RF) signal crosses the wall and reflects off objects and targeted humans [4]. The detection of human activity is realized by capturing and analyzing these reflections. The main challenge is to distinguish

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between reflections that generate from the wall itself and from other objects in the room from the actual target. The power of the received signal is also highly reduced, since it has to pass through the wall twice [4]. The initial strong reflection from the wall creates a "flash effect" [4], which can hinder the sensing of the environment behind the wall. The CSI shows the correlation between transmitted and received signal waves, making it possible to detect motion in the environment [6].

The paper is organized as follows. Relevant properties of the used signal processing techniques, such as OFDM and CSI are described in 2. Section 3 shows the common approaches to the through-wall detection and sensing problem by presenting relevant state of the art. Finally, the conclusion and key findings are given in Section 4.

2. Preliminaries

This section offers background information needed to determine how WiFi signals are used to detect and sense humans through surfaces. The underlying multiplexing technique used by WiFi is the OFDM. Furthermore, the PHY layer CSI uses information offered by OFDM to detect motion between transmitted and received signal waves. Therefore, the two are introduced below.

2.1. Orthogonal Frequency-Division Multiplexing

OFDM is a multiplexing technique used in wireless applications, such as the IEEE 802.11 WiFi [8]. The main principle of OFDM is to split a high volume of data into smaller parts which are then transmitted simultaneously through sub-carriers. This makes OFDM a multi-carrier system [9], meaning that the channel is transformed into a set of multiple orthogonal carriers, which do not interfere with each other. The total bandwidth from the spectrum is split into multiple bands corresponding to each carrier, making it possible to transmit data in parallel [10]. In OFDM, the sub-channels are able to overlap without having interfering frequency spectra at the peak of the subband due to the orthogonality [8], given by the following condition:

$$\int_0^T \cos(2\pi n f_0 t)\cos(2\pi m f_0 t)\,\mathrm{d}\,t = 0, \quad n \neq m \tag{1}$$

where $n, m \in \mathbb{Z}_{\neq 0}$, f_0 is the fundamental frequency and T the time period of the integration [10]. Furthermore, one sub-carrier signal can be described as follows [8]:

$$s_n(t) = a_n e^{j2\pi f_n t} \tag{2}$$

for the transmitted data $\{a_0, a_1, ..., a_{N-1}\}$ and carrier frequency f_n. The sum of these signals of the N sub-carriers represents the whole sent signal, which corresponds to the following equation [8]:

$$s_k = \sum_{n=0}^{N-1} a_n e^{\frac{j2\pi nk}{N}} \tag{3}$$

Using the discrete Fourier transform (DFT) on the signal defined in 3, the received data can be recovered [8].

Figure 2 depicts a typical OFDM system, containing an OFDM transmitter and receiver part. The input information sequence is modulated using quadrature amplitude modulation (QAM), thus modulating the OFDM subcarriers. The signals are then transformed using inverse fast Fourier transform (IFFT). The resulting OFDM signal is completed after being transported through a digital-to-analog (D/A) converter. On the receiving end, the process is similar, but uses an analog-to-digital (A/D) converter, FFT and is demodulated to create the resulting output data.

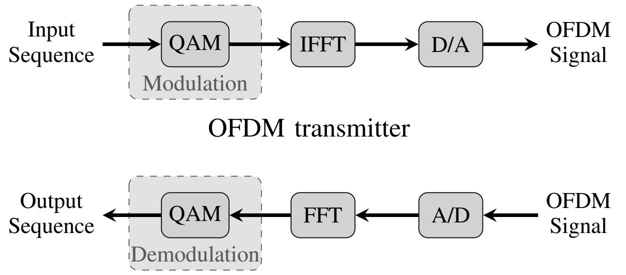

Figure 2: OFDM system based on [8], [10].

In a real OFDM application, for IEEE 802.11n WiFi, a 20 MHz bandwidth centered around a 2.4 GHz or 5 GHz central frequency is used [3]. Depending on the scenario, 30 up to 64 sub-carriers can share the channel. The bandwidth and sub-carrier number may also deviate.

2.2. Channel State Information

The first step towards human activity detection using wireless signal relies on the CSI given by the PHY layer. CSI describes the relation between transmitted and received signal wave [6]. Previously, the MAC layer received signal strength indicator (RSSI) was mainly used for wireless detection. Together with the sub-channel information of multiple-input-multiple-output (MIMO) and OFDM in IEEE 802.11 WiFi, CSI is able to deliver finer-grained information of the environment [5]. Being able to use the phase and amplitude information of each OFDM sub-carrier makes it more suitable and performant than its data-link layer counterpart [7].

In a WiFi channel, for each sub-carrier, transmitting a signal $\boldsymbol{x}$ and receiving a signal $\boldsymbol{y}$ denotes to:

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{n} \tag{4}$$

$$H_i = |H_i| e^{j\angle H_i} \tag{5}$$

where $\boldsymbol{H}$ is the CSI matrix and $\boldsymbol{n}$ the noise vector [11]. The CSI matrix estimates the modulated activity in the environment given the WiFi waves [5]. The three dimensions for the complex CSI matrix are for the i-th subcarrier with N_T transmitter and N_R receiver antennas [5]. Furthermore, the amplitude $|H_i|$ and phase $\angle H_i$ for each complex CSI value H_i of a sub-carrier can be denoted as in equation 5 [5], [7].

3. WiFi Detection Implementations

There are multiple approaches possible to the WiFi sensing problem. This Section gives an overview of the most relevant state of the art in the domain. Works that do

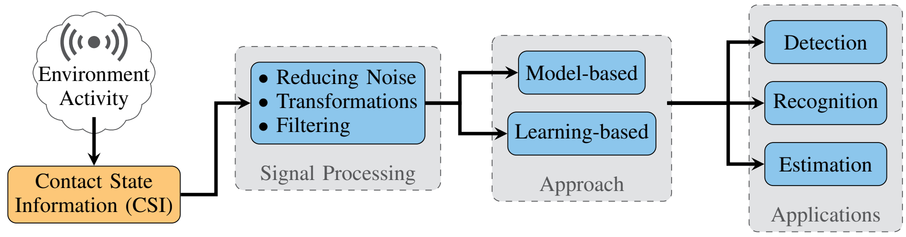

Figure 3: Approaches for through-wall human sensing using WiFi based on [3], [5], [11].

not necessarily cover through-wall detection play an important role in the ongoing research and are thus analyzed as well. Table 1 gives an overview of the main characteristics of the works, such as accuracy scores, used hardware and covered human positioning during the experiments. Even though there are multiple implementations, most of them follow a similar pattern. Figure 3 depicts a block diagram of the typical flow when it comes to human detection using WiFi waves. The first step is to generate the WiFi signals to capture environment activity. The fine granularity of CSI is used to extract information from the received signal. The captured CSI measurements are then processed by applying noise reduction, transformations (e.g., FFT, discrete wavelet transform) and filtering techniques to eliminate outliers and increase performance [11]. Processed CSI can be used by a model-based or learning-based approach for different applications, such as human detection, recognition or estimation.

Passive Bistatic WiFi Radar (PBWR). In [12], Chetty et al. present one of the first attempts (2012) for through-the-wall (TTW) detection with WiFi by using a passive bistatic WiFi radar. The authors test their implementation to detect a moving human. The WiFi wave signal transmitter is a 802.11 WiFi AP placed in the same room, 4 m away from the target. The passive bistatic radar consists of two receivers placed outside the room at a standoff distance. The data is processed offline first by applying range-Doppler mapping. The *CLEAN algorithm* is then introduced to remove digital signal interference (DSI) and additional stationary clutter. For target detection, a 2D constant false alarm rate is used. The signal-to-interference ratio (SIR) is the main metric for the TTW target responses. Results show that using CLEAN, the SIR is decreased by 19 dB, creating a more accurate detection.

Wi-Vi. Adib and Katabi [4] present Wi-Vi, a TTW detection device. The main components of the Wi-Vi device are two transmitter and one receiver antennas. Compared to the previous implementation, Wi-Vi does not need to have any device located within the same room as the target. One main aspect analyzed by this work is the initial reflection from the wall that is much stronger than the reflections off the objects behind the wall, creating a "flash effect". The authors use iterative nulling together with power boosting to tackle this challenge, by nulling the strongly reflected signal. An inverse synthetic aperture radar (ISAR) is used for motion tracking. Experiments are carried within a conference building having walls of different building materials and thickness. Wi-Vi can detect one or multiple moving human targets and gestures. The detection scores are 100% for 0 to 1 targets. For multiple humans, Wi-Vi shows an accuracy of 85%. When considering gesture detection, the accuracy reaches 93% for closer and 75% for longer standoff distances. Wi-Vi delivers high detection accuracy for thin building materials (wood, glass, door, 15 cm hollow wall), but drops at 87% for a concrete 20 cm wall.

DeMan. Wu et al. introduce DeMan [1], a solution for "non-invasive DEtection of moving and stationary huMAN with commodity WiFi devices". Unlike previous works, DeMan also focuses on detecting stationary humans by choosing breathing (chest motions) as a sensing factor. However, this work does not cover through-wall detection. The scheme is based on the amplitude and phase values of the OFDM sub-carriers given by CSI. The experimental hardware consists of a IEEE 802.11n WiFi AP transmitter and a laptop equipped with a NIC receiver. DeMan delivers high accuracy for the conducted experiments in true positive scenarios: 99.86% for absent, 93% for stationary and 95% for moving humans respectively.

WiSpy. Hanif et al. propose WiSpy [13], a CSI-based through-wall movement sensing and person counting scheme, which uses commodity WiFi waves. Two Intel NUCs are placed in front of a 33 cm brick wall. In their approach, the authors use machine learning (ML) algorithms on the processed CSI data to predict the amount of people behind the wall. Principal component analysis (PCA) is applied on the CSI measurements for dimensionality reduction. This work also compares multiple ML algorithms on the PCA data. Results show, that using decision trees (DT) delivers the best results, i.e., a detection accuracy of 96.97%. On the other hand, k-nearest neighbor (KNN) delivers the poorest performance, having a detection accuracy of under 80%.

Person-in-WiFi (PiW). In [14], Wang et al. introduce one of the first WiFi-based person perception schemes, implementing body segmentation and pose estimation. A deep learning approach is used to map WiFi samples to 2D human body segmentation using recorded RGB videos. During the experiments, subjects are placed between transmitter and receiver, without having any walls or obstructing stationary objects in-between. The setup consists of two WiFi NICs, one used for transmission, one for receiving, each having 3 antennas. To implement a deep learning approach for person perception, CSI measurements and video frames are taken at the same time stamps. Body segmentation maps are constructed using region-based convolutional neural networks (R-CNN). For pose estimation, however, the Body25 model of OpenPose is used. The proposed approach shows high performance

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TABLE 1: WiFi radar sensing implementations comparison.

	PBWR [12]	**Wi-Vi** [4]	**DeMan** [1]	**WiSpy** [13]	**PiW** [14]	**HARNN** [3]	**DensePose** [6]	**GoPose** [15]
General								
accuracy	–	>85%	>94%	96.97%	>85%	>95%	>87%	<5cm error
carrier freq.	2.4 GHz	2.4 GHz	2.4 GHz	5.18 GHz	2.4 GHz	5 GHz	5 GHz	5.32 GHz
bandwidth	16 MHz	20 MHz	20 MHz	20 MHz	20 MHz	20 MHz	20 MHz	40 MHz
hardware	DWL 2000AP+	WiFi antennas	Intel 5300 NIC	Intel NUC	Intel 5300 NIC	Intel 5300 NIC	WiFi antennas	Intel 5300 NIC
Human position								
moving	✓	✓	✓	✓	✓	✓	✓	✓
stationary	✗	✗	✓	✗	✗	✓	✓	✓
pose estimation	✗	✗	✗	✗	✓	✗	✓	✓
through-wall	✓	✓	✗	✓	✗	✗	✗	✓

for whole person profiles, having detection scores between 85% and 91%. Low performance of WiFi signal detection is demonstrated for small body parts due to WiFi's wavelength of 12.5 cm.

HARNN. A CSI-based WiFi detection scheme for human activity recognition using recurrent neural networks (HARNN) is introduced by Ding et al. in [3]. This work firstly uses a two-level decision tree leveraging the variance and correlation coefficient of the CSI measurements to detect activity in the environment. Moreover, the noise is eliminated from the raw CSI using channel power variation (CPV) and time-frequency analysis (TFA) in time and frequency domain respectively. Detection of various human activities (e.g., running, walking, sitting etc.) is achieved using a RNN model with a long short-term memory (LSTM) block. A WiFi device is used for transmission together with a Intel 5300 NIC as a receiver. The experiments are carried in a closed off environment, through-wall detection, however, is not covered. HARNN reaches detection accuracies of 95% and 96% for all the mentioned activities. The authors also point out, that increasing the amount of receivers yields better detection rates of 96% up to 98% on average.

DensePose. Geng et al. propose DensePose [6], a study that aims to achieve body segmentation and key-point body detection using commodity WiFi signals. Similar to HARNN, after sanitizing the raw CSI data, the amplitude and phase of the 30 OFDM sub-carriers are mapped to 2D feature maps. The data is passed through a DensePose-RCNN architecture, used to predict UV coordinates of the human body. UV maps create a correlation between 3D and 2D human data. The main goal here is to map 1D CSI data to UV maps, thus transforming the data into spatial domain. The correlation between CSI samples and video captures is achieved similar to HARNN. In addition, DensePose uses transfer learning from the image-based network to the WiFi-based one to reduce training time. The testing environment uses three transmission and three emission antennas. The authors test out their approach in multiple layout scenarios. The implementation yields high accuracies of over 87% for the same layout used in training. However, when deployed within an unknown layout, the average precision (AP) of the model drops (e.g., from 43 AP to 27 AP). The detection accuracy also suffers when faced with human body poses, which did not occur during training. Moreover, the results are not entirely clear once there are more than three human targets in the testing space. The authors thus motivate generating more training data to solve the failure cases.

GoPose. In [15], Ren et al. present GoPose, a scheme used to estimate human pose using WiFi signals. The novelty relies on the tracking of 3D skeleton-based human poses, compared to the 2D version of PiW. The implementation is able to track both stationary and moving targets. Unlike previous works, GoPose manages to estimate unseen activities as well. It also works when being faced with walls, screens or other stationary objects. The scheme builds up on sanitized CSI measurements of 30 OFDM sub-carriers. In addition, it uses the 2D angle of arrival (AoA) spectrum to determine between reflections off objects and targeted bodies. To map 2D AoA spectra to 3D skeletons of humans, the authors use a deep learning approach based on CNN and LSTM. Estimating the 3D pose of people requires a higher amount of devices for the setup. One transmitter and four receivers are used in the testing environment. The transmitter uses three linear antennas, whereas the receivers are equipped with L-shaped antennas. Results are evaluated using joint localization errors. GoPose is able to accurately track stationary human targets, having low errors of 0.4 cm. Testing through-wall detection yields errors of an average 4.7 cm. Similar to prior works, the estimation success rate decreases when faced with multiple people due to multiple reflections.

4. Conclusion

This paper analyzes the use of commodity WiFi signal waves for human sensing. Preliminaries required for the standard IEEE 802.11 WiFi signal analysis, such as CSI and OFDM, are introduced. The analyzed related works show that WiFi radar is a competitor to cameras or wearable sensors due to its wide availability, power efficiency and low cost. Under normal circumstances, most implementations reach detection accuracies over 85%.

With the rise of machine learning over the years, previous CSI-based sensing schemes have been improved using more complex deep learning architectures to be able to estimate 3D posing of humans. Current research still faces issues when it comes to detecting smaller body parts, large stand-off distances and multiple human targets. Moreover, the proved accurate WiFi sensing also raises an issue to the networking community regarding security and regulations of WiFi signals.

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