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A Robust Person Identification Method Through Wi-Fi Signals

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Abstract

This thesis deals with myself.

Contents

| | | |
|----------|--|----------|
| 1 | Introduction | 1 |
| 2 | The Wireless Channel | 3 |
| 2.1 | Electromagnetic Waves | 3 |
| 2.2 | I/Q sampling | 5 |
| 2.3 | Orthogonal Frequency-Division Multiplexing | 6 |
| 2.4 | Channel State Information | 7 |
| 3 | Signal Preprocessing | 8 |
| 3.1 | Amplitude Sanitization | 8 |
| 3.2 | Phase Sanitization | 9 |
| 3.3 | Data exploration and structuring | 11 |

Chapter 1

Introduction

In the last years, Wi-Fi technology is turning into a ubiquitous and fundamental tool, not only for providing constant and easy-access internet connection but also for enabling the development of the Internet of Things and radio-based sensing applications. Cutting-edge Wi-Fi sensing systems use wireless signals to detect events or changes, such as motion and gesture recognition [1], in the permeated environment leveraging the disturbances and variations in the received radio signal. In this work, Wi-Fi sensing technology is employed for person Identification, a task usually achieved by vision-based systems through the use of RGB cameras. In common scenarios, person Identification is a classification task where the input features, such as an image or a video of a particular individual, is examined in order to recognize him among a specific set of people. To reach this goal, in modern approaches the raw input image is analyzed in order to model a person appearance and physical constitution, by extracting some key features that will be use for inference, as shown in Fig. 1.1. State-of-the-art methods include leveraging deep learning models trained to identify a human, like: Convolutional Neural Network for detecting the face of the person [2] and recognize him; Recurrent Neural Networks [3] and their variants, such as LSTMs, for working with sequences of data like video sequences and exploiting the unique person behavior like the walking gait [4]; Attention mechanisms, as seen in models like Transformers [5], for their ability to focus on relevant parts of an image or sequence therefore locating the discriminative features. Although vision-based methods have achieved remarkable results, several issues arise during real-world scenarios, including: subject occlusion and pose; different viewing angles and image scale; ambient changes in illumination; modifications in personal look (clothes, haircut, glasses) and privacy concerns due to the sensitive nature of personal imaging data. To address these challenges, a non-conventional approach can be adopted, that walks away from images and vision avoiding the aforementioned issues, through the use of completely different types of data: Wi-Fi signals.

Wi-Fi technology has revolutionized the way we connect and communicate in the digital age. It enables wireless communication between devices by utilizing radio signals transmitted by access points (APs). The signals can be influenced by various factors, such as objects and people, leading to signal variations along their path. These variations, essential for understanding the wireless environment, are captured through measurements like the Received Signal Strength Indicator (RSSI) and



Figure 1.1. Image-based person ID within a group of 5 people.

Channel State Information (CSI), which play a pivotal role in implementing wireless sensing applications. The RSSI serves as a measure of the reduction in the strength of radio signals as they travel through space, capturing the way signals diminish over distance. Even though this metric has found widespread utilization within numerous indoor localization systems [6, 7], which goal is to find where a certain target is in an enclosed location with meter-precision, it experiences unsustainable performance drops in complex situations, due to several limitations. The problems associated with RSSI stem from its simplicity and lack of granularity, which restrict its ability to capture detailed signal characteristics and changes accurately. In fact, for a given wireless data packet, RSSI provides a single value computed at MAC layer, that represents the overall signal strength, without differentiating between the effects of multipath interference, signal reflections, or other external factors. Moreover, the relationship between RSSI values and the real signal strength is often non-linear, so that small changes in RSSI may not correspond to proportional changes in signal strength, making it challenging to interpret signal variations accurately. For these relevant reasons, RSSI fails to provide detailed insights into how the signal interacts with the surrounding environment [8]. On the other hand, the CSI is derived from the PHY layer's orthogonal frequency-division multiplexing (OFDM) transmission technology and includes detailed signal information defined at the subcarrier level, making it more stable and capable of carrying a higher level of signal information. CSI measurements offer access to a broader range of signal properties, including amplitude and phase for each subcarrier, providing higher granularity than RSSI [9]. Furthermore, CSI can be computed using commodity Wi-Fi devices, making it a popular choice in Wireless sensing applications. To ensure the quality of received CSI measurements, signal pre-processing techniques are often employed, such as removing amplitude outliers and phase offsets, and machine learning or deep learning approaches are subsequently applied to address the specific final task.

Ultimately, previous investigations on electromagnetic waves interactions with biological tissues [10] have revealed that signal propagation around a human body is highly dependent on biometric characteristics, such as body structure, weight, height, skin and tissues composition, with a great variability among different individuals. The aim of this work is then to harness the biological-related radio signals fluctuations, captured by CSI, that occur in a Wi-Fi-pervaded environment when a person is present, and extract important insights to enable the person Identification.

Chapter 2

The Wireless Channel

This section introduces the theoretical concepts related to the wireless communication channel, that are necessary to grasp the foundational technology behind Wi-Fi sensing applications, such as Human Identification

2.1 Electromagnetic Waves

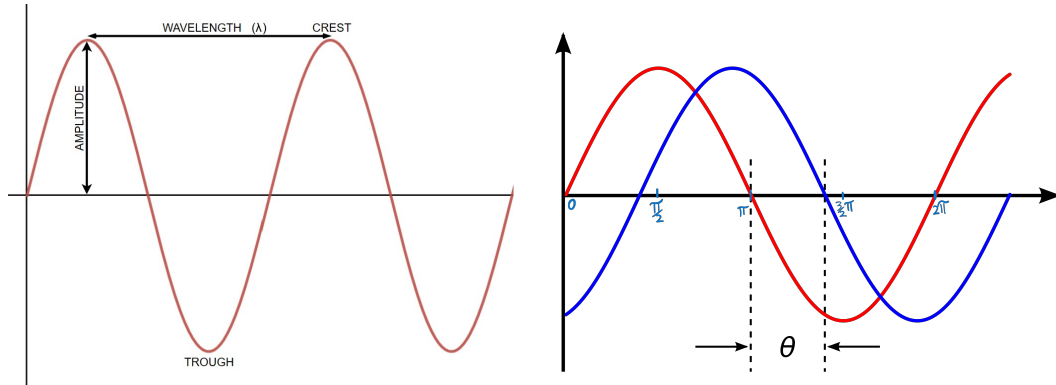
The fundamental characteristic of all wireless communications, including Wi-Fi transmission, is the use of Electromagnetic (EM) radiation to carry information, encapsulating data in the form of EM waves. In a vacuum, electromagnetic waves travel at the speed of light (around 299 792 km/s) denoted by the letter c . When passing through a material medium, they are slowed depending on the medium's permeability and permittivity but the air in the Earth's atmosphere is thin enough that EM waves travel very close to the speed of light. Each wave is produced by a transmitting antenna (TX) that generates synchronous oscillations between electric and magnetic fields, and it is characterized by several properties, shown in Fig. 2.1a: The wavelength, measured in meters, which is the distance between consecutive corresponding points of the same phase on the wave, such as two adjacent crests (the highest points), troughs (the lowest points), or zero crossings; The amplitude, in meters, that is the distance from the resting position to the maximum displacement of the wave; The frequency, measured in Hertz (Hz), that is the number of oscillation cycles per second or how many crests (or troughs) pass a location in a certain amount of time. The frequency is equal to $1/p$, where p is the period of the wave, which is the time in seconds that the signal takes to return to the equilibrium position, starting from the previous one (also called a full "cycle"). The mathematical link between the frequency f , the wavelength λ , and the wave propagation velocity v is expressed as follows:

$$f = \frac{v}{\lambda}$$

Where in vacuum $v = c$, the speed of light, as explained before. From the previous equation we get:

$$v = f\lambda \quad \text{and} \quad \lambda = \frac{v}{f}$$

indicating how the frequency and wavelength of an EM wave are directly proportional to the propagation velocity and inversely proportional to each other.



(a) Representation of a wave's properties

(b) Illustration of a phase shift.

The last key component used to describe a wave is the phase. The phase of a wave refers to its position within one complete cycle, describing how much of the cycle has occurred at a specific point in space and time. It is often measured in radians or degrees, and it helps determine where a wave is in its oscillation at a given moment. A phase angle of 0 represents the starting point of a cycle, while 2π (or 360°) corresponds to one complete cycle. When comparing two waves, the phase difference, or phase shift, is the angular difference between their phase angles, and it indicates how "out of sync" or "in sync" they are, as seen in Fig. 2.1b. Considering two sinusoidal waves, when the phase difference is a multiple of 2π , the addition of the two waves results in a constructive interference, leading to reinforcement and a larger amplitude. Vice versa, destructive interference occurs when the phase difference is an odd multiple of π , leading to cancellation and a smaller amplitude.

With those characteristic we can formulate the mathematical representation of a periodic wave, that tells us the momentary amplitude at instant t :

$$a(t) = A \cos(2\pi ft + \phi)$$

made up of the following components:

- $a(t)$: The instantaneous amplitude of the wave at time t .
- A : The amplitude of the wave, its maximum value.
- $2\pi f$: The angular frequency in rad/s , where f is the frequency in Hertz ($1/s$)
- t : The time in seconds, indicating the instant at which you evaluate $a(t)$
- ϕ : The phase offset, in radians, that determines the wave' starting position.

When ϕ is non-zero, the entire waveform appears to be shifted in time by $\frac{\phi}{2\pi f}$ seconds. A negative value represents a delay, and a positive value represents an advance. The above equation describes a sinusoidal wave as a function of time, and it's a fundamental building block in understanding and modeling periodic oscillations and waveforms in various fields of science.

2.2 I/Q sampling

In many real-world applications, information is transmitted through analog signals, which vary continuously over time. To process and analyze these signals using digital electronics, they need to be converted into a discrete digital form, a process known as sampling. I/Q sampling is a method used to sample and represent a complex-valued analog signal, from which we can retrieve both amplitude and phase information. The "I" component represents the in-phase or real part of the signal, while the "Q" component represents the quadrature or imaginary part of the signal. Denoting with A the amplitude and with ϕ_t the phase of the wave at instant t , we got:

$$I(t) = A \cos(\phi_t) \quad \text{and} \quad Q(t) = A \sin(\phi_t)$$

Now, we can construct the complex number at any given time t by combining the "I" and "Q" components

$$Z(t) = I(t) + jQ(t)$$

Where j is the imaginary unit ($j^2 = -1$). Therefore, as depicted in Fig. 2.2, any sinusoidal wave can be described by a composition of those two components (that is, by a single complex number), from which it is possible to obtain the amplitude and the phase using the following equations:

$$A = \sqrt{I(t)^2 + Q(t)^2} \quad \text{and} \quad \phi_t = \text{atan2}(I(t), Q(t))$$

The first formula is simply the Pythagorean theorem applied to the two sides, in our case I and Q, to find the hypotenuse, that matches the amplitude. The second one uses $\text{atan2}(x, y)$, a function that returns the angle formed by any vector $[x, y]$ with the positive x-axis, bounded in the interval $(-\pi, \pi]$. The angle is positive if counterclockwise, negative if clockwise. Additionally, since $\cos(x) + j \sin(x) = e^{jx}$, we can represent the I/Q sample in the Euler's form:

$$Z(t) = A(\cos(\phi_t) + j \sin(\phi_t)) = Ae^{j\phi_t}$$



Figure 2.2. Decomposition of a wave in I/Q components.

2.3 Orthogonal Frequency-Division Multiplexing

Orthogonal frequency-division multiplexing (OFDM) is a modulation scheme used in wireless communication systems such as 802.11n which encodes data streams into multiple overlapping subcarrier frequencies. In a traditional single-channel modulation scheme, each data bit is sent serially or sequentially one after another. With OFDM a single information stream is split among several closely spaced narrowband subchannel frequencies instead of a single Wideband channel [11]. This enables each substream's data rate to be lower than would be required by a single stream of similar bandwidth and makes the system less susceptible to corruption. Even though the subchannel frequencies are closely spaced and do overlap to a degree, they remain orthogonal, maintaining their distinct separation due to meticulous selection. This strategy ensures that any interference is effectively negated.

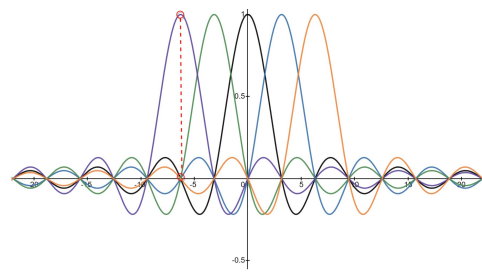
OFDM signals are modelled in the frequency domain as the *sinc* function:

$$\text{sinc}(f) = \frac{\sin(f)}{f}$$

The *sinc* function has a central peak at zero frequency and then oscillates symmetrically around zero. It is characterized by its main lobe, which contains most of its energy, and smaller side lobes that decrease in amplitude as you move away from the central peak, as seen in Fig. 2.3a. The choice of the *sinc* function is made due to its property of enabling orthogonal placement of each subcarrier with respect to the others [12], as illustrated in Fig. 2.3b where five *sinc* functions are strategically positioned so that the primary subcarrier frequency (one is marked in red) coincides with a frequency at which all accompanying *sinc* functions assume a value of zero. This orthogonal configuration ensures that the summation of all five selected subcarriers maintains its peak values, as presented in Fig. 2.3c.



(a) The *sinc* function for a single subcarrier signal.



(b) Orthogonal *sinc* functions for multiple subcarriers.



(c) Signals summation.

In order to transmit bits, a signal undergoes modulation. In wireless communication, modulation is the process of altering one or more characteristics of a periodic waveform, called the carrier signal, with a separate signal called the modulation signal that typically contains information to be transmitted. With OFDM, each subcarrier represents a single digital symbol that is being transmitted and can be modulated through various methods [13] such as Amplitude Shift Keying (ASK), Binary Phase-Shift Keying (BPSK) or Quadrature Amplitude Modulation (QAM). ASK involves switching the amplitude of the carrier signal between two different levels (high and low) to represent binary data while BPSK achieves the same thing by altering the phase (usually 0° and 180°) to represent the travelling bits. QAM, widely used in Wi-Fi communication systems, combines instead both amplitude and phase modulation to convey multiple bits of digital information in each modulation symbol, resulting in a higher data rate. Every OFDM symbol encodes binary data into a complex number by means of I/Q samples, as explained in Section 2.2. For instance, 16-QAM has the capacity to express 4 bits of information using just one complex number [14].

2.4 Channel State Information

CSI is the metric used in OFDM systems for describing amplitude and phase variations across subcarrier frequencies as wireless signals are transmitted between a transmitter and a receiver. To detect these variations across subcarriers, OFDM systems transmit a set of known shared pilot symbols (either interleaved in the transmitted message or as a preamble) which are then used to estimate the CSI vector H as:

$$y = H \odot x + \eta$$

where y is a vector indicating the signal detected at the receiver, x is the signal vector that was transmitted based on the agreed upon pilot symbols, \odot is the element-wise multiplication and finally η is an additive white Gaussian noise vector. H is a complex vector containing a complex number (I and Q components) for each subcarrier representing the Channel Frequency Response (CFR), from which we can retrieve the amplitude and phase of the specific subcarrier signal. Throughout this work, two ESP32 microcontrollers are employed as TX and RX antennas [15], that perform OFDM communication with a bandwidth of 20MHz using a total of 64 subcarriers. Multiple CSI samples are collected over a time window of size W , which can be represented as the $W \times S$ matrix

$$H = \begin{bmatrix} IQ_{11} & IQ_{12} & \dots & IQ_{1S} \\ IQ_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ IQ_{W1} & IQ_{W2} & \dots & IQ_{WS} \end{bmatrix}$$

where S is the total number of subcarriers. In our case, 64 are employed, of which 12 are guard (null) subcarriers, resulting in having a final set of 52 usable informative subcarriers, at a rate of transmission of 100 packets (observations) per second.

Chapter 3

Signal Preprocessing

This chapter explains the various methods used for preprocessing the available data, an essential procedure applied for structuring the dataset and cleaning the CSI acquisitions, therefore making the system more robust and less susceptible to noise.

3.1 Amplitude Sanitization

During wireless transmissions, signal amplitudes can experience outliers or anomalies due to various factors and causes. These outliers can adversely affect the quality of the received signal and the overall performance of the Wi-Fi system. Electrical spikes, equipment instability, external interference and sudden movements in the environment are some possible sources of noise. To mitigate the effect of spurious data, the Hampel Filter [16, 17] is employed, that exploits a sliding window and compares its central value with the Median Absolute Deviation (MAD), a robust statistical measure of the variability of a dataset defined as:

$$MAD_w = \text{Median}\{ |x - \text{median}(X_w)| \mid \forall x \in X_w \}$$

where X_w is a portion of the entire dataset defined by a sliding window w of fixed length, where the length is an odd number. Then, the central point $x_{w/2}$ in the sliding window is considered an outlier if:

$$|x_{w/2} - \text{median}(X_w)| > \beta MAD_w$$

where β is an application dependent hyperparameter: in our case $\beta = 3$, in alignment with the prevalent choice in the literature. The detection procedure is performed independently on each subcarrier's amplitude series, and every discovered outlier is substituted with a prediction made by the Exponential Smoothing of the previous values in the window, to preserve temporal information consistency, formalized by:

$$s_0 = x_0$$

$$s_{i+1} = \alpha x_i + (1 - \alpha)s_i \quad \forall i \in [0, w/2)$$

Where i indexes the samples in the first half of the window, s_i is the smoothed value, x_i is the observation and α is the smoothing factor. A lower value of alpha

gives more weight to past observations and produces a smoother forecast, while a higher value of α gives more weight to current observations and responds faster to changes. In this work the value is set to $\alpha = 0.8$, but further testing and tuning could be required. For what regards the initial and last values of the dataset, those that have a number of observations to their left or their right less than half of the window size, a static MAD filter is applied over the corresponding slices of size $= w/2 - 1$, and the outliers are substituted with the median. As an extra relevant characteristic, the Hampel Identifier doesn't pose any strong assumption on the distribution of the data and works well even with non-normally distributed points. This is a clear distinction with respect to other outlier detection statistical methods such as the Z-Score, that uses the mean and the standard deviation to discern anomalies from the rest of the dataset. These measures assume that the data follows a symmetric Gaussian distribution, and they can be highly affected by skewness or extreme outliers in case of non-normally distributed data. On the other hand, using the Median ensures resistance to skewness and to outliers with large magnitude, and does not require any normality assumption.

The effect of the outlier removal procedure just described is the substitution of the most relevant outliers, but the series still preserve overall impurities causing large variance and heteroscedasticity. To get rid of the noise, Discrete Wavelet Transforms (DWT) is employed, a common method for signal denoising. Other possible solutions include the application of a smoothing function, such as Weighted Moving Average and Exponential Smoothing, but using more complex frequency based methods like Fourier Transforms and DWT is usually preferred. Fig. 3.1 shows the effect of applying Hampel Filtering with window size set to 51 and smoothing factor of 0.8 followed by DWT to the amplitudes of subcarrier 12^{th} . The DWT decomposes a signal into multiple scales using wavelet filters. High-frequency noise is concentrated in detail coefficients, while signal features are found in approximation coefficients. By applying a threshold to detail coefficients that modifies them and reconstructing the signal with the inverse DWT, this technique effectively removes noise while preserving essential signal information [18] at different frequency scales, producing a smoothed version of the original data.

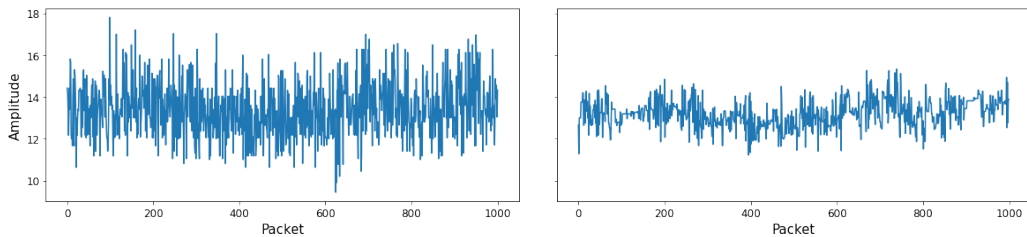


Figure 3.1. Raw and filtered amplitudes of a single subcarrier over 10 seconds of acquisitions.

3.2 Phase Sanitization

Due to random noise and unsynchronized time clock between transmitter and receiver, raw phase information behaves extremely random, making it almost inapplicable for any task. The issue is that phase data is affected by the carrier frequency

offset (CFO) and sampling frequency offset (SFO) [19]. The CFO arises when the transmitter and receiver do not precisely synchronize their timing and phases before transmitting a packet, while the SFO is caused by analogue to digital converter, and it also varies by subcarrier, so each of them has a different error in the end. The key observation is that significant component of random phase offsets can be removed by employing a linear transformation [20, 21] on the raw phase readings. Indeed, the measured phase $\hat{\phi}_i$ for the i^{th} subcarrier can be expressed as:

$$\hat{\phi}_i = \phi_i - 2\pi \frac{k_i}{N} \delta + \beta + \eta$$

where ϕ_i is the true phase, δ is the timing offset at the receiver that leads to the error expressed as the second term, β is an unknown phase offset and η is some measurement noise. k_i is the subcarrier index, ranging from -26 to +26 and N is the Fast Fourier Transform (FFT) size, a parameter found in the IEEE 802.11 specifications. To mitigate the impact of random noises, linear transformation on the raw phases is performed. The key idea is to eliminate δ and β by considering the phase across the entire frequency band. Firstly, we define two terms a and b as follows:

$$a = \frac{\hat{\phi}_n - \hat{\phi}_1}{k_n - k_1} \quad b = \frac{1}{n} \sum_{j=1}^n \hat{\phi}_j$$

Subtracting the linear term $ak_i + b$ from the raw phase $\hat{\phi}_i$, we obtain a linear combination of true phases, denoted as Φ_i , from which the random phase offsets have been removed (omitting the small measurement noise η):

$$\Phi_i = \hat{\phi}_i - ak_i - b$$

Fig. 3.2 illustrates an example of the phases after transformation, which distributes relatively stable as expected compared to the original random version. Although it cannot be claimed the sanitized information is just the true phase, a usable and effective feature of the true phases is derived [22].

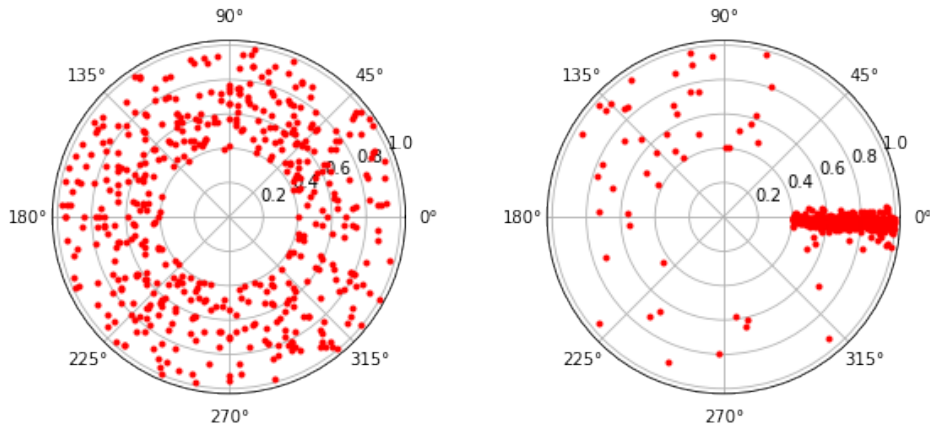


Figure 3.2. Raw and sanitized phases of subcarrier 9^{th} of 500 consecutive packets.

3.3 Data exploration and structuring

The main idea behind this work is that the presence of a human being in an area where a wireless communication is occurring, distorts the EM waves in a unique manner, resulting in a person-specific CSI acquisition. Body characteristics such as shape, weight, mass distribution, height, tissues and cellular composition have different levels of radiation absorption and reflection, affecting the phase and amplitude of the arriving signals. This effect is of a particular magnitude if the distortion element, an object or a person, is located in the Line-Of-Sight (LOS) path between the communicating antennas. This is because during a wireless transmission, the final signal is the result of a multipath propagation of the initial signal that is altered by the room structure and furniture, but the LOS part of the wave usually overwhelms the other components coming from the multipath since it hasn't been affected by any object. Moreover, the transmission distance is the shortest when considering the LOS with respect to other paths, leading to less signal fading and attenuation.

Fig. 3.3 represents the amplitude of each subcarrier over time as a heatmap plot, where the scale goes incrementally from darker to lighter color, after the outlier filtering procedure describe in Section 3.1. The x-axis values are the different subcarriers, ranging from index -26 to +26, while the y-axis represent the time steps for a total of 200 observations (2 seconds). The first image is the acquisition of a room with no person in it, while the second and third images are the data of the same room but with a different person standing at the center of the LOS path. The empty room heatmap looks way more stable over time, with the amplitudes linearly decreasing from the lowest subcarrier index to the highest one. This structure is more or less maintained whatever time frame it is selected. A person between the antennas instead, introduces notable noise caused by overall amplitude modifications, with clear differences between two distinct people. Indeed, by analyzing the data points, it can be seen that the distribution of the amplitudes of each subcarrier for the empty room approximates quite well a Gaussian distribution, while on the other hand the distribution of the people-related data presents irregularities and some skewness. For what regards the signal phases, visualizing the differences between

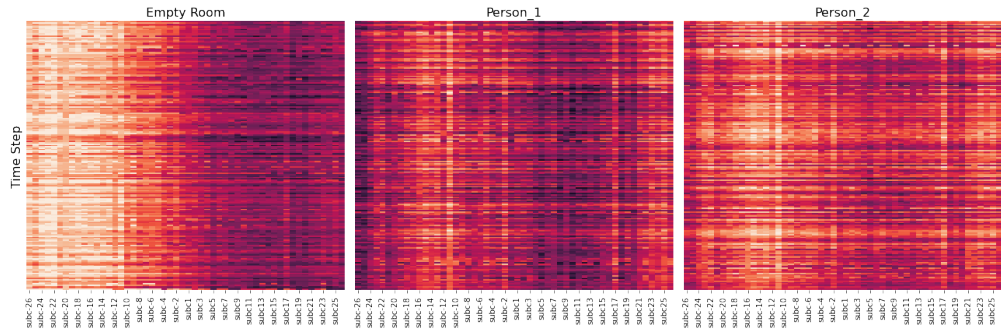


Figure 3.3. Heatmaps of the amplitudes of an empty room vs the same room with 2 different people standing in the LOS path between the antennas.

classes is harder due to the angle-nature of the data and the calibration procedure explained in Section 3.2, that tends to normalize and center the points around the mean. However, experimental results show a significant improvement in the

classification task when combining both amplitude and phase information versus using the amplitude data alone, suggesting that also phases could be used to extract features that are important for mapping signals to a specific person.

One logical approach to merge amplitude and phase data into a single data point is to create 2 different channels by concatenating them along the depth dimension, obtaining a tensor with shape $(2 \times T \times S)$, where T are the considered time steps and S the number of subcarriers, and passing it into a model ready to handle this kind of input shapes. Despite that, in this research an experimental method is tested, that consists into combining both measurements into a single bi-dimensional image, by alternating amplitude and phase of their respective subcarriers. Precisely, if we indicate with A_{ts} and ϕ_{ts} the amplitude and phase of subcarrier s at time t the image is constructed as follows:

$$H = \begin{bmatrix} A_{11} & \phi_{11} & A_{12} & \phi_{12} & \dots & \dots & A_{1s} & \phi_{1s} \\ A_{21} & \phi_{21} & \ddots & \ddots & \ddots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \vdots & \vdots \\ A_{t1} & \phi_{t1} & \dots & \dots & \dots & \dots & A_{ts} & \phi_{ts} \end{bmatrix}$$

getting a final image of shape $(T \times 2S)$. In this particular project, since 52 subcarriers are used and 200 time steps are observed, the shape of an input point is (200×104) . Since the acquired data consists of thousands of observations, to extract the various portions from the whole sequence a sliding window of length 200 moves along the series making steps of 100 points each time and then the observations falling in the window are saved as a data point. This means that the entire series is not exactly divided in disjoint sections of length 200 each, rather in several portions where each one has the first half that overlaps with the second half of the previous portion and consequently the second half that overlaps with first half of the next portion. The purpose of this mechanism is to capture the temporal dependencies between consecutive segments of the dataset, since during testing and inference any point in time could be captured without control over it. Furthermore, a form of data augmentation is achieved as well, resulting into a larger training set.

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