Imaging With 2.4GHz

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Abstract

The use of Wi-Fi waves for non-destructive imaging and sensing has become a popular area of research in recent years. This is due to the fact that Wi-Fi waves have the ability to penetrate solid objects and provide information about the interior of a structure, making them ideal for detecting people through walls. This paper aims to test the feasibility of detecting individuals through walls using Wi-Fi waves. The system developed in this work uses a combination of signal-processing techniques and machine-learning algorithms to produce an image of a person behind a wall.

The proposed method first collects raw Wi-Fi signals from a target area and then processes these signals to extract relevant information. This information is then used to construct an image which is then used to detect the presence of the person behind the wall.

The proposed system has several advantages over existing techniques for detecting people through walls. Firstly, the use of Wi-Fi waves eliminates the need for any physical contact with the target, making the method non-intrusive. Secondly, the system is less expensive compared to other existing techniques, such as millimeter-wave radar, which are often complex and expensive to implement.

In conclusion, this paper presents a new approach to detecting individuals through walls using Wi-Fi waves. The proposed system has the potential to make a significant impact in various applications and provides a foundation for further research in this field. The results of this study demonstrate the feasibility of using Wi-Fi waves for this purpose and highlight the potential of Wi-Fi waves for use in non-destructive imaging and sensing.

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1 Introduction

The detection of individuals through walls is a challenging problem with significant implications for various fields, including security, healthcare, and search and rescue operations. Traditional methods for detecting people through walls often rely on physical contact or are expensive and too complex to implement. In recent years, the use of Wi-Fi waves for non-destructive imaging and sensing has emerged as a promising alternative for detecting individuals through walls. Wi-Fi waves have the unique ability to penetrate solid objects and provide information about the interior of a structure, making them ideal for detecting people behind walls.

In this paper, we will be testing the feasibility of using off-the-shelf and easy-to-obtain hardware to accomplish this task. The solution will be evaluated based on accuracy, speed, practicality, and ethical/privacy concerns. Accuracy will be determined by comparing the output of the solution to the tag on tagged images. The tags being the state of whether a person is present or not. Speed will be the measure of the total completion time to determine occupancy. Practicality will be based on availability, cost, and ease of use of the system in comparison to existing systems. Lastly, ethical and privacy concerns of the proposed solution will be mentioned and evaluated on severity.

The proposed system uses a combination of signal processing techniques and machine learning algorithms to extract relevant information from raw Wi-Fi signals collected from a target area using a motorized directional antenna to scan received signal strength indicator values and construct an image of a person, or lack thereof, behind a wall using these values. The proposed system is non-intrusive, less expensive, and less complex compared to other existing techniques, making it a promising alternative for practical applications. The results of this study provide a foundation for further research in this field and demonstrate the potential impact of Wi-Fi waves in various applications.

2 Existing Technologies

2.1 Ground Penetration Radar

Ground penetrating radar (GPR) works by sending electromagnetic waves (in the 10 to 1000 Hz range) into the probed material and receiving the reflected pulses as they encounter discontinuities. [Karbhari, 2011]. GPR data is usually recorded from a number of spatial positions by dragging the antennas along the surface of the ground or walls. A transmit and receive occur at each of the observation positions. The recorded data are then combined to form an image [Saleem et al., 2014]. GPR is mostly used for geological applications, but it is now being used for forensic [Solla et al., 2012] and archaeological applications [Mazurkiewicz et al., 2016] as well. GPR has its advantages such as its speed, it's non-destructive, and its high resolution. it is also very expensive. However, GPR can also be affected by the moisture content of certain materials, causing it to reflect in an undesirable manner [GPRS, 2023].

2.2 Millimeter Radar

Millimeter wave radar is a technology that uses waves in high-frequency bands ranging from 30-300GHz which have a wavelength of 1-10mm. It is particularly useful in cases when detecting through things such as fog, smoke, and dust, but can also even be expanded to detection through walls [Guan et al., 2020]. A complete millimeter wave radar system includes transmit (TX) and receive (RX) radio frequency (RF) components; analog components such as clocking; and digital components such as analog-to-digital converters (ADCs), microcontrollers (MCUs) and digital signal processors (DSPs). Traditionally, these systems were implemented with discrete components, which increased power consumption and overall system cost. System design is challenging due to the complexity and high frequencies [Gonzalez-Partida et al., 2009].

A common type of millimeter wave radar is called frequency-modulated continuous wave (FMCW) radar. FMCW radars transmit a frequency-modulated signal continuously in order to measure range as well as angle and velocity. This differs from traditional pulsed-radar systems, which transmit short pulses periodically [Gonzalez-Partida et al., 2009]. A common application for this system is in automobile proximity sensors [Guan et al., 2020], meteorological data collection on clouds [Bu et al., 2016], and even medical applications such as detecting heartbeats [Wu and Dahnoun, 2022]. The main advantages to these millimeter-wave radar systems are that they are relatively small in size, very accurate because of the wavelengths of the frequencies used, and resistant to interference. However, they are vulnerable to electrical towers and electromagnetic hotspots.

2.3 DensePose With WiFi

The most similar technology to the methods used in our paper is DensePose in combination with WiFi. This uses a very similar approach to the one proposed in this paper of using WiFi signals to generate input for a neural network. It then estimates the pose of a human. To accomplish this the raw channel state information (CSI) signals are collected by three antennas that are receiving information from another three antennas that are connected to a transmitter. The CSI is then cleaned by amplitude and phase sanitization. Then, a two-branch encoder-decoder network performs domain translation from sanitized CSI samples to 2D feature maps that resemble images. The 2D features are then fed to a modified DensePose architecture to estimate the UV map, a representation of the dense correspondence between 2D and 3D humans. This method is capable of estimating poses with reasonable accuracy, but struggles for poses that are not, or are rarely within the dataset [Geng et al., 2022].

3 Methodology

This project required the creation of a device that could generate an image using received signal strength indicator (RSSI) levels. In order to do this, custom hardware and software needed to be sourced and or created. The theory on why humans would be detectable is due to the fact that humans are 70% water which absorbs RF [Accolate, 2016]. As listed in Fig 1, a person should generate a 3dB low spot if they are in between the access point and the device. Since concrete and steel absorb more than wood concrete, brick, and metal-sheathed builds would be harder to image through.

Material	2.4 GHz	5 GHz
Wooden Door	4 dB	7 dB
Concrete Wall	20 dB	30 dB
Plain Glass Window	3 dB	8 dB
Steel Door	20 dB	30 dB
Human body	3 dB	5 dB
Trees/Vegetation	0.5 dB/mtr	1 dB/mtr

Attenuation/Absorption Figures For Common Objects

Figure 1: Attenuation Table from Accolade Wireless [Saleem et al., 2014].

3.1 Hardware

3.1.1 Antenna

Modern cameras have active-pixel sensors so they can simultaneously detect light values in a large grid. Due to scope and budget, this project needed to come up with a cheaper alternative. The use of a focused unidirectional antenna would grant us one pixel. One pixel isn't very useful as an image but the method of getting more pixels will be explained later in this paper. There are many different types of antennas, but the two common designs that fit the requirements are the Yagi style and the Cantenna. Yagi antennas are antennas that have multiple elements in parallel and are insulated from each other. These parallel rods can be used to amplify or absorb frequencies. Cantenna antennas are antennas that use a metal cylinder to boost signal strength in a direction. They are typically made of cans hence the name. These antennas are directional and both designs are fairly light. However, the yagi style antenna is smaller in footprint, which leads to less weight.

3.1.2 Mechanism

Physically moving the antenna to different x and y locations is the compromise made to keep this solution affordable. There are a few different methods that could be used to move the antenna. Corexy [Chiffey, 2022] or cartesian could be used to move the antenna to these different positions. Corexy is a motion system that moves on a horizontal plane combining the x and y. The motor's power increases since neither motor has to move another motor. Cartesian motion systems have two linear axes but one is mounted on the other so one motor will move another motor [Narayanan, 2018]. However, this would generate an isometric image of the room. Linear x and y movement could give really fine detail but the device would need to be the same scale as the image. Since isometric has problems with scale and cost. We used a movement method that can generate a perspective image on the panoramic plane. To achieve a panoramic x y plane we used a pan and tilt design. This had the benefit of being fairly compact, easy to design, and cost-effective since the mechanisms are centralized.

3.1.3 Radio Transceiver

In this application, an off-the-shelf motherboard equipped with a Wi-Fi transceiver was used. This hardware was chosen because of its availability and relatively cheap price. Note that any type of motherboard equipped with a Wi-Fi transceiver should be capable of accomplishing the scans performed in this application, it will only affect the speed at which the scans can be executed.

3.2 Software

3.2.1 Firmware

The device used to drive the stepper motors was an Arduino nano. Arduinos are microcontrollers that allow the user to connect software to hardware. This enabled the driving of the motors needed to move the antenna to different x and y locations. The requirement of this firmware was that it needed to listen to serial inputs and drive the motors accordingly. Serial inputs are used to connect the computer program to the Arduino via USB. This is useful since syncing the movement and the collection of data gives the ability to get RSSI in specified areas.

3.2.2 RSSI Collection

The RSSI collection can be done through multiple different libraries their names being Network-Manager, IW, and Aircrack-ng. All of these are Linux-only programs and all have pros and cons. The speed differentials and data output streams are the major differences. The IW library was the slowest since it generated the most amount of data that needed to be parsed through and it also had a hard-coded two-second cooldown. Extra data could prove to be useful since it allows the ability to exclude routers that cause noise. Network-Manager or Nmcli was quicker taking less than a tenth of a second to get data. However, the data does not update every time Nmcli is called. Nmcli stores the data and only refreshes every two seconds. Image banding was a result prior to this discovery.

The last RSSI collection library used was a modified version of Aircrack-ng. Aircrack-ng is a Linux tool used to do security checks on routers. The command Airodump-ng gives a continuous stream of live updating data of RSSI values and other information. This is useful when monitoring wireless networks but not useful when you need discrete results. The modification was one line of code that broke the program after the first cycle. Airodump-ng takes about half a second per call. It occasionally needs to be called multiple times if it does not find a device in the first cycle.

3.2.3 Image Generation

The images were generated using the RSSI value and then a heatmap was applied according to strength. After the scans were completed a CSV (comma-separated values) file was generated, each value was in between the range -30 dBm(decibel-milliwatt) and -120 dBm. For the image generation, the values were normalized into a range from 0 to 255 for the green channel and inverted for the red channel. The greener the pixel the better the signal strength and vice-versa for redness. When reading the CSV every other line was inverted and the image was rotated due to the scan method. The antenna scanned up a column, right one step, and down a column, in a zig-zag fashion. In Figure 2 the hypothesis is that the person reflected the signal. Figure 3 shows the room setup and how this is a possible explanation.

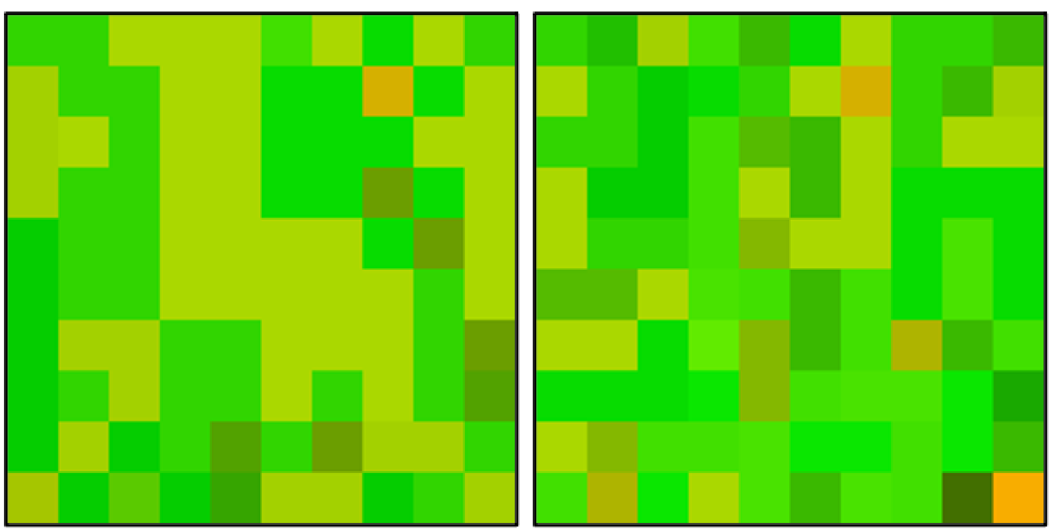

Figure 2: No Human (left) and Human (right).

3.2.4 Neural Network

There was no clear/consistent indicator of human presence to the naked eye when looking at the images produced by this solution. In order to see if there was any

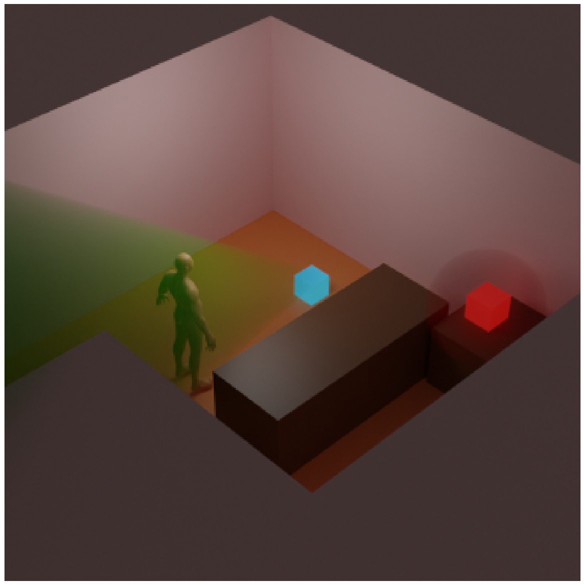

Figure 3: Render of Room the green volume is the area scanned and the red is a router in the room (not to scale).

pattern associated with this, an artificial neural network (ANN) was used to process the resulting data produced by the scan to create a pre-trained model. This model was used to predict the presence of a human between the antenna and the Wi-Fi source.

The layout of the neural network was as follows: 100 input nodes, 1 hidden layer of 50 nodes plus one bias node, a sigmoid activation function, and one output. All weights were given random initial weights. The 100 inputs were given the 100 pixels generated by the previously mentioned systems. The network was trained on the 46 training images and RSSI data that was generated for 1000 epochs at a learning rate of 0.001.

The network's weights were then saved and used to predict the presence of a human in 20 additional photos. The training data used a 0 to indicate that there was no human present and a 1 to indicate a human presence. To accomplish this, every output of the model was rounded to the nearest integer. If the value was 0 or below it was classified as a prediction of no human, and a value of 1 or higher was a human.

4 Results

4.1 Accuracy

Accuracy was hard to measure with insufficient data and a non-controlled environment. The ANN was able to reach an RMSE of 0.38 on the training data, but once applied to the testing data the predictions were not consistent or accurate. The majority of results ranged between 45-55% accuracy. In some cases, the model was able to reach up to 75% accuracy, but this is likely due to the randomization of initial weights in the ANN, and with such a limited size of test cases, it may have just been an anomaly. Another concern is that the ANN may have been overfitting the training data, leading to inaccuracies. All of this is likely due to a very small number of training points in relation to the degrees of freedom in the network. Professor Yaser Abu-Mostafa from Caltech states that as a rule of thumb, you need roughly 10 times as many examples as there are degrees of freedom in your model [Narayanan, 2018], which would mean in the case of our 50 nodes in the hidden layer we would require thousands of samples.

4.2 Speed

4.2.1 Wi-Fi Data Collection

The speed of the proposed solution is highly dependent on the hardware being used. Many motherboard's report rate on their Wi-Fi transceivers or the software associated with getting the required information is not high enough. This can cause each image to take upwards of 5 minutes for something as simple as a 10-pixel by 10-pixel scan. In testing, the proposed solution was able to get an image in anywhere from 67 seconds with no slowdowns to about 5 minutes with many slowdowns. This large range is caused by the device waiting to receive enough signal to collect the RSSI data. If there are many failures to receive the data, the routers rate-limit the number of times the data can be requested, the time increases significantly.

Another issue with the collection is the speed of the motors used to manipulate the direction of the antenna. Due to the weight of the antenna, and the relatively weak motors used to turn it, a gear reduction had to be used. This slowed the movement of the antenna as well as slowed the scans slightly because of this movement. However, this could be overcome by simply adding stronger motors, but that would in turn increase the price.

4.2.2 Neural Network Prediction

After the image is obtained, a pre-trained neural network is used to determine the human occupancy status is near instantaneous. With this network we were able to achieve a prediction from the complete Wi-Fi data in less than a millisecond, so a majority of the time taken with this implementation is due to the slow scan speed of the device. With this in mind, there is likely still room for optimization in the speed of the neural network.

4.3 Practicality

One of the main concerns with the proposed solution is its speed. With a 10-pixel by 10-pixel image taking on average 2-3 minutes, it would take an unreasonably long time to generate enough data to get a detailed image. Also, a moving person may not be detected at all, because they are not in the path of the signal for long enough.

This speed issue also leads into the problem of not being able to generate enough training data. At the current speed, generating the thousands of images required to train an ANN properly would take days of scan time, with a person in the focus of the antenna for some of these.

Additionally, the physical size of the antenna can limit its range and sensitivity, making it impractical for certain applications. The size of the antenna can affect the distance over which it can detect RF signals. A larger antenna may have a longer range, but it can be impractical to use in certain situations due to its size. On the other hand, a smaller antenna may not have a long-range or be sensitive enough to detect weak signals.

In an ideal scenario, a software-defined radio (SDR) would be used to get signal strength values, since it can directly control the gain applied to the antenna signal. It would also allow for faster communication between devices because it could directly interface with the custom software more easily.

While our solution may not have been the most accurate, it was cheap, with a material cost of less than $100. In comparison to things like GPR, Millimeter Wave Radar, and DensePose with WiFi, this is a great alternative in regards to price. GPR starts around $14,000 [GPRS, 2023] while millimeter wave radar [Lin and Hu, 2017] and DensePose fall in the $100-200 range depending on the equipment used [Geng et al., 2022].

4.4 Ethical Concerns

The ethical concerns for the method proposed are similar to that of current technologies. The capability to detect whether a person is present through walls can be an invasion of privacy. At a more affordable price point such as the proposed method, it is even more of a concern because it could be widely available to anyone.

The main issue with this device is that it is usable without the consent of those it's being used on, as well as without them knowing. If an accurate enough image could be obtained, whether it's through a long scan or through some other breakthrough, information could be captured about individuals that was not intended to be seen or monitored.

Another concern is that if a user of this implementation was able to speed up the collection of Wi-Fi data it may cause a denial of service to people in the area because of the constant polling of network information caused by the proposed solution. Even in the case that it does not cause complete outages it may degrade the experience for others in the area.

Lastly, because this is using information that is produced via radio waves, someone could potentially broadcast waves to lead to inaccuracy, since there is no way to validate which waves or lack of waves are authentic. This could lead to biased images, which could result in unfair treatment of individuals.

5 Conclusion

This project had a few shortcomings like slow imaging, not enough data for the neural network, poor design, and ineffective planning. These problems will need to be addressed for future iterations. The lack of resources played a role, using a wireless network card was a cheap alternative to a real SDR but it proved to be slow and hard to work with. Writing software for the network card was more of a hack rather than elegant code. Without properly rewriting firmware the network card could send out too much data causing a denial of service attack on local routers.

There were many unforeseen challenges that came up in this project. A lot of time was spent on the design of the robot that moves the antenna. There were countless redesigns due to the strength of the motors and tolerances. But the majority of time was devoted to finding a solution to the slow speed of scan times. Three different libraries gave results but there were many that either never worked or did not work in this application. Recompiling Aircrack-ng was a challenge but in the end, it did increase the speed by three times.

Rushing to implement ideas prior to proper research cause many dead ends and wasted time. Prior to the use of the wireless network card, a USB CrazyRadio-PA was used. There were many GitHub repositories that were using the device to get RSSI values in the 2.4ghz band. This was promising until the device arrive and we found out the device itself doesn't calculate the RSSI it gets it from the drones this device is typically used in combination with.

While the proposed implementation was not a complete success, it was able to generate images using WiFi waves. The images had slight differences between ambient and a person being in front but it was unclear if it was random noise.

Overall, in its current state, this implementation is not feasible. A few more things will be required to make it feasible. These are things such as increasing the speed of scanning for RSSI data, such as through an SDR, training the ANN on larger datasets, and collecting data in a more isolated environment. The method does however show promise for future research and may be capable of human detection through walls with further improvement.

6 Future Research Areas

6.1 Frequencies

Making a device to scan 5GHz could yield different results. Many routers output 5GHz alongside 2.4GHz. 5GHz has less of a penetration distance compared to 2.4GHz [Accolate, 2016]. The downside to 5GHz for users is a benefit when it comes to imaging. The waves are more likely to be absorbed by a human's presence and RSSI can be measured faster. Measurements occurring faster is due to the wave periods being faster so the amplitude can be measured more often. 5GHz antennas are about half the size of 2.4GHz antennas so the scanning device can be smaller. The con to 5GHz antennas is that their manufacturing tolerance is more precise. Making a Yagi antenna would require printing circuit boards.

6.2 Design

Redesigning the XY movement system would reduce backlash and make the device sturdier. The entire build was 3d printed including the antenna and some parts were reused from previous prototypes. A total redesign would make the movement less of a worry so more images could be taken automatically generating more data.

6.3 RSSI Collection methods

The major limiting factor of this device is the scan times. Reducing the scan times would require better-measuring equipment. The use of a proper SDR would reduce this time per pixel. It might be possible to reduce the time on the wireless network card method we used but that would require modifying the firmware or more workarounds. A system that used multiple antennas could generate speed up the collection process as well.

6.4 Controlled Environment

Controlling the environment was a challenge with this project. All of the scans took place in an apartment complex with many wireless access points and unknown whereabouts of people. Having a location with only one access point would be a better control scenario. Additionally, the device always had a person in the same room since it need to be monitored. A person in the room could throw off the RSSI values since wifi bounces off walls like a room of mirrors.

6.5 Different OS

The operating system used was a non-GUI(Graphical User Interface) version of Archlinux. The computer used was used for other projects where a GUI was not important and the speed gains were. Since this project's outputs were images a webserver was required to view the images. This made the computer less mobile since it needed to be connected to an ethernet cable since the wifi was disabled when scanning. Limited mobility caused issues when trying to image through different walls. Also since it had to be directly wired to the access point it was in the same room as the router. The 2.4 Ghz was turned off for some scans to get RSSI values from outside the room.

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