Radiohead: A headway into existing techniques on activity and object detection via radio waves

Yash More
Ashoka University

Debayan Gupta
Ashoka University

***Abstract*— There has been extensive use of radio signals in the realm of object detection and tracking of activities. There have been multiple approaches to solve this problem, including different forms of RADAR. However, the detection techniques aren't limited to active radars. Wifi signals which offer immense potential in spilling spatial information. Wifi signals can be used for object detection, motion detection, and activity detection purposes, by simply utilizing different characteristics/information of the signal like received signal strength, phase differences, CSI, etc. The implementation of these methods, however, can rely on different algorithms and statistical models. It often becomes difficult to choose one particular method. In the following paper, we introduce several such techniques and their caveats that come along with it. We also explore an experimental approach that involves Software-defined radios, and low-frequency radio signals for object detection.** **Keywords: Object detection, Wifi, SDR, rf signal detection, Human detection, Activity detection, motion device-free localization, rf networks, CSI, RSS.**

I. INTRODUCTION

Generic localization methods often employ a large number of devices for detection and monitoring purposes. For example, surveillance often relies on a network of cameras. The potential to replace such systems with cost-effective sensor/sensorless systems which are based on rf-signals should be looked into. RF-based detection allows us to achieve human monitoring for a plethora of purposes in a very convenient manner. It can utilize already existing devices in one's environment for tracking purposes(passive radar). RF-based spatial data can also span across dark and smoky environments which are difficult to monitor. There are several other benefits offered by RF-based wireless systems. We shall look into the benefits offered by each system and a brief overview of their functioning to realize the importance of RF-based localization techniques. The following section offers a brief overview of the past literature related to the subject. This review is a drop in the ocean of research done around RF-based localization and tries to cover the most commonly/popularly used techniques. It is followed by an experimental approach to rf-based detection via low-frequency rf signals.

II. LITERATURE REVIEW

A. Device-Free Localization

1) Overview: The term device-free localization offers an umbrella to a wide range of systems, which commonly make use of wireless radio networks for detection, tracking and localization purposes. Wireless-localization systems can be both active, and passive. The former consists of methods such as *Radio-Frequency Identification Devices(RFID)*, *Real Time Location Systems (RTLS)*, *Infrared Radio(IR)*, and *Global Positioning systems(GPS)*.These systems require the entities to carry a device to be tracked or located. Quite often, however, there have been several scenarios where it is not feasible to do so. For example, in situations of emergency where people are trapped in buildings due to some accident or mishap, one can't rely on active- wireless localization systems. Moreover, from a design and logistical perspective, shipping trackers with people puts the onus on the person of whether they want to keep it on them, as they might feel that they are being monitored. Passive Device-free localization takes away the issues related to on-body trackers. Often termed as device-free sensing, *DFL* can locate, track, or detect people/objects when no device is attached to the entity. This method also provides certain other advantages when compared to active-wireless localization techniques.[1][2]. Some of its advantages are:

• *DFL* systems can be used for intrusion detection[3].

• The commercial wireless devices used are usually low-cost and easy to maintain.

• RF-based DFL can penetrate through obstructions such as non-metal walls, furniture, trees, and smokes, which would be hard to cover with active-wireless localization systems. This further allows it to track objects and people behind walls.

• Detects the presence/location of people without actually revealing their identities, therefore, offers relative more privacy than other systems.

Apart from the above advantages of DFL, there are several applications of it:

• Security, alarm, and surveillance: To already existing IoT ecosystems, DFL enhances the functioning and makes them more efficient. DFL systems can provide information about occupants in real-time, which can prove to be valuable data to monitoring systems.For example, the DFL can be used to provide the body temperature of occupants, the humidity of the environment, number of electronic devices being used. This would allow IoT devices to control external factors such as temperature and lighting more flexibly.

• Military operations:

DFL-based systems can be immensely helpful in both locating targets, and in locating hostages.The location of intruders can be tracked likewise. The feasibility of deploying an RF sensor network based on *Radio Tomomgraphic Imaging*(DFL-based method) has been studied by Patwari et al [5], and they proposed an easily deployable real time tracking system based on *Radio Tomographic Imaging*.

•Occupational safety in industries:
DFL can be used to detect the working conditions of people working in hazardous areas, and correspondingly identify the risks within those.

• Assisted living:
DFL-based systems can also ascertain the health conditions of people who constantly need to be monitored. One can develop patterns from the routine of people, and if the routine is disrupted then the sytem can trigger an alert/alarm. This is not completely foolproof, but offers a much cheaper alternative to surveillance via cameras. Moreover, surveillance videos need additional workforce to spot the discrepancy in the daily ongoings of a person.

2) Measurements:

•**Ultra wideband recievers** measure the amplitude, phase-shifts, and time delays of the *multipath signals*. These meauserements can allow one to infer the changes in the environemt, which in-turn might hint towards a moving object/human[6].
One can potentially measure the *channel impulse response (CIR)*. The channel impulse response can be seen as the summation of each multipath component. Each multipath component is comprised of a complex amplitude gain, time delay, and the dirac function, all expressed as: $h(t,\tau) = \sum_{i=1}^{N} \alpha_i(t)\delta(\tau - \tau_i(t))$.

Time delay is critical to calculating the CIR, and when measured for multiple links allows a rough estimation of the object location in respect to the transmitter and receiver.

• *Narrowband:*
Narrowband channel measurements do not provide information of individual multipath, but only the magnitude of the signal , and phase as a whole. A complex baseband voltage which is the summation of the contributions of all multi-path, is calculated both at the transmitter and receiver, and compared accordingly. The comparison allows us to retrieve the positional information. One of the advantages of using Narrowband is that its really cost effective and can be used to build large rf networks. The disadvantage, however, is that these large scale rf networks would host several sensors, and are very susceptible to errors in timing synchronization. To prevent this one needs to have phase coherent measurements.
• *Received Signal strength (RSS)* If we compare RSS, with the above discussed methods of measurements, we see that RSS is a magnitude-only measurement. RSS-measurements can be commonly obtained through all wireless devices. The Received signal strength is a measurement which can be calculated both for a narrowband receiver and a UWB receiver, and simply is in the form of received power in terms of decibels. The complex base-band voltage carries information about the phase of a signal as well. This information can tell us whether phases for two different instances of the baseband voltage, has same phase or different phases. Depending on each phase, the sum can be either destructive or constructive which will either attenuate or amplify the signal power. a destructive interference is commonly referred as a deep fade, which may result in temporary failure of communication between the transmitter and receiver, and also might cause a sharp drop in the signal to noise ratio.
As RSS measurements are calculated over a multi-path channel,i.e there are several paths which the transmitted signal can take before reaching the receiver, hence it is prone to effects of multipath-fading. Additionaly, the presence of reflecting objects in the environment surrounding either the transmitter or the receiver can potentially create multiple paths in which the signal can travel. As a consequence, the receiver sees multiple copies of the transmitted signal superimposed on each other, which again leads to differences in attenuation.
RSS measurements can also be taken via an UWB receiver, which is more effective in revealing location data, however, we see that narrowband based rss measurements are more cost effective.

3) Models and algorithms:

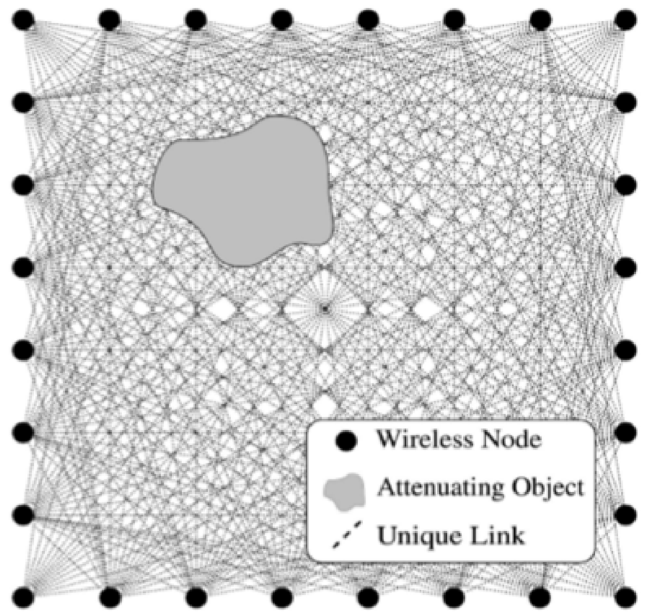
• MIMO radar with RSS:
Multiple transmit antennas, coupled with mutiple receivers, can help us improve the performance achieved by a single transmitter-receiver pair. Transmitters in a MIMO radar system use *orthogonal waveforms.* These waveforms may result from *time-division multiplexing.* or *frequency division multiplexing*.FDM splits the available bandwith of the transmission medium into a series of frequency bands and uses of the frequency bands to transmits one of the signals.TDM on the other hand, splits the transmission into a chain or series of time slots, and allocates certain time slots in a cyclical manner for the transmission of one signal. The MIMO radar is a multiple antenna radar system which is capable of transmitting arbitrary waveforms from each antenna element. In a traditional phased array radar, the transmitting antennas are limited to transmit scaled versions of the waveforms.The radar system uses orthogonal waveforms so that it is easily separable at the receiving end. MIMO radar uses the RSS-based measurements for object and human detection. Unsurprisingly, the challenges

faced by this model are related to multi-path propagation. A MIMO radar often operates in a rich multipath environment in which objects often block or disrupt other multipath.

• *Detection of human activity via variance in RSS links*:
A wireless network is capable of utilising the *RSS* on the links in a network to infer the locations of people or objects in motion under a specific area. This method relies on a statistical model to calculate the variance of RSS, as a function of the position of object/person being located.[7]
The object/person's location is expressed relative to the transmitter and receiver. This method aims to measure the total power in an affected multipath via the measurements of variance of RSS. A relationship between Total estimated power(ETAP) and the variance of RSS is drawn.[8]
The statistical model which can be used for this approach, models the human being as a metallic circular cylinder. This approximation comes from comparable signal variations produced by the two, and similar variations in terms of fading.The model relies on the phenomenon undergone by propagating electromagnetic waves such as:
reflection, diffraction and transmission, to estimate the position of the human.
• Motion tracking via RTN (Radio Tomography Network):
Radio tomographic Network is based on the principles of variance-based RTI. RTI, or radio tomographic imaging has its measurements in terms of received signal strength(RSS) or the power measured in decibel terms. One of the commonly used modelling techniques is the linear image model. The goal of this model is to use RSS variance measurements on multiple links in a wireless network to determine vector of an image, that describes the presence of motion with some degree of proximity (measured in voxels) from the physical space of the setup. One uses indicator random variables to identify whether a particular voxel hosts any motion or not. Then we calculate the total variance as a linear combination of movement happening in each voxel, which is weighted by the amount of variance motion in a particular pixel.

If all links are taken into consideration then the system can be expressed in a matrix form where each vector represents the variance of a link. This matrix is represented as a product of the weight matrix with the image matrix.The image model proposes an inverse problem which needs to be solved to estimate the image. This inverse problem depends on measurements which are highly sensitive. For regularization , *Tikhonov* least squares regularization is used.
This RTI network has the potential to track objects though walls , and has multiple real world applications which involve real time tracking of large spaces.[9]
• *Activity Recognition based on RSS:*
Fingerprinting techniques based on RSS, allow us to perform activity recognition. Each signal can be identified by a RSS-fingerprint, which can be captured at the receivers. As each wifi signal is affected by the activities in its environmenr, we can measure the differences captured by each signal, to

Fig. 1. RTI based network of nodes

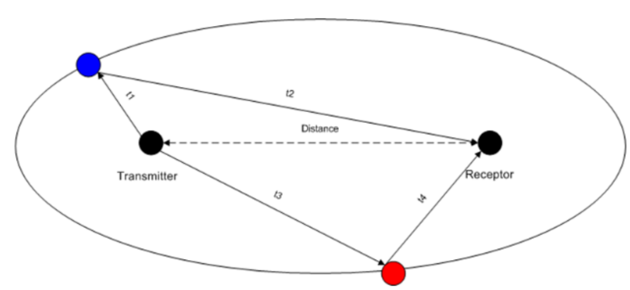


detect object/human motion.

B. Passive Radar

Instead of using collocated transmitting and receiving antennas, a passive radar system relies on a signal transmission which can randomly originate.The receptor receives the signal which has undergone multiple reflections. The principle of passive radar is based on the time delay between transmission and reception. One often relies on multiple receivers to finely determine the elliptic curve on which the object might be. Each elliptic curve would essentially have two foci one of which would be the transmitter. Multiple intersecting ellipses might allow us to narrow down the vicinity of the object.
A passive radar's accuracy depends on three factors:

Fig. 2. Passive Radar



1) Ambiguity function of signals
2) Bandwith
3) Integration time
Wifi proves to be a good choice for a passive radar system because of the ambiguity function analysis of OFDM(used

by wifi-signals), and the higher bandwith.
Passive radar can be implemented via three techniques or radar processing methods:
1)2d-cross correllation
2)Frequency domain channel estimation
3)Time domain channel estimation
Time domain channel estimation gains higher accuracies, but is harder to implement.

C. CSI

CSI or *Channel State Information* represents information of transmission channel between transmitter and receiver. For example, for a wifi-based MIMO radar, CSI can be represented as a three dimensional matrix of complex values representing the amplitude attenuation and phase shift of multi-path channels. CSI amplitude and phase shift are impacted by multi-path propagation effects like fading. CSI-measurements allow us to capture how wireless signals travel through surrounding objects and humans in frequency, time and spatial domains. Hence CSI offers the possibility to be applied to a variety of wireless sensing applications.
Even though RSS has been popular in DFL-based applications, it comes with a lot of challenges. The primary challenge lies in countering the effects of multipath fading. CSI on the other hand, has tried to discriminate between multipath characteristics to introduce finer detection.

Some of the CSI-based approaches to wifi-sensing are:

• Device free localization via CSI:
The PHY layer CSI available on commercial Wifi devices, has raised excitement over CSI based indoor localization. Since CSI has the potential to derive the frequency diversity at the granularity of OFDM subcarriers, it benefits in a wide variety of detection and activity techniques. CSI overcomes the challenges faced by RSS due to multipath propagation (RSS fails to characterize multipath propagation). For CSI, we see that since the subcarriers fade independently CSI offers to optimize and derive the patterns leveraging frequency diversity[10]. The research done by Chenshu Wu et al. uses CSI-based information to perform moving/stationary target detection. Chenshu et al proposes an architecture of DeMan, which consists two components: one for moving object detection and the other for stationary items. DeMan firtsly extracts the CSI information from the wifi-signals , and then the raw CSI information is passed through the Hampel identifier to sift the outlier observations.[11] After this, the CSI is processed by a lightweight motion indicator , which allows us to decide whether there is a moving person or not. For movement detection, one exploits both amplitude, and phase information derived through CSI measurements.
There have been other motion detection systems which use CSI , WiFall by Chunmei et Al, is a signal propagation model which employs time variability and special diversity of Channel state information, as the indicator of human activities.As CSI is readily available , WiFall doesn't need hardware modifications to be done.
There has been attempts at improving LOS and NLOS-based localization and identification systems via CSI as well. PhaseU, for example, a realtime LOS identification system which works on both static and mobile scenarios and has an accuracy of over 8o% in each case.[14]

• Learning algorithms based on CSI:
Apart from the statistical methods we have been discussing so far, there can be learning algorithms based on machine learning and deep learning methods. There are several shallow learning algorithms such as kNN(k Nearest neighbours), SOM(Self-organizing map), and SVM(Support vector machines). These algorithms compute the distance between each testing sample and every training sample. SOM represents training samples in low-dimensional space, it is a type of neural network using competitive learning instead of backpropagation with gradient descent as the optimization algorithm.The k-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression.[12] K Nearest Neighbour is a simple algorithm that stores all the available cases and classifies the new data or case based on a similarity measure. It is mostly used to classifies a data point based on how its neighbors are classified.In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.[13] Jialin Lie et al has proposed the usage of one-class support vector machines to detect multi-target strenous human motion. This method is tried out in both NLOS(Non-line of sight) and LOS based conditions. Research done on gesture recognition by Virmani et al, shows the potential of a classification models in a wifi-based gesture recogintion system. WiAG proposed by Virmani et al, requests the user to perform a gesture, automatically generates virtual samples of different configurations based on the input and then generates a classification model using the virtual samples. [15]

Even though shallow learning algorithms we described above do a great job at classification, they lack at effective feature learning and selection for the right features in certain cases. Here comes in the DNNs, or Deep Neural Networks, which try to tackle this problem. DNNs require very little or almost none signal processing, and feature engineering. Hence these are great for multi-class classification applications. A proposal by Qizhen Zhou et al, attempts at a gesture recognition system using deep learning methods on CSI-based device free networks[16].It describes a CSI-based approach which applies deep learning methods in de-noised CSI to extract features from both amplitude and phase information from the signal. A four layer deep learning model is adopted after obtaining the gesture information. The results show an average accuracy of 94% in indoor scenarios.

Hybrid Algorithms combines learning based and modelling based algorithms. Learning based algorithms have certain pros and cons. The advantages of using learning based algorithms:

1)consist of little or no signal processing
2)reusable- models which can be updated easily
3) models are versatile and show high accuracy
The cons however are: 1)need a lot of effort for data collection and training.
2) Need precise training data.
3) Instance based learning methods have high costs during the inference stage.
Certain hybrid algorithms use modelling based methods for coarse grained information and the learning algorithms for the finer grained information.

III. EXPERIMENT

This section describes the experimental approach to track the presence of objects within a short-range in an indoor environment using low-frequency RF signals. The methods employed to achieve the same, follow the principles of time-frequency domain analysis, to perceive differences in the transmitted, and received signals. Human and object detection using RF signals has been tried and implemented using different theoretical, statistical models, and learning algorithms. This experiment uses a hybrid approach, and tries to combine some of the techniques we have already discussed above.

Aim: To try and detect the presence of objects using low frequency radio waves, with help of spectrograms,PSDs, and further processing of each using CNNs.

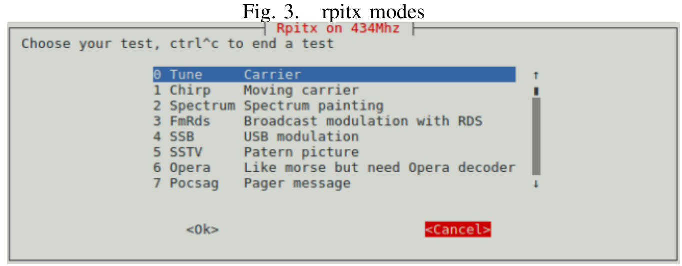
Experimental setup:

- Laptop 1 (Macbook pro)
- Raspberry Pi
- USB cable
- Dipole Antenna
- GPIO-compatible wires
- RTL-SDR(RealTek)
- Laptop 2 (Lenovo Ideapad 320)

The experiment entails the usage of a software-defined radio (RTL-SDR) to receive and interpret the radio signals involved in the experiment.A laptop(macbook pro) is used to interface the sdr. The dipole antennae, connected to the sdr allows us to detect the rf signals transmitted by the transmitter. The transmitter is a raspberry pi equipped to transmit rf signals at the frequency of $433MHz$. The connector wires which can be snuck right onto the GPIO 7 port of the raspberry pi, allows the pi to transmit the signals at any desired frequency between 0 to $433MHz$ The raspberry pi is interfaced via laptop 1 (Ideapad) through an ssh connection. The software responsible for the transmission of radio waves is the $rpitx$ library which enables the raspberry pi to choose the carrier frequency, and offers transmitting at different bandwiths as well.*Figure below* shows the different modes in which one can transmit via rpitx.

The experimental setup consisting of the transmitter and receiver mimics the setup of *bistatic radar* in terms of positioning of the transmitter and the receiver i.e each of

Fig. 3. rpitx modes

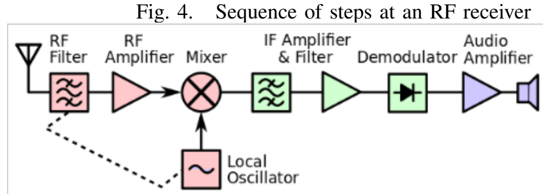


them are placed at two different locations, spaced at a distance $<$ 2 *metres*.Unlike a bistatic radar however, the distance to target is not comparable to the distance between the transmitter and receiver. The experimental setup is kept in a closed room, which houses other objects other than the setup itself.and the experiments are repeated in the same environment every time.

Methodology and concepts involved:

Radio signals are fundamentally in the form of physical/analog waves. If we look at the configuration of a radio, we see that it has components such as the mixer, low band pass filter and the amplifier. Each component plays a critical role in transforming the radio signal into an audio signal. The mixer combines or multiplies two radio waves and generates two waves at different frequencies(the difference of the two signal frequencies and at the sum of the two), this technique enables in frequency translation as it helps the radio to move the signal of a particular band to the other. A *low band pass filter* only allows certain frequencies to pass through, and helps to clean up the signal from additional noise. An *amplifier* is used to increase the sensitivity, by amplifying the signals. Finally a *demodulator* demodulates the incoming rf signals into audio waves. A sequence of the steps is shown in Figure.

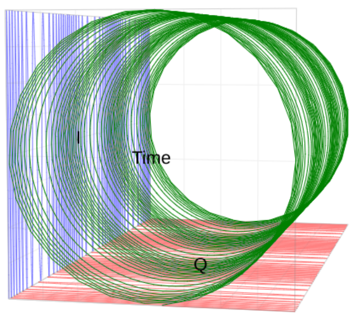
Fig. 4. Sequence of steps at an RF receiver



An SDR however tries to replace the replace the most of the processing of radio signals with software. So the mixer,filter,amplifier, etc. are all implemented by the means of a software running on a computer, or an *embedded system*. The hardware housed by the SDR, is essential to convert the signals from audio signal to digital baseband signal. The rf tuner in the SDR is responsible for the same job as the the first three blocks of a radio, it converts the analog signal to an intermediate frequency , and then passes this onto the *ADC* or the Analog-to-Digital converter.After we get the digital sample at an intermediate frequency, we pass it onto a Digital downconverter (DDC) which allows the frequency band to be moved down so that the sample rate is reduced, and further processing becomes easy.

The data is collected via the SDR is in the form of I/Q signals i.e the received RF signals are IQ-demodulated.Quadrature signals or IQ signals form the basis of signal modulation and demodulation. I/Q demodulation comprises of three steps: *Down-mixing,Low-pass filtering, and decimation.*
After down-mixing, the signal is no longer real, and is represented in a complex form.The representation of a signal as I/Q allows us to look at at the signal in the three dimensions,as a helix.

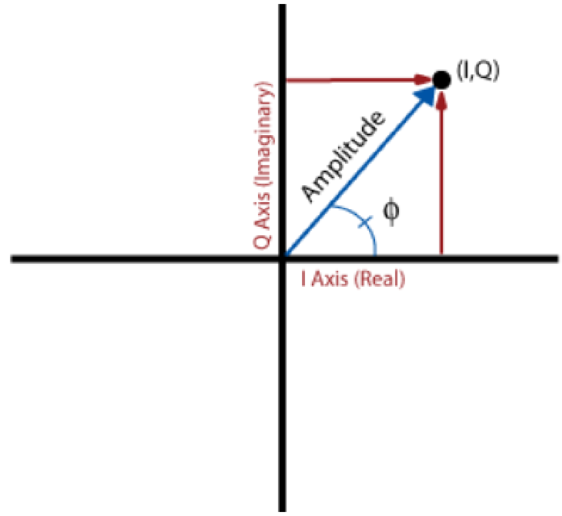
Fig. 5. IQ signals in 3 dimensions



The change in Inphase and Quadrature, occurs with the passage of time which is the third dimension. The I in I/Q signal allows us to determine the momentary amplitude of the real signal, as it is the real part, while Q being the imaginary part. Each combine to form a vector whose length gives us the amplitude of the real signal. We can look at I/Q as the polar representation of amplitude of the signal. I gives the current momentary amplitude of the signal, and Q gives us the momentary amplitude of the signal phase shifted by 90 *degrees*.
The collected I/Q data is utilised to form a *spectrogram.* A *spectrogram* allows a visual representation of the frequencies of a signal with the passage of time. The I/Q signals are captured in the time-domain, and need to be converted to the frequency domain to facilitate that. Hence, we use the technique of *Short-time Fourier transform (STFT)* to convert the signal into the frequency domain.
STFT is based on *Fast-Fourier-Transform*.
The short-time fourier transform, allows us to determine the sinusoidal frequency and phase content of local sections as the received signal changes over time.[18] The procedure to compute *STFT*, is however, to divide the time signal into shorter lengths. and then compute *FT* over each of the segments. This allows us to plot the changing spectra as a function of time, commonly referred as the spectrogram.

PSD graph or a power spectral density graph is a

Fig. 6. I/Q signals



power versus frequency graph which allows us to monitor the spikes in power with respect to certain frequencies or a range of frequency. A PSD maybe useful in the case where we want to verify whether the signal is being transmitted at a particular frequency. One can however, also try to discern the differences of two PSD plots while performing object-detection. Li et al, has relied on spectral analysis as one of their key methods in performing metallic object detection using rf signal measurements.[19]

A CNN or a ConvNet, a class of deep neural networks, consist of a input and output layer, and multiple hidden layers. The hidden layers consist of a series of *convolutional layers* that *convolve* with a dot product. The *activation function* a *RELU* layer which is followed by additional convolutions such as *pooling layers*, and *normalization layers*.
A CNN has been a go to model for image related research, and has been seen to one of the better learning algorithms for understanding image content.[20] They have shown great performance in image classification,detection and retrieval related tasks.[21][22][23] In our experiment,therefore, CNN became a favourable option to extract features not visible to us in spectrograms and PSDs, and further detect differences in a plot which has an object and one which hasn't.

Data Collection and Processing:
The RTL-SDR was interfaced through a laptop(Macbook Pro), via a library: `pyrtlsdr`. The library is a wrapper to `librtlsdr`, and ports a lot of its functionalities. We use pyrtlsdr, to write python scripts which can store and manipulate the incoming data via the SDR. The script is modified to adjust the sample rate of the sdr, and add the required library-calls to convert the raw IQ data into a spectrogram (via *SFFT*)
Along with the generation of the spectrogram we also generate a PSD plot of the data as well. The transmission

of the radio signals is handled by a different computer,i.e a laptop(Lenovo Ideapad 320), and the software interface used to transmit is the $rpitx$ library as mentioned above. The carrier wave is set to transmit at $433Mhz$ (The maximum possible frequency at which Raspberry Pi can transmit) in `Narrow Band FM mode`. The entire setup is placed in a closed room which doesn't house other equipment other than the ones required for the *Experimental Setup*. This close-to-ideal environment is setup to ensure that noise from static objects is minimized.The data collection procedure is repeated for object and non-object. For object detection we place a filled water bottle of size approximately 12-15 inches in height, between the antennae, and the Raspberry pi. Its position is equally spaced from the transmitter and receiver. A filled water bottle was chosen, so that the radio-signals aren't blocked as we were trying to mimic a LOS connection, and to minimise the amount of radio-waves which are reflected and absorbed by the object.
Around 1000 samples were collected for each object and without object cases. These samples are subjected to multiple processing methods:

• **PSD:** A power density plot allows us to check whether there is any discernible difference between the plots of the two cases: object and no object. Hence, we had plotted a PSD for the received samples for each case (with and without object.)

Fig. 7. PSD With Object

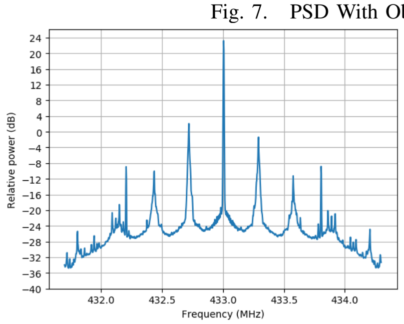
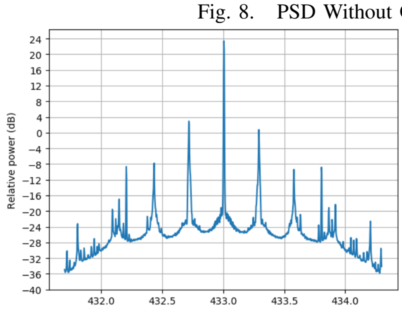


Fig. 8. PSD Without Object



• **Spectrogram :** A spectrogram is generated on 3-4 samples each. The spectrograms are generated for both object and no object cases, and then compared to check for discernible differences.
. We also feed the generated spectrograms into a convolutional neural network, and adjust the weights of the filters used in the network using a stochastic gradient descent algorithm.

Results:
Both PSD's ,and spectrogram fail to produce discernible differences between the object and no-object setups.We see that the CNN model which has been trained over the spectrogram samples is very prone to overfitting, and is unable to differentiate between the two classes.

Fig. 9. Spectrogram With object

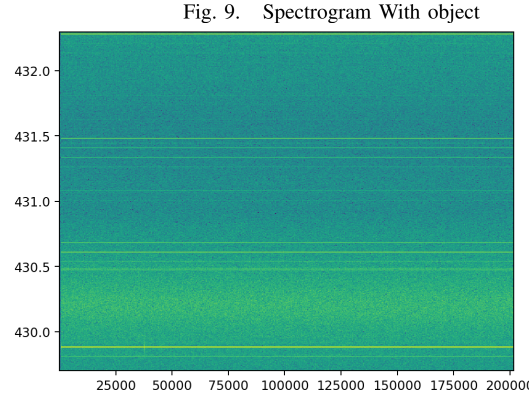
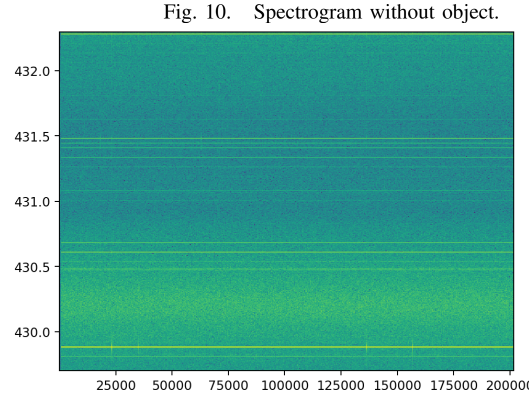


Fig. 10. Spectrogram without object.



There might be several issues with the setup and the approach we've followed. Some of the issues are:
• The wave transmitted s of low frequency. Most of the energy of the wave is lost either through reflections or via absorbtion by the object. As the wave is low in frequency, we see that the energy carried by it also proportionally less. Moreover, the lesser frequency waves have longer wavelength which is not ideal for our setup. We ideally need a wavelength comparable to the object we are trying to detect. But however, in this case we see that the wavelength is way more than the actual size of the object. The object is barely 10-12cms, while the wavelength comes out to be 70cm-100cm.

• Beamwidth or the ability of a radar to focus the radiated energy in a narrow region, is also dependent on the antenna,its size, and the frequency of the waves. Given a particular antenna size a higher frequency wave allows the antenna to be more focussed. As we have been using low-frequency signals the 'focusing' of the antenna is also affected.

• The transmission isn't appropriate as we are merely using a connector wire, instead of a monopole/dipole antennae to transmit the radio signals.

• The entire setup doesn't have adequate communciation range , i,e the distance between the transmitter and receiver was quite less. The choice of choosing a smaller distance was primarily made keeping in mind the low frequency.

• *The overall size of the sampled data, and variability of the conditions the experiment was conducted in*. The effectivity of the experiment could be gauged better if we performed the same experiment keeping in mind the above points, in different environments, and replicated it to produce enough data samples.

• *Unclear spectrograms*. The spectrograms generated via the collected IQ data is very noisy, and data needs to be preprocessed or cleaned in a better manner, so that change in frequency over time is more discernible. Moreover, a less noisy environment should be selected if the experiment is performed again in the future, as the noise masks most of the received IQ data.

IV. CONCLUSION

The classical approaches to signal processing coupled with statistical methods are better at estimation and validation, but come to be more harder to implement in real life. Moreover modelling data according to the statistical models seems to be more complex. Machine learning methods however, offer a much user-friendly dive into the world of signal processing and allow more people to experiment with the ideas revolving around object and activity detection. As real world applications of cost effective wifi-enabled sensing are limitless, one can hope for more development of hybrid algorithms which combine best of both the worlds, in an intuitive yet simple manner. A lucrative source of development of such methods would be to exploit the cost-effective setup offered by software-defined radios, and develop prototypes which could potentially be extended to wifi-routers. The concluding experiment shows the vast potentitial of SDRs in the realm of object detection, and further pushes us to make necessary amends to attain the objectives of object detection soon.

APPENDIX

Multipath propagation: In radio communication, multipath is the propagation phenomenon that results in radio signals reaching the receiving antenna by two or more paths.

Rayleigh distribution: In probability theory and statistics, the Rayleigh distribution is a continuous probability distribution for nonnegative-valued random variables

Rician fading: the signal arrives at the receiver by several different paths (hence exhibiting multipath interference), and at least one of the paths is changing (lengthening or shortening)

Shadowing/fading: variation of the attenuation of a signal with various variables. These variables include time, geographical position, and radio frequency

RTI/Radio tomographic imaging: WHEN an object moves into the area of a wireless network, links which pass through that objectwill experience shadowing losses. This paper explores in detail the use of shadowing losses on links between many pairs of nodes in a wireless network to image the attenuation of objects within the network area. We refer to this problem as radio tomographic imaging

OFDM: Orthogonal frequency division multiplexing: In telecommunications, orthogonal frequency-division multiplexing (OFDM) is a type of digital transmission and a method of encoding digital data on multiple carrier frequencies.

Complex baseband signal: An equivalent baseband signal or equivalent lowpass signal is—in analog and digital modulation methods for (band-pass) signals with constant or varying carrier frequency- complex valued representation of the modulated physical signal

TDM: Time-division multiplexing (TDM) is a method of transmitting and receiving independent signals over a common signal path by means of synchronized switches at each end of the transmission line so that each signal appears on the line only a fraction of time in an alternating pattern.

FDM: In telecommunications, frequency-division multiplexing (FDM) is a technique by which the total bandwidth available in a communication medium is divided into a series of non-overlapping frequency bands, each of which is used to carry a separate signal. This allows a single transmission medium such as a cable or optical fiber to be shared by multiple independent signals. Another use is to carry separate serial bits or segments of a higher rate signal in parallel.

ABBREVIATIONS

CFR: Constant False Alarm Rate
CFR: Channel Frequency Response
CIR: Channel Impulse Response
CSI:Channel State Information

CNN: Convolutional neural network
FMCW:Frequency Modulated Continuous Wave
GHz: Gigahertz
GPS: Global Positioning system
kHz: kilohertz
LOS: Line of Sight
MHz:Megahertz
LOS: Line of sight
NLOS: Non-line-of sight
OFDM: Orthogonal Frequency Division Multiplexing
PHY: Physical layer
RADAR: RAdio Direction And Ranging
RF: Radio Frequency
RSS: Received Signal strength
MIMO: multiple input multiple output
FDM : Frequency division multiplexing
TDM: Time division multiplexing
ETAP: Total estimated power
RTI: Radio tomographic imaging
RTN: Radio tomography network

ACKNOWLEDGMENT

I would like to thank Prof. Debayan Gupta for his endless support and guidance.

REFERENCES

[1] R.R Rogers and W.O.J Brown, "Radar observations of a major industrial fire" *Bulletin of the Samer.Meteorologial Soc.,vol. 78, pp. 803-814.May 1997*

[2] Shukri, Shaufikah, and Latifah Munirah Kamarudin. "Device Free Localization Technology for Human Detection and Counting with RF Sensor Networks: A Review." *Journal of Network and Computer Applications* 97 (2017): 157–174. Crossref. Web.

[3] Pirzada, Nasrullah, et al. "Device-free localization technique for indoor detection and tracking of human body: A survey." *Procedia-Social and Behavioral Sciences* 129.422-429 (2014): 2nd.

[4] Adib, Fadel, and Dina Katabi. "See through walls with WiFi!." Proceedings of the ACM SIGCOMM 2013 conference on SIGCOMM. 2013.

[5] D. Maas, J. Wilson, and N. Patwari, "Toward a Rapidly Deployable Radio Tomographic Imaging System for Tactical Operations. In *IEEE 38th Conference on Local Computer Networks Workshops* (LCN Workshops), pp. 203-210, October 2013.

[6] N. Patwari and J. Wilson, "RF sensor networks for device-free localization and tracking," *Proceedings of the IEEE*, voL 98, no. 11, pp. 1961-1973, Nov. 2010.

[7] Patwari, Neal, and Joey Wilson. "Spatial models for human motion-induced signal strength variance on static links." *IEEE Transactions on Information Forensics and Security* 6.3 (2011): 791-802.

[8] Huang, Yongming, et al. "Effect of human body upon line-of-sight indoor radio propagation." *2006 Canadian Conference on Electrical and Computer Engineering*. IEEE, 2006.

[9] Wilson, Joey, and Neal Patwari. "Through-wall tracking using variance-based radio tomography networks." arXiv preprint arXiv:0909.5417 (2009).

[10] Wu, Chenshu, et al. "Non-invasive detection of moving and stationary human with wifi." *IEEE Journal on Selected Areas in Communications* 33.11 (2015): 2329-2342.

[11] Y. Wang, J. Liu, Y. Chen, M. Gruteser, J. Yang, and H. Liu,"E-eyes: In-home Device-free Activity Identification Using Fine-grained WiFi Signatures," in *Proceedings of ACM MobiCom*, 2014.

[12] Altman, Naomi S. (1992). "An introduction to kernel and nearest-neighbor nonparametric regression" (PDF). The American Statistician. 46 (3): 175–185. doi:10.1080/00031305.1992.10475879. hdl:1813/31637

[13] Cortes, Corinna; Vapnik, Vladimir N. (1995). "Support-vector networks" (PDF). *Machine Learning*. 20 (3): 273–297. CiteSeerX 10.1.1.15.9362. doi:10.1007/BF00994018.

[14] Wu, Chenshu, et al. "PhaseU: Real-time LOS identification with WiFi." 2015 *IEEE conference on computer communications* (INFOCOM). IEEE, 2015.

[15] Virmani, Aditya, and Muhammad Shahzad. "Position and orientation agnostic gesture recognition using wifi." *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services.* 2017.

[16] Zhou, Qizhen, et al. "A device-free number gesture recognition approach based on deep learning." 2016 12th *International Conference on Computational Intelligence and Security (CIS)*. IEEE, 2016.

[17] Yildirim, Hasan Can, et al. "Passive Radar based on 802.11 ac Signals for Indoor Object Detection." 2019 16th *European Radar Conference (EuRAD)*. IEEE, 2019.

[18] Sejdić E.; Djurović I.; Jiang J. (2009). "Time-frequency feature representation using energy concentration: An overview of recent advances". Digital Signal Processing. 19 (1): 153–183. doi:10.1016/j.dsp.2007.12.004

[19] Li, Yong and Gui Yun Tian. “A radio-frequency measurement system for metallic object detection using pulse modulation excitation.” (2008).

[20] Ciresan D, Giusti A, Gambardella LM, Schmidhuber J (2012) Deep neural networks segment neuronal membranes in electron microscopy images. In: Advances in neural information processing systems. pp 2843–2851

[21] Cireşan D, Meier U, Masci J, Schmidhuber J (2012) Multi-column deep neural network for traffic sign classification. Neural Networks 32:333–338. doi: 10.1016/j.neunet.2012.02.023

[22] Ciresan DC, Ciresan DC, Meier U, Schmidhuber J (2018) Multi-column deep neural networks for image classification. IEEE Comput Soc Conf Comput Vis Pattern Recognition.

[23] Chen Y-N, Han C-C, Wang C-T, et al (2006) The application of a convolution neural network on face and license plate detection. In: Pattern Recognition, 2006. ICPR 2006. 18th International Conference on. pp 552–555