Passive Human Motion Detection Using Wi-Fi Sensing

Wi-Fi Sensing is the use of 802.11 signals to detect events/changes in the environment. Often using signal processing and machine learning.

Wi-Fi is ubiquitous in homes and enterprises.

Using Wi-Fi Sensing for passive human detection expands the use of Wi-Fi beyond just communication.

We have utilized Wi-Fi CSI information to devise passive human motion detection system.

Wi-Fi can overcome drawbacks from alternative technologies such as

→ Camera -- Field of view, Privacy, Power consumption.

→ Ultrasonic/Laser -- Objects other than humans can be a big hurdle.

CSI (Channel State Information)

Orthogonal Frequency Division Multiplexing (OFDM) is a bandwidth efficient digital multi-carrier modulation scheme, which has been widely adopted in many modern wireless communication systems.

In OFDM, signals are transmitted over many orthogonal frequencies called **"subcarriers"**.

Based on OFDM, CSI describes how a signal propagates from the transmitter to the receiver at the subcarrier level, revealing the combined effect of, for instance reflection, scattering and power decay with distance.

CSI (Channel State Information)

Leveraging the off-the-shelf NIC with slight driver modification, a group of CFRs on N=30 sub-carriers can be exported to up-layer users for every one packet in the format of CSI:

$$\mathbf{H} = [\, \mathbf{H}(\mathbf{f}_1), \ldots, \mathbf{H}(\mathbf{f}_i), \ldots, \mathbf{H}(\mathbf{f}_N) \,]$$

$H(f_i)$ is the CSI at subcarrier i with central frequency f_i

Each CSI $H(f_i)$ represents the amplitude and phase of an OFDM subcarrier:

$$\mathbf{H}(\mathbf{f}_i) = \|\mathbf{H}(\mathbf{f}_i)\| \; \mathbf{exp}(\mathbf{j}\angle \mathbf{H}(\mathbf{f}_i))$$

CSI (Channel State Information)

With OFDM, the WiFi channel at the 5GHz band can be considered as a narrowband flat fading channel.

In the frequency domain, the channel model can be expressed as

$$Y = \mathrm{CSI} \cdot X + N,$$

Where Y and X denote the received and transmitted signal vectors, respectively, N is the additive white Gaussian noise, and CSI represents the channel's frequency response, which can be estimated from Y and X.

Progress **until** mid-term review

We chose the variances and IQR information of Wi-Fi CSI amplitude as features for detection.

We implemented a **ONE CLASS SVM** model for human detection and we were able to detect human motion with an **accuracy of 98.67%.**

We also implemented an **LSTM model on raw CSI amplitude** information and this model was able to detect human presence with an **accuracy of 96%.**

Progress after mid-term review

We have utilized the previously unused **CSI phase information** for human detection.

We have preprocessed the **CSI amplitude** and **Phase information** in order to filter out noises.

→ Discrete Wavelet Transform for amplitude denoising

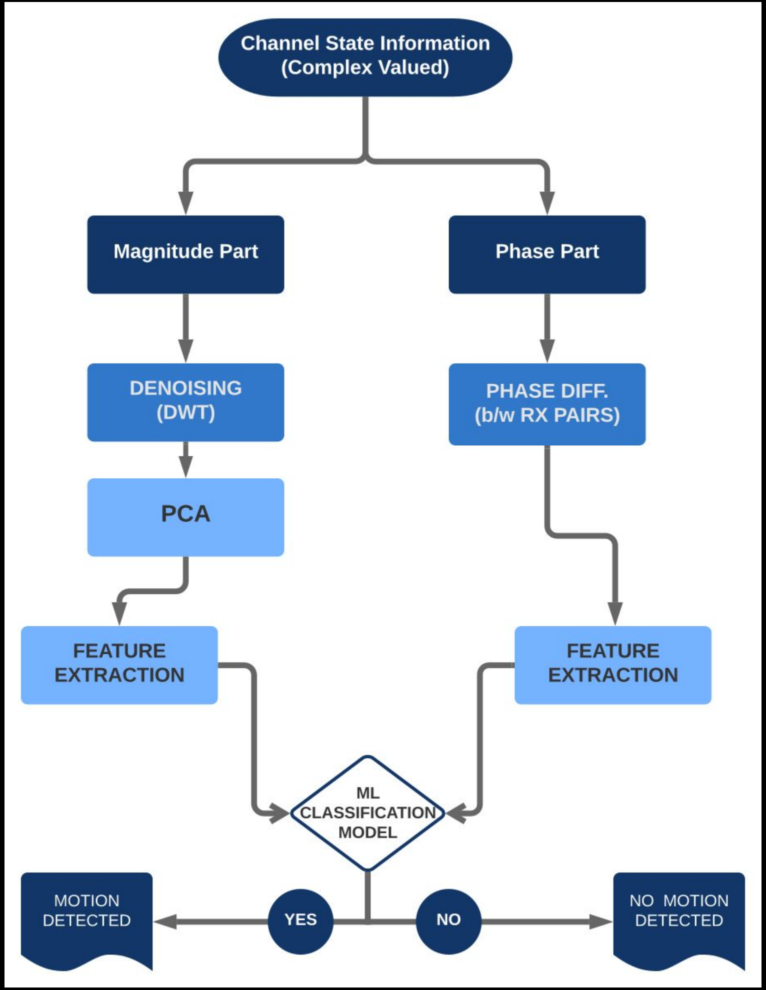
→ Phase difference for phase denoising

We have extracted better features from CSI phase and amplitude information for human presence detection.

We also implemented the **detection system for through the wall detection** scenarios.

Overview

The following flowchart provides the overall architecture of the human presence detection system we have implemented.



Data preprocessing

Leveraging the off-the-shelf NIC with slightdriver modification, a group of CFRs on N=30 sub-carriers can be exported to up-layer users for everyone packet in the format of CSI

$$\mathbf{H} = [\mathbf{H}(\mathbf{f}_1), \mathbf{H}(\mathbf{f}_2), \ldots, \mathbf{H}(\mathbf{f}_{30})]$$

To monitor an area of interest, CSIs are continuously collected and K measurements within a specific time window form the CSI sequence, which can be denoted as

$$\mathbf{H} = [\mathbf{H}_1, \mathbf{H}_2, \ldots, \mathbf{H}_k]$$

These K measurements of CFR values are parsed and downsampled to create CFR of 300 measurements across 3 receivers consisting of 30 subcarriers each.

Amplitude preprocessing

Wavelet denoising for the amplitude part

- Why is there a need to denoise ??

The collected CSI samples are noisy, because the commercial Wi-Fi devices are susceptible to complex indoor environment, such as surrounding electromagnetic interference e.t.c

- How to remove this noise ??

The noise mainly consists of high frequencies, hence a **low pass filter** will do the job for us.

Why not use a conventional LPF ??

We argue that it is not appropriate to use a conventional filter, such as Butterworth filter since the passband for the low-pass filter usually needs to be less than one-twentieth of the sampling rate, so that the energy of the residual noise in the passband becomes negligible compared to the signal energy.

Another reason being the non-stationarity of the signal, Discrete Wavelet Transform has a specialised way to analyse such signals.

The sampling rate is just 60 samples per second. As a result , we perform a wavelet-based denoising scheme to remove random noise and smooth the CSI data.

The denoising scheme involves 3 steps :

1. **Decomposition :**

   During the decomposition procedure, discrete wavelet transform recursively splits into two parts, high frequency coefficients (details) and low frequency coefficients (approximations), at different frequency levels.

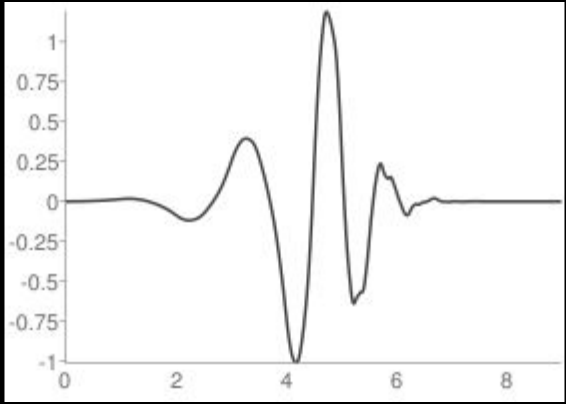
2. **Thresholding :**

   Thresholding is applied to the high frequency parts thereby decreasing the contribution of high frequency parts.

3. Reconstruction :

Finally, we reconstruct the denoised signal by combining the approximation coefficient of the last level with thresholded details.

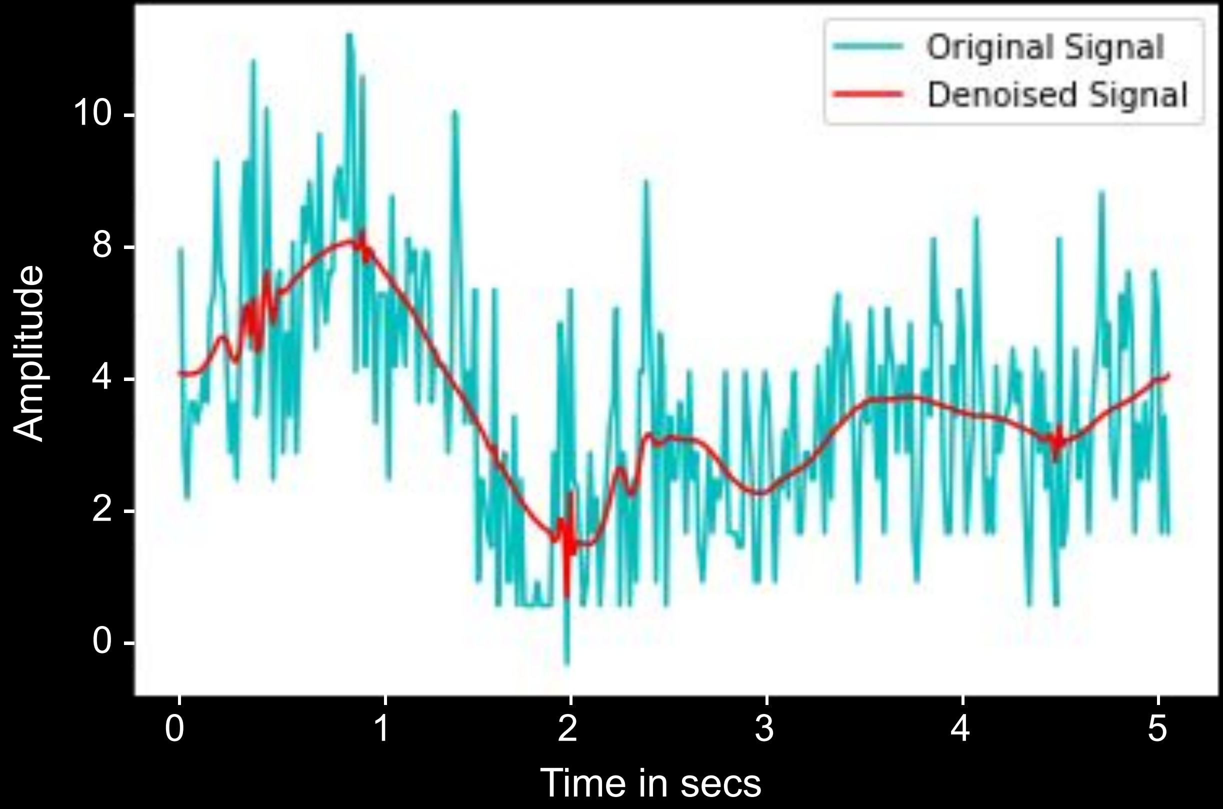
Hence in the end we just get the low-frequency portion of the signal, thus we denoise the high frequency portions of the signal.



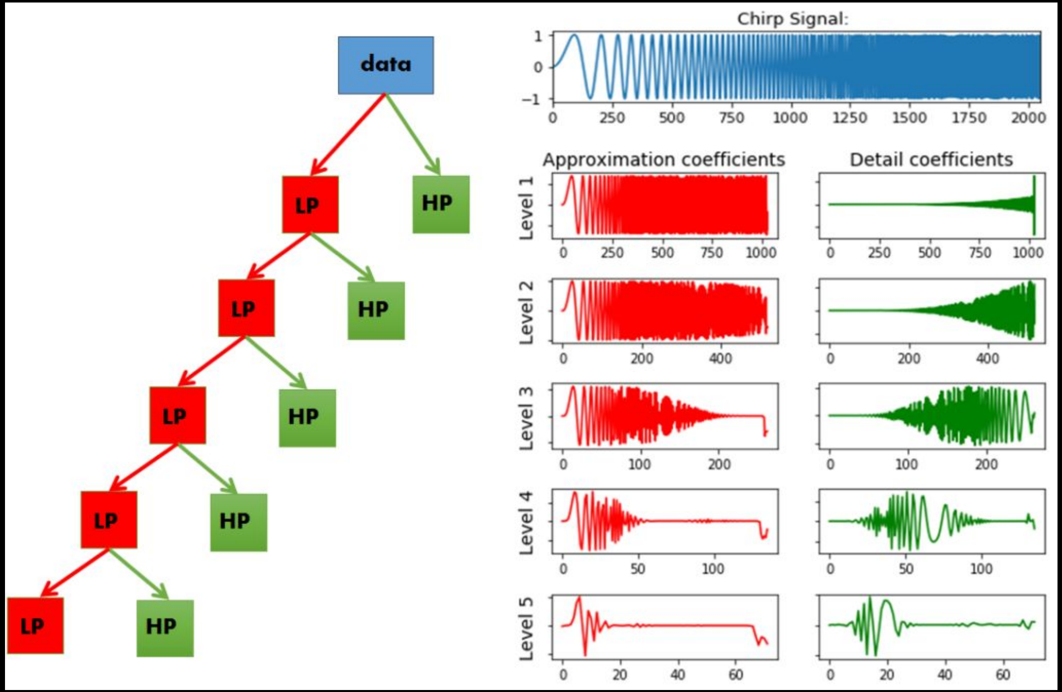
dB5 wavelet

Wavelet we used : dB5

Demonstrating the denoising scheme using DWT :



A great visualisation of how DWT can be used to parse out the high and low frequency components on a chirp signal :



Source :

http://ataspinar.com/2018/12/21/a-guide-for-using-the-wavelet-transform-in-machine-learning/

Phase preprocessing

Due to random noise and an unsynchronized time clock between transmitter and receiver, raw phase information behaves extremely randomly making it inapplicable for any detection.

Let $\angle \hat{CSI}_i$ denote the measured phase of subcarrier i, which is given by

$$\angle \hat{CSI}_i = \angle CSI_i + (\lambda_p + \lambda_s)m_i + \lambda_c + \beta + Z$$

$$\lambda_p = 2\pi\,(\Delta t/N)\ ,\ \lambda_s = 2\pi\,((T' - T)/T)\ (T_s/T_u),\ \lambda_c = 2\pi\,\Delta f T_s n$$

We cannot obtain the exact values for Δt, $(T'-T)/T$, n, Δf, and β in the equations mentioned in the previous slide.

So true phase cannot be derived from the measured phase value and thus measured phase cannot be used directly for detection as it is not stable.

But the measured phase difference on subcarrier i between two receiver antennas is stable.

Measured phase difference on subcarrier i between two antennas can be approximated as

$$\boldsymbol{\Delta}\angle \hat{CSI}_i = \boldsymbol{\Delta}\angle CSI_i + \boldsymbol{\Delta}\beta + \boldsymbol{\Delta} Z$$

Since Δt,Δf and n are all removed, $\boldsymbol{\Delta}\angle \hat{CSI}_i$ becomes highly stable for consecutive packets. It can also be seen that $\mathbb{E}(\Delta\angle \hat{CSI}_i) - \mathbb{E}(\Delta\angle CSI_i)$ is a constant $\Delta\beta$.

Feature Extraction

An appropriate feature plays a crucial role in device-free detection.

Previously we have explored **features like variance and IQR**, but the feature metric selected should be absolute power irrelevant and possibly variance dependent.

Due to lack of knowledge on transmit power at the receiver side,variance and IQR cannot be normalized to adapt to diverse scenarios and thus cannot be directly used for human detection.

As a consequence, we have extracted the features from the respective correlation matrices of CSI amplitude and phase data for 300 sequential measurements over a certain time window.

Amplitude Feature

PCA is performed on the CSI amplitude time series resulting from wavelet filtering.

Denote $H_{t,r}(i)$ as the N*1 dimension vector representing the CSI amplitude values of the N= 30 subcarriers between a TX-RX antenna pair t-r for the ith CSI sample. Then, let $H_{t,r}$ be a K*N dimension matrix containing the CSI amplitude values of N subcarriers between a TX-RX antenna pair t-r for K consecutive samples

$$H_{t,r} = [H_{t.r}(1), H_{t,r}(2), H_{t,r}(3), \ldots. H_{t,r}(K)]^T$$

Standardise the matrix $H_{t,r}$ so that each column has zero mean and unit variance,which is then denoted as $Z_{t,r}$.

Calculate the corresponding correlation matrix for $Z_{t,r}$.

$$
\begin{bmatrix}
C(1,1) & C(1,2) & \cdots & C(1,N) \\
C(2,1) & C(2,2) & \cdots & C(2,N) \\
\vdots & \vdots & \ddots & \vdots \\
C(N,1) & C(N,2) & \cdots & C(N,N)
\end{bmatrix}
$$

After computing the correlation matrix, perform eigen decomposition to obtain eigenvalues and eigenvectors $E = (e_1, e_2, \ldots\ldots, e_N)$

Based on these observations, we can calculate the mean of first order difference of eigenvectors as

$$\mathrm{Diff}(e_i)=(1/N-1)\ \sum_{k=2}^{N} |e_i(k)-e_i(k-1)|$$

We are going to use $\mathrm{Diff}(e_1)$, $\mathrm{Diff}(e_2)$, $\mathrm{Diff}(e_3)$ and $\mathrm{Diff}(e_4)$ as features for the human detection model.

Phase Features

PCA is performed on the time series resulting from phase difference on CSI phase information.

We first standardise these Phase CSI streams and calculate their corresponding correlation matrix. Similar to what we did for amplitude , we perform eigendecomposition and calculate the corresponding eigenvalues and select the maximum eigenvalue as feature.

In order to guarantee the robustness of the detection system we select the first two eigenvalues of the correlation matrix after they are sorted from maximum to minimum.

Experiments

The CSI samples dataset has been collected by wifi - commodity devices. The Tx has been set to operate in AP mode. The Rx is equipped with INTEL 5300 Nic.

• During the experiment the receiver pings packets from the router at a rate of 1KHz packets/sec, and records CSI from each packet.

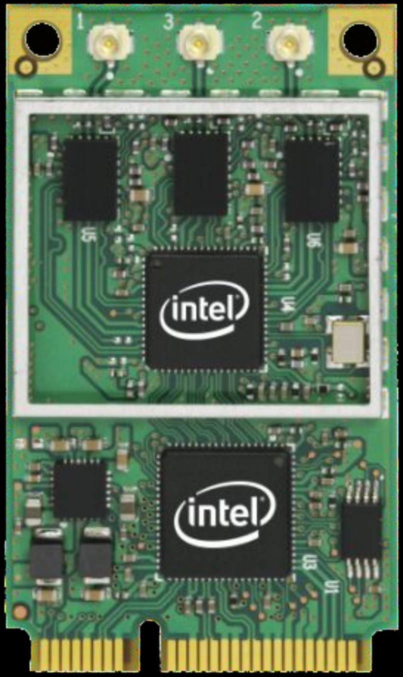
• A recording lasts upto 30 sec.

• We later downsampled and performed Time parsing so as to enhance the dataset for better learning.

Collection Of CSI data from INTEL NIC 5300

The INTEL NIC 5300 provides 802.11n channel state information in a format that reports the channel matrices for 30 subcarrier groups, which is about one group for every 2 subcarriers at 20 MHz or one in 4 at 40 MHz.

For eg; For a 20 MHz channel : The 60 Subcarriers are have a spaced by 312.5 kHz , and 30 are chosen.



More info ...

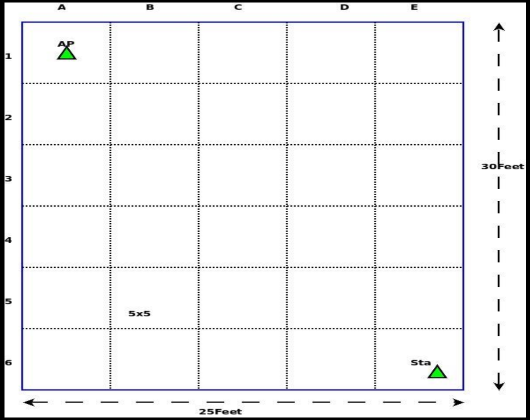
Each channel matrix entry is a complex number. It specifies the gain and phase of the signal path between a single transmit-receive antenna pair.So since we have 3 receivers on the INTEL NIC, The channel matrix for a recording consist of (30sec* 1KHz) samples, collected fo 30 subcarriers at 3 receivers.

** P.S : The raw CSI data has been captured in different environments and provided to us by the company GYRUS.

Environments:

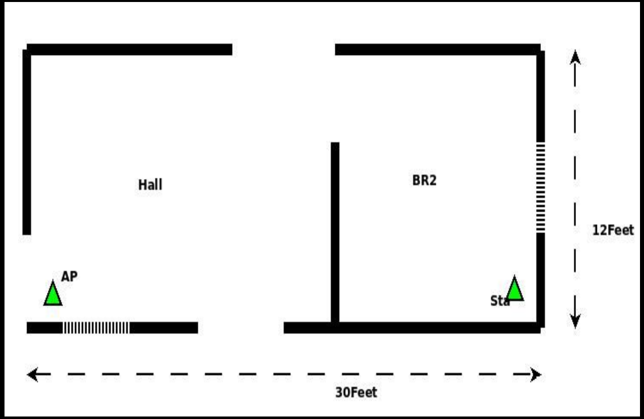
Single Room

Here a Tx and Rx are arranged at the diagonal corners and people are made to move in the room.



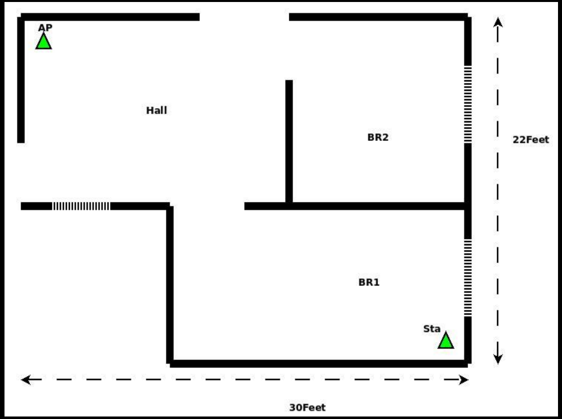
1BHK flat

Here a Tx and Rx are placed in different rooms which are divided by a wall.



2BHK flat

This is the same as the previous scenario, rather we have more rooms here and recordings are recorded in every room.



The data is collected for two different scenarios , while we devised a ML model to predict the same.

- **Static data:** CSI samples are collected where there is no human movement
- **Dynamic data :** When few people were made to move in the area.

Hence we build a ML classification model , that classifies if the time series chunk consists static data or dynamic data.

DATASET IN DETAIL :

From the raw dataset provided from the INTEL NIC 5300, where each recording has lasted for 30 sec at a 1Khz rate. We intended to enhance the data for better learning and testing.

For this, we downsampled the data from 1KHz to **60 Hz** and chopped the data into 5-sec chunks.

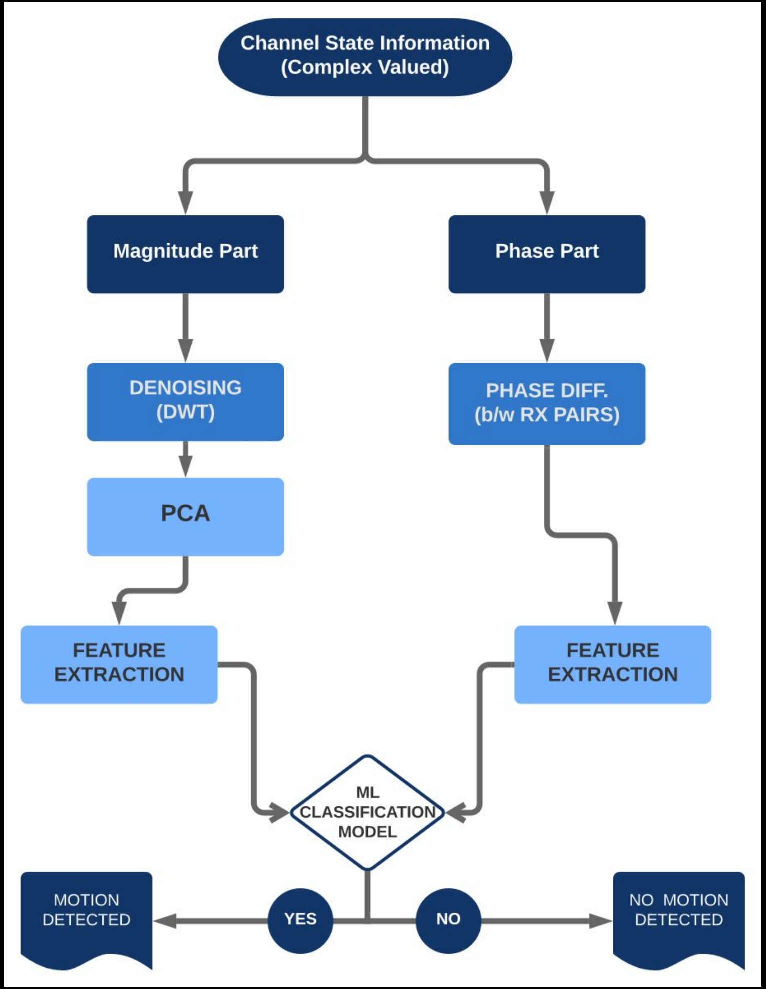
WHY 60 Hz and how doppler effect is related to it ?

** An average human moves at a 1m/sec in a room, it will lead to a ~10 Hz Doppler Shift. This shift leads to a change in phase for $2\pi f_C t_S$.The finer the t_S , the better resolution of change is observed.

Hence a **f_S of 60 Hz** is seen as a sufficient sampling rate to capture this.

Overview

The following flowchart provides the overall architecture of the human presence detection system we have implemented.



EVALUATION

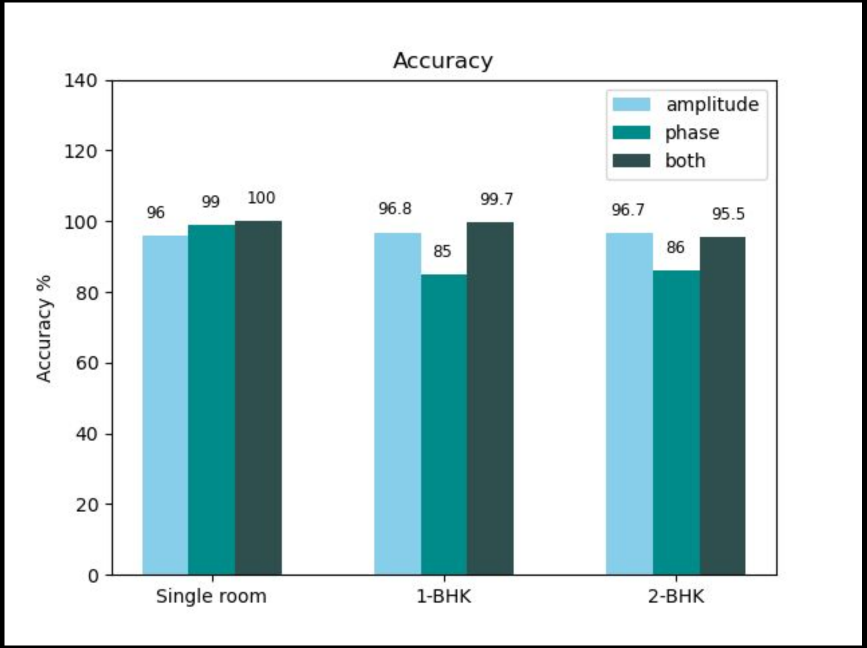
Machine Learning model :

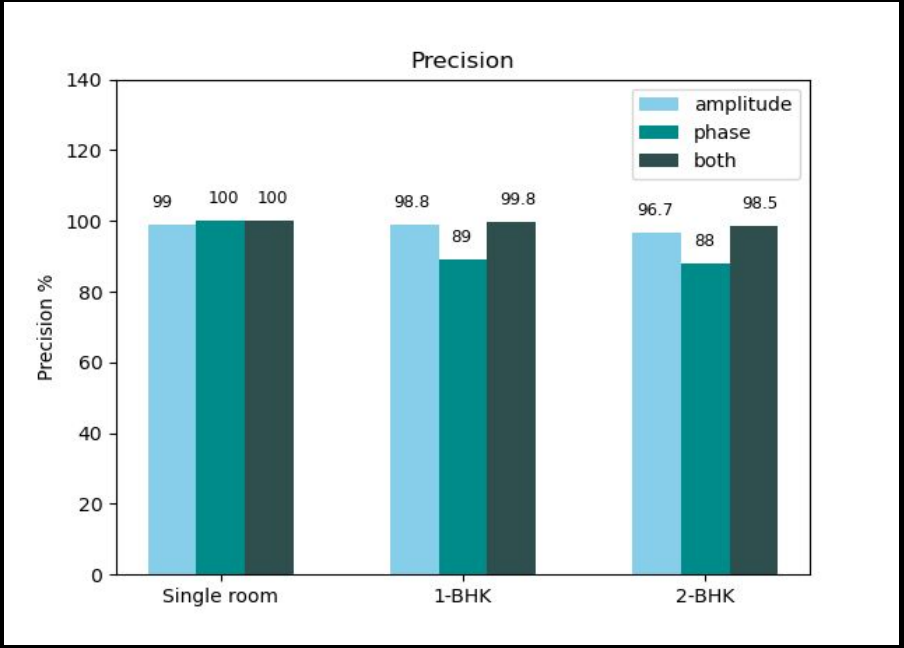
Since they are few features which are obtained through feature extraction. We landed up using **SVM(Support Vector Machine)** model for classification. We evaluated the model using features of amplitude , features of phase only and also features consisting the cumulative information of both phase and amplitude .

Evaluation Metrics :

We chose Accuracy and Precision to be metrics for evaluations. The results are portrayed in the form of histograms.

Results


Accuracy
140
120
100
80
60
40
20
0
Accuracy %
amplitude
phase
both
96
99
100
96.8
85
99.7
96.7
86
95.5
Single room
1-BHK
2-BHK


Precision
140
120
100
80
60
40
20
0
Precision %
amplitude
phase
both
99
100
100
98.8
89
99.8
96.7
88
98.5
Single room
1-BHK
2-BHK

OBSERVATIONS

- The first environment consists of a LOS(Line of Sight) path , since there are no obstacles between Tx and Rx. While the latter environments are setup in a NLOS path, here signals tend to reflect from walls and increase the number of multipaths.

- The Single room environment has a direct LOS path from Rx to Tx , hence there will be less multipaths here, and adding to that a human obstructing the LOS path acts as a obstacle (like a wall) and thus the signal bounces of from there as well. Hence we were able to predict the result better in this case , rather than other cases.

- The phase feature though was not much of a help here , but usually consists information about finer changes. Hence it is usually used for detecting small scale action like breathing etc;

By...

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>>> Special Thanks <<<

Dr. Sai DHIRAJ Amuru

GYRUS (DataSet Provider)

For more information...

Surya291/WiFi_Sensing