Clustering-Based Spectrum Sensing with OFDM Modulation for Cognitive Radio Networks



Motivation

- The exponential growth of wireless devices has led to increasing spectrum scarcity.
- Cognitive Radio Networks (CRNs) provide a dynamic solution by allowing secondary users to access underutilized frequency bands.
- This project explores how unsupervised machine learning can enhance OFDM-based spectrum sensing, making it more adaptive and robust.



Historical Context

- Traditional spectrum sensing techniques such as:
 - **Energy Detection** 0
 - Matched Filtering 0
 - Cyclostationary Detection 0

have limitations under **noise uncertainty** and **unknown signal conditions**.

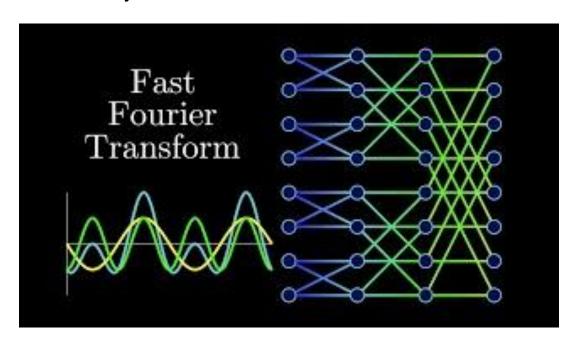
Clustering, an unsupervised learning approach, bypasses the need for fixed thresholds, making it suitable for dynamic environments—aligning with the growing use of AI in wireless communications.

Key Learnings & Contributions

- Built a complete OFDM transmitter and receiver using custom FFT/IFFT
- Implemented **KMeans-based clustering** for threshold-free signal detection
- Visualized signal energy, clustering output, and performance metrics
- Evaluated system using:
 - **ROC** Curve
 - X Bit Error Rate (BER)

FFT & IFFT Algorithm Explanation

 Following video by Reducible provides a clear and intuitive explanation of FFT and IFFT, crucial to OFDM systems:



FFT and IFFT algorithm from Scratch

$$\begin{pmatrix} F[0] \\ F[1] \\ F[2] \\ \vdots \\ F[N-1] \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \omega^{-1\cdot 1} & \omega^{-1\cdot 2} & \cdots & \omega^{-(N-1)} \\ 1 & \omega^{-2\cdot 1} & \omega^{-2\cdot 2} & \cdots & \omega^{-2(N-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{-(N-1)\cdot 1} & \omega^{-(N-1)\cdot 2} & \cdots & \omega^{-(N-1)^2} \end{pmatrix} \begin{pmatrix} f[0] \\ f[1] \\ f[2] \\ \vdots \\ f[N-1] \end{pmatrix}$$

Fourier Transform vector

DFT Square Matrix Data vector

We know that the fourier transform using this method take O(N2) time complexity.

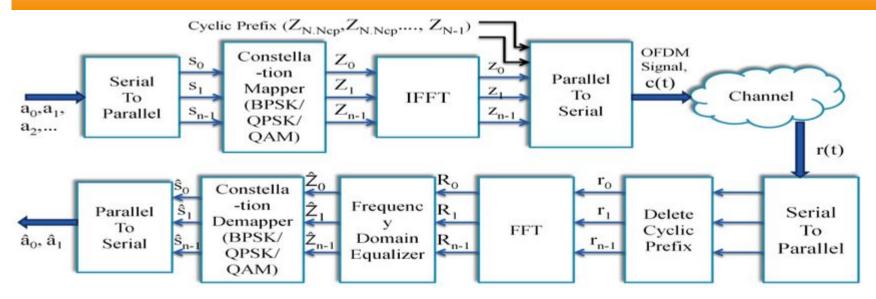
But, in FFT and IFFT algorithm we reduce this complexity to O(NlogN).

FFT and IFFT algorithm from Scratch

```
def FFT(P):
                                                      def IFFT(P):
n = len(P)
                                                           n = len(P)
                                                           if n == 1:
if n == 1:
                                                               return P
    return P
                                                           omega inv = cmath.exp(-2j * cmath.pi / n)
omega = cmath.exp(2j * cmath.pi / n)
                                                           P e = P[0::2]
P e = P[0::2]
                                                           P \circ = P[1::2]
P \circ = P[1::2]
                                                           y e = IFFT(P e)
y e = FFT(P e)
                                                           y \circ = IFFT(P \circ)
y \circ = FFT(P \circ)
                                                           v = [0] * n
v = [0] * n
                                                           for j in range(n // 2):
for j in range(n // 2):
                                                               omega j = omega inv ** j
    omega j = omega**j
                                                               y[j] = y e[j] + omega j * y o[j]
    y[j] = y e[j] + omega j * y o[j]
                                                               y[j + n // 2] = y e[j] - omega j * y o[j]
    y[j + n // 2] = y e[j] - omega j * y o[j]
                                                           # Scale the result by 1/n
                                                           return [val / n for val in y]
return y
```



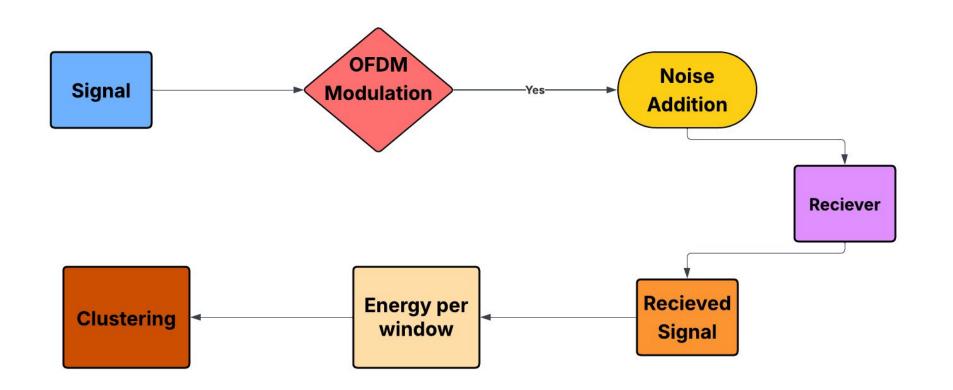
OFDM System Overview



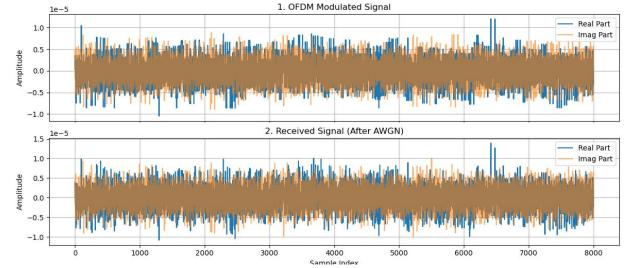
Reference:

https://www.researchgate.net/figure/Transmitter-and-Receiver-architecture-of -OFDM fig2 325283793

Framework

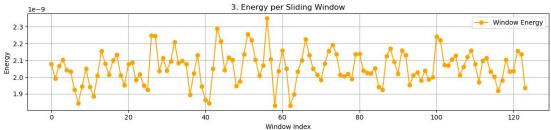


Signals Visualization



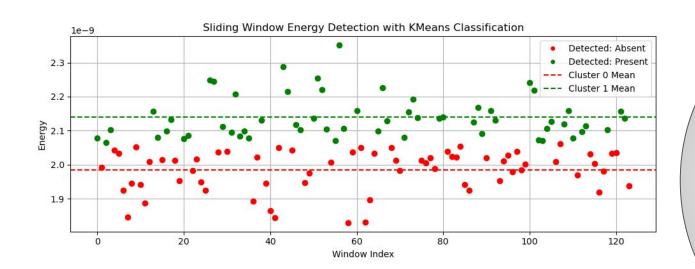
A Received Signal :



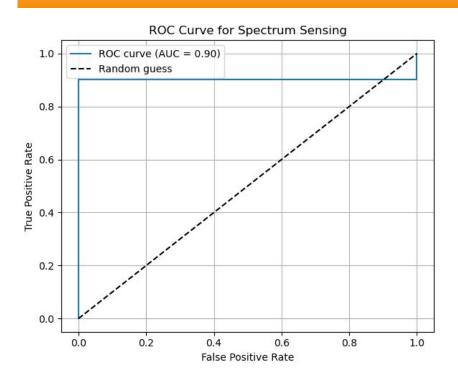




Energy and Clustering Visualization



We can see that above a threshold energy are classified as present and below that is classified as absent. Also the two dotted lines represents mean energy of that class.



We can see that Area of ROC curve is 0.9 means our classifier is behaving far better than random guess.

Results and Future Works

We obtained Block Error Rate nearly 0.

Future works:

- We can use multiple Reciever to solve real-world problems.
- We can use different Fusion Rules like Addition, Max, Majority Rule.
- Also co-operative sensing can be implemented using RL to select best neighbors and take all data and then we may use Unsupervised Learning or diff techniques to classify channel is free or busy.

Thank You!

- Colab Notebook: Click to Open
- Github Repository: visit github
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