CNN-based Signal Modulation Classifier For Shared Spectrum in Cognitive Radio Networks

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What is this presentation about?

The Role of Signal Modulation Classification in Shared Spectrum Systems

- 5G Promises and Challenges
- Shared Spectrum and Spectrum Sensing
- CNNs for modulation classification tasks
- Deep learning processor for inferencing on SDR Hardware targets (FPGA SoCs)

Rising Demand for Connectivity

- Over 2 billion devices connected to the internet
- E-commerce activities have reached $8 trillion annually[1]
- Higher data rates with ultra-low latency in emerging civilian and military applications.
- Large scale IoT, Vehicular connectivity, Virtual Reality applications, Advanced warefare etc.

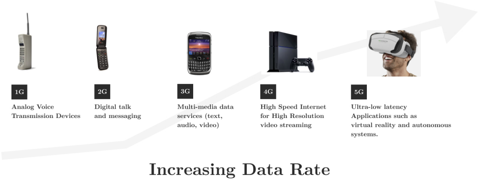


Figure: Internet growth trend

[1] McKinsey Global Institute

5G Promises

How do we meet the connectivity demands of these emerging applications and systems?

Continuous innovation in wireless communications has led to wireless technological evolution leading up to 5G Wireless Technology

5G Promises

- **Faster Speeds**: Higher data rates compared to 4G, with speeds up to 100 times faster
- **Increased Capacity**: Up to 1,000 times higher mobile data volume per area. [2]
- **Network Slicing**: Multiple virtual networks within a single physical 5G network.
- Lower latency, Economic and Environmental benefits

[2] What is 5G

5G Spectrum Layers

Super Data Layer

- Massive Capacity and Data Rates
- Atleast **800 MHz** of contiguous spectrum bandwidth per network

Coverage & Capacity Layer

- Low-frequency spectrum sharing with C-band spectrum (3.7 and 4.2 GHz)
- Best trade-off between capacity (> 100MHz wide) and wide area coverage

Coverage Layer

- Enabling 5G experience wide area & deep indoor settings.
- Supports LTE/NR coexistence via Uplink spectrum sharing

Figure: 5G Network Layers

5G Challenges

Summary

Challenges faced in 5G wireless technologies arise from the lack of radio spectrum bandwidth for envisioned data services

Some proposed solutions to the lack of available bandwidth

- Spectrum Re-farming
- Millimeter Wave (mmWave) Technology
- Spetrum Sharing

Proposed solutions landscape

- Economic and execution costs makes Spectrum Re-farming infeasible
- Inherrent propagation characteristics of mmWave Technology makes execution complex and costly (network densifications costs).
- Spectrum Sharing offers a faster and affordable solution to recovering bandwidth necessary to fulfil the promises of 5G technology.

Taxonomy of Spectrum sharing gives the classification and organization of methods and technologies that support effective spectrum sharing

- Sharing in Licensed Bands (DSS, LSA, SAS, etc.)
- Sharing in Unlicensed Bands (LTE-U, NR-U, etc.)

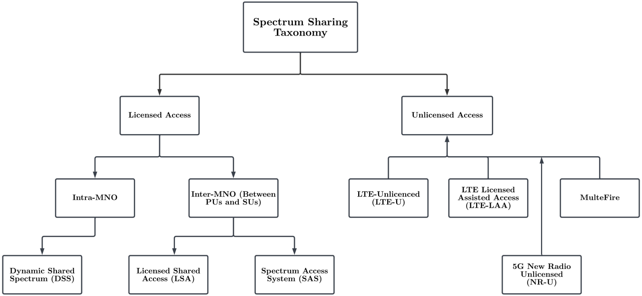
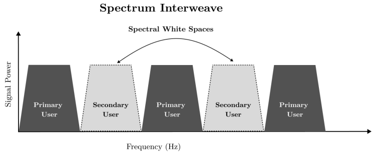


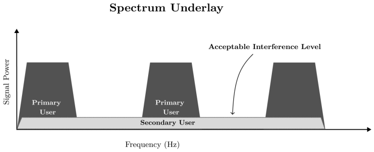
Figure: Spectrum Sharing Taxonomy

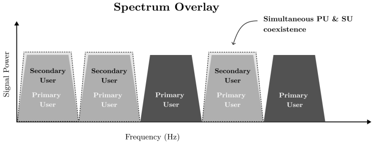
Spectrum Sharing Modes

Dynamic Spectrum Access (DSA) Modes

- **Spectrum Interleave** —Interference avoiding in both TDMA and FDMA modes.
- **Spectrum Underlay** —Interference-permitted. Secondary User (SU) nodes adhere to the *permitted interference* levels
- **Spectrum Overlay** —Concurrent frequency band usage. Knowledge of Primary User's (PU) encoding methods (codebooks) is required.







Sensing Techniques

Summary

Spectrum Sensing gives cognitive radios the ability to gather information about surrounding spectrum. Such information can be used to implement effective sharing strategies

Traditional Techniques

- **Energy Detection Method** — $E = \frac{1}{N} \sum_{n=1}^{N} |x[n]|^2$
  Threshold $= \alpha\sigma^2$
- **Matched-Filter Detection** — $R = \int_{-\infty}^{\infty} x(t)\, s^*(t-\tau)\, dt$
- **Feature-Based Methods** — Some Techniques for extracting features from surroundings signals
  - Spectral Based feature extraction
  - Moment-based feature extraction
  - Cyclostationary feature extraction

Sensing Techniques (cont.)

Advanced Techniques (signal modulation sensing/classification)

Involves the application of Deep learning algorithms at the PHY layer for sensing and understanding surrounding radio spectrum.

- **Multilayer Perceptron**—Fully connected Feedforward Networks, Deep Belief Networks.
- **Convolutional Neural Networks (CNNs)**—utilizing *convolution* operations to process spatial hierarchies in multidimensional signals.
- **Recurrent Neural Networks (RNNs)**—well-suited for tasks involving sequential data processing.

Sensing Techniques (cont.)

Convolutional Neural Networks (CNNs)

- **Convolution Operation**—involves sliding a filter (kernel) over the input data followed by element-wise multiplication
- **Sparse Connectivity**—sparse connection pattern resulting from filter sizes (small) compared to input signal size (large).
- **Parameter Sharing**—filter (kernel) reuse at each convolutional layer results in computationally efficient performance.

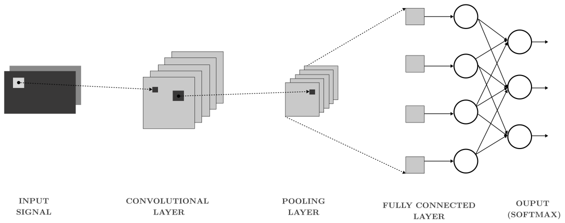


Figure: Convolutional Neural Network Architecture

Why signal modulation classification?

When the modulation technique of a signal is known, several information needed to characterize the signal can be further extracted, eliminating the need for centralized information storage.

- Signal Demodulation—receiver can effectively demodulate the signal
- Channel characterization—channel impulse response derivation
- Signal quality measurement—signal SNR can be calculated
- Signal phase and timing information

CNN-based Signal Modulation Classifier

Design Objectives

- Retrieve the RadioML dataset and perform a brief exploratory data analysis to become familiar with the dataset's content
- Train and evaluate the performance of a Convolutional Neural Network (CNN) for signal modulation classification.
- Investigate the effect of the model's receptive field (filter size) on the classification accuracy.
- Develop and optimize a deep learning processor for the CNN model, and generate an implementation and timing report for the design.

Dataset Selection

RadioML *by DeepSig*

- Consists of synthetic signals and signals received via an over-the-air transmission channel.
- Signal generation involved pulse shaping, interpolation, and carrier frequency mixing stages
- Signal response to Rayleigh Channel Impulse Response to simulate multipath fading in wireless channels + additive Gaussian white noise (AGWN)

Property	Value
SNR levels	26 SNRs per modulation (-20 dB to +30 dB in steps of 2dB).
Frame size	1024 complex time-series samples per frame.
Dataset size	2,555,904
Modulation types	24
Signal sourcing	Mixed (synthetic and recieved over-the-air signals)

Table: Radio ML Dataset Properties

Exploratory Data Analysis

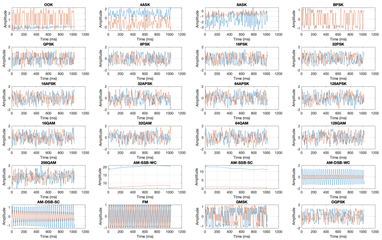


Figure: All Signal Modulations at 30dB SNR

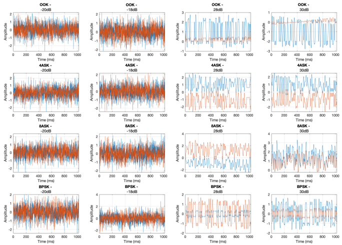


Figure: Signal Modulation SNR extremes (worst - best)

Model Training

CNN network architecture desinged and trained on Matlab

- VGG inspired network architecture
- 4 different networks with varying filter size is trained to investigate impact of receptive field (filter size) on model's accuracy.
- Input data (Raw IQ time-series frames)
- Output data (Signal modulation class)

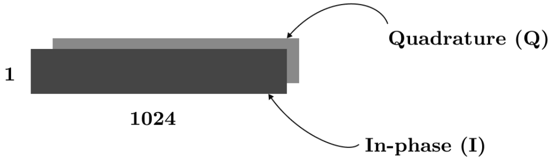


Figure: CNN Model Input Data Schema

Model Training

Network and training parameters

Property	Value
Conv Layer	2-D Conv $\rightarrow$ Batch Norm $\rightarrow$ ReLU $\rightarrow$ 2D Max Pool
Output Layer	Softmax $\rightarrow$ Output (cross entropy)
Network Input	$1 \times 1024 \times 2 \times$ miniBatchSize
Number of FC Layers	11
Number of Conv Layers	6

Table: CNN Network Parameters

Property	Value
Solver	sgdm (stochastic gradient descent with momentum)
Max. Epochs	20
Validation Frequency	1 per epoch
Training set	80%
Validation & Test set	10%

Table: Model Hyperparameters

Receptive Field Investigation

Training was done on 4 similar CNN Network architecture with varying filter sizes

- We aim to determine the ideal filter size to be used in CNNs for radio signal classification tasks
- Filter size determines the convolutional layer resolution

Model	Receptive Field
Model I	1×2
Model II	1×4
Model III	1×8
Model IV	1×16

Table: Model Receptive Fields

Deep learning processor for target SDR (FPGA)

- Designed using MATLAB Deep Learning HDL Toolbox
- Utilizes pre-built bitstreams for running a variety of deep learning networks on supported hardware targets.
- Xilinx Zynq Ultrascale+ Device family was targeted

Steps to build DL Processor on Matlab

Load the best performing model → **Create** FPGA processor configuration → **Set** target frequency to 100 → **Optimize** the configuration for the network → **Validate** the configuration → **Estimate** the performance → **Build** the processor configuration

Model Accuracy

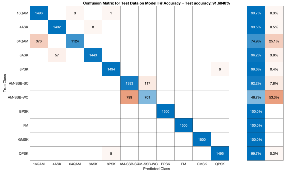


Figure: Model I (Accuracy 91.68%)

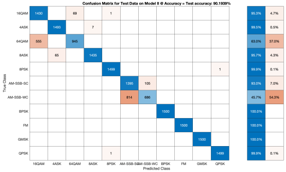


Figure: Model II (Accuracy 90.19%)

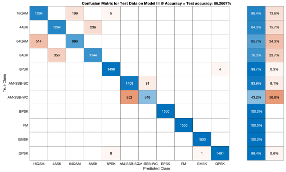


Figure: Model III (Accuracy 86.26%)

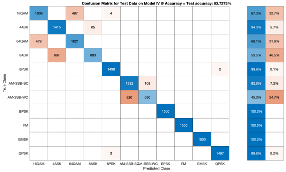


Figure: Model IV (Accuracy 83.72%)

Model Results

Table: Model Training Results

Model	Training Duration	Total Learnables	Accuracy
Model I	114min 2secs	25.7k	91.68%
Model II	102 mins 12secs	49.6k	90.19%
Model III	91 mins 33secs	97.3k	86.26%
Model IV	109 mins 59secs	192.8k	83.72%

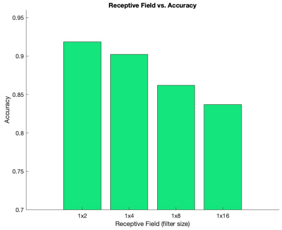


Figure: Model Receptive Vs Accuracy

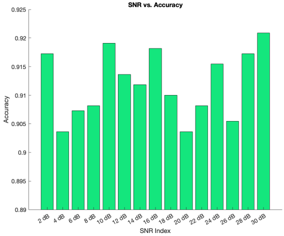


Figure: Model Accuracy Vs Signal SNR (2dB - 30dB)

Hardware Design Results

Best Performing Model Hardware Implementation

Table: Post Implementation Timing Summary

	Setup (ns)	Hold (ns)
Worst Negative Slack (WNS)	0.312	0.010
Total Negative Slack (TNS)	0.000	0.000
Total Number of Endpoints	833611	833023

Table: Post Implementation Hardware Utilization Report

Resource	Utilization	Available	Utilization %
LUT	236554	274080	86.31
LUTRAM	33290	144000	23.12
FF	250539	548160	45.71
BRAM	555.50	912	60.91
IO	52	328	15.85

Hardware Design Results

Overall Performance

According to estimate from Matlab DLHDL total latency is estimated to be **1,468,083 clock cycles**.

$$\text{Time (s)} = \frac{\text{Latency (in clock cycles)}}{\text{Clock Frequency (in Hz)}}$$

$$\text{Time} = \frac{\text{1,467,925 clock cycles}}{100 \times 10^6}$$

$$= 14.68 \text{ milliseconds}$$

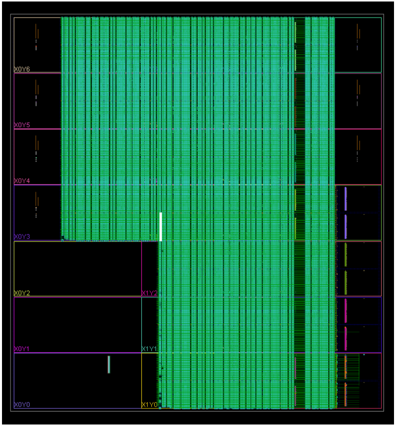


Figure: FPGA Routing Resources on Xilinx Zynq UltraScale+ Product Family

1. Internet Growth Trend
2. Spectrum Sharing
3. Spectrum Sensing
4. Signal Modulation Sensing
5. Methodology
6. Results & Discussion
7. Conclusion

CNNs are effective for handling signal modulation classification task on raw time-series radio signals

Future directions

- Deeper CNNs that are trained for longer epochs are likely to yield better performance.
- Other neural network architectures like Deep Belief Network (DBNs), Recurrent Neural Networks (RNNs) have the potential to handle signal modulation classification
- Quantization (Quantized Aware Training) will potentially result in more efficient and sustainable hardware implementation

Conclusion

Thank You!

Any Questions?