Enhancing Modulation Recognition in Cognitive Radios through Dyadic Downsampling Schemes and Artificial Intelligence

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Context

Automatic Modulation Recognition (AMR) or Automatic Modulation Classification (AMC) is the act of detecting and identifying a received signal. More precisely, the objective is to determine the employed modulation type of a sensed Radio Frequency (RF) signal at a given time, space and frequency. AMR is done after signal detection and prior to demodulation of the signal.

Goals

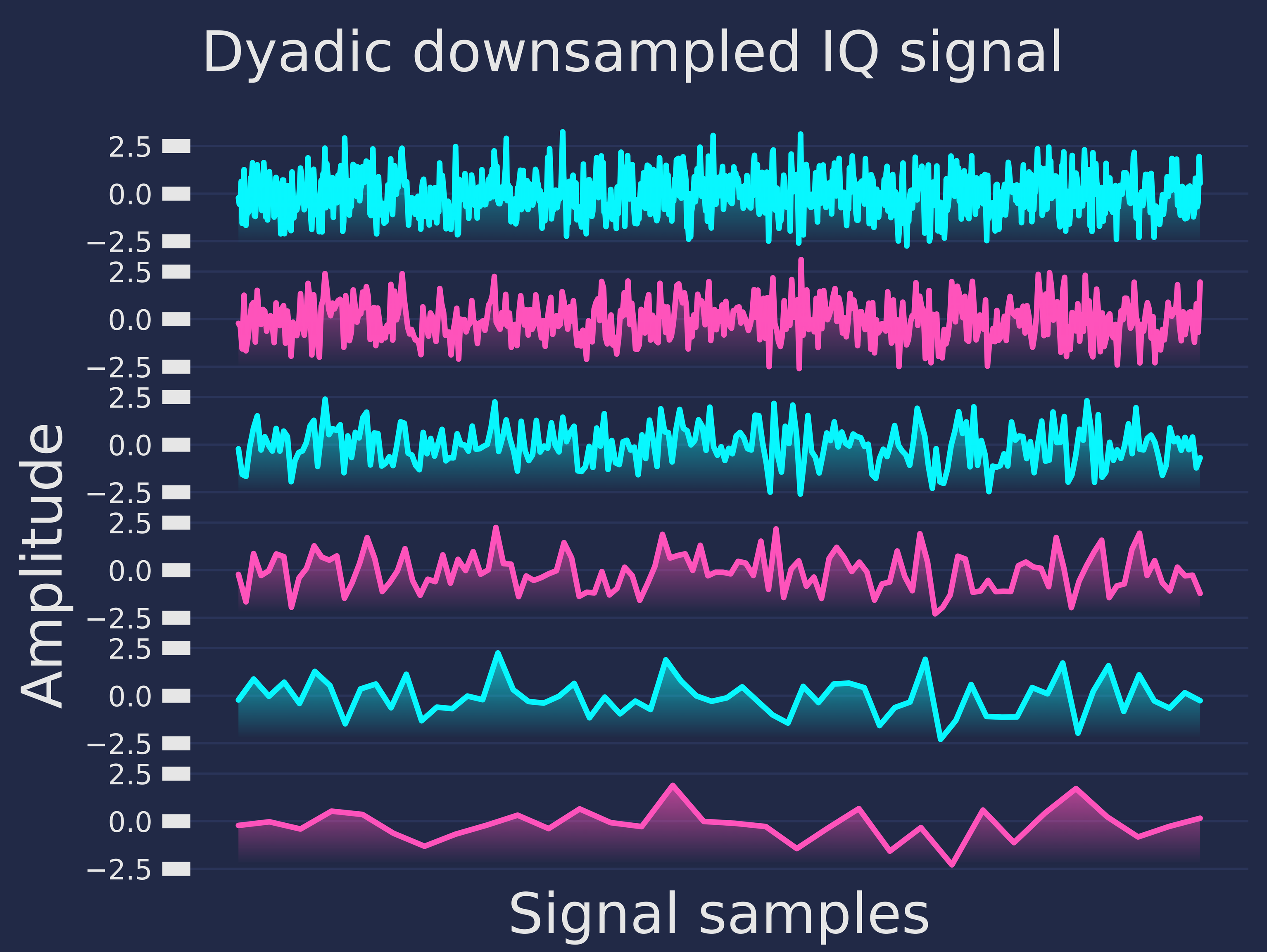
Recognizing digital modulation schemes without prior knowledge is vital for cognitive radios' evolution. These radios dynamically adjust their modulation according to external factors. Precise detection serves to minimize control header overhead. Automatic modulation classification is instrumental for applications like monitoring and electronic warfare. Integrating a dyadic sampling scheme is pivotal as it enables rapid, lightweight decomposition into scales. This research highlights the dyadic sampling impact of IQ based signals and explores its implications in conjunction with CNN-based modulation classification. The database used is the "Dataset for the Machine-Learning Challenge [CSPB.ML.2018]" from the cyclostationary.blog. For additional references, please refer to the QR code.

Dyadic Downsampling

A dyadic filter is a type of filter designed to analyze or modify signals through a process that involves successive divisions or decompositions of the signal into sub-bands or levels, with each level representing a different frequency range. The decomposition is typically performed using a dyadic sampling scheme, where the signal is repeatedly subsampled by a factor of 2. The dyadic sampling scheme allows for a multi-resolution analysis, making dyadic filters valuable in scenarios where a signal's features are distributed across different frequency scales.

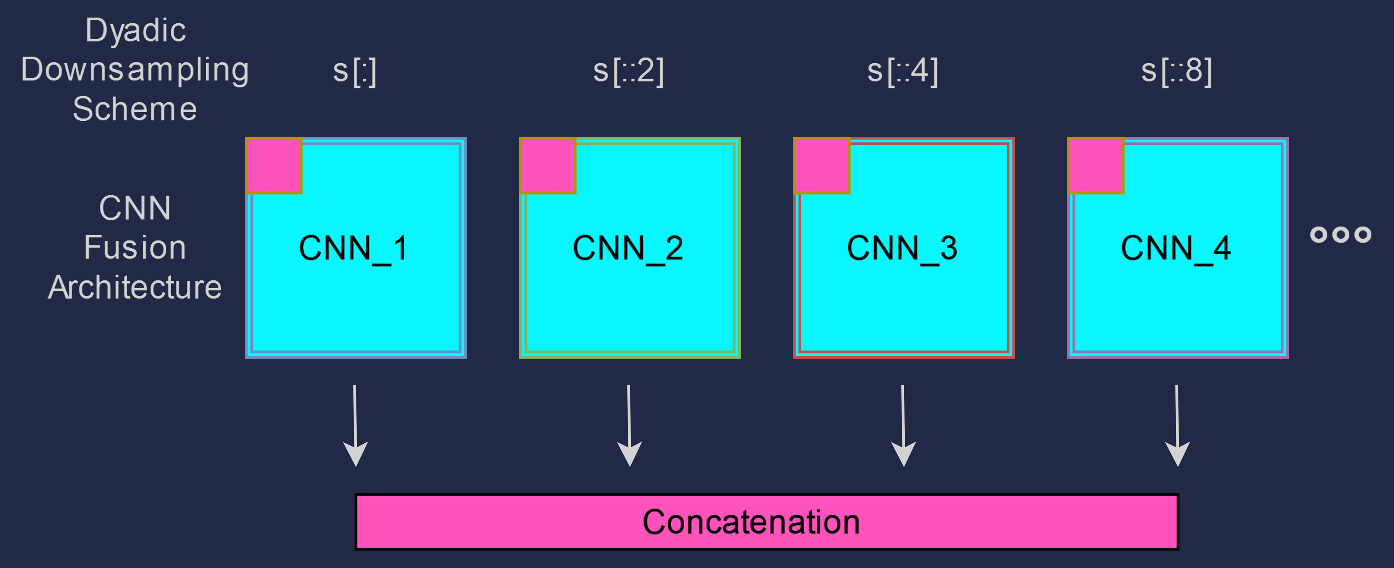
Signal scales

By extracting five scales we double the number of input samples. The following figure shows the real part of the original IQ signal and its first five Dyadic down-sampled versions.



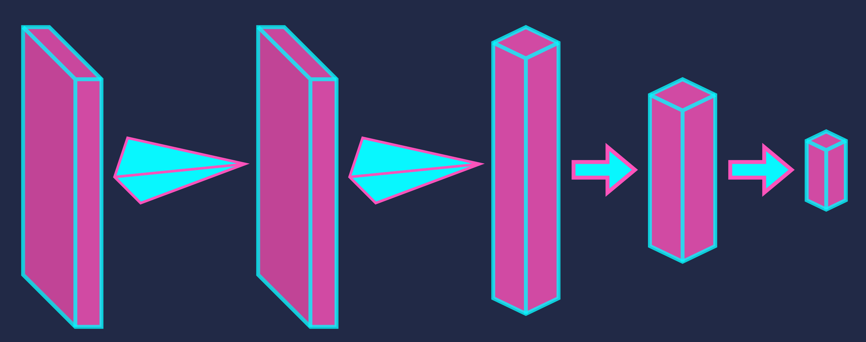
Fusion Architecture

Global overview of the CNN architecture, each dyadic sub-sampled version of the IQ signal has its own CNN layer.



Sub-CNN architectures

The architecture comprises two CNN layers followed by a concatenation and a dense layer. The output layer comprises 8 neurons, each corresponding to one of the 8 modulation types. The kernels used in these layers have dimensions of 2x8 and 1x4, respectively. The dense layer size is chosen to maintain uniform compression factors for both single IQ and dyadic schemes.



First results and classification improvements

Table: Classification results of the Dyadic Fusion architecture and the original IQ (given in absolute validation accuracy (%))

Data-length (samples)	Original IQ	Dyadic scheme
512	75.9	79.6
1024	84.0	87.5
2048	85.0	91.0
4096	86.3	92.3

Conclusion

Utilizing Dyadic down-sampling as input for an AI recognition system allows enhancement in classification accuracy, all achieved without imposing substantial computational overhead.

Next steps

- Analysis of which sampling schemes has the most impact
- Which combination of scales gives the most accurate classification results
- How to improve the overall architecture by training a Hyper model