CS 5033: Final Project Proposal

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1 Problem Statement

The rapid evolution of wireless communications technologies such as 4G/5G and the internet-of-things (IoT) has radically altered daily life. These technologies utilize the radio frequency (RF) portion of the electromagnetic spectrum, which is a finite resource. To effectively access and regulate the spectrum, it is essential that the next generation of wireless devices be able to rapidly classify and monitor signals in the spectrum. Information gained from sensing the spectrum can be used for tasks such as cognitive radio, interference detection, and dynamic spectrum access [2]. Traditionally, signal detection and classification has been accomplished through static filtering and signal processing using expert features, which for the most part is not data-adaptive [1].

In this project, I propose to apply deep learning to the modulation recognition problem. I will formulate this as a multi-class classification task that I will solve using convolutional neural networks (CNNs). The network(s) will take RF data as input and output the signal type along with a confidence score. My central research question is *how accurate are convolutional neural networks for signal classification in a congested spectrum?*

To address the above question, I propose the following research activities:

– create a framework to easily synthesize in-phase/quadrature (IQ) data, which is a sampled version of the signal received by an RF antenna

– Develop a CNN that can localize and classify RF signals from raw IQ data

– Evaluate the network on a testing set which will also be synthetically generated

– Stretch goal 1: Explore alternative representations of the IQ data, such as spectrograms (time-frequency plots) and constellation diagram (real-imaginary plots) For example, rather than training on the raw data itself the model might be trained on the signal spectrogram (a time-frequency plot). This would allow the model to better distinguish between signals that are similar in the time domain but have different frequency content and vice-versa.

– Stretch goal 2: Collect over-the-air (not simulated) data using a commercial software-defined radio.

– Stretch goal 3: Extend the data synthesizer to simulate radar signals

2 Methodology

The goal of this project is to implement (and hopefully improve upon) the methodology from [4], which uses raw IQ data to train a CNN to classify different modulation types. Since my primary focus is dataset generation, this network will be constructed using libraries such as Keras and Tensorflow. Time permitting, I would also like to explore the approach taken in [6], which uses the YOLO algorithm [5] to train a CNN from spectrogram images. The YOLO algorithm is designed for real-time implementation, which is an obvious requirement for deployment in spectrum-monitoring cognitive radios.

3 Data Preparation

A major component of this project will be to develop an RF data synthesis tool. Since radio communications signals are already synthetically generated in practice, it should be possible to mass-produce synthetic IQ data that is representative of real-world scenarios. The synthesis architecture will largely follow the general model outlined in [3]. I will implement it in Python/GNU Radio, and it will be able to simulate phenomena such as thermal noise, channel effects (e.g., multipath and fading), and center frequency/sampling offsets. Coupled with the methodology outlined above, my project primarily falls under category I (Application).

4 Evaluation Plan

I plan to develop a dataset generation tool that can simulate at least five different communications modulation schemes. This tool will be able to simulate the common signal imperfections described in the previous section in order to make the dataset more representative of real-world scenarios. Next, I will train a CNN on the generated datasets to replicate the results from [4], which achieves a classification accuracy of about 70% at high signal-to-noise ratios ($\geq$20 dB).

References

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