CS 5033: Final Project Report

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1 Introduction

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 [4]. Signal detection and classification has traditionally been accomplished through static filtering and signal processing using expert features [1]. However, a data-adaptive approach is needed to improve spectrum efficiency to meet modern wireless data demands.

For this project, I have developed a training and testing dataset generation tool for RF signal classification networks. This tool follows the process outlined in [5], which uses GNU Radio to simulate the effects of hardware and propagation through a channel (e.g., free space). The tool is currently capable of simulating six different types of signals (four communications-based, two radar-based) and my object-oriented approach makes it easily extensible to others. To verify the output of the tool, I have also implemented a modified version of the convolutional neural network (CNN) described in [6].

2 Methodology

For this project, I have implemented a number of radar and communications signals along with a script to simulate various effects of propagation through a channel.

2.1 Signals

I will first outline the mathematical definitions of the various signals (also known as waveforms) I have simulated. The first waveform is known as binary phase-shift keying (BPSK), which is defined as

$$x(t) = \cos(2\pi f_c t + \pi(1-n)), n \in 0, 1 \tag{1}$$

BPSK is the most fundamental type of phase modulation used by the communications community. When the bit to be transmitted is 0, the signal phase is π, and when the bit is 1 the phase is 0. As equation 1 and figure 1 show, BPSK is entirely real-valued.

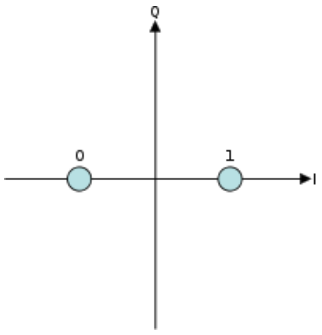


Figure 1: BPSK constellation diagram

I have also implemented higher-order PSK signals: QPSK and 8PSK. QPSK is defined as

$$x(t) = \cos(2\pi f_c t + \frac{\pi}{4}(2n-1)), n \in 0, 1, 2, 3 \tag{2}$$

With this definition, there are four different phase states corresponding to bits 00, 01, 10, and 11 (figure 2). Therefore, twice as many bits can be transmitted at once, and the signal is no longer purely real.

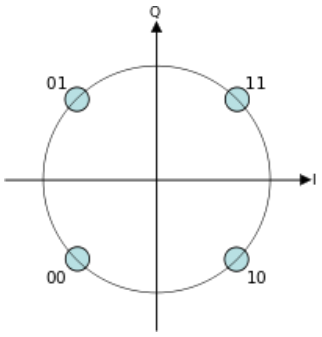


Figure 2: QPSK constellation diagram

8PSK is defined similarly, with eight phase states corresponding to bit sequences 000, 001, . . . , 111.

The final communications waveform simulated for this project is known as 16-QAM, whose constellation diagram is given below

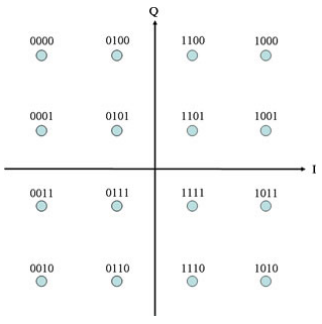


Figure 3: 16-QAM constellation diagram

Unlike the previous modulation schemes, the 16-QAM phase states do not lie on the unit circle. While this allows more bits to be encoded, the phase states become closer together and are harder to identify in the presence of noise. This will be important when classification performance is discussed.

To diversify the types of waveforms in the dataset, I have simulated some radar waveforms as well. The first waveform of this class is known as the simple pulse or square wave of time duration T, which is defined simply as

$$x(t) = \begin{cases} 1 & \text{if } t \in [0, T] \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The second, known as the linear frequency-modulated (LFM) pulse, is more complicated and more common in practice

$$x(t) = \begin{cases} \exp\left(j\pi \frac{B}{T} t^2\right) & 0 \leq t \leq T \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Here, the waveform frequency sweeps linearly through the bandwidth B over the pulse duration T. The real and imagninary parts of each waveform is shown in figure 4. This representation of the data serves as the input to the CNN.

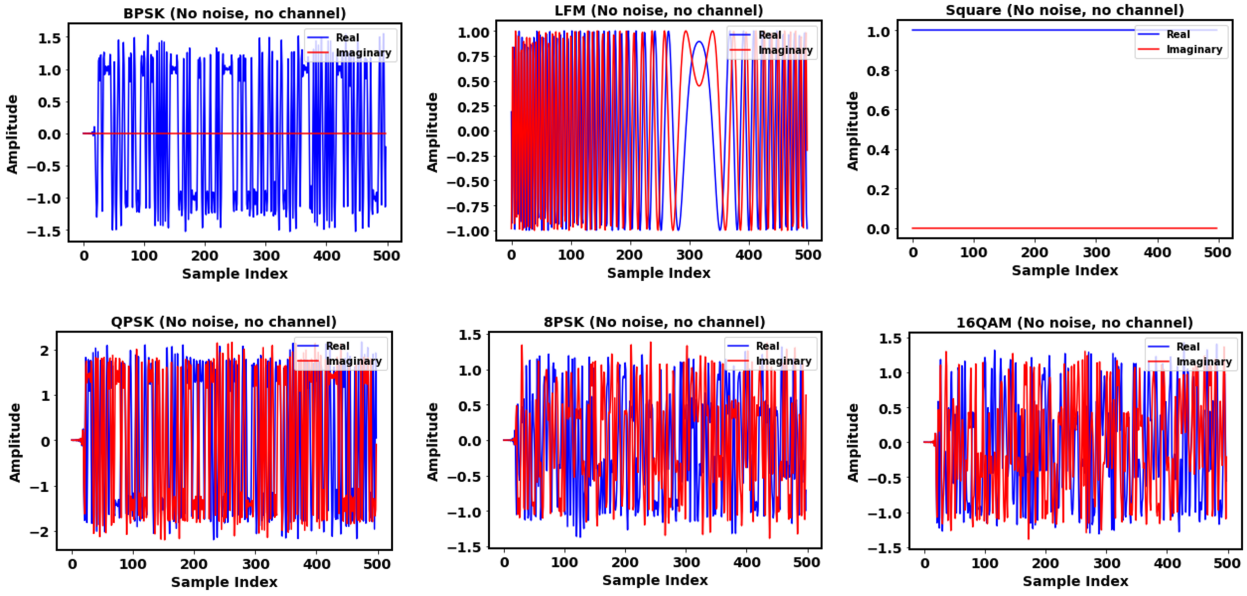


Figure 4: Waveforms used for Experiment

2.2 Channel Model

To make the simulated waveforms more representative of real-world scenarios, I used GNU Radio primitive blocks to implement a channel model. The full mathematical description of the channel model is

$$s(t) = \exp(jn_{CFO}(t)) \int_{\tau=0}^{\infty} x(n_{SRO}(\tau)h(t-\tau))d\tau + n_{AWGN}(t) \tag{5}$$

Here, $\exp(jn_{CFO}(t))$ is the carrier frequency offset due to free-running oscillators in the RF hardware. Although the oscillators in the transmitter and receiver are initially synchronized, they drift apart over time. This phase/frequency shift was modeled as a random walk process with a Gaussian step size (with user-defined standard deviation).

The clock timing in each system may also be slightly different, which is captured in the $n_{SRO}(t)$ term. This is modeled by interpolating the output signal by a factor of $1+\beta$, where β is the sample rate difference between systems (normalized by the expected sample rate). For example, if $\beta = 0.1$, then the receiver collects 11 samples for every 10 samples transmitted. Ideally, $\beta = 0$.

Figure 5: Example propagation path

The model also takes into account the effects of propagation through the environment, as shown in figure 5. Ideally, the signal propagates directly from the transmitter to the receiver, but in practice it will scatter off other objects in the environment to produce scaled and shifted copies of the original signal. This phenomenon is modeled as a convolution with an FIR filter $h(t)$, where each filter coefficient represents an object in the environment. These coefficients also include a time-varying phase shift to simulate motion and the doppler effect. The final component of the channel model simulates thermal additive white Gaussian noise from the receiver. The impact of each of these individual distortions is shown in figure 6 for the reference signal in figure 6(a).

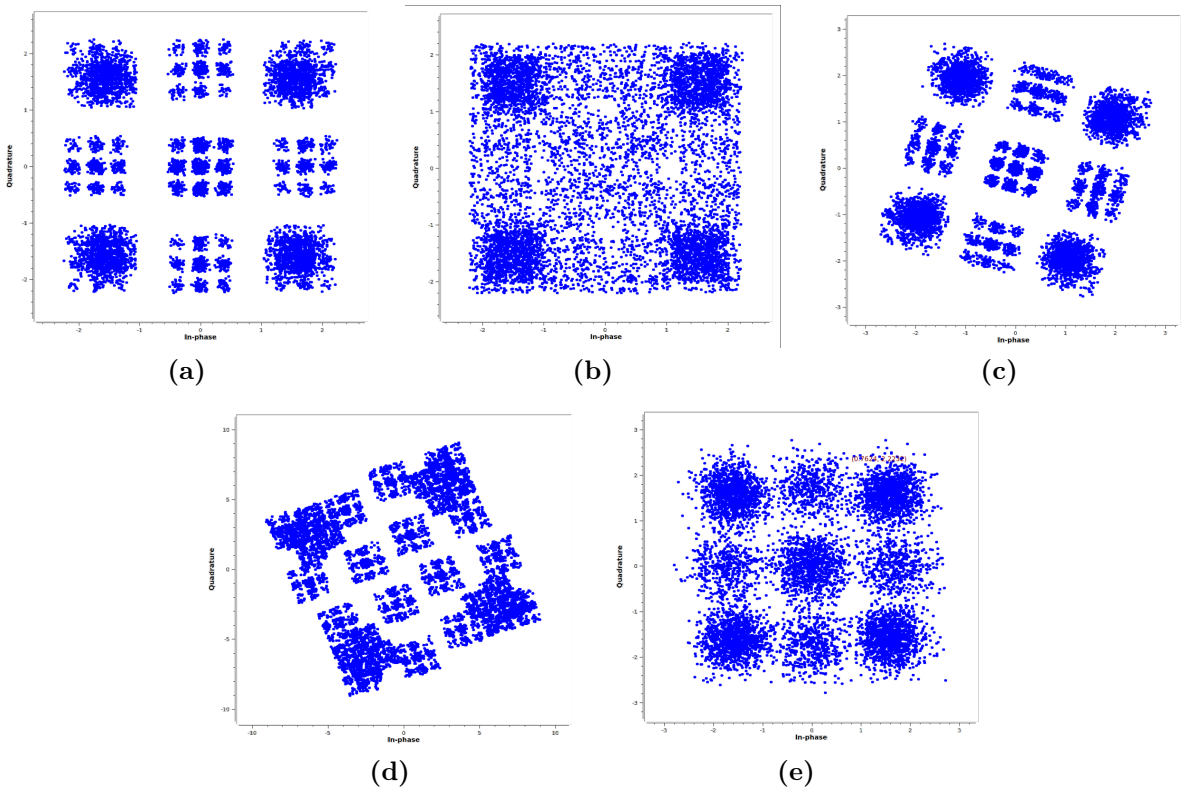


Figure 6: **(a)** Root-raised cosine (RRC) filtered QPSK **(b)** Sample rate offset **(c)** Center frequency offset **(d)** Channel fading **(e)** Additive white Gaussian noise

I also developed a CNN to classify the waveforms using Tensorflow and Keras. The general architecture given in figure 7 is mostly the same as in [6], but with larger convolution/dense layers and less signals to classify at the output. Although not shown in the figure, the hidden layers all use softmax activation functions. Each convolution layer is also preceded by a zero padding layer to maintain the input size and a dropout layer to mitigate overfitting. Finally, the Adam optimizer [3] was used for training.

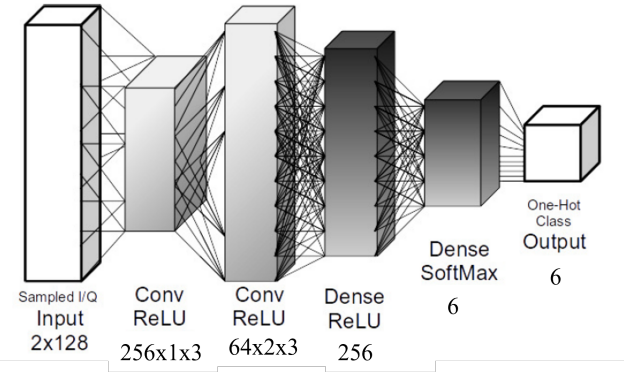


Figure 7: Classification network architecture

3 Experiment

3.1 Data Preparation

After implementing GNU Radio blocks for the components described above, I used the GNU Radio streaming architecture to generate the dataset. For each waveform and noise voltage, I generated 8192 samples of data, then chose a random length-128 subset of the data to be used as the input to the CNN. For the data used to generate the figures in this report, I simulated 500 vectors of 10 different noise voltages for each of the six waveform, resulting in a dataset of size $30000 \times 2 \times 128$. Thus, each training instance was a 2×128 image, where the first row is the real part of the signal and the second row is the imaginary part. These vectors were then normalized to have unit energy, and were programatically labeled to comply with the SigMF metadata standard [2].

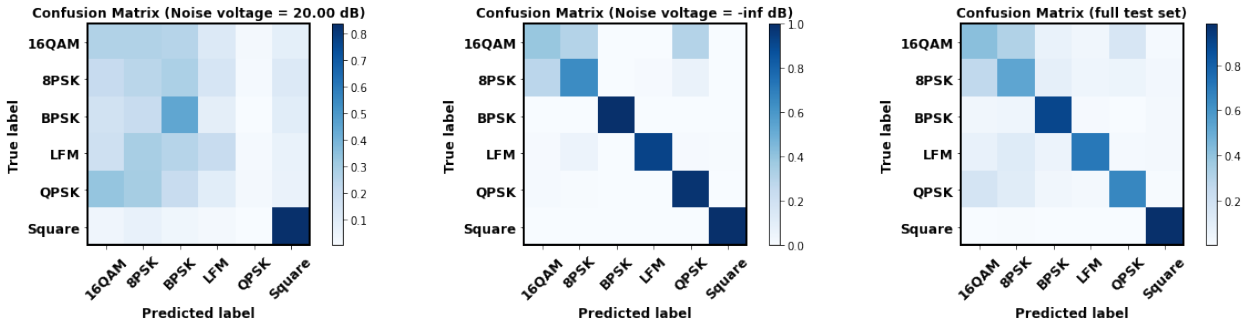
3.2 Experiment Design

Since my simulation tool allows me to generate an arbitrary amount of training data, I used a 50/50 traning/testing split. There were several channel hyperparameters to consider such as the magnitude of carrier frequency/sample rate offset, noise voltage, and channel fading filter parameters. The noise voltage was the variable I wanted to test, so I varied it over the range -20 dB to 20 dB. The rest of the channel parameters were chosen to match a "realistic" system. For example, a clock drift of 500 Hz was used because it gives a reasonable mismatch of 10 parts-per-million for a system operating at a center frequency of 5 GHz. Since the CNN I built is meant to classify different waveforms, I have chosen to evaluate performance using classification accuracy.

3.3 Results and Discussion

Figure 8 gives the model confusion matrix for several different noise voltages. At high noise voltages (or equivalently, low signal-to-noise ratios), the model struggles to accurately predict all waveform classes (figure 8a) aside from square waves. This result is intuitive; looking back at figure 4, it is easy to see that most waveforms will look similar after noise is added. The square wave, however, is different enough from the

others that it is easy to classify even with noise. The other extreme is shown in figure 8b, where there is still a channel but no noise is present. Here, classification accuracy is above 80% for all classes except for 16-QAM and 8PSK, which again makes sense since they look similar even under ideal conditions. Figure 8c gives a more realistic scenario, where all noise voltage values are present in the training and testing set. Here, the model still does a poor job of classifying 8PSK and 16-QAM and in some high-noise situations it had trouble classifying QPSK, but the overall classification accuracy is about 75% on average.



(a) Noise Voltage = 20 dB (b) Noise Voltage = -∞ dB (c) Full Test Set

Figure 8: Confusion Matrices

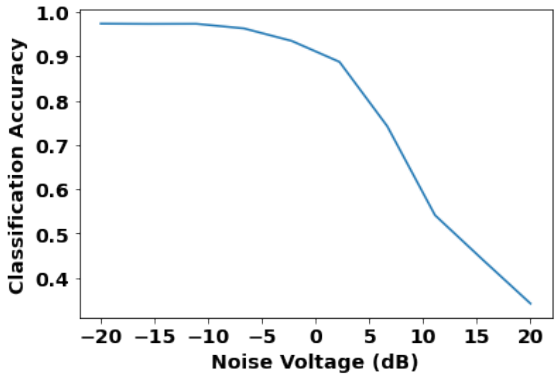


Figure 9: Classification Accuracy vs SNR

Figure 9 more concisely shows the relationship between classification accuracy and noise voltage. Overall accuracy remains above 90% until the noise voltage exceeds around 0 dB, and then it quickly degrades. Therefore, systems with low-quality (i.e., high noise figure) receiers would not be able to take full advantage of this classification network, but it would be quite useful in high-quality hardware.

References

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