Classification of Cross-Ambiguity Function (CAF) Surfaces Using Convolutional Neural Networks (CNN) for Coherent and Non-Coherent Signals in Digital Communications

Clifford Tatum
Virginia Tech. University
Blacksburg, Virginia, United States
cliffordt@vt.edu

Hayden Brundage
Virginia Tech. University
Blacksburg, Virginia, United States
YOUREMAIL@vt.edu

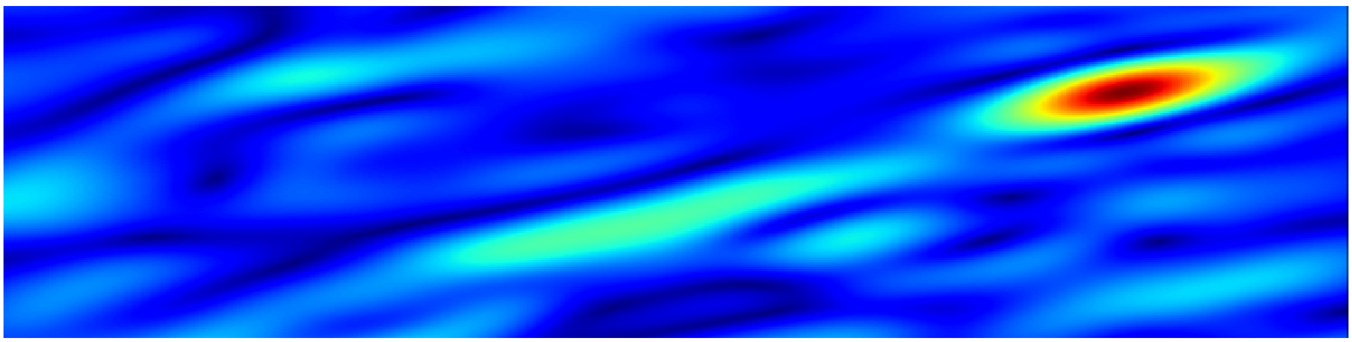

Figure 1. CAF Surface

Abstract

In digital communication systems, distinguishing between coherent and non-coherent signals is critical for efficient channel monitoring and signal processing. Coherent signals carry meaningful data, while non-coherent signals, typically alternating 0s and 1s, represent idle periods. This project proposes a Convolutional Neural Network (CNN) model to classify Cross-Ambiguity Function (CAF) surfaces generated from Frequency Shift Keying (FSK) signals as either coherent or non-coherent. By analyzing the time-frequency correlations in CAF surfaces, the CNN will quickly and efficiently determine whether a received signal contains significant data or is merely idling. This capability can be instrumental in improving the performance of receivers by allowing them to prioritize coherent signals for processing, thus saving computational resources during non-coherent periods. The training data will consist of CAF surface images generated from simulated FSK signals with varying degrees of coherence, channel impairments, and environmental noise. With this approach, the model can enhance real-time signal monitoring in dynamic communication environments.

Keywords: Cross Ambiguity Function, Convectional Neural Network, Deep learning, Digital communications, Signal detection, Modulation Classification

Intro. Deep Learning, 2024, Virginia Tech. University
.

1 Introduction

In modern digital communication systems, the process of signal detection, acquisition, and modulation classification is crucial for efficient signal processing. One useful metric in this context is the Cross-Ambiguity Function (CAF), which provides valuable insights into the time and frequency relationship between a known signal template and an incoming signal. CAF surfaces are often used for spectrum monitoring, signal acquisition, and synchronization by analyzing time delays and frequency offsets.

A common challenge in such systems is determining whether the received signal contains meaningful information or simply represents an idle state. Signals can either be coherent, where the bits being transmitted represent significant, meaningful data, or non-coherent, where the transmitter is merely alternating between 0s and 1s—an indicator that the system is idling. This idling period often signals that no important communication is occurring, and it can waste computational resources if unnecessarily processed. A key tool in this analysis is the Cross-Ambiguity Function (CAF), which evaluates time and frequency correlations between a known signal template and the received signal, generating a surface that highlights these correlations. In the case of Frequency Shift Keying (FSK) signals, coherent versus non-coherent signals produce distinctive CAF surfaces. However, interpreting these surfaces manually or using traditional methods can be computationally expensive, especially in real-time applications. This project seeks to automate this process by using a Convolutional Neural Network (CNN) to classify CAF surfaces as either coherent or non-coherent, allowing for faster and more efficient signal monitoring. The challenge, however, lies in interpreting these surfaces, as they present smooth, convex patterns that vary based on channel impairments and coherence.

2 Related Work

Recent advances in machine learning, particularly Convolutional Neural Networks (CNNs), have demonstrated significant success in tasks involving complex image classification. While CNNs have been widely applied to various fields, their application to communication systems, especially for the classification of modulation schemes based on CAF surfaces, remains underexplored. Previous studies have applied CNNs to modulation classification using other forms of signal representations, such as spectrograms and constellation diagrams, with promising results. TODO - NEED TO ADD MEAT TO BONES HERE : perhaps cite som other shit CAF/AI thats out there; here are some dummy citations you can populate, they will show up in references at the end: [1], [3] [2],[4]

3 Proposed Contributions

1. **CNN-Based Classification of Coherent vs. Non-Coherent FSK Signals**: We aim to develop a CNN model capable of classifying FSK-based CAF surfaces as either coherent (containing meaningful data) or non-coherent (idle, alternating 0s and 1s). This classification will allow communication systems to quickly determine whether a signal is worth processing or can be ignored during idle periods, thus improving efficiency.

2. **Generation of Realistic Training Data**: A dataset of CAF surface images will be generated using synthetic FSK signals. The dataset will include both coherent and non-coherent signals, and various channel impairments such as time delays, frequency offsets, frequency smearing and noise will be introduced to simulate real-world communication environments. Between 2000 and 4000 training examples per class will be generated.

4 Evaluation Plan

1. **Dataset Generation**: The first step involves generating a large dataset of CAF surfaces using simulated FSK signals. Two classes will be defined: coherent (meaningful data) and non-coherent (alternating 0s and 1s). Each class dataset will have the following channel impairments imparted to the signals to simulate realistic signals: time delays, frequency shifts, frequency smearing and noise. Each class will contain between 2000 and 4000 CAF surface images to ensure the model has sufficient training data.

2. **Model Training and Validation**: The CNN will be trained using 80 percent of the dataset, with 10percent reserved for validation and 10percent for testing. During training, standard metrics such as accuracy, precision, recall, and F1-score will be used to track performance. Drop-out will also be employed to prevent overfitting.

5 Primary Experiments

1. **Data Generation**: The experiment will begin by generating FSK signals with varying degrees of coherence. Coherent signals will contain meaningful data, while non-coherent signals will consist of alternating 0s and 1s, each signal will be channel impaired via frequency and time delays, frequency smearing, and additive noise.The corresponding CAF surfaces will be generated, producing images that serve as input to the CNN.

2. **CNN Training and Hyperparameter Tuning**: The dataset will be used to train a deep CNN model, with a focus on optimizing hyperparameters such as the number of layers, filter sizes, and learning rates. The model will be trained to classify the CAF surfaces into two categories: coherent or non-coherent. Various training techniques, such as early stopping and data augmentation, will be employed to improve the model's generalizability.

3. **Performance Evaluation**: After training, the CNN will be tested on validation data. Performance metrics such as classification accuracy, confusion matrix, and computation time will be used to evaluate the model's effectiveness. Particular attention will be paid to the model's ability to correctly identify non-coherent signals in noisy environments, as this represents the primary utility of the system.

6 Work Distribution

6.1 Data Generation

Clifford Tatum

6.2 Model Development

Clifford Tatum and Hayden Brundage

6.3

Clifford Tatum and Hayden Brundage

6.4 Integration and Final Report

Clifford Tatum and Hayden Brundage

References

[1] Patricia S. Abril and Robert Plant. 2007. The patent holder's dilemma: Buy, sell, or troll? *Commun. ACM* 50, 1 (Jan. 2007), 36–44. https://doi.org/10.1145/1188913.1188915

[2] Jacques Cohen (Ed.). 1996. Special issue: Digital Libraries. *Commun. ACM* 39, 11 (Nov. 1996).

[3] Sarah Cohen, Werner Nutt, and Yehoshua Sagic. 2007. Deciding equivalances among conjunctive aggregate queries. *J. ACM* 54, 2, Article 5 (April 2007), 50 pages. https://doi.org/10.1145/1219092.1219093

[4] David Kosiur. 2001. *Understanding Policy-Based Networking* (2nd. ed.). Wiley, New York, NY.