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
brundagh@vt.edu

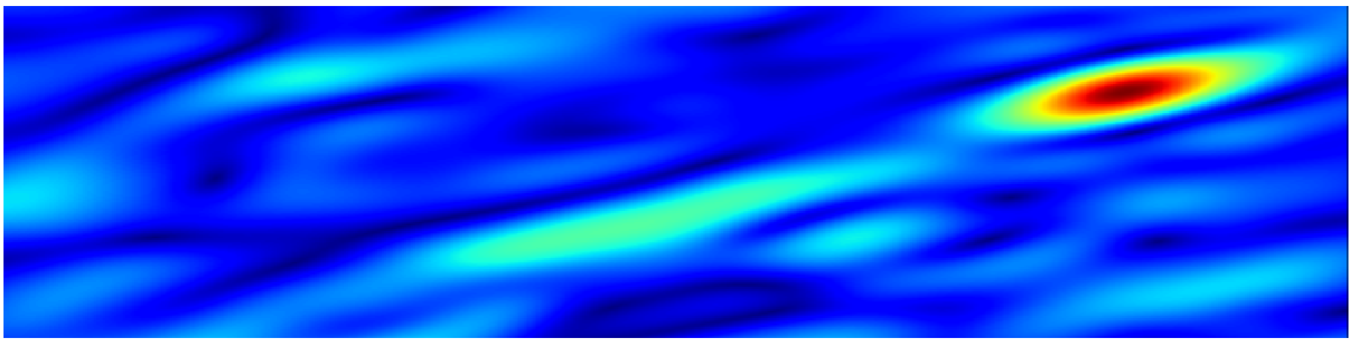

Figure 1. CAF Surface

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

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1 Introduction

In digital communication systems signal detection and acquisition are crucial for efficient signal processing. The Cross-Ambiguity Function (CAF) is an approached implemented for these tasks. The CAF is an algorithm which computes time and frequency relationship between a known transmitted signal and an incoming signal and are used for spectrum monitoring, signal acquisition, and synchronization by analyzing time delays and frequency offsets. For two signals, a definition for a cross-ambiguity function is:

$$A(\tau, f_d) = \int_{-\infty}^{\infty} r(t) \cdot s^*(t-\tau) \cdot e^{-j2\pi f_d t} \, dt \tag{1}$$

The surface defined by the above function is known as the CAF surface and has a wide range of applications in signal processing. A know digital communications challenge is determining whether the received signal contains meaningful information or represents an idle state. Signals can either be coherent, where the bits being transmitted represent significant, meaningful data, or non-coherent; the transmitter is only 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. 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

Convolutional Neural Networks (CNNs), have have been know to be very proficient with regard to complex image classification and have been applied to various fields; although an application to classification of modulation coherence based on CAF surfaces has yet to be explored. Previous studies have applied CNNs to modulation classification using other forms of signal representations, such as spectrograms and constellation diagrams, with promising results.

CNNs have historically been applied to the processing of radar signal data. Radar target detection (RTD) is a widely used technique in both civilian and military radar systems. CNNs have been applied to the task of target detection efficiently, needing to only use radar echo data without processing it at all to detect targets[1]. This relates to the work proposed in this document, as the proposed model is intended to inference based on the CAF surface determined by an incoming signal.

Another application in defense where CNNs may be used to process signals is in electronic warfare. Jamming and spoofing are common problems in electronic warfare space, and solutions to these problems often lead to degraded information. The detection of jamming patterns may be possible using CNNs by training a network on known patterns and using the trained model to determine if a signal is being jammed and subsequently processed to counteract jamming. CNNs have been applied directly to this problem and shown promise in countering jamming without significant information loss[3]. Additionally, such CNNs may be used to authenticate incoming signals. These networks may then be used to determine authentic signals in environments where spoofing may occur.

In a more general application, using CNNs to enhance signal detection in low signal-to-noise ratio environments has been demonstrated. In domains where signals are noticeably weak or corrupted (as they often are in radar or sonar scenarios), invariant signal characteristics may be learned through model training. Detection of signals under unfavorable conditions in low-SNR environments with CNNs has been demonstrated and shown to be superior to other methods, if more computationally expensive.[2]. In these scenarios, it may also be interesting to see if defining a CAF surface would add even better performance.

3 Proposed Contributions

3.1 CNN-Based Classification of FSK Signals

The primary contribution of this work is the development of a CNN architecture tailored to the classification of CAF surfaces in FSK signals. After development and training, the model should be able to classifying meaningful signals from otherwise uninteresting, idle signals that are unnecessary to process. Communication or radar systems may therefore more rapidly and accurately determine the usefulness of received signals. Automatically classifying signals prior to processing ultimately allows system resources to be more efficiently used. In these application domains, the overhead of classifying signals before processing may significantly reduce computational load and optimize system performance.

3.2 Generation of Realistic Training Data

This work also seeks to establish a comprehensive dataset of synthetic CAF surfaces useful for training CNNs on simulated FSK signals under realistic conditions. The dataset will comprise both coherent and non-coherent signals with channel impairments applied to ensure it reflects realistic signal environments. Channel impairments may include time delay, frequency shifting and smearing, and the addition of various levels of noise. These should capture a wide range of real-life communication scenarios. By generating several thousand training samples for each class, the synthetic dataset should provide sufficient training and evaluation data for the CNN model. This will enhance model robustness and provide a dataset for future work in this field.

4 Evaluation Plan

4.1 Dataset Generation

We will generate CAF surface images using simulated FSK signals. Two classes will be defined: coherent and non-coherent. To create a realistic dataset, all generated data will undergo channel impairment through time delay, frequency shifting and smearing, and the incorporation of noise. Each class will contain between 2000 and 4000 CAF surface images, which will support robust model training through a diverse dataset. Ideally, the generated dataset will capture a wide range of signals in various conditions, supporting the ability of the network to generalize to different signal environments.

4.2 Model Training and Validation

The CNN will be trained using 80 percent of the dataset with an additional 10 percent for validation during network training. The final 10 percent will be reserved for testing as unseen data, ensuring we may evaluate the ability of the model to generalize beyond training data. The training process will be evaluated through performance metrics including accuracy, precision, recall, and F-1 scoring, which will provide an accurate and comprehensive measure of the effectiveness of the training process. To mitigate overfitting, dropout regularization will be utilized during the training process. These relatively standard approaches to model training and evaluation should provide a sufficient assessment of the developed model at classifying signals.

5 Primary Experiments

5.1 Data Generation

Initially, FSK signals must be generated for each of the two distinct classes: coherent and non-coherent signals. The coherent signals shall be designed to emulate realistic digital communication signals. These signals contain meaningful data fit for processing, such as modulated bit sequences. In contrast, the non-coherent signals are idle patterns and will be represented as alternating 0s and 1s. These essentially represent periods of inactivity. As discussed in prior sections, the accurate reflection of real-world conditions will be captured through channel impairments applied to each of the generated signals.

After signal generation, the corresponding CAF surfaces will be computed to generate 2-dimensional representations of the signals. More specifically, these representations will capture the time-delay and Doppler shift charactersitics of the signal. These CAF surfaces will serve as inputs into the CNN and form a diverse dataset suitable for training, validating, and testing the model. Before using this data to train and evaluate the model, statistical analysis of the data will be performed. Evaluation will include checking to see if signal SNRs and MSEs compared to ideal signals are sufficiently varied. Distribution checks across a range of impairment levels may also be implemented. Ensuring signal conditions are varied within the dataset is essential to training the CNN on a dataset that allows it to generalize well.

5.2 CNN Training and Hyperparameter Tuning

The training phase will involve the development of a CNN to perform the classification operation on CAF surface images. Network architecture and training will be optimized systematically. This will involve investigating different hyperparameter configurations, such as the number of convolutional layers, the size and number of filters, stride and padding settings, and the learning rate. Grid search or random search may be employed to find the optimal hyperparameter combinations that lead to ideal model performance.

Regularization strategies will be employed to both improve generalizability and avoid overfitting the model to training data. Early stopping will be used to halt the training process after validation performance plateaus. This should prevent excessive training and thereby lower the chance of overfitting. Data augmentation techniques, such as noise generation, frequency shift variation, and distortion the CAF surfaces may also be applied to increase dataset diversity. Ideally, this will provide more varied conditions under which the model discovers the various coherent and non-coherent patterns. Dropout will also be used to further reduce overfitting, which will encourage the network to more robustly learn features.

5.3 Performance Evaluation

After the network has been trained, it will be evaluated using validation and test sets reserved from the generated dataset. The goal of this process is to assess model capabilities in the classification of CAF surfaces. Metrics will include:

- Classification Accuracy: The overall percentage of correct classification of CAF surfaces. This is the fundamental indicator of model performance.
- Confusion Matrix: The confusion matrix provides a detailed visualization of model predictions, highlighting true and false positives as well as true and false negatives. Analyzing the confusion matrix may help identify model bias and whether it struggles identifying one class versus the other.
- Precision, Recall, and F1-Score: These indicators help evaluate the quality of predicted classifications. Model precision quantifies how often model predictions are correct. Recall assesses how well the model determines classes correctly relative to all actual examples in the dataset. The F1-score represents a harmonic mean of both quantities and gives an overall balanced measure of performance.
- Computation Time: Computational efficiency is essential in this application space and during inference, it will be necessary to ensure that the process of classification is fast enough.

Depending on time constraints, analysis may expand to evaluating performance in difference signal impairment levels (i.e. high/low SNR, etc.), which may provide insight into model limitations and conditions in which is excels. Thorough evaluation of the model will guide further refinements of the network architecture and training.

6 Work Distribution

6.1 Data Generation

Clifford Tatum

6.2 Model Development

Clifford Tatum and Hayden Brundage

6.3 Evaluation and Testing

Clifford Tatum and Hayden Brundage

6.4 Integration and Final Report

Clifford Tatum and Hayden Brundage

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