QUADRATURE AMPLITUDE MODULATION RECOGNITION USING CONVOLUTIONAL NEURAL NETWORK

Abstract

Across several sectors, automatic modulation categorization is essential in determining the type of modulation used in wireless transmissions. We add deep learning to signal recognition in this study. In order to achieve equal recognition accuracy of modulation classification, we used real signal data generated by instruments as a dataset and proposed an improved CNN design based on an architectural study of the convolutional neural network (CNN). We evaluate the proposed CNN architecture using actual sampled data under various signal-noise ratio (SNR) situations.

As the cornerstone of deep learning models, convolutional neural networks (CNNs) are frequently used in the area of automatic modulation classification. We predict that the signal sample formats render them ineffective for usage as direct CNN inputs. It is suggested to significantly enhance CNN-based automatic modulation categorization by using a novel data preparation technique. CNN will be used in this scenario to identify digital modulation techniques with low SINR. The waveform ranging from low to high interference networks will be trained. This article will describe how to classify modulated signals using deep learning (DL). It is carried out using the CNN algorithm, which is extensively used for data processing. Images of waveform are also fed as part of the network broadcast.

Keywords: CNN, Waveforms, Signal to noise ratio (SNR), Digital modulation, Automatic modulation, Quadrature Amplitude Modulation (QAM)

Objective

The main aim of our implementation, we intend to precisely forecast the modulation strategy employed for waveforms with low SINR. To replicate a real-time system without costly hardware.

When training a CNN network and evaluating recognition accuracy under various SNR settings, real signal data produced by instruments is used. It is discovered that, because of the overfitting issue, the shallow layer network architecture is more effective and is not required for high SNR signals. In order to simplify the network topology and ease the difficulty of training, CNN's fully linked layer is removed.

1. Introduction

In order to recover signals through demodulation, automatic modulation classification aims to determine the modulation type of received signals. In order to identify signal modulation, likelihood-based (LB) approaches and feature-based methods are both frequently employed (FB). It is only carried out once the modulation of a particular signal is identified. The communication system has grown more complicated and diverse as a result of the quick development of wireless communication technology. This setting has led to the automatic classification of various forms of modulations and their complexity; this idea is known as automatic modulation classification (AMC). Therefore, in addition to a network that can discriminate between various modulation types, we also want a network that can automatically learn features from the original data.

a. What is Quadrature Amplitude Modulation?

The benefit of using modulation in communications systems is that the modulated waves will have a smaller bandwidth and frequency than the carrier frequency. In essence, this enables more data to be moved through the pipeline more effectively. It is a mixed modulation method.

In digital communication, QAM is frequently employed in a variety of configurations. The most popular ones include 4qam (also known as qpsk), 16qam, and 64qam. In a waveforms.

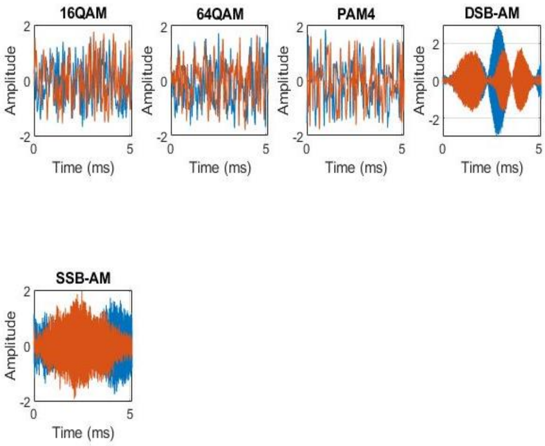

Fig.1.1 Waveforms of QAM

2. Literature Survey

The signal detection issue is made more difficult by modulation categorization, which permits the existence of more output classes. Knowing whether a signal is present is no longer sufficient; it is now desirable to know what kind of signal is present. The 1980s included some of the early research in this field. In these early works, features like zero crossing locations, square law classifiers, statistical moment classifiers, and phase-based classifiers were manually generated from the raw time domain information. Surprisingly, this was also the time that the first neural network technique to modulation categorization was developed. Although the authors in this study still developed hand-crafted features, they ultimately classified data using a neural network.

3. Methodology

We need to transform the targeted signal into a wave signal in order to better apply CNN classification. The modulated signal will exhibit an aggregated characteristic in the coordinate XY plane and have a shape resembling with a wave as a result of the conversion of the wave signal. Modulation recognition issues can be successfully converted into pattern recognition issues via wave signal to classification. This signal is referred to as a waveform. Modulation recognition issues can be successfully converted into pattern recognition issues via waveform to classification.

CNN can interpret three-channel images in addition to one-channel images, therefore data conversion techniques like direct mapping do not fully use the model's potential. This is true even if feeding the waveform into CNN can already produce good classification accuracy. Utilizing CNN's potential and the information contained in the signal that was received to its fullest. Because they present signal performance characteristics of a communication system in a simple visual. We may infer the modulation method, SINR, and signal performance issues from the diagram. RF engineers often analyze this data, we'd like to automate this procedure for a real-time system. We'll use a convolutional neural network to accomplish this.

b. Convolutional Neural Network

The convolutional layer and fully connected layer, are the two fundamental components of CNN. This technique brings together an image's characteristics for analysis. It pinpoints the aspects that are most beneficial for the feature extraction procedure. Additionally, based on the extracted features, it forecasts the image's class.

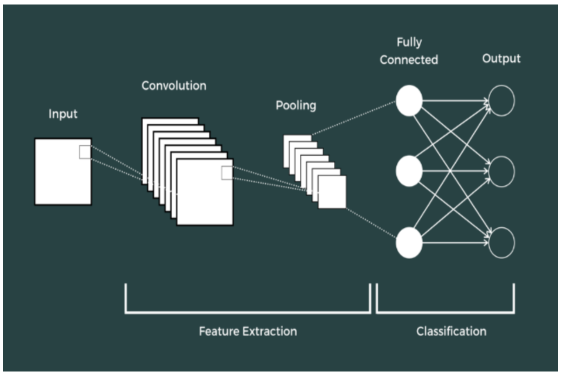

Fig.1.2 Basic structure of Convolutional Neural Network (CNN)

c. CNN Architecture

The convolutional neural network architecture that we will use is shown below. A number of convolutional and max-pooling layers are applied to an input image. After every convolution, we'll use an activation function discussed below that we'll apply.

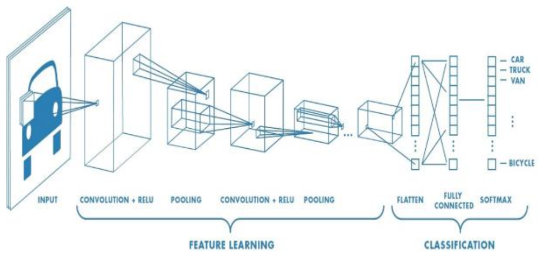

Fig 1.3 Architecture of CNN

We have three convolutional layers and three pooling layers for this model. Convolution layer 1 applies 32 5x5 filters to the photos. 50 5x5 filters are applied to the image in layer 2. 80 5x5 filters are applied to the image by Layer 3. We employ a kernel size of 5, and a stride of 1. In order to prevent overfitting, a dropout rate of 50% was included. Below is a tensorboard representation of our network. Layer 1's output size is [64,64,32] with 832 trainable parameters. Layer 2's output size is [13,13,50] with 40050 trainable parameters. The output size of layer 3 is [3,3,80] with 10080 trainable parameters. After flattening, the 2 completely connected layers will have output sizes of [1,512] with 41472 trainable parameters and [1,5] with 2565 trainable parameters. There will be 184,999 trainable parameters in total.

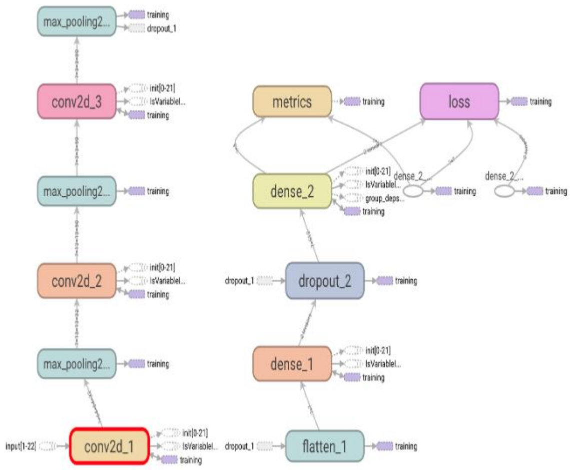

Fig 1.4 Network Topology

4. Results

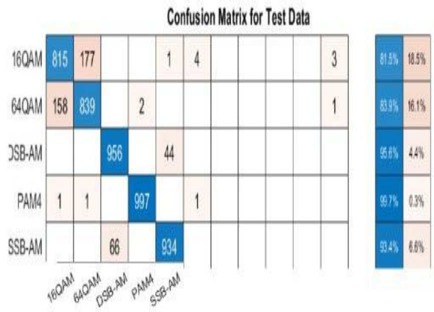

Fig 1.7 Confusion Matrix for test data

5. Conclusion

It has been demonstrated that neural networks perform quite accurately for the task of classifying modulations over a wide variety of modulation types with nominal channel aberrations. Over 80% accuracy was attained by the convolutional neural network. Similar modulation types were understood. Additionally, we observed that the method by which CNN classifies QAM modulation in experiments utilizing a subset of classes. In order to compare performance, we used CNN on constellation graphs. According to the simulation results are performed better than expected. Future versions of this project might simply train the model to forecast the modulation scheme in addition to providing an assessment of the signal-to-noise ratio given a specific constellation diagram.

6. References

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