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ADAPTIVE MODULATION AND DETECTION USING MACHINE LEARNING

A MINOR PROJECT-18TE64 REPORT

Submitted by

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Submitted in partial fulfillment for the sixth semester examination of

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Certified that the minor project work titled ***"ADAPTIVE MODULATION AND DETECTION USING MACHINE LEARNING"*** is carried out by **Deekshith Anantha (1RV19ET019) , Sagar H M (1RV19ET046)** who are bonafide students of RV College of Engineering, Bengaluru, submitted in partial fulfilment for the sixth semester examination of **Bachelor of Engineering** in **Electronics and Telecommunication Engineering** of the Visvesvaraya Technological University, Belagavi during the year 2021-2022. It is certified that all corrections/suggestions indicated for the Internal Assessment have been incorporated in the minor project report deposited in the departmental library. The minor project report has been approved as it satisfies the academic requirements in respect of minor project work prescribed by the institution for the said degree.

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DECLARATION

We, **Deekshith Anantha and Sagar H M** students of sixth semester B.E., Department of Electronics and Telecommunication Engineering, RV College of Engineering, Bengaluru, hereby declare that the minor project titled ***"ADAPTIVE MODULATION AND DETECTION USING MACHINE LEARNING"*** has been carried out by us and submitted in partial fulfilment for the sixth semester examination of **Bachelor of Engineering** in **Electronics and Telecommunication Engineering** during the year 2021-2022.

Further we declare that the content of the dissertation has not been submitted previously by anybody for the award of any degree or diploma to any other university.

We also declare that any Intellectual Property Rights generated out of this project carried out at RVCE will be the property of RV College of Engineering, Bengaluru and we will be one of the authors of the same.

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2. Sagar H M (1RV19ET046)	

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Deekshith Anantha

Sagar H M

Abstract

Machine Learning (ML) is a powerful classification technique that has great success in many application domains. However, its usage in communication systems has not been well explored. In this paper, we address the issue of using ML in communication systems, especially for modulation classification. Convolutional neural network (CNN) is utilized to complete the classification task. We convert the raw modulated signals into images that have a grid-like topology and feed them to CNN for network training. Two existing approaches, including cumulant and support vector machine (SVM) based classification algorithms, are involved for performance comparison. Simulation results indicate that the proposed CNN based modulation classification approach achieves comparable classification accuracy without the necessity of manual feature selection.

The architecture of the proposed network is based on the Inception-ResNet network by changing the several kernel sizes and the repeated times of modules to adapt to modulation classification. The modules in the proposed architecture are repeated more times to increase the depth of neural network and the model's ability to learn features. The modules in the proposed network combine the advantages of Inception network and ResNet, which have faster convergence rate and larger receptive field.

The major result was the accuracy of the machine learning model. The CCN model was trained with different learning rates and different modulation method which will be analyzed here.

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List of Acronyms

AM	Amplitude Modulation
AMC	Automatic modulation classification
CCN	Convolutional Neural Network
DL	Deep Learning
SDR	Software Defined Radios
QAM	Quadrature amplitude modulation

CHAPTER 1

INTRODUCTION TO ADAPTIVE MODULATION AND DETECTION USING MACHINE LEARNING

Chapter 1

INTRODUCTION

1.1 BACKGROUND

We are currently part of an era where technological developments is happening at a very high rate. With the advancement of technology, communication systems also play an important role in it. Hence resulting in an ever-growing demand for the improvement in spectral efficiency, energy enhancement and security in transmission. One of the most effective methods used to solve the above requirement use the Adaptive Modulation technique.

They are many situations where channel conditions may vary, in these situations fixed modulation conditions doesn't result in a standard output. Using simple modulation methods such as BPSK and QPSK allow us to transmit less amount of data and these modulation schemes are more immune to noise. 16/64/256-QAM techniques provide us to transmit more amount of data and are also less immune to noise during transmission. Fixed modulation may use lower order modulation scheme for a less noisy channel which is not spectrally efficient for a wireless communication system. Hence, Adaptive modulation is used where the transmission characteristics is varied or adapted according to the channel conditions.

However, the problem faced here is on using the methods to detect the modulation scheme transmitted and received. One of the solutions that we intend to use to solve the above-mentioned problem is to use machine learning and identify which modulation techniques are used in the transmitted data and to also demodulate the received signal based on the adaptive modulation technique used.

In recent years, machine learning (ML) has attracted a great deal of attention by leading substantial performance improvement compared with conventional techniques in complex problems. ML learns the model for the relationship between input and output according to the collected data and has adaptability according to various situations.

Hence building a machine learning model to analyse the received signal and analyse which modulation techniques are used to transmit at sender site would be the main objective of this project.

Adaptive modulation is a method to improve the spectral efficiency of a radio link for a given maximum required quality (error probability). The idea of adapting the modulation and coding to the channel conditions is not at all new; it has been mentioned in numerous papers at least since the 1970s.It is, however, not until much later those optimum schemes for this purpose became available. Many papers on good schemes started to appear in the middle of the 1990s.

The purpose of this topic is to introduce the reader to the topic of adaptive modulation to get an understanding of the differences between fixed and adaptive modulations schemes. We are especially focusing on illustrating the big advantage in both error performance and spectral efficiency of adaptive schemes compared with fixed schemes on varying channels. This is done by describing some of the simpler adaptive quadrature amplitude modulation (QAM) schemes, when the channel is perfectly known in the transmitter and when the predicted channel is available in the transmitter. For simplicity, only the simplest spectrally flat channels are considered, where one parameter alone describes the channel.

The approach taken is to describe, in some detail, some of the schemes for perfectly known channels published in and some of the schemes for predicted channels. The reason for choosing these schemes is that they are reasonably simple schemes which are optimized for different criteria. Moreover, they illustrate the design rules and performance of adaptive schemes in a simple and illustrative way. Some examples of other contributions to adaptive modulation are presented. There are many other studies on various topics related to adaptive modulation schemes published in the literature. To list all of these contributions is outside the scope of this introductory paper on adaptive modulation. The interested reader is referred to other papers in this Special Issue, which all taken together should give a rather complete picture on adaptive modulation and transmission schemes, and to the open literature.

1.2 LITERATURE REVIEW

1. M. N. Rajesh, B. K. Shrisha, N. Rao and H. V. Kumaraswamy, **"An analysis of BER comparison of various digital modulation schemes used for adaptive modulation**," 2016 IEEE International Conference on Recent Trends in

Electronics, Information & Communication Technology (RTEICT), 2016, pp. 241-245, Doi: 10.1109/RTEICT.2016.7807820.

Got a precise idea regarding the usage of adaptive modulation in various conditions. The type of modulation techniques needed to be used based on the SNR ratio of the signal at that particular instance .BER performance comparison for various modulation schemes that can be used to set the SNR ranges for adaptive modulation.

2. Ammari, Mohamed L. & Gagnon, François. (2009). **On Combining Adaptive Modulation and Unbiased MMSE-DFE Receiver to Increase the Capacity of Frequency Selective Channels**. 203-208. 10.1109/AICT.2009.42.

An adaptive quadrature amplitude modulation (AQAM) scheme for an equalized system over a selective channel is investigated.

In order to select the appropriate modulation mode, the receiver estimates the MSE at the equalizer output. This estimated MSE is then sent back to the transmitter which adjusts the modulation level.

3. P. Gupta and R. K. Singh, **"Highly optimized Selected Mapping based peak to average power ratio reduction OFDM system using different modulation schemes,**" 2015 Third International Conference on Image Information Processing (ICIIP), 2015, pp. 261-264, doi: 10.1109/ICIIP.2015.7414777.

Highly optimized phases are derived and analysed from proposed algorithm for selected mapping using several modulation schemes such as binary phase shift keying (BPSK), quadrature phase shift keying (QPSK), 8-PSK, 64-PSK, and 64-quadrature amplitude modulation (QAM).

4. Huang, Junkai & Yang, Liang. (2009). **MIMO MRT-MRC Systems with Rate Adaptive Modulation. Networks Security, Wireless Communications and Trusted Computing**, International Conference on. 1. 12-16. 10.1109/NSWCTC.2009.115.

A comprehensive analysis of multiple-input multiple-output transmit maximal ratio transmission and receive maximal ratio combining systems with rate adaptive modulation. The performance of MIMO MRT-MRC systems with data rate adaptation.

5. Ha, Chang-Bin & You, Young-Hwan & Song, Hyoung-Kyu. (2018). **Machine Learning Model for Adaptive Modulation of Multi-Stream in MIMO-OFDM System**. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2889076.

   The adaptive modulation (AM) model based on machine learning for a multiple-input multiple-output (MIMO) orthogonal frequency-division multiplexing (OFDM) system.The conventional AM schemes are implemented by defining modulation schemes to be used according to each channel condition as table in advance.

6. Shi, Jie & Hong, Sheng & Cai, Changxin & Wang, Yu & Huang, Hao & Gui, Guan. (2020). **Deep Learning-Based Automatic Modulation Recognition Method in the Presence of Phase Offset**. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.2978094.

   The capability of adaptive modulation to adapt various complicate environment.

   A deep learning-based method to distinguish frequency shift keying, phase shift keying and quadrature amplitude modulation with high accuracy.

1.3 MOTIVATION

Automatic modulation classification (AMC) was first motivated by its application in military scenarios where electronic warfare, surveillance and threat analysis requires the recognition of signal modulations in order to identify adversary transmitting units, to prepare jamming signals, and to recover the intercepted signal. The term ‘automatic’ is used as opposed to the initial implementation of manual modulation classification where signals are processed by engineers with the aid of signal observation and processing equipment. Most modulation classifiers developed in the past 20 years are implemented through electronic processors. During the 1980s and 1990s there were considerable numbers of researchers in the field of signal processing and communications who dedicated their work to the problem of automatic modulation classification. This led to the publication of the first well received book on the subject by Azzouz and Nandi (1996). The interest in AMC for military purposes is sustained to this very day.

1.4 PROBLEM DEFINITION

To apply machine learning and identify the modulation technique used to modulate the signal when adaptive modulation technique is used. Demodulation does become a tedious process when there is mixed modulation of different techniques. Normal methods used, produce a lot of error and reduces the quality of the signal. One of the reliable methods which can be used is to create a machine learning model which can predict the modulation technique and produce the demodulated signal.

1.5 OBJECTIVE

The objective is to identify the received signal analyze the modulation scheme used and to demodulate the received signal using the required protocols.

i. To figure out the best modulation technique to be used in various transmitting conditions.

ii. To develop the adaptive modulation model to transmit the signal.

iii. To develop a machine learning model to predict the received modulation and also try to produce the demodulated signal.

1.6 BRIEF INTRODUCTION TO MODULATION CLASSIFICATION

Modulated signal / Data set:

In receiver we will receive the modulated wave transmitted by the transmitter. Receiving the modulated wave also called the data collection.

Pre-Processing:

Classify and clearing unwanted noise from the data set we collected. Collected data classify into two groups Testing and Training data.

Machine learning Algorithm:

Applying the deep neural network to solve modulation classification is matter of

i. Designing a network architecture

ii. Training the network to select weights which minimizes loss

iii. Validating and testing in practice to solve problem

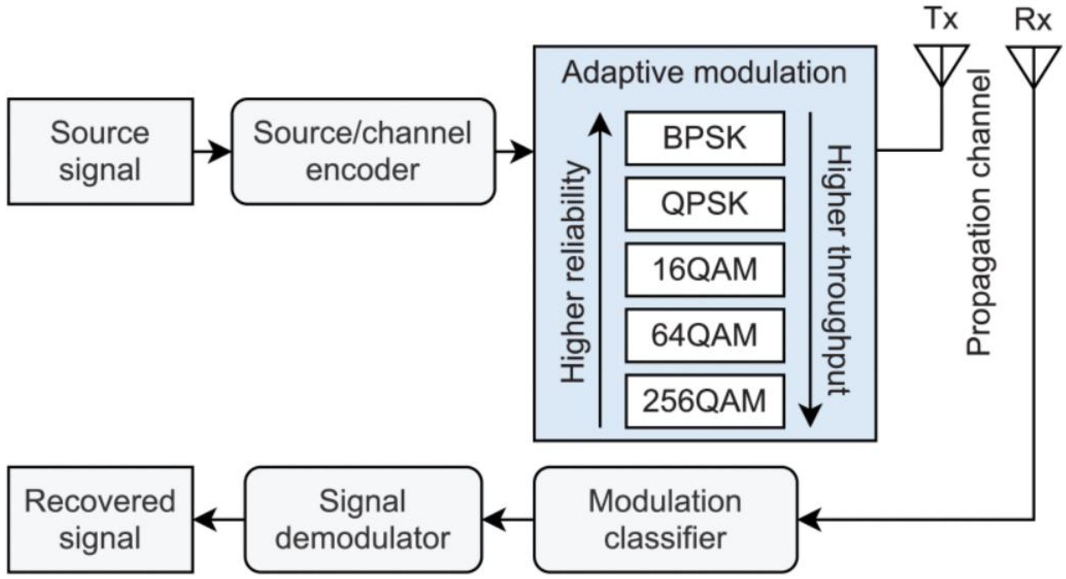

Fig 1.1. Adaptive Modulation Block diagram [4]

CHAPTER 2

THEORY OF MODULATION

Chapter 2

THEORY OF MODULATION

2.1 BACKGROUND

In electronics and telecommunications, modulation is the process of varying one or more properties of a periodic waveform, called the carrier signal, with a separate signal called the modulation signal that typically contains information to be transmitted. For example, the modulation signal might be an audio signal representing sound from a microphone, a video signal representing moving images from a video camera, or a digital signal representing a sequence of binary digits, a bitstream from a computer. The carrier is higher in frequency than the modulation signal. In radio communication the modulated carrier is transmitted through space as a radio wave to a radio receiver. Another purpose is to transmit multiple channels of information through a single communication medium, using frequency-division multiplexing (FDM). For example, in cable television which uses FDM, many carrier signals, each modulated with a different television channel, are transported through a single cable to customers. Since each carrier occupies a different frequency, the channels do not interfere with each other. At the destination end, the carrier signal is demodulated to extract the information bearing modulation signal.

A modulator is a device or circuit that performs modulation. A demodulator (sometimes detector) is a circuit that performs demodulation, the inverse of modulation. A modem (from modulator–demodulator), used in bidirectional communication, can perform both operations. The frequency band occupied by the modulation signal is called the baseband, while the higher frequency band occupied by the modulated carrier is called the passband.

In analog modulation an analog modulation signal is impressed on the carrier. Examples are amplitude modulation (AM) in which the amplitude (strength) of the carrier wave is varied by the modulation signal, and frequency modulation (FM) in which the frequency of the carrier wave is varied by the modulation signal. These were the earliest types of modulation, and are used to transmit an audio signal representing sound, in AM and FM radio broadcasting. More recent systems use digital modulation, which impresses a digital signal consisting of a sequence of binary digits (bits), a bitstream, on the carrier, by means of mapping bits to elements from a discrete alphabet to be transmitted. This alphabet can consist of a set of real or complex numbers, or sequences, like oscillations of different frequencies, so-called frequency-shift keying (FSK) modulation. A more complicated digital modulation method that employs multiple carriers, orthogonal frequency-division multiplexing (OFDM), is used in WiFi networks, digital radio stations and digital cable television transmission.

2.2 TYPES OF MODULATION

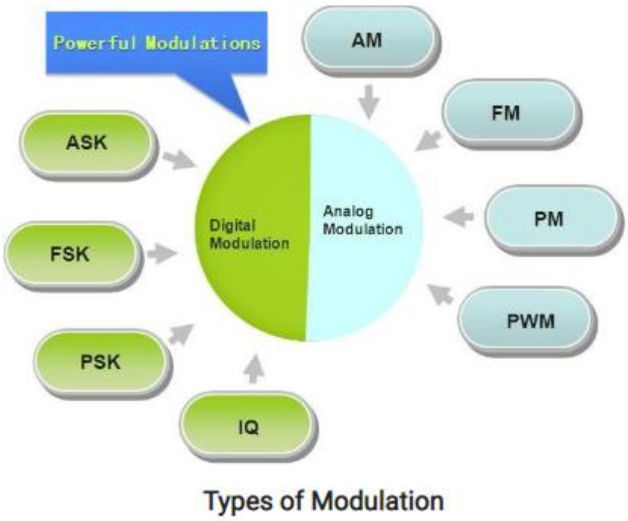

Fig 2.1 Types of Modulation

1. Analog Modulation

An analog signal is a continuous wave where the time differing variable of the wave is represented in the relation of other time differing quality which is analogous to other time changing signals. And analog modulation is the procedure of transmitting low-frequency signals such as TV signals or audio signals with that of high-frequency carrier signals like that of radio frequency signals. In this type of modulation, a bandpass channel is required where it corresponds to the specified range of frequencies. These frequencies are transmitted over a bandpass filter which allows certain frequencies to pass preventing signals at undesirable frequencies.

The type of analog modulation is based on the type of carrier signal property and so there are mainly three kinds of analog modulations and are

- Amplitude Modulation
- Frequency Modulation
- Phase Modulation

2. **Digital Modulation**

In digital modulation, an analog carrier signal is modulated by a discrete signal. Digital modulation methods can be considered as digital-to-analog conversion and the corresponding demodulation or detection as analog-to-digital conversion. The changes in the carrier signal are chosen from a finite number of M alternative symbols (the modulation alphabet). Digital modulation is defined as the modulation process in which discrete signals are used for modulating carrier waves and it is used for removing noise from the waves.

Fundamental digital modulation methods

The most fundamental digital modulation techniques are based on keying:

- PSK (phase-shift keying): a finite number of phases are used.
- FSK (frequency-shift keying): a finite number of frequencies are used.
- ASK (amplitude-shift keying): a finite number of amplitudes are used.
- QAM (quadrature amplitude modulation): a finite number of at least two phases and at least two amplitudes are used.

2.3 Fixed Modulation

With adaptive modulation, a radio link's spectrum efficiency can be increased for a specified maximum needed quality (error probability). Modulation and coding adaptation to channel circumstances is not a novel concept; it has been discussed extensively in several works at least since the 1970s. However, the best solutions for this purpose weren't made available until much later. Starting in the middle of the 1990s, a lot of papers on sound schemes began to appear.

In order to help the reader, comprehend the distinctions between fixed and adaptive modulation schemes, this essay will provide an introduction to the subject of adaptive modulation. We are putting a lot of emphasis on demonstrating how adaptive schemes outperform fixed schemes in terms of both error performance and spectral efficiency on a variety of channels. This is accomplished by explaining some of the less complex adaptive quadrature amplitude modulation (QAM) methods where the transmitter has perfect knowledge of the channel and access to the expected channel. For the sake of simplicity, only the simplest spectrally flat channels are taken into account, where the channel may be described by a single parameter. The strategy is to briefly describe several published schemes for precisely known channels as well as some schemes for predicted channels.

2.4 FIXED MODULATION IN NOISE

In a fixed modulation method transmits a predetermined number of bits per symbol through a channel, and the detector detects the bits or symbols with a predetermined probability of bit or symbol error. Although this paper won't go into detail, the actual bandwidth needed to transmit the modulation without distortion relies on the set of waveforms employed. For the modulations taken into consideration in this study, the bandwidth efficiency will be calculated as the average number of bits per transmitted symbol that equals the maximum spectrum efficiency measured in bits per second per Hertz (b/s/Hz). The average error probability, which depends on both the detector and the channel, is calculated as the average number of errors per transmission divided by the average number of transmitted bits. The signal-to-noise ratio (SNR) in the detector completely specifies the error probability for a channel that only adds white Gaussian noise.

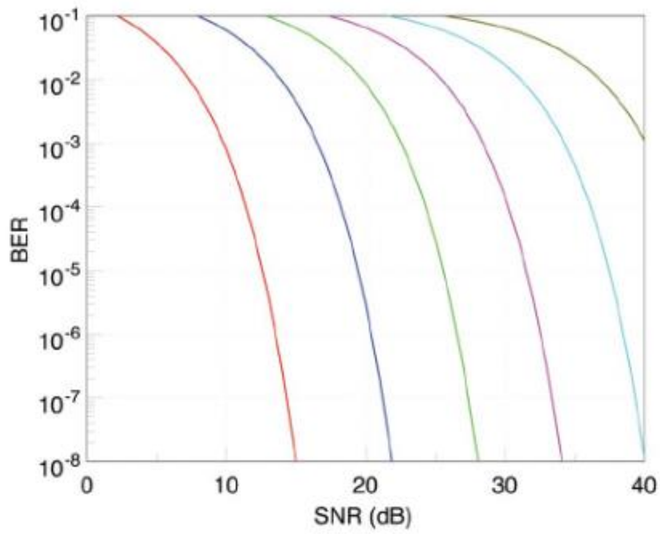

Fig 2.2. SNR VS BER

BER versus SNR per symbol for Gray coded QAMs. The curves from left to right correspond to 2, 4, 6, 8, 10, and 12 bits per symbol.

For Gray coded quadrature amplitude modulation (QAM), we demonstrate an example of bit error probability5 vs SNR per symbol (received SNR) in Figure 2.2 with the best (symbol) detection for 2 (red), 4 (blue), 6 (green), 8 (magenta), 10 (cyan), and 12 bits per symbol (brown), respectively.

2.5 FIXED MODUALTION IN FADING

Fading affects most wireless channels, in addition to additional noise and interference. Multipath propagation between the transmit and receive antennas is what causes fading. In its most basic form, so-called flat fading occurs when the temporal delays between these multipath components are short in comparison to the modulation's symbol time. The result is that the signals arriving at the receive antenna go through various carrier phases, which causes the received signal's power (i.e., the total of all the multipath components) to depend on the multipath components' carrier phases. An AWGN channel with an exponentially distributed instantaneous SNR and a uniformly distributed carrier phase of the received signal is frequently used to represent a flat fading channel. Since the received amplitude is Rayleigh distributed, this particular fading channel is known as a Rayleigh-fading channel.

2.6 ADAPTIVE MODULATION

The modulator (transmitter) of fixed modulation does not have (use) any knowledge of the received SNR or other channel parameters. In order to ensure that the maximum permitted error probability is assured within the coverage area, it is typically designed for a specific minimum (average) SNR that is connected to the link's maximum coverage distance. On the other side, the transmitter is given access to channel information when using an adaptive modulation technique. The instantaneous SNR is provided in its most basic form, however for more complicated channels, extra channel information can be provided. Figure 4 depicts a straightforward block diagram of an adaptive modulation scheme that highlights only the crucial components.

The channel is represented by the green box. Anything from simple noise addition to intricate time-varying filtering of the broadcast signal along with noise addition and interference is possible. In this study, we restrict the channel to a flat, simple fading channel that merely adds Gaussian noise, modifies the carrier phase of the transmitted signal, and attenuates the signal amplitude. The link designer has no control over the channel.

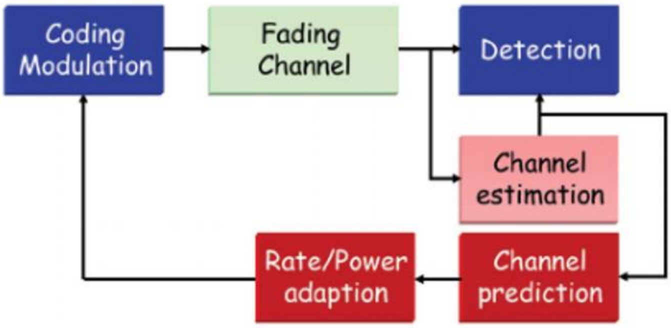

Fig 2.3. Major functions in an adaptive modulation system.

The modulation in the transmitter and the signal detection in the receiver are shown by the two blue boxes. Given the information known regarding the channel, the link designer must properly create these schemes. To enhance the quality of the wireless link, almost all transmitters in wireless systems employ some type of channel coding, which is why the blue transmitter block also includes the word coding. The coding can be done in one of two ways: jointly with modulation, or in the conventional manner of coding followed by modulation (one done separately from the other). Of course, the detection block needs to be created for the chosen coding and modulation.

Channel estimate is shown in the pink block. The majority of detection strategies presumptively rely on the detector having access to some channel characteristics that have already been computed. The carrier phase offset, which is supposed to be known by so-called coherent detectors is an example of such a parameter. The amplitude and carrier phase of the received signal must be known for various signaling configurations. It may be necessary to estimate and make available to the detector an impulse response channel model for even more sophisticated channels. Furthermore, the link designer must create this block.

The previously mentioned blocks also show up in fixed modulation. However, the two remaining blocks are unique to adaptive modulations. The transmitter is given access to the estimated channel parameters in their most basic form when the channel changes very slowly. Rate/power adaptation (the left red block in Fig. 2.3) is the process by which the transmitter determines the modulation and coding parameters to be employed based on these factors. However, the transmitter is not restricted to merely modifying the rate and/or power; it may also vary various modulation and coding scheme parameters that affect the scheme's performance. On a flat fading channel, however, and in more detail later when discussing adaptive QAM modulations, Typically, the rate and power are adjusted to achieve the desired BER (or lower) with the maximum spectral efficiency achievable in the link's available channel bandwidth.

Both channel estimation and rate adaptation will have some latency since they require the processing of information. Additionally, on many lines, the return channel from the receiver to the transmitter is required to send the channel parameters or the modulation parameters, which increases latency. If the channel undergoes a major change during this time, the modulation parameters will no longer be effective, leading to subpar adaptation. The block diagram contains a second red block labelled "channel prediction" to help with this latency. This block's goal is to create a channel model using the most recent and available channel estimates, then utilize that model to forecast future channel parameters. In this instance, the anticipated parameters are employed for the rate adaption.

2.7 MACHINE LEARNING

Machine learning is a subfield of artificial intelligence (AI). The goal of machine learning generally is to understand the structure of data and fit that data into models that can be understood and utilized by people.

Although machine learning is a field within computer science, it differs from traditional computational approaches. In traditional computing, algorithms are sets of explicitly programmed instructions used by computers to calculate or problem solve. Machine learning algorithms instead allow for computers to train on data inputs and use statistical analysis in order to output values that fall within a specific range. Because of this, machine learning facilitates computers in building models from sample data in order to automate decision-making processes based on data inputs.

Any technology user today has benefitted from machine learning. Facial recognition technology allows social media platforms to help users tag and share photos of friends. Optical character recognition (OCR) technology converts images of text into movable type. Recommendation engines, powered by machine learning, suggest what movies or television shows to watch next based on user preferences. Self-driving cars that rely on machine learning to navigate may soon be available to consumers.

Machine learning is a continuously developing field. Because of this, there are some considerations to keep in mind as you work with machine learning methodologies, or analyze the impact of machine learning processes.

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers, but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. Some implementations of machine learning use data and neural networks in a way that mimics the working of a biological brain. In its application across business problems, machine learning is also referred to as predictive analytics.

2.7.1 Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

A convolutional neural network, or CNN, is a deep learning neural network sketched for processing structured arrays of data such as portrayals. CNN are very satisfactory at picking up on design in the input image, such as lines, gradients, circles, or even eyes and faces. This characteristic that makes convolutional neural network so robust for computer vision.

CNN can run directly on a underdone image and do not need any preprocessing. A convolutional neural network is a feed forward neural network, seldom with up to

20.The strength of a convolutional neural network comes from a particular kind of layer called the convolutional layer. CNN contains many convolutional layers assembled on top of each other, each one competent of recognizing more sophisticated shapes.

With three or four convolutional layers it is viable to recognize handwritten digits and with 25 layers it is possible to differentiate human faces. The agenda for this sphere is to activate machines to view the world as humans do, perceive it in a alike fashion and even use the knowledge for a multitude of duty such as image and video recognition, image inspection and classification, media recreation, recommendation systems, natural language processing, etc.

As shown figure 2.4 we can see how convolution neural network works and we can see different blocks in CNN

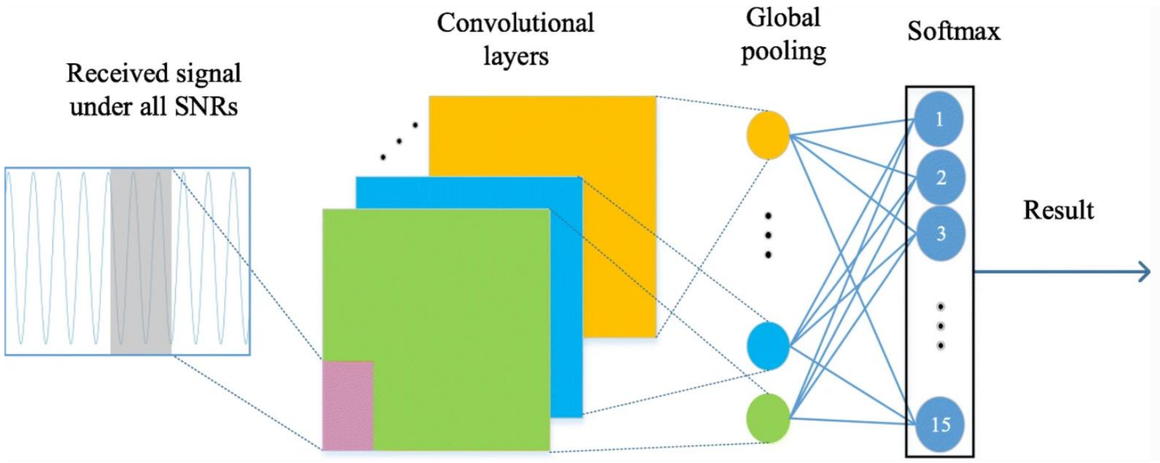

Fig 2.4. Convolutional Neural Network

2.7.2 Convolutional Neural Network Design:

The construction of a convolutional neural network is a multi-layered feed-forward neural network, made by assembling many unseen layers on top of each other in a particular order. It is the sequential design that give permission to CNN to learn hierarchical attributes. In CNN, some of them followed by grouping layers and hidden layers are typically convolutional layers followed by activation layers. The pre-processing needed in a ConvNet is kindred to that of the related pattern of neurons in the human brain and was motivated by the organization of the Visual Cortex.

CHAPTER 3

IMPLEMENTATION OF ADPATIVE MODULATION

Chapter 3

IMPLEMENTATION OF ADPATIVE MODULATION

3.1 COLLECTION OF DATA SET

The basic step of any machine learning project is collection of datasets. For any machine learning model to learn, it requires information to learn from, which are generally referred as dataset. This chapter discusses about grapes, dataset collection and its grading process. This dataset has 11 sets of feature data extracted with different signal-to-noise and a set of simulation results of modulation classification. The data set has been generated using Matlab at 20 dB SNR.

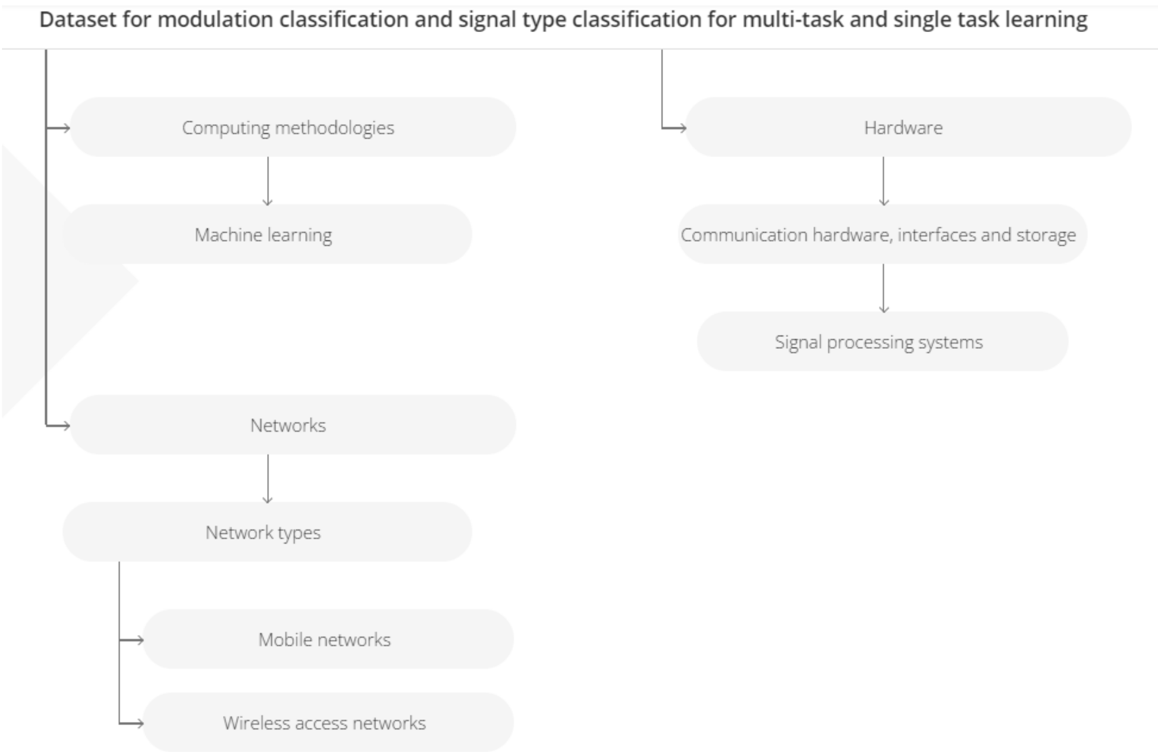

Fig 3.1. Data sets Collection

In figure 3.1 we can see how can we take data sets from different methodologies that is

Computing methodologies

Hardware

Networks

For our modulation classification we used machine learning for generating data sets and we and some noise and errors because in real time signals have error and unwanted noise.

The used modulation types are

Binary phase shift keying (BPSK)
Quadrature phase shift keying (QPSK)
8-ary phase shift keying (8-PSK)
16-ary quadrature amplitude modulation (16-QAM)
64-ary quadrature amplitude modulation (64-QAM)
4-ary pulse amplitude modulation (PAM4)
Gaussian frequency shift keying (GFSK)
Continuous phase frequency shift keying (CPFSK)
Broadcast FM (B-FM)
Double sideband amplitude modulation (DSB-AM)
Single sideband amplitude modulation (SSB-AM)

In above modulation types there is 8 digital and 3 analog modulations. You generate synthetic, channel-impaired waveforms. Using the generated waveforms as training data, you train a CNN for modulation classification. Then test the CNN with software-defined radio (SDR) hardware and over-the-air signals. In this adaptive modulation and detection, we are using convolutional neural network (CNN) for modulation classification.

The training dataset contains 10k training examples where each training example is a collection of 1024 I/Q samples of a specific modulation scheme recorded through either a simulated or a real noisy channel. The test set is of the same format with 8k training examples. Class labels represent 11 types of modulation schemes namely one frequency modulation scheme FM, four amplitude modulation schemes AM-SSB-SC, AM-DSB-SC, OOK, 4ASK, and five phase modulation schemes BPSK, QPSK, OQPSK, 8PSK, 16PSK. You can refer to further details on this specific dataset in this paper.

For training a data we need 80% of data and for validation and testing module we required other 20%. First, load the trained network. For details on network training, see the Training a CNN section. The trained CNN takes 1024 channel-impaired samples and predicts the modulation type of each frame. Generate several PAM4 frames that are impaired with Rician multipath fading, center frequency and sampling time drift, and AWGN. Use following function to generate synthetic signals to test the CNN. Then use the

CNN to predict the modulation type of the frames.

randi: Generate random bits.

pammod (Communications Toolbox): PAM4-modulate the bits.

rcosdesign (Signal Processing Toolbox): Design a square-root raised cosine pulse shaping filter.

filter: Pulse shape the symbols.

comm.RicianChannel (Communications Toolbox): Apply Rician multipath channel.

comm.PhaseFrequencyOffset (Communications Toolbox): Apply phase and/or frequency shift due to clock offset.

interp1: Apply timing drift due to clock offset.

awgn (Communications Toolbox): Add AWGN.

3.2 WAVEFORM GENERATION FOR TRAINING

Generate 10,000 frames for each modulation type, where 80% is used for training, 10% is used for validation and 10% is used for testing. We use training and validation frames during the network training phase. Final classification accuracy is obtained using test frames. Each frame is 1024 samples long and has a sample rate of 200 kHz. For digital modulation types, eight samples represent a symbol. The network makes each decision based on single frames rather than on multiple consecutive frames (as in video). Assume a center frequency of 902 MHz and 100 MHz for the digital and analog modulation types, respectively.

3.2.2 Create Channel Impairments

Pass each frame through a channel with

- AWGN
- Rician multipath fading
- Clock offset, resulting in center frequency offset and sampling time drift

Because the network in this example makes decisions based on single frames, each frame must pass through an independent channel.

AWGN: The channel adds AWGN with an SNR of 30 dB. Implement the channel using awgn (Communications Toolbox) function.

Rician Multipath

The channel passes the signals through a Rician multipath fading channel using the comm.RicianChannel (Communications Toolbox) System object. Assume a delay profile of [0 1.8 3.4] samples with corresponding average path gains of [0 -2 -10] dB. The K-factor is 4 and the maximum Doppler shift is 4 Hz, which is equivalent to a walking speed at 902 MHz. Implement the channel with the following settings.

Clock Offset

Clock offset occurs because of the inaccuracies of internal clock sources of transmitters and receivers. Clock offset causes the center frequency, which is used to downconvert the signal to baseband, and the digital-to-analog converter sampling rate to differ from the ideal values.

```
maxDeltaOff = 5;
deltaOff = (rand()*2*maxDeltaOff) - maxDeltaOff;
C = 1 + (deltaOff/1e6);(C=clock offset)
```

Frequency Offset

Subject each frame to a frequency offset based on clock offset factor C and the center frequency. Implement the channel using comm.PhaseFrequencyOffset (Communications Toolbox).

Sampling Rate Offset

Subject each frame to a sampling rate offset based on clock offset factor C. Implement the channel using the interp1 function to resample the frame at the new rate of C×fs.

3.3 WAVE FORM GENERATION

Create a loop that generates channel-impaired frames for each modulation type and stores the frames with their corresponding labels in MAT files. By saving the data into files, you eliminate the need to generate the data every time you run this example. You can also share the data more effectively. Remove a random number of samples from the beginning of each frame to remove transients and to make sure that the frames have a random starting point with respect to the symbol boundaries.

Generating the modulation using matlab. In figure 3.2 we can see the modulation plot in time domain.

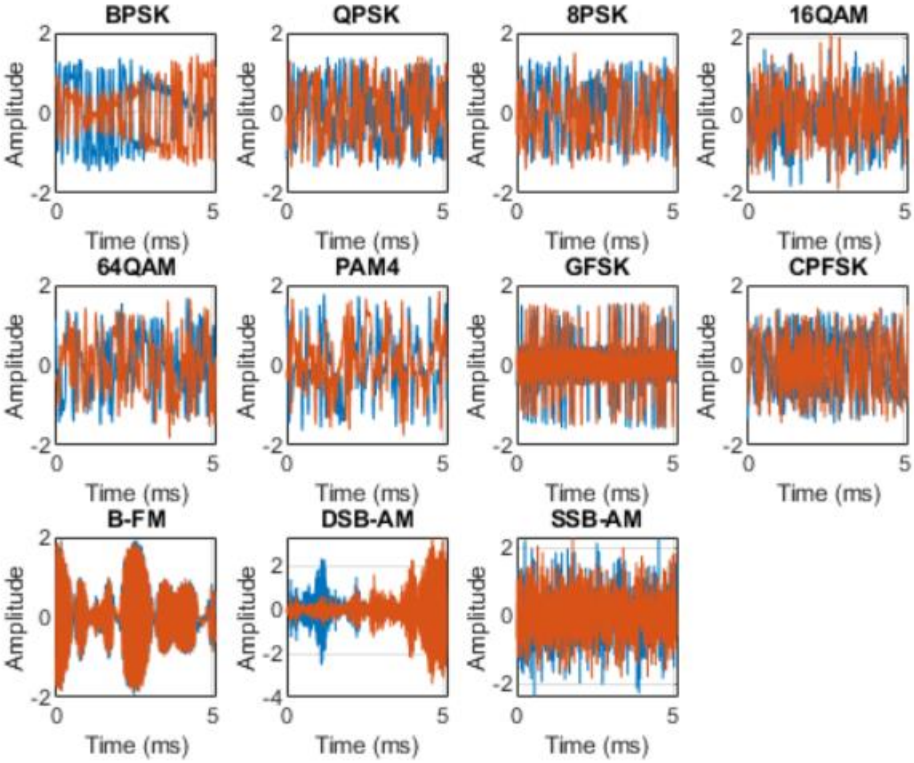

Fig 3.2. Modulation in time domain

In figure 3.3 shows modulation in frequency domain.

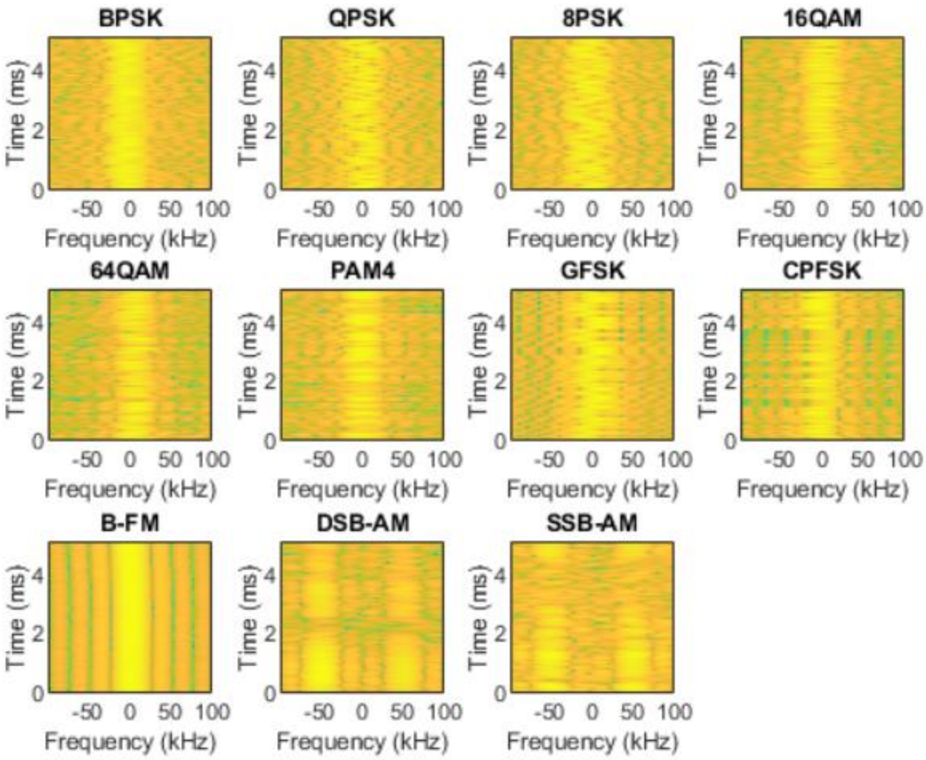

Fig 3.3. Modulation in Frequency domain

Create a Datastore

Use a signal Datastore object to manage the files that contain the generated complex waveforms. Datastores are especially useful when each individual file fits in memory, but the entire collection does not necessarily fit.

```
frameDS = signalDatastore(dataDirectory,'SignalVariableNames',["frame","label"]);
```

Transform Complex Signals to Real Arrays

The deep learning network in this example expects real inputs while the received signal has complex baseband samples. Transform the complex signals into real valued 4-D arrays. The output frames have size 1-by-spf-by-2-by-N, where the first page (3rd dimension) is in-phase samples and the second page is quadrature samples. When the convolutional filters are of size 1-by-spf, this approach ensures that the information in the I and Q gets mixed even in the convolutional layers and makes better use of the phase information.

```
frameDSTrans = transform(frameDS,@helperModClassIQAsPages)
```

Next divide the frames into training, validation, and test data

```
splitPercentages =
[percentTrainingSamples,percentValidationSamples,percentTestSamples];
[trainDSTrans,validDSTrans,testDSTrans] =
helperModClassSplitData(frameDSTrans,splitPercentages);
```

CHAPTER 4
RESULT AND ANALYSIS

Chapter 4

RESULTS AND ANALYSIS

This Chapter discusses on the result and inferences obtained in different phases of this project. The major result was the accuracy of the machine learning model. The CCN model was trained with different learning rates and different modulation method which will be analyzed here.

4.1 TRAIN WITH SDR

This example uses a CNN that consists of six convolution layers and one fully connected layer. Each convolution layer except the last is followed by a batch normalization layer, rectified linear unit (ReLU) activation layer, and max pooling layer. In the last convolution layer, the max pooling layer is replaced with an average pooling layer. The output layer has softmax activation.

```
modClassNet = helperModClassCNN(modulationTypes,sps,spf);
```

Next configure TrainingOptionsSGDM to use an SGDM solver with a mini-batch size of 256. Set the maximum number of epochs to 12, since a larger number of epochs provides no further training advantage. By default, the 'ExecutionEnvironment' property is set to 'auto', where the trainNetwork function uses a GPU if one is available or uses the CPU, if not. To use the GPU, you must have a Parallel Computing Toolbox license. Set the initial learning rate to 2x10^-2. Reduce the learning rate by a factor of 10 every 9 epochs. Set 'Plots' to 'training-progress' to plot the training progress. On an NVIDIA® Titan Xp GPU, the network takes approximately 25 minutes to train.

```
maxEpochs = 12;
miniBatchSize = 256;
options = helperModClassTrainingOptions(maxEpochs,miniBatchSize,...
numel(rxTrainLabels),rxValidFrames,rxValidLabels);
```

Either train the network or use the already trained network. By default, this example uses the trained network. As the plot of the training progress shows, the network converges in about 12 epochs to more than 95% accuracy. In figure 4.1 we can see the accuracy rate 95.33%.

Plot the confusion matrix for the test frames. As the matrix shows, the network confuses 16-QAM and 64-QAM frames. This problem is expected since each frame carries only 128 symbols and 16-QAM is a subset of 64-QAM. The network also confuses QPSK and 8-PSK frames, since the constellations of these modulation types look similar once phase-rotated due to the fading channel and frequency offset.

```
Figure;
cm = confusionchart(rxTestLabels, rxTestPred);
cm.Title = 'Confusion Matrix for Test Data';
cm.RowSummary = 'row-normalized';
cm.Parent.Position = [cm.Parent.Position(1:2) 740 424];
```

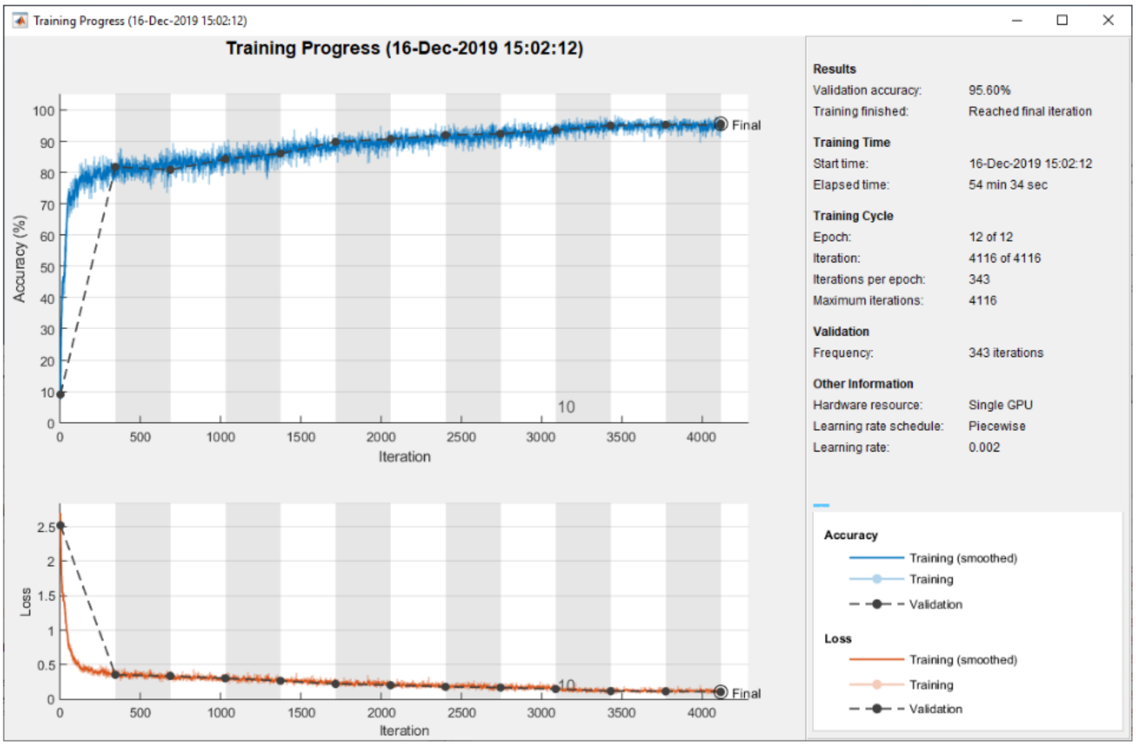

Fig 4.1. Training progress

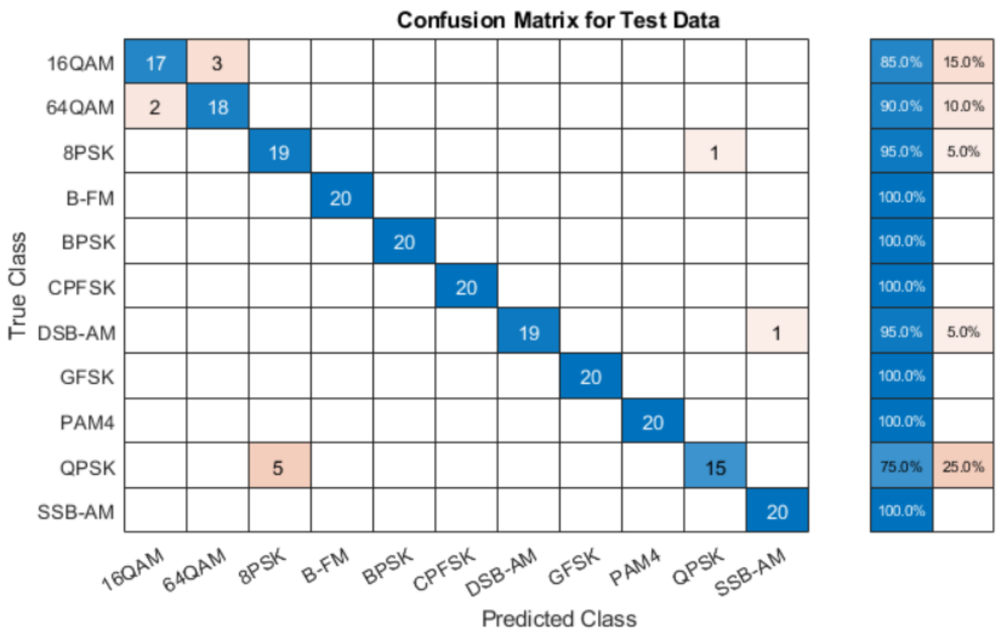

Fig 4.2. Confusion Matrix for Test Data

4.2 TEST WITH SDR

Test the performance of the trained network with over-the-air signals using the helperModClassSDRTest function. To perform this test, you must have dedicated SDRs for transmission and reception. You can use two ADALM-PLUTO radios, or one ADALM-PLUTO radio for transmission and one USRP® radio for reception. You must install Communications Toolbox™ Support Package for Analog Devices® ADALM-Pluto Radio. If you are using a USRP® radio, you must also install Communications Toolbox Support Package for USRP® Radio. The helperModClassSDRTest function uses the same modulation functions as used for generating the training signals, and then transmits them using an ADALM-PLUTO radio. Instead of simulating the channel, capture the channel-impaired signals using the SDR that is configured for signal reception (ADALM-PLUTO or USRP® radio). Use the trained network with the same classify function used previously to predict the modulation type. Running the next code segment produces a confusion matrix and prints out the test accuracy.

When using two stationary ADALM-PLUTO radios separated by about 2 feet, the network achieves 99% overall accuracy with the following confusion matrix. Results will vary based on experimental setup.

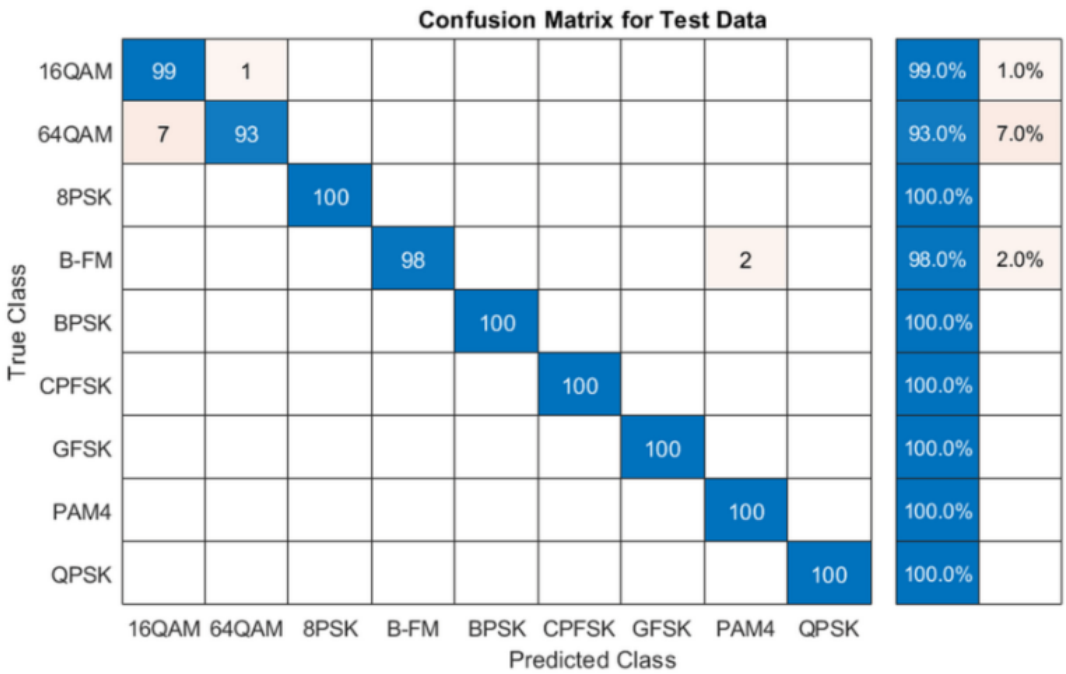

Fig 4.3. Confusion Matrix for Test Data

In figure 4.2 shows the confusion matrix for test data without SDR and figure 4.3 is for confusion matrix for test data with SDR.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

Chapter 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In this project different digital and analog modulation schemes were generated and analyzed for different environmental scenarios. This included the addition of gaussian noise, clock offset, frequency offset and a sampling time drift. About 10000 frames of each modulation type was used where 80% of it was used for training, 10% for testing and another 10% was used for validation. Then it was followed by a waveform generation of the different modulation schemes. The required datastore was created through which the complex signals were transformed to real arrays. Next, deep learning model was developed to predict the test data. It was concluded that a CNN model would be perfect for this set of generated data. Initially we had developed the model to achieve a 94% accuracy for the test frames. However, since the data used was a digitally generated data, the accuracy had to be increased. So, the test was done with a software defined ratio using two stationary ADALM-PLUTO radios separated about 2 feet apart, which led us to achieve a model with greatly increased accuracy. We finally conclude that the trained model successfully satisfies the testing data with 99%accuracy.

5.2 Future scope

Adaptive Coding and Modulation is a statistical, non-static advantage that enables dynamic changes in user throughput. Benefits and value vary over time and are not guaranteed, but are predictable. These schemes are used in all sorts of satellite communication links are designed to function at a certain annual availability. The closer to 100% we demand of our link availability. Can be developed in mobile communication and long-distance transmission where the environment conditions don’t always favor our needs for a error less channel. Hence the use of adaptive modulation, gives a upper hand over the normal modulation schemes. Adaptive Modulation is of significance in networks requiring high reliability. A radio network incorporating adaptive modulation has a key advantage as only the radio(s) experiencing the changes in coverage or interference will decrease their modulation rate in response. The rest of the radios in the system will continue to operate at the highest modulation rate possible. By working independently of one another, isolated network conditions have less impact on the system as a whole, thereby creating higher reliability for mission critical operations.

It is possible to optimize the hyperparameters parameters, such as number of filters, filter size, or optimize the network structure, such as adding more layers, using different activation layers, etc. to improve the accuracy.

Communication Toolbox provides many more modulation types and channel impairments. For more information see Modulation (Communications Toolbox) and Propagation and Channel Models (Communications Toolbox) sections. You can also add standard specific signals with LTE Toolbox, WLAN Toolbox, and 5G Toolbox. You can also add radar signals with Phased Array System Toolbox.

REFERENCES

[1]. O'Shea, T. J., J. Corgan, and T. C. Clancy. "Convolutional Radio Modulation Recognition Networks." Preprint, submitted June 10, 2016.

[2]. O'Shea, T. J., T. Roy, and T. C. Clancy. "Over-the-Air Deep Learning Based Radio Signal Classification." *IEEE Journal of Selected Topics in Signal Processing*. Vol. 12, Number 1, 2018, pp. 168–179.

[3]. Liu, X., D. Yang, and A. E. Gamal. "Deep Neural Network Architectures for Modulation Classification." Preprint, submitted January 5, 2018.

[4]. M. N. Rajesh, B. K. Shrisha, N. Rao and H. V. Kumaraswamy, "An analysis of BER comparison of various digital modulation schemes used for adaptive modulation,"

[5]. Ammari, Mohamed L. & Gagnon, François. (2009). On Combining Adaptive Modulation and Unbiased MMSE-DFE Receiver to Increase the Capacity of Frequency Selective Channels. 203-208. 10.1109/AICT.2009.42.

[6]. P. Gupta and R. K. Singh, "Highly optimized Selected Mapping based peak to average power ratio reduction OFDM system using different modulation schemes," 2015 *Third International Conference on Image Information Processing* (ICIIP), 2015, pp. 261-264, doi: 10.1109/ICIIP.2015.7414777.

[7]. Huang, Junkai & Yang, Liang. (2009). MIMO MRT-MRC Systems with Rate Adaptive Modulation. Networks Security, Wireless Communications and Trusted Computing, *International Conference* on. 1. 12-16. 10.1109/NSWCTC.2009.115

[8]. Ha, Chang-Bin & You, Young-Hwan & Song, Hyoung-Kyu. (2018). Machine Learning Model for Adaptive Modulation of Multi-Stream in MIMO-OFDM System. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2889076.

[9]. Shi, Jie & Hong, Sheng & Cai, Changxin & Wang, Yu & Huang, Hao & Gui, Guan. (2020). Deep Learning-Based Automatic Modulation Recognition Method in the Presence of Phase Offset. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.2978094.

CO – PO Mapping

Mapping of “Adaptive Modulation Detection Using Machine Learning” to Program Outcomes (PO)

Program Outcomes	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
Adaptive Modulation Detection Using Machine Learning	H	L	M	H	L	H	M	M	H	L	M	H

Mapping of **“**Adaptive Modulation Detection Using Machine Learning**”** to Course Outcomes (CO)

Course Outcomes	CO1	CO2	CO3	CO4
Adaptive Modulation Detection Using Machine Learning	H	L	M	M

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