ADAPTIVE MODULATION AND DETECTION USING MACHINE LEARNING

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***Abstract*—This paper introduces a study that uses a machine learning-based approach with Convolutional Neural Networks (CNNs) to automatically classify modulation schemes. The framework addresses challenges in dynamic channel conditions by leveraging CNNs to classify signals affected by noise, fading, and other real-world impairments. Raw modulated signals were transformed into grid-like images, which were used by the CNN architecture to classify the signal effectively. The study compares the proposed CNN-based approach with traditional methods, including cumulant and support vector machine (SVM)-based classification algorithms. Experimental results demonstrate classification accuracies of 99.4% in simulations, highlighting the model's potential in real-world applications. The network achieves faster convergence and a larger receptive field, making it highly suitable for modulation classification tasks. The proposed system provides an efficient solution for applications requiring robust adaptive modulation in wireless communication.**

Keywords—Adaptive Modulation, Modulation Classification, Machine Learning (ML), Convolutional Neural Networks (CNN), Signal Processing, Spectral Efficiency, AWG, Communication Systems, Pulse Shaping Filters

I. INTRODUCTION

The current era is characterized by rapid technological advancements, which significantly impact various industries and domains. With the advancement of technology, communication systems also play an important role. Hence, there is an ever-growing demand for improving spectral efficiency, energy enhancement, and transmission security. One of the most effective methods used to solve the above requirement is the Adaptive Modulation technique.

Channel conditions are often subject to variability, and under such circumstances, fixed modulation schemes fail to deliver optimal performance consistently. Using simple modulation methods such as BPSK and QPSK allows us to transmit less amount of data and these modulation schemes are more immune to noise. 16/64/256-QAM techniques allow us to transmit more amount of data and are also less immune to noise during transmission. Fixed modulation may use a 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 are varied or adapted according to the channel conditions.

A key challenge lies in the detection of the modulation scheme employed during signal transmission and reception. One of the solutions intended to solve the 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 to substantial performance improvement compared with conventional techniques in complex problems.

ML trains the model for the relationship between input and output according to the collected data and is adaptable to various situations. 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.

The emphasis is on demonstrating the significant advantages of adaptive schemes in terms of error performance and spectral efficiency compared to fixed schemes, particularly in varying channel conditions. This is achieved by describing some of the simpler adaptive quadrature amplitude modulation (QAM) schemes under two scenarios: when the channel is perfectly known at the transmitter and when the predicted channel information is available at the transmitter. For simplicity, the discussion is limited to spectrally flat channels, where a single parameter characterizes the channel. The approach involves detailing selected schemes for perfectly known channels and predicted channels. These schemes are chosen for their relative simplicity and their optimization for different criteria. Additionally, they effectively illustrate the design principles and performance benefits of adaptive schemes straightforwardly. Examples of other contributions to adaptive modulation are also presented. However, this introductory paper does not aim to provide an exhaustive list of studies on adaptive modulation. Readers are encouraged to refer to other papers in this Special Issue, which collectively offer a comprehensive overview of adaptive modulation and transmission schemes, as well as the broader literature on the subject. Here’s a more refined and professional conclusion for the introduction, tailored for a research paper:

This research investigates the integration of machine learning techniques with adaptive modulation to address the challenges in communication systems operating under varying channel conditions. By employing convolutional neural networks (CNNs), the study aims to enhance the accuracy and efficiency of automatic modulation classification, particularly for adaptive quadrature amplitude modulation (QAM) schemes. The focus is on scenarios where the transmitter has either perfect or predicted channel knowledge, enabling dynamic adaptation to optimize spectral efficiency and minimize error rates. This work highlights the superiority of adaptive modulation schemes over fixed schemes in terms of performance metrics while offering a methodical approach to the application of deep learning models in communication systems. The findings of this study aim to contribute to the advancement of adaptive communication methodologies and establish a foundation for future research in this domain.

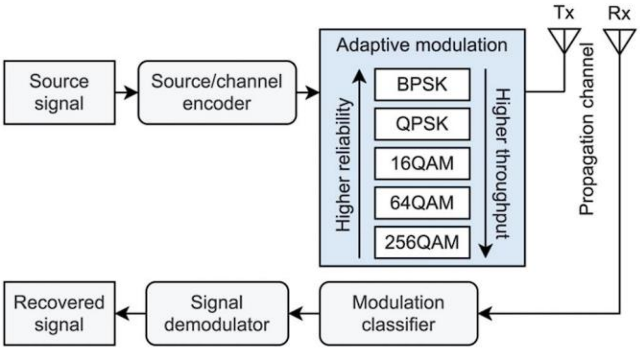

Fig. 1. Adaptive Modulation Block diagram

II. DESIGN

In analog modulation, the modulation signal is superimposed onto a carrier wave. For example, in amplitude modulation (AM), the carrier's amplitude is varied based on the modulation signal, while in frequency modulation (FM), the carrier's frequency is altered accordingly. 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 bit stream, on the carrier, using 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 Wi-Fi networks, digital radio stations and digital cable television transmission.

A. *Modulation Schemes*

Analog Modulation involves varying a continuous carrier wave based on an analog signal. Common techniques include Amplitude Modulation, Frequency Modulation (FM): altering the carrier's frequency, and Phase Modulation. This process requires a bandpass channel and a bandpass filter to allow desired frequencies while suppressing unwanted ones.

Digital Modulation uses discrete signals to modulate an analog carrier wave, effectively performing digital-to-analog conversion, with demodulation as the reverse process. Key techniques include Phase-Shift Keying, Frequency-Shift Keying (FSK), Amplitude-Shift Keying (ASK), and Quadrature Amplitude Modulation (QAM). Digital modulation enhances noise immunity and enables efficient signal transmission.

Fixed modulation employs static modulation schemes designed for a specific minimum signal-to-noise ratio (SNR), limiting its efficiency in dynamic channel conditions. Conversely, adaptive modulation dynamically adjusts modulation and coding based on channel conditions, optimizing spectral efficiency and maintaining error performance. Adaptive Quadrature Amplitude Modulation (QAM) schemes are particularly notable, demonstrating superior performance compared to fixed schemes, especially in varying channel conditions. These schemes rely on either perfect or predicted channel knowledge to adjust transmission parameters. For simplicity, most studies, including this one, focus on spectrally flat channels, where a single parameter characterizes the channel.

B. *Fixed Modulation with Noise and Fading*

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. 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 to 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.

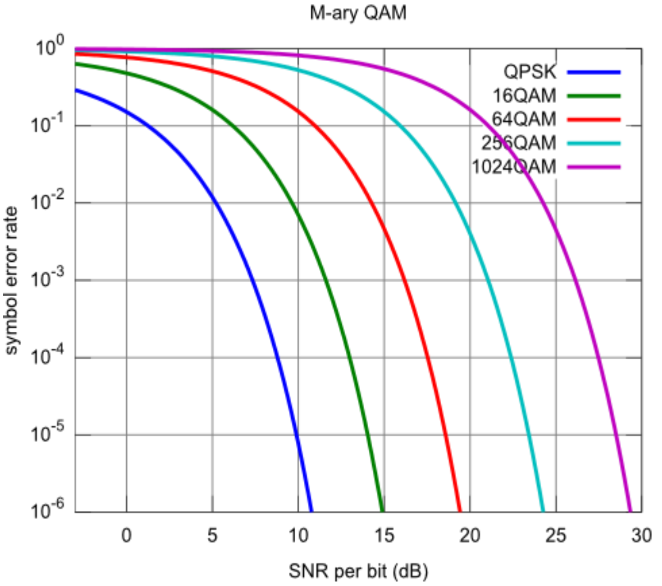

Fig. 2. SNR vs BER

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 probability vs SNR per symbol (received SNR) in Figure 2 with the best (symbol) detection for 2 (red), 4 (blue), 6 (green), 8 (magenta), 10 (cyan), and 12 bits per symbol (brown), respectively.

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.

C. Adaptive Modulation

The modulator (transmitter) in fixed modulation operates without real-time knowledge of the received SNR or channel parameters. To maintain a specified error probability within the coverage area, it is designed for a fixed minimum average SNR corresponding to the link's maximum coverage distance. Conversely, 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. Anything from simple noise addition to intricate time-varying filtering of the broadcast signal along with noise addition and interference is possible. The signals have been restricted 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. In the transmitter, modulation and in the receiver, signal detection are represented by two interconnected blue blocks. These blocks rely on channel knowledge to design effective schemes. To enhance the quality of wireless links, virtually all transmitters in wireless systems incorporate some form of channel coding. This coding can be implemented either jointly with modulation or through the conventional approach of coding followed by modulation.

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 labeled "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, and then utilize that model to forecast future channel parameters. In this instance, the anticipated parameters are employed for the rate adaption.

D. Waveform generation

The training dataset comprises 10,000 examples, each consisting of 1024 I/Q samples representing a specific modulation scheme, recorded through either a simulated or real noisy channel. The test set is in the same format with 8000 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.

For training data, we need 80% of the data and for the validation and testing module, we require another 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.

E. Channel Impairments

In order to replicate the real-case scenario the signal is added noise if the following impairments.

- AWGN: The channel adds AWGN with an SNR of 30 dB.
- Rician Multipath: A delay profile of [0 1.8 3.4] samples with corresponding average path gains of [0 -2 -10] dB. The Kfactor is 4 and the maximum Doppler shift is 4 Hz, which is equivalent to a walking speed at 902 MHz.
- Clock Offset: Causes the center frequency, which is used to down-convert the signal to baseband, and the digital-to-analog converter sampling rate to differ from the ideal values.

$$\text{Setting Maximum Delta offset (MD)} = 5 \tag{1}$$

$$\text{Delta Offset} = (\text{rand()}*2*\text{MD}) - \text{MD} \tag{2}$$

$$\text{Clock Offset} = 1 + (\text{Delta Offset}/1\text{e}6) \tag{3}$$

Where rand() = generates a random Integer

- Frequency Offset: Apply a frequency offset to each frame based on the clock offset factor C and the center frequency.
- 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.

These impairments are crucial for testing the robustness of the system under real-world conditions, ensuring reliable signal transmission and processing.

F. Waveform 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 concerning the symbol boundaries. In Fig 3 we can see the modulation plot in the time domain.

Using a signal Data store object to manage the files that contain the generated complex waveforms. Data stores are especially useful when each file fits in memory, but the entire collection does not necessarily fit.

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

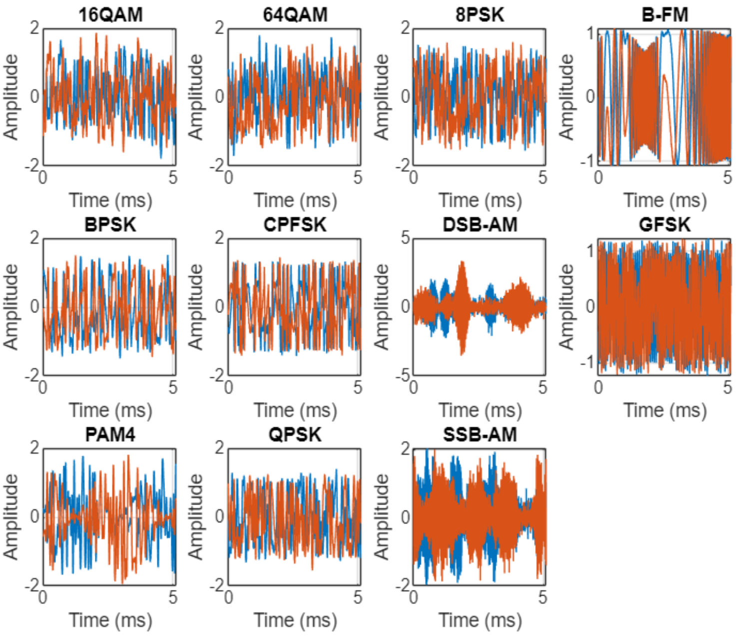

Fig. 3. Modulation in time domain

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.

III. RESULTS

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

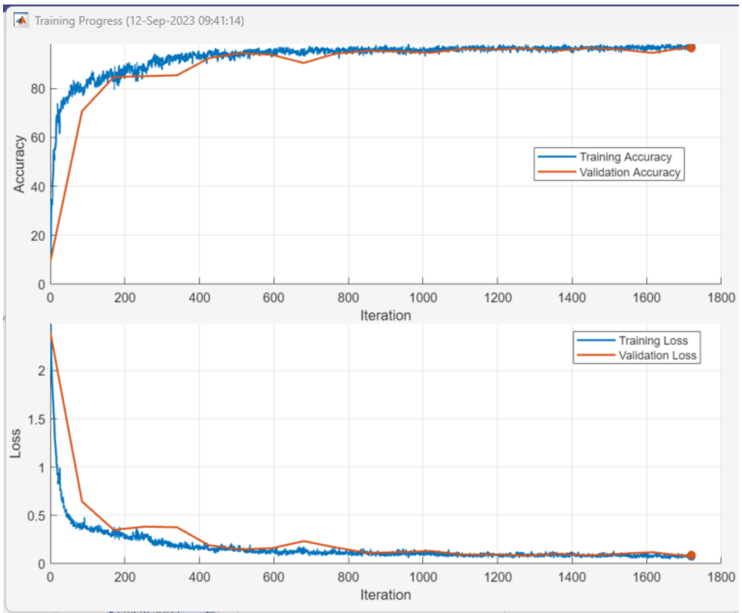

Fig. 4. Training progress

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. Setting the maximum number of epochs to 12, since a larger number of epochs provides no further training advantage Setting the initial learning rate to 2x10^-2. Reduce the learning rate by a factor of 10 every 9 epochs.

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 with more than 95% accuracy. In Figure 4 we can see the accuracy rate is 95.33%.

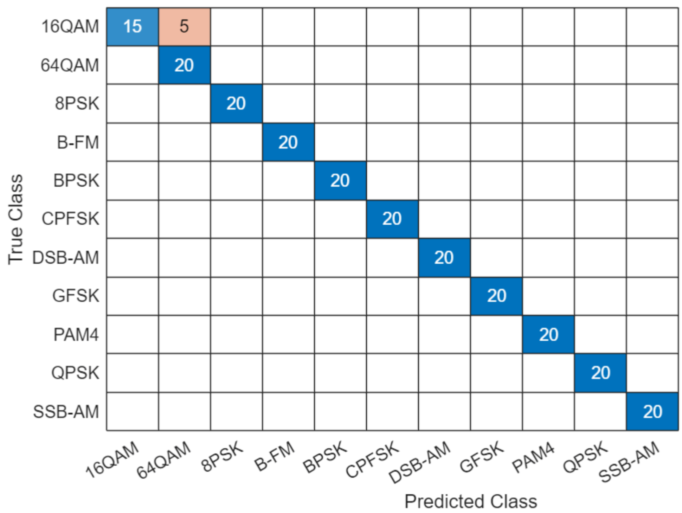

Fig. 5. Confusion Matrix for Test Data

The Plot for the confusion matrix for the test frames can be shown in Figure 5. 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.

To evaluate the performance of the trained network using an over-the-air approach, capture channel-impaired signals with a Software Defined Radio (SDR) such as the ADALM-PLUTO or USRP® radio, instead of simulating the channel. Use the trained network with the same classification function that was used previously to determine the modulation type. Running the following code segment will generate a confusion matrix and display the test accuracy. When deploying two stationary ADALM-PLUTO radios positioned approximately 2 feet apart, the network achieves an impressive overall accuracy of 99%, as shown by the confusion matrix. Please note that results may vary depending on the specific experimental setup.

IV. CONCLUSION AND FUTURE SCOPE

In this project, various digital and analog modulation schemes were generated and analysed under diverse environmental conditions, including Gaussian noise, clock offset, frequency offset, and sampling time drift. A dataset consisting of 10,000 frames was utilized, with 80% allocated for training, 10% for testing, and 10% for validation. A deep learning model, specifically a Convolutional Neural Network (CNN), was developed to predict test data, achieving a significant increase in accuracy from an initial 94% to 99% through the use of a software-defined radio setup.

This study underscores the critical role of adaptive modulation in enhancing reliability and performance within wireless communication systems, particularly in scenarios where fixed schemes fall short. By dynamically adjusting modulation rates based on real-time channel conditions, adaptive modulation ensures superior reliability for mission-critical operations. Moreover, continuous optimization of hyper parameters and network architectures holds promise for further advancements in accuracy and efficiency.

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