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Modelling of Wireless OFDM System with Deep Learning-based Modulation Detection

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***Abstract*—Deep learning (DL) is a powerful classification technique that has excellent performance in processing audio, image, and video data. In this paper, we use DL in communication systems, especially for modulation classification. Convolutional neural network (CNN) is then utilized to complete the classification task. The deep learning methods are implemented in an OFDM system using Software Defined Radio (SDR). Experimental results indicate that the proposed CNN based modulation classification achieves comparable classification accuracy without the necessity of manual feature selection.**

***Index Terms*—Wireless system, OFDM, 5G, Deep Learning, Modulation Detection**

I. Introduction

In the recent years, automatic modulation classification (AMC) that identifies the modulation type of the received signal is an essential part of noncooperative communication systems. With adaptive coding and modulation, the modulation type that is used by the transmitter and the receiver can adapt to the channel condition. In the fifth generation (5G) and beyond (B5G) communication systems [1], the base station can select the appropriate modulation and coding scheme according to the channel state to achieve the required error rate.

OFDM is an orthogonal digital modulation technique which is used in various wireless technology standards such as 5G as aforementioned. OFDM is generally known as an effective technique for high bit rate applications since it can prevent inter-symbol interference (ISI) by inserting a guard interval and can mitigate frequency selectivity of a multipath channel using a simple one- tap equalizer. A practical implementation of ODFM involves the inverse fast Fourier transform (IFFT) at the transmitter and the fast Fourier transform (FFT) at the receiver as shown in figure 1. Compared to other modulation methods, OFDM symbols have a relatively long time duration, whereas each subcarrier has a narrow bandwidth. The bandwidth of each subcarrier is small enough to assume a flat (nonselective) fading in a moderately frequency-selective channel [2].

Existing AMC algorithms can be divided into two main categories [3], namely, likelihood-based (LB) methods and feature-based (FB) methods. LB methods require calculating the likelihood function of received signals for all modulation modes and then making decisions based on the maximum likelihood ratio value. Even though LB methods usually obtain high accuracy, they suffer from high-latency classification or require complete priori knowledge, e.g., clock frequency offset.

Alternatively, a traditional FB method consists of two parts, namely, feature extraction and classifier, where the classifier identifies digital modulation modes in accordance with the effective feature vectors extracted from the signals. The FB methods are less computationally complex but may not be as accurate as LB methods. Several FB methods have been validated as effective for the AMC problem to extract features from various time domain waveforms, such as cyclic spectrum [4] and wavelet coefficients.

The development of learning algorithms has improved the performances of classification methods [5], for example using the convolutional neural network (CNN) [6]. CNNs exploit spatially local correlation by enforcing a local connectivity pattern between neurons of adjacent layers. Each sample data shared the convolution kernels for the rapid expansion of parameters using the fully connected structure. Recently, deep learning has been widely applied to audio and video processing applications such as voice and facial recognition.

In this paper, we propose to realize AMC using convolutional neural networks (CNNs) based model to directly process the time domain waveform data, which is collected with various signal-to-noise ratios (SNRs) based on experimental setup using Software Defined Radio (SDR).

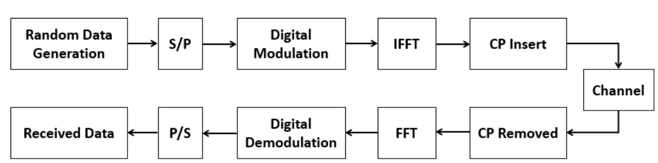

Fig. 1. OFDM block diagram.

II. OFDM-based Wireless System

The discrete-time baseband equivalent model of the OFDM system under consideration is shown in figure 1. In an OFDM system, several input bits are first encoded into one symbol (X_m), and then symbols are transferred by the serial-to-parallel converter (S/P) to the OFDM modulator. After each symbol is modulated by the corresponding subcarrier, it is sampled, and D/A converted. Samples of an OFDM signal, implemented by an inverse fast Fourier transform (IFFT), can be expressed as follows [7]

$$x_n = \sum_{m=0}^{N-1} X_m e^{j2\pi n/m} \quad (1)$$

where x_n represents the n-th sample of the output of the IFFT, 0 n N. Assuming that the multipath fading channel consists of discrete paths, the received signal can be written as

$$\begin{aligned} y_n &= (\sum_{l=0}^{L-1} h_{n,l} x_{n-l}) + w_n \\ &= h_{n,0} x_n + h_{n,1} x_{n-1} + ... \\ &+ h_{n,L-1} x_{n-L+1} + w_n \end{aligned} \quad (2)$$

where $h_{n,l}$ and w_n represent the complex random variable for the l-th path of the CIR and additive white Gaussian noise (AWGN) at time n, respectively. A cyclic extension of length N_G is used to avoid ISI and to preserve the orthogonality of subchannels. It is also assumed that the entire CIR lies inside the guard interval, (0 $(L1){\cdot}T_s$ N_G $\cdot T_s$), where T_s is the sampling interval. The demodulated signal in the frequency domain is obtained by taking the FFT of as

$$\begin{aligned} Y_m &= \sum_{k=0}^{N-1} \sum_{l=0}^{L-1} X_k H_l^{(m-k)} e^{-j2\pi lk/N} + W_m \\ &= (\sum_{l=0}^{L-1} H_l^{(0)} e^{-j2\pi lk/N}) X_m \\ &+ \sum_{k \neq m}^{N-1} \sum_{l=0}^{L-1} X_k H_l^{(m-k)} e^{-j2\pi lk/N} + W_m \\ &= \alpha_m X_m + \beta_m + W_m \end{aligned} \quad (3)$$

where W_m denotes the FFT of w_n and $0 \leq m \leq N$-1. Also, $H_l^{(m-k)}$ represents the FFT of a time-variant multipath channel $h_{n,l}$ as follows:

$$H_l^{(m-k)} = \frac{1}{N} \sum_{n=0}^{N-1} h_{(n,l)} e^{-j\pi n(m-k)/N} \quad (4)$$

Here, α_m and β_m represent the multiplicative distortion at the desired subchannel and the ICI, respectively [8]. If the channel is assumed to be time-invariant during a block period, $H_l^{(m-k)}$ in (4) vanishes, implying that there exists no ICI for time-invariant channels. In this case, Y_m in (3) contains only the multiplicative distortion, which can be easily compensated for by a one-tap frequency-domain equalizer and (3) can be simplified as

$$Y(n,k) = X(n,k)H(n,k) + W(n,k) \quad (5)$$

where $H^{(n,k)}$ is the channel frequency response and $W^{(n,k)}$ represents the additive white Gaussian noise (AWGN).

To estimate the channel impulse response (CIR), P pilot symbols $X(k_p)$ are inserted in every OFDM symbol at the known subcarrier locations $k_0, k_1, , k_{(p-1)}$. The vector $\hat{H}_P$ = $[H(k_0), H(k_1), , H(k_{p-1})]^T$ consisting of the LS estimates of channel responses at pilot subcarriers is obtained as

$$\hat{H}_P = X_p^{-1} Y_p \quad (6)$$

where $X_p = diag[X(k_0), X(k_1), , X(k_{p-1})]$ and $Y_p = [Y(k_0), Y(k_1), , Y(k_{p-1})]^T$. For given value of P, minimization of MSE occurs when all eigenvalues are identical. The desired value of eigen values matrix is obtained by using uniformly spaced pilot symbols with separation interval $\triangle = N/P$, *i.e.*, $k_p - k_{p-1}$ = N/P where $1 \leq p \leq P$-1. It is desirable that the number of pilot symbols should be more than the channel length L because estimation accuracy improves as the number of pilot symbols increases. Since the use of pilot symbols introduces overhead, it is very necessary to determine that how often to insert pilot symbols along subcarrier index and OFDM symbol index. Therefore, a careful selection of pilot pattern is required according to the channel statistics.

III. Experimental Setup

In this experiment, bitstream data are constructed into medium access control (MAC) protocol data unit (MPDU), therefore it can be used to exchange between datalink layer. Frame is then encapsulated into physical layer protocol data unit (PPDU). The encapsulated frame is then transmitted over-the-air and captured using Adalm-Pluto SDR. On the receiver side, after the frame is received, it is then resampled and synchronized. Synchronization process consists of packet detection, timing synchronization, and carrier frequency offset correction as refered to [9].

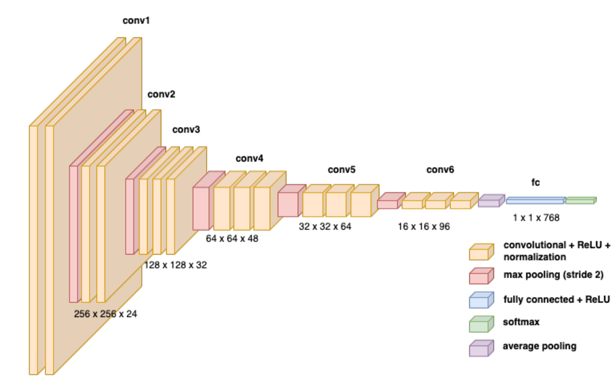

Fig. 2. CNN architecture.

Signal generation is done for 4 types of modulation which is BPSK, QPSK, 16QAM, and 64QAM with 10000 of data, respectively. Generated datasets are modulated using OFDM then transmitted over-the-air as well as received using Adalm-Pluto. 2 Adalm-Pluto SDRs are placed 50cm to each other, a laptop is used to process the data. The setup scheme is shown in figure 3. Deep-learning model used to train and classify is based on the methods in [6]. As shown in figure 2, used

CNN model consists of 6 hidden layers followed by a fully connected layer and a softmax layer. The first 5 hidden layer is composed by a convolution layer, batch normalization layer, ReLu layer, and max pooling layer with the stride of 2. As for the last hidden layer, it is composed by a convolution layer, batch normalization layer, ReLu Layer, and average pooling layer. The number of filters for each hidden layer are 16, 24, 32, 48, 64, and 96, respectively [10].

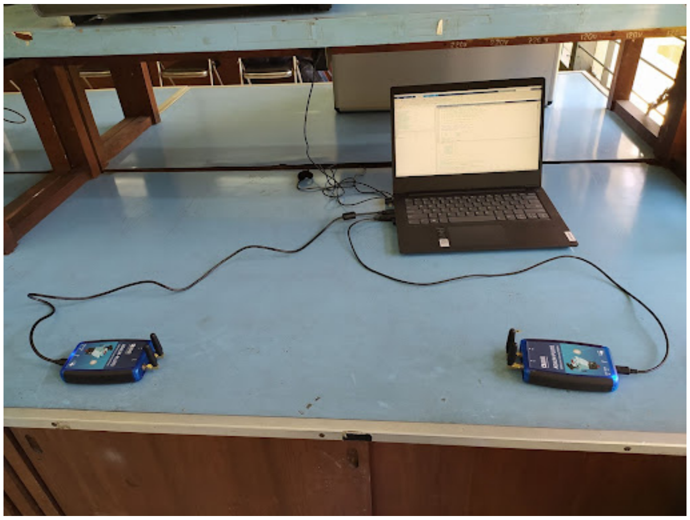

Fig. 3. Simulation setup.

The performance of the trained network is measured with over-the-air signal. Each signal modulation type is transmitted repeatedly until receiver captures 100 frame. The received signal then is classified using trained network. The Accuracy of the CNN is obtained by comparing the real transmitted signal modulation type with prediction signal modulation type. As for the simulation diagram block can be seen in figure 4.

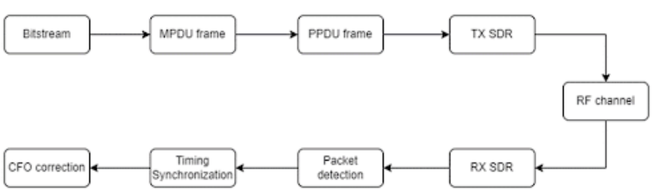

Fig. 4. Simulation Diagram Block.

IV. RESULT

A. Training Process

CNN network is trained using generated waveform dataset with total 12 epochs and divided into 1500 of iterations. For every generated waveform, 80% of data is used for training, and the remaining is used for validation and testing with 10% data each. The trained CNN achieved validation accuracy of 94.78% as figure 5 shows. Figure 5 shows the significant performance validation enhancement in the first three epoch and increasing steadily for the rest epochs.

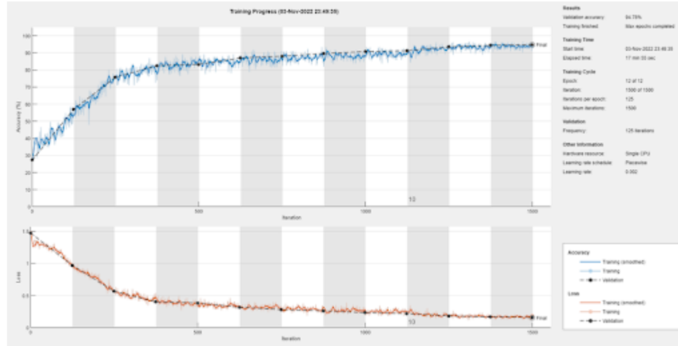

Fig. 5. Training Progress.

Fig. 6. Confusion matrix for training data.

After we performed the training process, we then perform the validation of the trained network by using training data. As shown in figure 6, we obtain 94.025% of the average accuracy, this result confirms that the trained network has been trained well.

B. Evaluating Process

As mentioned before, the trained network is tested with over-the-air signal. We then evaluate the test data to obtain the confusion matrix as shown in figure 7. We obtain 91.375% of the average accuracy. From the figure, it can be known that BPSK, QPSK, 16QAM, 64QAM get 100%, 98%, 81.1%, and 86.4%, respectively. This result shows that BPSK modulation doesn't get misclassified at all, whereas the rest does. We notice that 16QAM somehow gets classified as 64QAM with 14.4% of percentage and 64QAM gets classified as 16QAM with 12.6% of percentage.

V. DISCUSSION

TABLE I
MISCLASSIFICATION SUMMARY

Modulation Misclassification	Percentage
16QAM/64QAM	14.4%
64QAM/16QAM	12.6%
QPSK/64QAM	2%

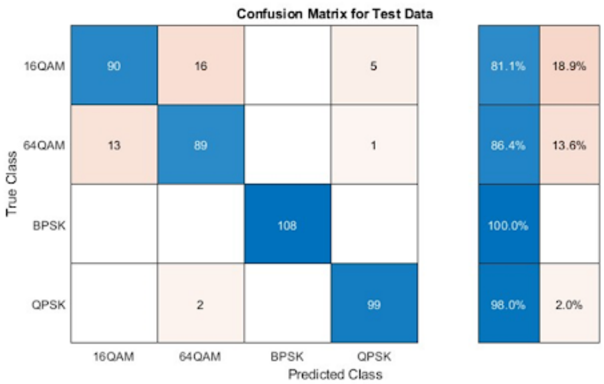

Fig. 7. Confusion matrix for test data.

After we performed the experiment, we compare two modulation performance, namely PSK and QAM. Table 1 depicts the summary of misclassification that is done by 3 pairs of modulation, as for the leftmost column, left hand side is the original modulation, meanwhile right hand side is the predicted modulation. Referring to table 1, it can be shown that PSK has better performance compared to QAM modulation which sometimes gets misclassified [11]. This can happen because of certain factors, for example, the margin of error in both 16QAM and 64QAM is relatively small compared to BPSK and QPSK which only depends on its phase which is 180° and 90°, respectively. This result shows that CNN implementation is feasible, although pre-processing input signal could help to alleviate this issue [6].

VI. Conclusion

In this paper, we described a deep learning-based method of automatic modulation classification in a wireless OFDM system. The system used CNN architecture as classifier. The network is trained and tested with real-time over-the air signal using a pair of Adalm Pluto SDR devices as transmitter and receiver. The result shows an accuracy of 91.375 % for classification of 4 types of modulation: BPSK, QPSK, 16 QAM, and 64QAM. The results also showed that similar modulation types are more prone to being misclassified as one another in general i.e. higher classification error occur in classification of QAM signals than PSK signals. There is still room for improvement for the CNN based approach in the future. To improve the performance, a larger amount of data for training is needed and more advanced DL models for modulation classification will be investigated.

Acknowledgment

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