Received Signal Classification of Modulation Scheme at Receiver using CNN Algorithm

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Abstract—Convolutional neural networks(CNNs) are the ways to determine the received signal without having any channel parameters and any prior proficiency of the incoming signal. A synthetic channel impairment waveform is generated. Using the generated waveform as training data and training the CNN for classifying the modulation. The CNN can also be tested with software-defined radio hardware and over-the-air signals and gives high accuracy than the traditional method. The proposed architecture performs six-layer convolution to the incoming signal and delivers around 95% of test accuracy with 30dB SNR, subjected to Racian multi-path fading, and also uses multiple modulation schemes for the classification at 30dB SNR.

Keywords—Signal generation, synthetic channel, CNN algorithm, classification, accuracy

I. INTRODUCTION

Signal or information is transmitted and received to establish connectivity between two nodes. Signals that are to be transmitted has to pass through various process to reach the destination from the source. The information or signal is converted into a digital signal, passes through source encoding, multiplexing, channel

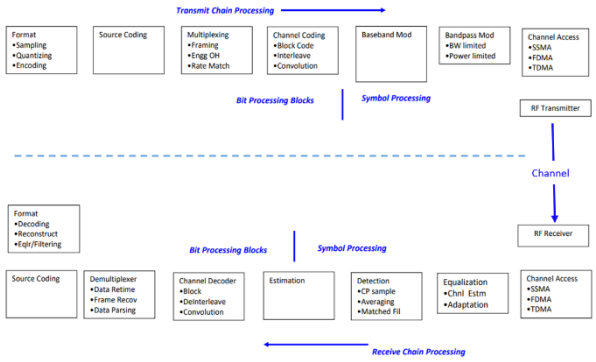

Fig.1: Various stages of signal processing at transmitter and receiver

coding, baseband through source encoding, multiplexing, channel coding, baseband modulation, bandpass modulation, channel access and then to the transmitter.
The signal then passes through the channel where noise is added, multi-path fading, and propagation delay takes place in the channel.
At the receiver, the process has to perform in reversed order as shown in Fig.1where the received signal is equalized, detected and estimated for further processing. Tradition method of detecting the modulation type of received signal takes more computation, to overcome this convolutional neural network is used. A convolutional neural network (CNN) is a form of artificial network. There are other neural network algorithms are also available. Deep Learning based automatic modulation classification is applied for recognition of patterns of the input frames[1] classification of modulation using Long-Short Term Memory(LSTM) and Bi-LSTM performance are compared[2] where LSTM can recognise the frame and is insensitive to time and frequency offset[3] under low SNR. To get high accuracy CNN model of a four-layer convolutional network gives roughly around 83.8 of delicacy[4]. The I/Q data of received classification of digital signal[5] using both residual network and CNN for classification which are separately calculated and compared and used their data set for training and testing. Classification of QAM signsl using different levels of phase noise gives additional benefits for the classification [6] in multipath fading channel environment with constellation diagram. By understanding the noise distribution denoising the radio signal using residual learning algorithm for classifying the input signal [7] modulation which is further recognized for classification.

II. EXPERIMENTAL PROCEDURE

This work concentrates on the prediction of modulation types using CNN. Examples of train CNN that recognize digital and analog modulation types are BPSK, QPSK, 8PSK, 16 QAM, 64QAM, PAM4, GFSK, CPFSK, B-FM, DSB-AM, and SSB-AM.

A. Generation of transmitted signal and channel impairment

The signal at the receiver that is to be detected has to undergo real-time environmental conditions such as the effect of noise, fading, multi-path, etc, generate the frames of random bits and perform the QAM modulation scheme. This modulated signal is subjected to Racian multi-path fading, centre frequency and sampling time drift, and AWGN.
At the RF transmitter, each modulated signal(frame) is passed through a channel with AWGN, Racian multi-path fading, and clock offset, resulting in the centre frequency of shift and sampling time drift. Based on the effect of these environmental factors the network must decide on these frames.

1) AWGN: Channel adds AWGN noise having SNR of 30 dB.
2) Racian Multi-path: The channel passes the signals through a Racian and multi-path fading where the signals are reflected, scattered, and deflected due to objects present in the environment which forms a multi-path along with the line of sight.
3) Clock Offset: Due to the inaccuracy of internal clock sources of the transmitter and receiver, clock offset occurs. Down conversion of signal from versious passband to baseband is performed.

4) Also, the digital signal is converted to an analog signal. The clock offset factor is given by eq(1) below.

$$C = 1 + \frac{\Delta_{clock}}{10^6} \qquad (1)$$

where Δ_{clock} is the lock offset, C is clock offset factor.
For every frame, the channel generates random Δ_{clock} values.

5) Frequency Offset: Every frame are subjected to frequency offset which is based on the central frequency and clock offset factor C.
6) Sampling Rate Offset: It is expressed as the product of the clock offset factor and sampling frequency.

$$S = C \times f_s \qquad (2)$$

where S is the sampling rate offset, f_s is sampling frequency, C is clock offset factor.

B. Generation of the waveform for training
10,000 frames of each type of modulation are generated, out of which 80% of them are used for training the frame, 10% for testing the frame and the remaining 10% of them are used for validation of the frames.
Each and every frame is sampled with 1024 long having 200KHz as the sampling rate. In the case of digital modulation type, 8 samples represent a symbol and the decision is made for one frame not for multiple frames keeping a centre frequency of about 902MHz for digital modulation and 100MHz for analog modulation.
The generated waveform of channel-impaired frames are subjected to a loop itself for every type of modulation and stores the frames.

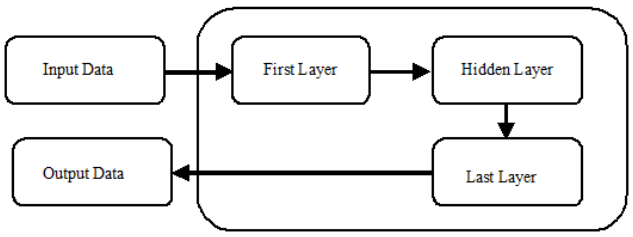

Fig.1: Modulation Classification block diagram using CNN

C. Transformation Of Complex Signals To Real Arrays
The signal received at the receiver has complex baseband samples whereas a neural network needs real-valued signal input. Transform the complex value into a real-valued signal of 4D arrays of frames having a size of 1-N, where 3D is in in-phase and 1D is in quadrature sample values.

D. Training, Testing And Validating Of Data
Split the array into three parts consisting of 80% of training data, 10% of testing data, and the remaining 10% as validation of the data. The CNN architecture uses six-layer convolution and all the layers are normalized except the last layer. A confusion matrix is used as a measure for performance evaluation of the classification algorithm.
After performing the confusion matrix of the received signal, the correlation of the received signal with other modulated signals takes place and the accuracy of the test data.

III. REULTS & DISCUSSION

The results from the experiment performed are as follows in this part. Classification of the received signal type is determined using the random generated data which is being modulated.

Random bits are generated and is modulated with QAM. Fig.3 shows the filter coefficient of square-root raised cosine filter with roll-off factor 0.35, symbols of 4 with samples as 8.

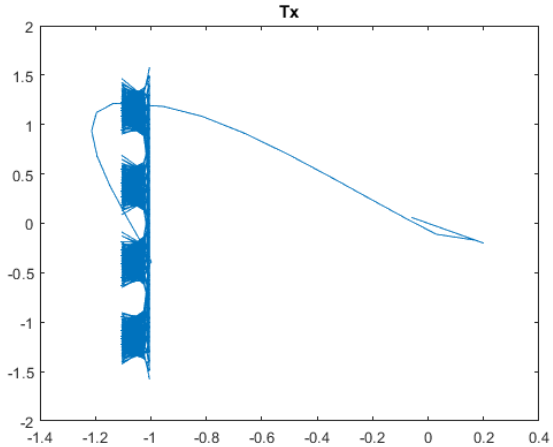

Fig.3: Filter coefficient of transmitted signal

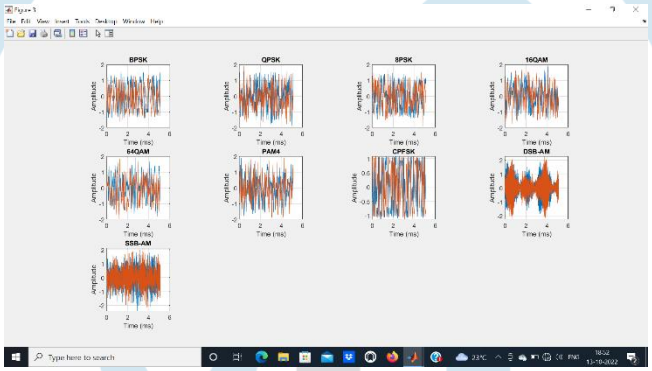

Fig. 2: Graph of amplitude of real and imaginary part of frames against sample number.

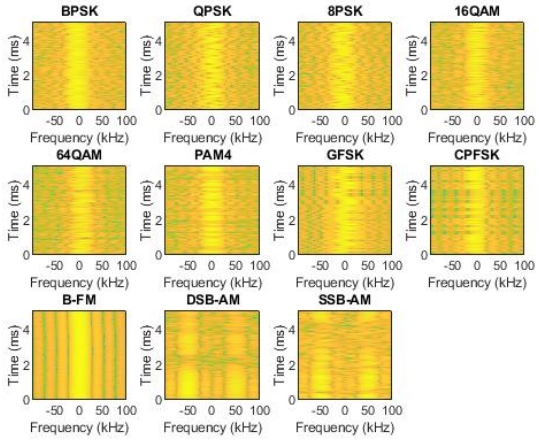

Fig.3: Spectrogram of the frames

The Fig.2 and Fig.3 shows the graph of amplitude of imaginary and real frames of all the considered modulation type, and Spectrogram of each and every modulation type respectively.

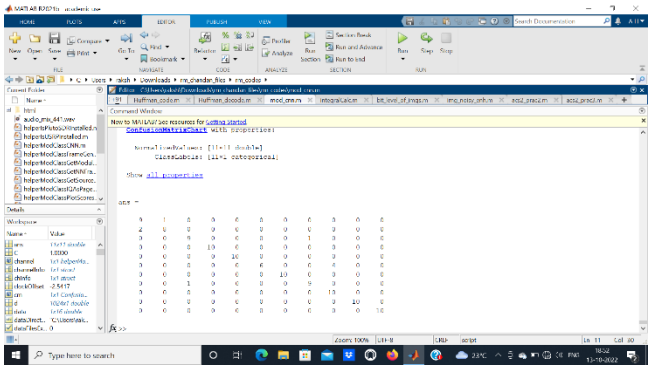

Fig.4: Confusion matrix in 2D matrix form

Fig.5: Graph of confusion matric of all the modulation type

The frames generated for every modulation scheme is divided into 3 parts. 80% of the frames are reserved for training of the data in first part, 10% of the generated frames are dedicated for validating of the CNN model in second part and the remaining frames i.e. 10% of frames for testing. Each frame is of 2^{10} samples long having 0.2MHz of sampling rate. Confusion matrix for classification of the modulation schemes using the generated test frames as shown in the Fig.3 and Fig.4 in which the transmitted signal is modulated with 16-QAM.

The accuracy is of 95.4545% for the received frames and some of the modulation type has similar constellation in the appearance and phase rotation due to channel fading and frequency offset.

IV. CONCLUSION

In this work, the received signal is subjected to CNN algorithm so that the receiver will classify the type of modulation that the signal it received without having the knowledge about channel parameters, and environment effects on the signal. This method even gives high accuracy in classification of the signal where traditional method can be avoided. This even increase the computation and makes further processing easy. Future direction is propose modified algorithm with involves ANN to solve problems which are complex and to distinguish the similar constellation diagram of different modulation type to increase more accuracy of test data in order to enhance the overall efficiency of the proposed model.

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