Modulation Classification using Convolutional Neural Network based on Deep Learning

COEN 6331

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Submitted to:
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April 28, 2022

Problem Statement

- Deep learning has not been well explored in many areas of Wireless communications.
- Modulation classification is one of the domain in communications where we can use deep learning to improve the performance of the network.
- The problem of recognizing the modulations correctly is a challenging task.

In this work, a Convolutional Neural Network (CNN) based on Deep learning (DL) technique has been designed to classify different types of modulation schemes.

Modulation Signals

- **Digital Modulations**
  - Binary phase shift keying (BPSK)
  - Quadrature PSK (QPSK)
  - 8-ary PSK (8-PSK)
  - 16-ary Quadrature amplitude modulation (16-QAM)
  - 64-ary QAM (64-QAM)
  - 4-ary Pulse amplitude modulation (4-PAM)
  - Gaussian frequency shift keying (GFSK)
  - Continuous phase FSK (CPFSK)
- **Analog Modulations**
  - Broadcast FM (B-FM)
  - Double sideband amplitude modulation (DSB-AM)
  - Single sideband amplitude modulation (SSB-AM)

Generation of Signal Waveforms

- Number of frames: 10,000 for each modulation
  - Training: 70%
  - Validation: 15%
  - Testing: 15%
- Training phase consists of training and validation.
- The test frames provides the classification accuracy.
- The number of samples in each frame are 2^{10} with a sampling rate of 0.2 MHz.
- For digital modulation, the number of samples per frame are 8 and the center frequency is 900 MHz.
- For analog modulation, the center frequency is 100 MHz.

Generation of Signal Waveforms

- Each of the generated frame is passed through Additive white gaussian noise (AWGN) channel with Rician multipath fading and a clock offset.
- The AWGN channel adds an SNR of 25 dB.
- The communications toolbox of matlab is used to implement this into the network.
- The Rician multipath fading channel has a delay profile of [0 1.6 3.2] samples with their corresponding path gains of [0 -3 -9].
- The K-factor[1] value is considered as 4 and the maximum Doppler shift[2] is considered as 3 Hz.
- The network is implemented with a clock offset[3] of 4.
- Frequency offset[4] and sampling rate offset[5] have also been applied for every frame.
- In this network, the decision is entirely based on single frame

[1] K-factor is the ratio of signal power in dominant component over the scattered, reflected power.

[2] The rate of change in observed wavelength, or frequency, is known as the Doppler shift.

[3] Offset of the clock is a delay of a given clock source

[4] An intentional slight shift of broadcast radio frequency (RF), to reduce interference with other transmitters.

[5] It is the relative offset between the sample rate of transmitter and receiver.

Generation of Signal Waveforms

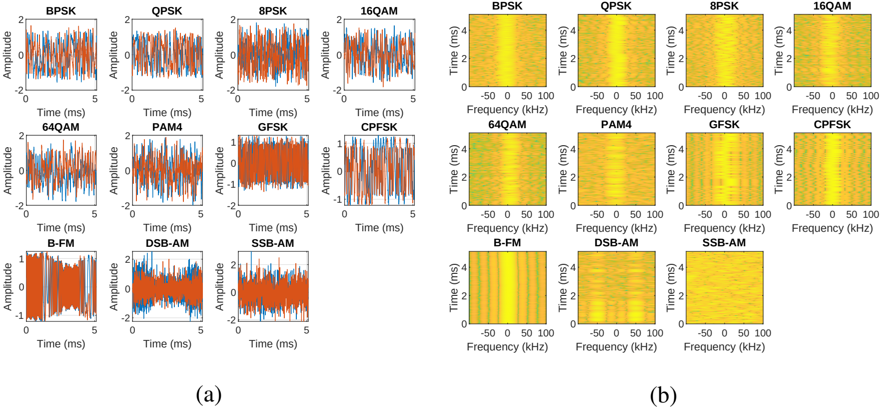

Fig. (a) Time domain representations of signal waveforms, and (b) Corresponding spectrograms[6]

[6] A spectrogram is a visual way of representing the signal strength, or "loudness", of a signal over time at various frequencies present in a particular waveform.

Training of the CNN

- CNN consists of 6 convolutional layers and one fully connected layer.
- Each convolution layer except the last layer 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.
- The stochastic gradient descent with momentum (SGDM) solver has been configured with a batch size of 256.
- Maximum number of epochs are set to 12.
- Initial learning rate is set to 2×10^{-2} and for every 9 epochs, the learning rate decreases by a factor of 10 modclass.

Training of the CNN

The network converges in about 12 epochs and the accuracy is 92.88%.

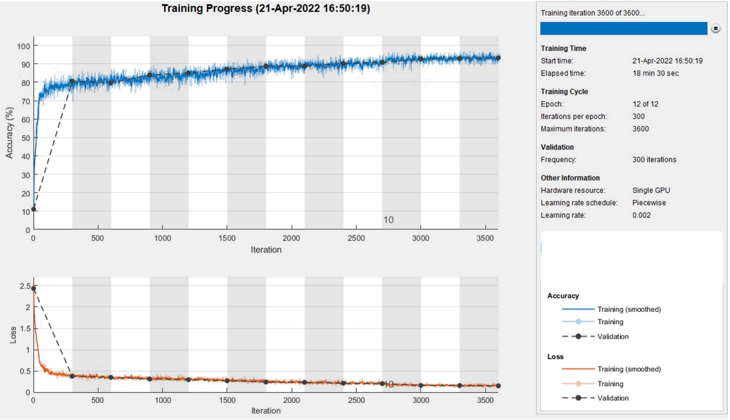

Fig. Training of the CNN

Testing of the CNN

Test accuracy: 93.5%

Confusion Matrix for Test Data

True Class \ Predicted Class	16QAM	64QAM	8PSK	B-FM	BPSK	CPFSK	DSB-AM	GFSK	PAM4	QPSK	SSB-AM		
16QAM	1176	311	5						2	6		78.4%	21.6%
64QAM	310	1188	2									79.2%	20.8%
8PSK	8		1392						2	98		92.8%	7.2%
B-FM				1500								100.0%	
BPSK					1497				2		1	99.8%	0.2%
CPFSK						1500						100.0%	
DSB-AM							1426				74	95.1%	4.9%
GFSK								1500				100.0%	
PAM4		1			1				1498			99.9%	0.1%
QPSK	3		100						2	1395		93.0%	7.0%
SSB-AM							145				1355	90.3%	9.7%

Fig. Confusion matrix for test data

Testing of the CNN

- 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.
  - This is based on the fact that the constellations of these modulation types look similar once phase-rotated due to the fading channel and frequency offset.
- The CNN network also confuses between DSB-AM and SSB-AM.
  - This problem arises since the DSB-SC has the same BW as AM and SSB has half of the bandwidth as AM.
- To test the performance of the trained network with over-the-air signals in Matlab, we must have dedicated SDRs for transmission and reception.
- Communications toolbox support package for analog radio devices is required which is unavailable in our lab computers.

Conclusion

- This project has used a CNN based DL model to classify modulations.
- Several waveforms have been generated and used for training and testing purposes.
- CNN based DL approach avoids manual feature selections and provide a higher classification accuracy.
- The CNN based DL network is successful in classifying modulations by 93.5% of accuracy.

References

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