# Robustness of Deep Modulation Recognition under AWGN and Rician Fading

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***Abstract*—We study the robustness of modulation recognition using deep neural networks. This is of critical importance for applying deep learning for radio modulation classification, because wireless propagation conditions could vary significantly under different communication environments. We compare the performance of radio modulation recognition using data and using expert features. While deep modulation recognition using data has been proposed in existing literature since it achieves better performance than crafted expert features, our results indicate that using expert features yields significantly more robustness.**

***Index Terms*—Modulation recognition, deep learning, robustness, feature-based.**

## I. Introduction

It is important to identify the modulation types of incoming signals for applications such as spectrum monitoring, interference identification, and spectrum management [1], and modulation recognition has been widely investigated over the past several decades [2]- [4] based on a decision-theoretic approach.

With the extensive application and significant success of deep neural networks in areas such as computer vision, natural language translation, and speech recognition, O'Shea et.al. in [6] demonstrated the viability and effectiveness of applying deep neural networks in modulation recognition. Similar to how the deep learning is applied in computer vision, the deep modulation recognition was carried out in a way that the samples of received radio waveform are utilized as the input of a neural network. Using a large number of radio samples with ground-truth labels (also termed training data) to train the neural network, it was shown to be effective in modulation recognition, with performance improvements compared to expert feature based methods.

However, wireless radio signals vary significantly in a variety of dimensions. Changes in factors, such as time, location, velocity, and propagation conditions of either the transmitter or the receiver, would cause deviations in the statistical characteristics of the received radio samples from that of training data. However, it is not feasible to obtain sufficient training data for all possible radio scenarios. Thus, it is necessary to examine whether the neural network is still effective in such environments.

In this paper, we examine the robustness of a deep neural network, and show that, directly using radio samples as inputs to neural network (termed data-based deep neural network or data-based deep modulation recognition) is sensitive to the operating environment and is not robust under different propagation conditions. In contrast, we show that using expert features as input to the deep neural network exhibits significant robustness.

The rest of this paper is organized as follows. The data-based deep modulation recognition framework is described in Section II. In Section III, a robust deep modulation recognition scheme using extracted features is given. Results and corresponding analysis are presented in Section. Finally, conclusions are discussed in Section V.

## II. Data-Based Deep Modulation Recognition

Modulation recognition can be formulated as a classification problem, where the modulation type is determined by classification of received radio signals. A deep neural network can be considered as a classifier, and was proposed in [6] for modulation recognition, where the received radio signal samples are fed into the network. Since it directly utilizes the radio signal data as the inputs, we call this data-based deep modulation recognition.

The signal samples are obtained by sampling the in-phase and quadrature components of the signal at discrete time steps by an analog-to-digital coverter with a carrier frequency roughly centered on the carrier of interest [6]. In this way, a $1 \times N$ complex-valued vector is formed. This complex-valued vector can be further decomposed as a $2{\times}N$ real-valued vector, with the first row being the in-phase components and the second row as the quadrature components. These vectors are the input of the deep neural network.

The deep modulation recognition network, as illustrated in Fig. 1, is a 4-layer neural network with two convolutional and two fully connected layers. The rectified linear (ReLU) activation is used for the convolutional and fully connected layers, and a softmax activation function is employed for the output layer. The last fully connected layer has $L$ neurons corresponding to the $L$ modulation classes.

To train the data-based deep neural network, each input vector is associated with a ground-truth label. The label is

This research was supported by the National Science Foundation of China under Grant No. 61301154, by the China Scholarship Council (201506075100), and by the Army Research Office under Grant W911NF-14-1-0340.

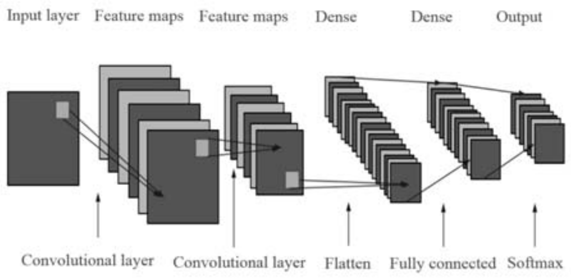


Fig. 1. Deep modulation reconition network

used to identify the modulation type of the input vector. This label is typically described by one-hot encoding [7].

By collecting a sufficiently large amount of input vectors with ground-truth labels, also called a labeled dataset, the neural network can be trained to fulfill the task of modulation classification. The model parameters of the neural network can be trained and validated with the training dataset. The output of the neural network is the class label indicating which modulation category the input vector falls in.

## III. Robust Deep Modulation Recognition Using Features

Data-based deep modulation recognition has been shown to be effective in [6] and [8]. However, training a neural network with sufficent labeled data to a specific communications scenario does not guarantee that it generalizes well in other communications environments. As discussed in Section I, wireless signals can vary significantly under different scenarios due to time, location, terrain profile, etc.. For example, the propagation could vary from line-of-sight to multipath fading and shadowing. In this way, the radio signals could be very different from those used for training the neural network. As a consequence, the patterns learned from the radio signals in one communication scenario might not apply for a different one. On the other hand, it is too difficult to collect all the radio data with ground-truth label. Therefore, robust deep modulation recognition, which can generalize well in different wireless communication scenarios, is needed.

In this paper, we propose to use a feature-based deep neural network. Instead of directly feeding the radio signal samples into the neural network, the feature-based deep modulation recognition first extracts features from radio signal samples that are suitable for modulation recognition, and then uses these features as inputs to the deep neural network. The block diagram of a feature-based scheme is illustrated in Fig. 2. For feature-based deep modulation recognition, we choose widely adopted features which are described in the following.

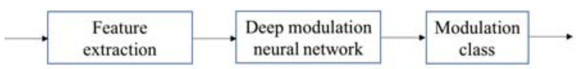


Fig. 2. Block diagram of feature-based deep modulation recognition.

### A. Modulation Features

Both statistical and instantaneous features can be extracted to discriminate among the modulation types of interest [1]. Higher-order moments and cumulants are among the most widely utilized statistical features. A higher-order moment of received signal $x$ is given by

$$M_{pq} = E[x^{(p-q)}(x^*)^q] \tag{1}$$

where $p$ and $q$ are non-negative integers. Higher order cumulants $C_{pq}$ can be obtained from $M_{pq}$, for example,

$$\begin{aligned} C_{40} &= M_{40} - 3M_{20}^2 \\ C_{42} &= M_{42} - \left|M_{20}\right|^2 - 2M_{21}^2 \\ C_{60} &= M_{60} - 15M_{40}M_{20} + 30M_{20}^3 \end{aligned} \tag{2}$$

We utilize the ratios of higher order cumulants as statistical features [5] in this paper. Specifically, we define $F_i$, $i = 1, 2, \cdots, 6$, as follows:

- $F_1 = \left|\frac{C_{40}}{C_{21}^2}\right|$, $F_2 = \left|\frac{C_{41}}{C_{21}^2}\right|$, $F_3 = \left|\frac{C_{42}}{C_{21}^2}\right|$
- $F_4 = \left|\frac{C_{60}}{C_{21}^3}\right|$, $F_5 = \left|\frac{C_{63}}{C_{21}^3}\right|$
- $F_6 = \left|\frac{C_{80}}{C_{21}^4}\right|$

Another statistical feature that is extracted for modulation recognition here is the ratio of variance $\sigma^2$ to square of mean $\mu$, i.e., $F_7 = \frac{\sigma^2}{\mu^2}$.

Instantaneous features can also be extracted to discriminate among different modulations and are shown to be effective [1]-[4]. Two widely used instantaneous features are adopted for deep modulation recognition in this paper. The first instantaneous feature, $\gamma_{\max}$, is defined by [1],

$$\gamma_{\max} = \frac{\max\left|DFT(x_{cn}(i))\right|^2}{N} \tag{3}$$

where $DFT(\cdot)$ denotes the discrete Fourier transform operation, $x_{cn}(i)$ is the $i$-th sample of the normalized-centered instantaneous amplitude, defined by

$$x_{cn}(i) = x_n(i) - 1, \quad \text{where } x_n(i) = \frac{x(i)}{\mu} \tag{4}$$

where $\mu$ is the average value of the instantaneous amplitude, i.e., $\mu = \frac{1}{N}\sum_{i=1}^{N} x(i)$.

The second feature is the kurtosis of the normalized-centered instantaneous amplitude of the signal, given by [9]

$$F_9 = \frac{E[x_{cn}^4(i)]}{\left\{E[x_{cn}^2(i)]\right\}^2} \tag{5}$$

## IV. Results and Analysis

In this section, we evaluate and compare the performances of data-based and feature-based deep modulation recognition. In order to examine the robustness of different deep modulation recognition schemes, we carry out the following experiments:

- Train the neural network with radio signals under AWGN, and test the neural network performance under AWGN as well.
- Train the neural network with radio signals under AWGN, and test the neural network performance under Rician fading.

We use the same setting for generating radio signals under AWGN as those in the GNU Radio ML dataset RML2016.10a [6] and [8]. The received signals are upsampled by a factor of 8, and $2 \times N$ real samples are collected to form one $1 \times N$ complex-valued input vector, which can be decomposed into two $1 \times N$ real-valued vectors. In the experiments, $N$ is set to either 128 or 1024. One input vector is also called one example. There are 11 different modulation formats, including both analog and digital modulation types: BPSK, QPSK, 8PSK, QAM16, QAM64, CPFSK, GFSK, PAM4, WBFM, AM-SSB, and AM-DSB. One thousand examples are generated for each SNR and each modulation type, whereby half of the examples are randomly chosen for training, and the remaining half are used for the test.

Radio signals with the 11 modulation formats under Rician fading are also generated in a GNU Radio. Specifically, frequency-selective Rician fading is considered, and the number of discrete paths is set to three. The first discrete path experiences Rician fading. The Rician K factor, which is the ratio of the power received via the line-of-sight (LOS) path to the power of the remaining non-LOS paths, is set to $K = 4$. The remaining discrete paths follow independent Rayleigh fading. Similarly, for each SNR and each modulation type, we generate 1000 examples under Rician fading, whereby 500 examples are randomly picked for training the neural network, and the remaining 500 examples are utilized for the test.

For clarity of description, the notation in Figs. 3 and 4 are elaborated in the following:

- "Data-based AWGN" corresponds to the performance of data-based deep modulation recognition, when the neural network is trained using the examples under AWGN and is tested with examples under AWGN.
- "Feature-based AWGN" is similar to data-based AWGN, except that feature-based deep modulation is utilized.
- "Data-based Rician" corresponds to neural network being trained using the dataset under AWGN, and being tested using the dataset under Rician fading.
- "Feature-based Rician" refers to the scenario where the neural network is trained with features extracted from examples under AWGN and tested using features from those under Rician fading.

The modulation classification accuracy versus SNR is plotted in Fig. 3, where the number of complex samples in one input vector $N = 128$. It can be seen that the classification accuracy for the data-based AWGN is higher than that of the feature-based AWGN. That is, the data-based deep modulation recognition achieves higher classification accuracy than the feature-based scheme. This coincides with O'Shea's pioneering work on deep modulation recognition [6] [8].

However, when the trained model is applied to a different communication environment, for example, when the modulated signals experience multipath Rician fading, as shown in Fig. 3, the classification accuracy significantly falls into the range of 20% to 30% for data-based deep modulation recognition, and the accuracy stays at a similar level even when the SNR is 20dB. On the contrary, there is a relatively small gap in the classification accuracy between AWGN and Rician fading when using expert features, and when SNR is above 10dB, the resulting classification accuracy is around 0.70. This decrease is much less significant than the data based scheme. It indicates to us that using expert features for deep modulation recognition is more robust than the data based method. This is reasonable, because the statistics of sampled data change when the communication channel varies. Accordingly, the patterns learned by the neural network under AWGN no longer hold for the scenario of Rician fading channels. Evidently, the expert features, such as high-order cumulants of received signals, are retaining their usefulness under some different channel conditions. As a result, the feature based scheme is more robust for radio modulation recognition.

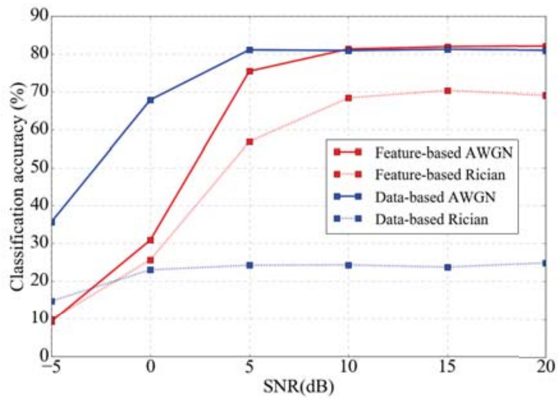


Fig. 3. Modulation classification performances under AWGN and Rician fading for $N = 128$

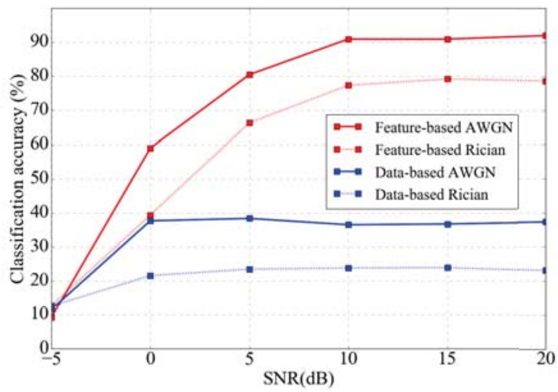


Fig. 4. Modulation classification performances under AWGN and Rician fading for $N = 1024$

Intuitively, increasing the input vector size will increase the classification accuracy, since more time-domain samples would bring in more information. With the same amount of data for training the neural network, we increase the input vector size from $N = 128$ to $N = 1024$, and the corresponding modulation classification performances are plotted in Fig. 4. It is seen that, when the input vector size increases, the performance of the data-based deep modulation recognition is significantly degraded. Even for very high SNR at 20dB, the classification accuracy is slightly below 40%. On the contrary, the performance of the feature-based deep modulation recognition is improved as compared with its performance when $N = 128$ in Fig. 3, that is, the classification accuracy increases from roughly 80% to slightly above 90% for SNR from 10dB to 20dB.

This is because, for the data-based neural network, when $N$ increases from 128 to 1024, the total number of signal patterns are exponentially increased. For example, for a modulation with alphabet size of $M$, the number of signal patterns for $N = 128$ with an upsampling factor of 8 is $M^{16}$, and for $N = 1024$ it becomes $M^{128}$. In other words, for the data-based scheme, in order to make the neural network learn as many as possible patterns so as to achieve satisfactory performance, the training dataset size needs to be significantly increased when $N$ increases. Obtaining a large amount of labeled data for certain scenarios, especially simulated scenarios, are feasible. However, it is difficult to obtain a large amount of labeled data for all possible communications scenarios. On the other hand, when the input vector size increases, the extracted features, especially these statistical ones, can better reflect the statistical characteristics of the received signal, and thus resulting in better performance in classification accuracy. From this perspective, we can also conclude that the feature-based deep modulation recognition is significantly more robust than the data-based approach.

## V. Conclusions

Robustness of deep modulation recognition has been investigated in this paper. Specifically, deep modulation recognition performances have been evaluated and compared under AWGN and Rician fading for data-based and feature-based schemes. Results show that feature-based deep modulation recognition has significantly more robustness than the data-based, and indicate that, for the current state-of-the-art of machine learning in wireless communications, where sufficiently large datasets with many possible communications scenarios are not yet available, feature-based deep modulation recognition is better than data-based one in terms of a robust deep modulation recognition.

## References


[1] E. E. Azzouz and A. K. Nandi, "Automatic modulation recognition-I," Elsevier Journal of the Franklin Institute, vol. 334, no. 2, pp. 241-273, Mar. 1997.

[2] C. S. Weaver, C. A. Cole, R. B. Krumland, and M. L. Miller, "The automatic classification of modulation types by pattern recognition," *Technical Report* No. 1829-2, Stanford Electronics Laboratories, Stanford University, Apr. 1969.

[3] E. E. Azzouz and A. K. Nandi, "Automatic identification of digital modulation types," *Signal Processing*, vol. 47, no. 1, pp. 55-69, Nov. 1995.

[4] A. K. Nandi and E. E. Azzouz, "Algorithms for automatic modulation recognition of communication signals," *IEEE Trans. on Communications*, vol. 46, no. 4, Apr. 1998.

[5] Y. Zhao, Y. Xu, H. Jiang, Y. Luo, and Z. Wang, "Recognition of digital modulation signals based on high-order cumulants," *International Conference on Wireless Communications & Signal Processing*, Oct. 15-17, 2015.

[6] T. J. O'Shea, J. Corgan, and T. C. Clancy, "Convolutional radio modulation recognition networks," *International Conference on Engineering Applications of Neural Networks*, pp. 213-226, 2016.

[7] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, http://deeplearningbook.org, 2016.

[8] T. J. O'Shea and N. West, "Radio machine learning dataset generation with GNU Radio," *Proceedings of the 6th GNU Radio Conference*, vol. 1, no. 1, 2016.

[9] A. Kubankova, H. Atassi, and A. Abilov, "Selection of optimal features for digital modulation recognition," in *Proceedings of the International Conference on System Science and Simulation in Engineering*, Oct. 3-5, 2011.