# Automatic Modulation Classification in the Presence of Interference

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***Abstract*—A modulation recognition method based on a convolutional neural network (CNN) architecture is assessed through classification of synthetic baseband signals in the presence of a second interfering signal source. The complexity and adaptability of CNNs is leveraged so as to forgo statistical feature extraction procedures and efficiently classify based on raw signals or their modified forms. Both scenarios with the interfering signal's modulation scheme known and unknown, are considered. Simulation results show that the CNN architecture achieves considerable accuracy despite the presence of interference, and the knowledge of the modulation scheme of the interfering signal significantly improves the accuracy.**

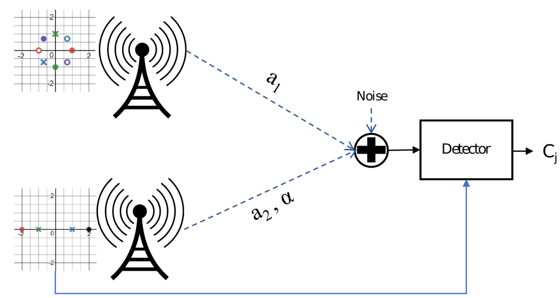


Figure 1: AMC in the presence of interference.

## I. Introduction

In recent years, automatic modulation classification (AMC) has been experiencing a resurgence in interest, due in part to the development of the 5th generation of telecommunication networks (5G), which is expected to result in the proliferation of end devices in use and an overcrowding of the electromagnetic spectrum. While military technology has always been a key driving factor behind the evolution of AMC, commercial applications are also numerous, and this would include *e.g.*, interference identification and spectrum sensing.

AMC is fundamentally a problem of pattern recognition. AMC methods can be roughly grouped into two categories: likelihood-based (LB) and feature-based (FB) [1]. The former is centred around the extraction of likelihood functions and statistical models from input signals, whereas a classifier's final decision is reached through a comparison of values to each other, or to a specified threshold [2], [3]. Instead, the latter employs, as a first step, feature selection, which subsequently informs the classifier's decision [4], [5]. While LB methods can be shown to be Bayesian-optimal, their computational complexity is a significant drawback, as is the degradation of classification efficiency when disjunctions between system models and actual systems are present; FB methods, on the other hand, are often preferred because they can achieve almost optimal performance if properly constructed, at only a fraction of the computational cost [1]. Commonly, the approach followed by the latter family involves an explicit *a priori* acquisition of predetermined features (these can range from simple statistical quantities, such as variance or signal power, to higher-order moments and cumulants), with the selection often made on a basis of trial-and-error. The classification of the feature vector is where aspects of machine learning first manifest, as the vector is rendered an input to a simpler (e.g., a decision tree [6]), or more sophisticated (e.g., an artificial neural network) classifier. Recent publications further exploit the capabilities of deep neural networks and feed the sampled raw time series signals [7], [8], or, alternatively, a transformed representation (e.g., a periodogram) [9] directly to a neural network, and the feature extraction process is considered part of the network's own function.

In our work, we sought to extend the scope of such methods to AMC in the presence of interference. Cognitive communications is becoming particularly important with the increasing number of wireless devices sharing the same spectrum. In addition to spectrum sensing to seek spectrum holes for interference-free communications [10], more advanced cognitive techniques would allow interference identification and cancellation to improve the rate and reliability of communication [11]. Here, our goal will be to detect the modulation scheme of an interference signal, a step towards cancelling or reducing it. This will have to be carried out in the presence of the desired signal, whose modulation scheme is typically known; although the case in which neither modulation schemes are known is also considered. Note that, from the AMC point of view, this is equivalent to AMC in the presence of interference, with or without known interference modulation.

Similarly to [7], [8], [9] we will use a deep neural network for AMC, and evaluate its performance in the presence of interference. It is observed that, as one would expect, the detection accuracy depends on the signal-to-interference ratio as much as the signal-to-noise ratio. AMC is particularly difficult when the interference and the desired signals have similar strengths and the modulation scheme of the interference signal is not known. Knowledge of the modulation scheme

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of the interference signal significantly improves the detection accuracy. Note that, we assume only the knowledge of the modulation scheme employed by the interferer, but not the particular transmitted signal.

The rest of the paper is organized as follows. The problem statement and the dataset used for numerical simulations are presented in Section II. Section III focuses on the problem when the modulation scheme of the interfering signal is known. In Section IV the results of the numerical experiments are presented. Finally, the paper is concluded in Section V.

## II. Problem statement

Let $y[n]$ be the discrete baseband received signal given by:

$$y[n] = h_1[n]b[n] + h_2[n]s[n] + w[n], \quad n = 1, \ldots, N, \quad (1)$$

where $b[n]$ are the samples of the interfering signal whose modulation scheme we wish to detect, $s[n]$ is the desired signal, whose modulation is known, $h_1$ and $h_2$ are the corresponding channel gains, and $w[n]$ denotes an additive noise term. The objective of our experiment is to build and train a deep-learning-based AMC method which shall successfully identify the modulation scheme $C_b \in \{1, \ldots, M_{int}\}$ of signal $s[n]$, without an explicit procedure of statistical feature extraction. Furthermore, it is desired to assess whether the knowledge of the modulation class of the desired signal, $C_s \in \{1, \ldots, M_d\}$ can be incorporated as an input into the classifier and improve the overall performance. Figure 1 is a visual representation of the problem as stated above.

A data-driven approach will be followed, and our deep learning AMC network trained using interference and desired signals from known modulation constellations. Next, we explain the dataset used for this purpose.

### A. Dataset

A dataset used in recent years in modulation-detection-related experimentation is RadioML 2016, proposed and described by O'Shea et al. in [12]. For our purposes, we have used an extended version of the RadioML dataset, with the following features:

- 1.2 million samples (separated into training, validation, and testing sets),
- 10 different modulation schemes (BPSK, QPSK, 8PSK, 16QAM, 64QAM, GFSK, CPFSK, and PAM4 as digital, and WB-FM and AM-DSB as analog modulation schemes),
- Sample format: $2 \times 128$ vectors (two channels corresponding to in-phase and quadrature components),
- SNR values $\in [-20, -18, \ldots, 16, 18]$ dB.

We will consider two settings: an "easy" setting, in which samples for $s[n]$ and $b[n]$ are selected from a subset of the available modulation schemes, and a more "difficult" one where all modulations participate as candidates for both signals. As such, samples are selected as follows:

- Only data for SNR values $\geqslant 6$ dB retained for $b[n]$ and $\geqslant 16$ dB for $s[n]$,
- In the easy setting, five classes for the interference (8PSK, PAM4, QAM64, QPSK, WBFM) are considered, and another four for the desired signal (AM-DSB, BPSK, CPFSK, QAM16).

Through repetition and shifting, the selected samples were combined so as to create 600000-large dataset for training and 100000-large for validation. Subsequently, the final datasets were created as follows:

Let $s_i$ be an instance of the final dataset, $x_i$ and $y_i$ sample sequences from the earlier primary and secondary (i.e., corresponding to interfering and desired signals, respectively) sets corresponding to the same index $i$. Each $s_i$ is created using the following equation:

$$s_i[j] = x_i[j] + \alpha_i y_i[j], \quad i = 1, \ldots, M, \quad j = 1, \ldots, N, \quad (2)$$

where $M$ is the dataset size ($M = 6 \times 10^5$ for the training set, $M = 10^5$ for the validation set), $N = 128$ is the number of symbols in each sequence as mentioned above, and $\alpha$ is a factor of attenuation or amplification that adjusts the signal-to-interference ratio, selected randomly for each instance, taking one of the following values:

$$\alpha \in [0, 0.1, \frac{\sqrt{10}}{10}, 0.5, \frac{\sqrt{2}}{2}, 1, \sqrt{2}, 2, \sqrt{10}],$$

or, equivalently,

$$\alpha \in [-\infty, -20, -10, -6, -3, 0, 3, 6, 10] \text{ dB}.$$

It is shown in [8] that feeding raw I/Q values to a CNN architecture provides impressive test accuracy, surpassing known feature-based techniques that have been developed over many years. We will explore whether this result extends in the presence of interference, as well as whether alternative data representations, instead of raw I/Q symbols as available in RadioML, may be of any use in improving classification accuracy. The experiments conducted in [9] include the conversion of the I/Q format into amplitude and phase values, and a small improvement in performance is reported.

## III. Exploiting desired signal modulation information

It is inherent in our system model that the modulation scheme used for the desired signal is known beforehand; and thus, we want to investigate whether this additional information could be exploited in order to improve the overall detection accuracy, and how significant this improvement would be.

The most straightforward manner to exploit this information would be to train a separate classifier for each class of modulation; *i.e.*, a separate neural network can be trained to detect the interference modulation for each kind of desired signal modulation. Although this approach is intuitive and potentially effective, its complexity and training time grows significantly in proportion with the number of available classes.

Instead, here the signal class information is incorporated into the neural network as an additional input. This will be done in the form of one-hot encoding, as commonly done for the use of categorical data as feature vectors [13]. In particular, a vector of length $M_d$ is appended, which consists of all zeros, save for a single 1 at the location corresponding to the index of the modulation class of the desired signal.

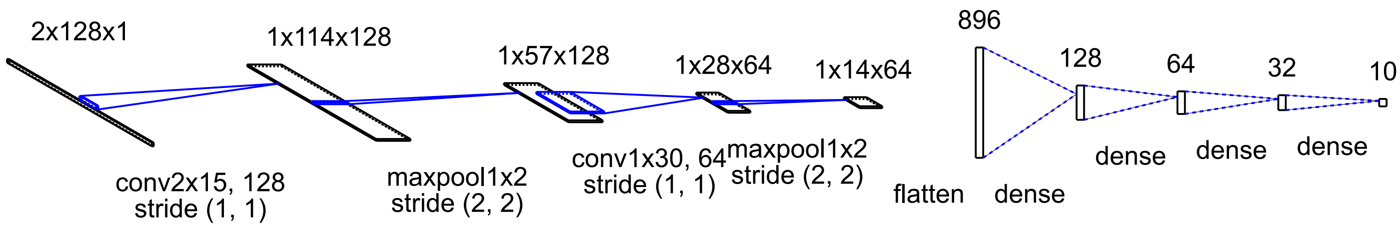
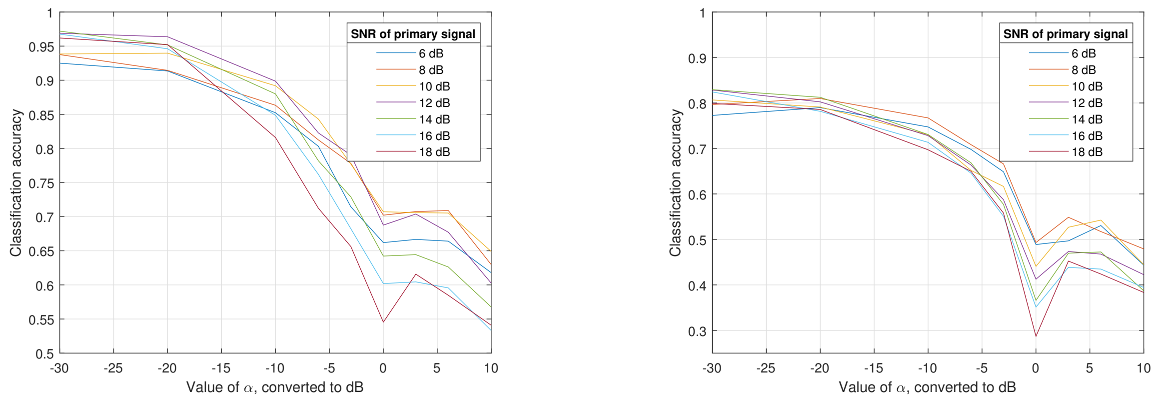



Figure 2: CNN classifier architecture.




(a) 5 classes

(b) 10 classes

Figure 3: Desired signal modulation unknown - I/Q input.

## IV. Experiments and Results

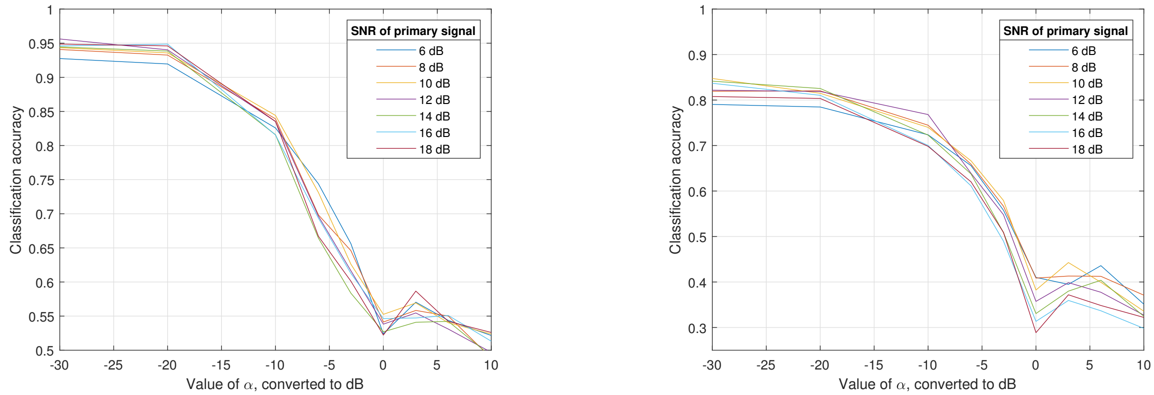
Unless otherwise stated, all experiments shown henceforth are conducted upon datasets with 600000 samples in the training set and 100000 in the validation and testing set. Each datapoint consists of 128 I/Q pairs sampled at the receiver. The distribution of modulation schemes is as described in Subsection II-A, and we shall consider both the setting in which all 10 modulation classes are present, and the restricted easy setting in order to assess the impact of the number of classes on accuracy.

The CNN architecture used for classification is presented in Figure 2, and it consists of two pairs of convolutional and max-pooling layers followed by three fully-connected layers, terminating in a *softmax* layer with either 10 or 5 outputs, depending on the setting. The fully-connected layers are initialised with the Xavier function, and the first two are also fitted with dropout mechanisms. The Leaky ReLU activation function is used throughout, with the exception of the final (softmax) layer.

Each figure represents the best results available for every separate sub-experiment after several runs with varied hyperparameter values. It is noted that only one CNN was trained per experiment, i.e. each training phase included all datapoints, without regard to SNR or SIR. Simulation results for the simpler (5 classes) and difficult settings (10 classes) will be presented next to each other for ease of comparison.

In Figures 3 and 4, we first test the performance when the desired signal is unknown. Note that $\alpha = -30$ dB corresponds to the case in which there is no desired signal, which is equivalent to the scenario in [8]. As the signal-to-interference ratio, $\alpha$, increases, the desired signal becomes gradually more dominant and the expected deterioration of performance is noticed. Worth noting is that the higher SNR values for the interference signal only provide better results when the desired signal is weak, whereas the high-SNR curves are outperformed by those derived by noisier inputs for higher $\alpha$, sometimes even by 10%. Also notable is a steep decline of most curves when the $\alpha$ factor is equal to 0 dB, which is accompanied by a stronger rise afterwards in the 10-class scenario. The most likely explanation for this behaviour is the confusion of the classifier over two independent components superposed at equal power, whereas in other areas it might be receiving training to locate the stronger signal, and somehow remove its impact.

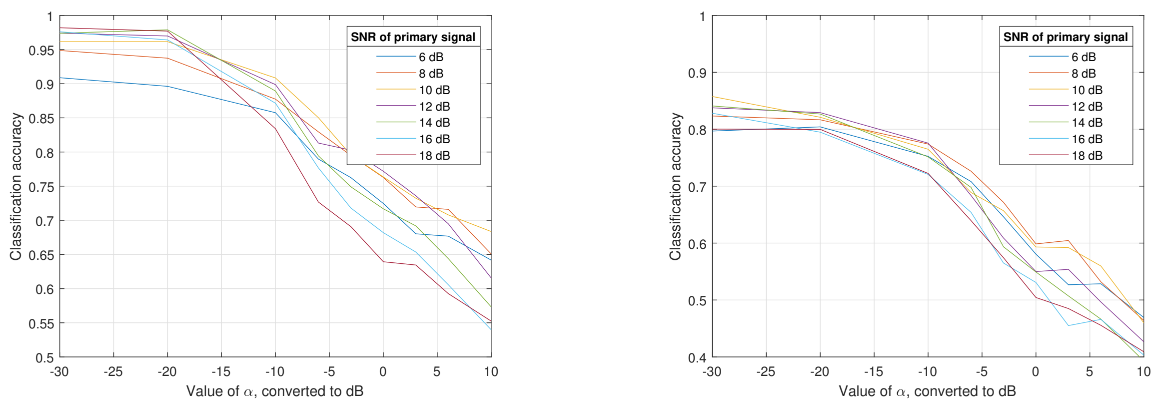
In Fig. 5 and 6 it is assumed that the desired signal's modulation class is known. In general, the one-hot encoding method, despite its simple nature, has proven effective. We observe that the detection accuracy has improved significantly compared to Fig. 3 and 4, with a slightly higher variance between the accuracy of different curves (corresponding to different SNR values). It is obvious that the performance degrades with the increase in $\alpha$; this is because, although the desired signal modulation class is unknown, we are unable to completely remove it. In the 10-class case, the application of one-hot encoding is especially noteworthy for its effect upon the 0dB "canyon"; notice how it has disappeared almost entirely. It is noted that in the easy setting all modulation schemes exhibit performance above 50%.




(a) Simple $A/\phi$ - 5 classes

(b) Simple $A/\phi$ - 10 classes

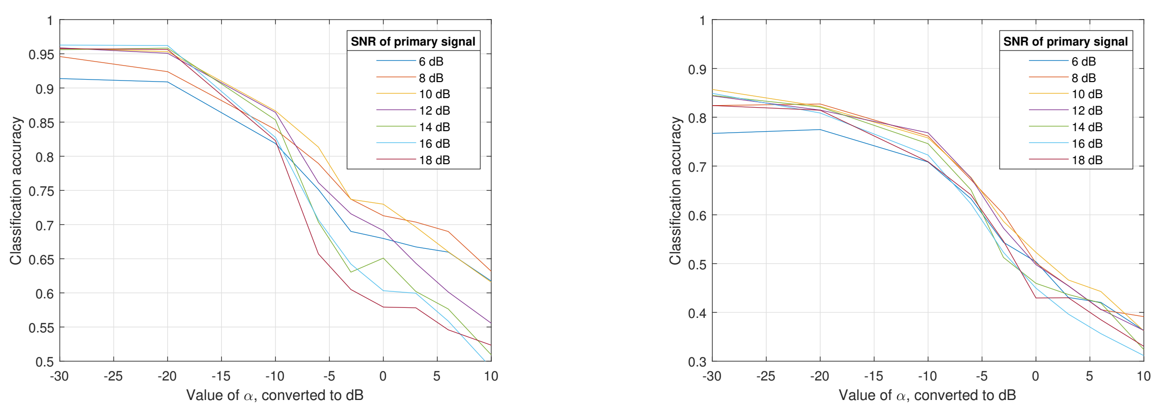
Figure 4: Effects of amplitude-phase transform.




(a) One-hot method - 5 classes

(b) One-hot method - 10 classes

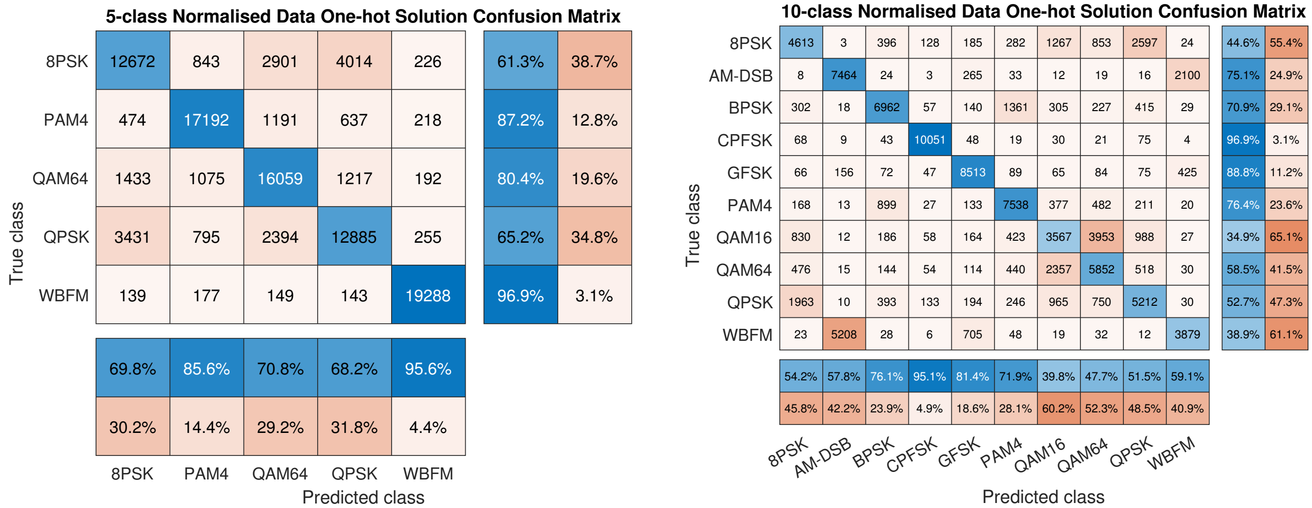
Figure 5: Desired signal modulation known - I/Q input with one-hot encoding.




(a) One-hot plus $A/\phi$ - 5 classes

(b) One-hot plus $A/\phi$ - 5 classes

Figure 6: Effects of combined $A/\phi$ and one-hot techniques




(a) One-hot solution, 5 classes

(b) One-hot solution, 10 classes

Figure 7: Confusion matrices for experiments with normalised signals

Although the amplitude/phase transformation was reasonably effective in its original context, in this superposition problem it does not seem to solve many of our problems; on the contrary, it seems to introduce extra confusion, which is more apparent for high values of $\alpha$.

Singling out the cases described in Figure 5 as the best possible achieved through our experiments (peaking at 78.2% accuracy for 5 classes, 55.7% for 10, over all sub-categories of SIR and SNR), we plot confusion matrices for the classification results on the validation set after the end of training so as to better understand the effectiveness of the algorithm in cases of different signals; the results are shown in Figure 7.

In the easy setting, it is reasonable to expect that WBFM shall be the most effective to recognize, as it is the only analog modulation present in the reduced dataset, while the two different PSK modulations are easier to confuse with each other. In the difficult setting, the most telling feature are the low performance rates for QAM16, which is most easily misclassified as the only other available QAM modulation scheme (QAM64), and a similar tendency observed with 8PSK and QPSK. Likewise, WBFM loses its formerly observed edge, as many of its instances are, instead, classified as AM-DSB signals (which, again, can be explained by the fact that those are the two available analog modulations). The two frequency-shifting modulations (CPFSK, GFSK) are proven the most robust, and do not mutually deteriorate their performance as it happens, e.g., with PSK or analog modulations.

## V. Conclusions

This paper presents a study on the efficiency of deep CNNs with regard to AMC under the effect of interference. An architecture consisting of two convolutional and three fully-connected layers is trained to classify 5 or 10 modulation formats transmitted over imperfect channels in the presence of interference, bypassing the traditional process of *a priori* feature extraction. The incorporation of the knowledge of the interfering signal's modulation scheme is assessed, and is shown to significantly improve classification accuracy.

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