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Low-SNR Modulation Recognition based on Deep Learning on Software Defined Radio

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***Abstract*—Automatic modulation classification (AMC) and recognition (AMR) of received wireless signals have a significant role for various commercial and military areas. These methods are able to identify the modulation type and recognize the received signal by extracting discriminating features from the signals. Deep neural network (DNN) offer a great tool that assist the identification of signal modulation because of its capability to extract complex features from the received signals. In this work, we propose a convolutional network model to classify the modulation type of a wireless signal at low-SNR values. The experimental results demonstrate that the proposed model correctly classify 72% digital signals at -4 dB. The accuracy can be increased if the similarities between QAM4 and QAM64, 8PSK and QPSK is reduced.**

***Index Terms*—Cognitive Radio, Deep Neural Network, Digital Signal Processing**

I. Introduction

In the recent years, automatic modulation recognition (AMR, also known as modulation classification (AMC)) has been widely applied to classify and detect the modulation type of the transmitted signal. While the transmitter can freely employ any modulation type, the receiver incorporates AMC to determine the modulation type and associated parameters from a received signal. AMC has several military and civilian applications such as spectrum analysis and management, transmitter identification, and threat analysis [1]. In addition, AMC becomes an integral part of intelligent software-defined radios (SDR) for 5G communication [2].

AMC is a significant task for the full awareness of the wireless environment in cognitive radio (CR). According to Tim O'Shea *et al.*, AMC has been fulfilled by handcrafting specialized feature extractors for particular signals, properties and determining compact decision bounds from them using either analytically derived decision boundaries or statistical learned boundaries within low-dimensional feature spaces [3], [4]. The model accuracy from learned features can be increased by carefully selecting the appropriate set of features as well as applying new extraction features techniques.

Because traditional modulation recognition methods, e.g. PSK and ASK, usually require prior knowledge of signal and channel parameters in order to accurately classify the received signal and recognize the carried data [5], [6], machine learning algorithms have become one of the key enabling features of AMC in many applications. In the literature, many techniques and algorithms have been applied to AMC, such as the artificial neural network (ANN), hidden Markov model (HMM), fuzzy logic control, meta-heuristic algorithms (evolutionary/genetic algorithm) and rule-based systems [7], [8], [18]. Nowadays, convolutional neural networks (CNNs) has been introduced gradually to [10], [11].

This article does not present a new AMC approach for radio communications signals using CNN, but it highlights directly learning features from simple wireless signal representations without requiring hand-crafted expert features. Previous works on AMC methods have examined the performance at mid SNR values, e.g. greater than 2 dB. In fact, this work demonstrates that the CNN offers good classification performance even at low SNR signal values that are below than 2 dB.

The paramount contribution of this work is that the ability to detect and recognize different signals at low SNR values without constructing a new demodulation circuits for each modulation type. We investigate how different techniques from CNN can be used to design detection algorithms for communication systems that learn directly from data. Thanks to CNN, we show that these algorithms are robust enough to perform detection under very low-SNR, without knowing the underlying channel models, which is particularly effective in noisy channels or in the presence of communication jamming.

The reminder of this paper is arranged as follows. Section II explains AMC and Deep Neural Network. Section III introduces the method that is used in this work. Section IV presents analysis of the simulation result and followed by concluding state in section V.

II. Modulation recognition in SDR

Automatic modulation recognition (AMR) is, in fact, a classification problem that is used to classify different modulation types of unknown signals without auxiliary information at the receiver side. There are two categories of traditional AMR algorithms, the method based on likelihood estimation and artificial intelligence (AI)-based handcraft feature extraction with expert experience [11], [15].

The statistical-based blind modulation classifications (MC) [16], such as likelihood-based (LB) and Maximum a Posteriori

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(MAP) approaches, require prior knowledge of signal and channel parameters in order to accurately classify the received signal and recognize the carried data. As an example, only two decision points at the receiver of binary phase shift keying (BPSK) are required to retrieve the original binary information with unknown signal amplitude, phase, and noise power.

In contrast, AI-based algorithms and deep learning (DL)-based AMR [2], [17] have been proposed as alternatives to the present statistical-based approaches. These methods have the capability for automatic extraction of complex and application-suitable features from the received signals. A. Nandi *et al.* utilize an artificial neural networks (ANN) for analog and digital modulation recognition [5]. Y. Ettefagh *et al.* present an adaptive system of feature extraction and multi-class using ANN followed by a voting system to ensure the robustness of the algorithm [12]. The main disadvantage of using ANN is how the features are extracted from the received signal. Another issue is related to its low accuracy at low-SNR values [18].

Thanks to convolutional neural networks (CNNs), the task of exploring new features that are suitable for classification under various SNRs achieved great success not only identifying the modulation type, but also retrieving the data [10], [11], [14], [19], [20]. For instance, W. Peng *et al.* [11] have developed an architecture that is based on the Inception-ResNet network by changing the several kernel sizes and the repeated times of modules to adapt to modulation classification. Y. Wang, *et al.* [14] propose a deep learning-based algorithm that combined with two CNNs trained on different datasets to achieve higher-accuracy AMR.

Due to the fact that modulation method of multi-carrier signals is more complicated versus single-carrier signals, researchers often combine CNN with LSTM algorithm as in [20], [21]. X. Liu *et al.* investigate a hybrid deep neural network architectures for AMC [20] including convolutional neural network (CNN), residual networks (ResNet), densely connected convolutional network (DenseNet), and convolutional Long Short-Term deep neural network (CLDNN). The classification accuracy of the hybrid model is limited without any modifications of the network structure. Huang et al. [21] proposed a gated recurrent residual network (GrrNet) to identify modulations that consists of three modules, ResNet-based feature extraction, feature fusion, and GRU-based classification. This network exploited intra-class compactness and inter-class separability using a compressive loss constraint to improve the accuracy of higher-order digital modulation.

Most of aforementioned techniques implicitly assume that the signal components have a sufficiently high SNR values such that they can be clearly discriminated from the background noise, determined by the receiver noise floor. However, their performance degrades significantly at low SNR values. This work delve deeper into considering the effect of low SNR value on the differentiating between the modulation types.

III. The Proposed Deep Learning Technique

The main objective on this work is the adaptation of convolutional neural network (CNN) to the real complex-valued radio signal for signal modulation recognition and classification at the receiver. The key role of the receiver is to detect, discriminate and then recognize the wireless received signals [12].

In real life, the received signal can be fuzzy or unclear. Moreover, due to large distance, the problem might be deteriorated under low SNR values, which limits the receiver to recognize the received signal. The accuracy of the receiver model increases as the learning features from the received signals capture more local, fine-grained details of the received signal. In this section, we explore the radio signal classification methods at the receiver in more detail.

A. Convolutional neural network

Convolutional neural networks (CNNs) [22] are very powerful deep learning (DL) architectures that achieves very high performance in image and video analysis such as image processing [23], object detection [24], face recognition [25], plant leaf disease detection [26] and hand-writing character recognition [27]. CNNs also show enormous promise in improving radio signal identification and classification in many different wireless application. In this work, we apply CNNs to perform a classification task on different signal modulations types because of its ability to precisely detect different pattern of the signal.

Generally, CNN is a special form of feed-forward neural network with one or more hidden layer known as convolutional layers. The convolutional layer perform filtering process on the received input, which allows for detecting complex patterns of signals.

CNN models [22], [28] consists of one or more convolution layer (conv) followed by pooling layer then fully connected layers (FC), as shown in Figure 1. While the convolutional layer are generally used to extract discriminative feature representations of the signals and detect useful pattern, the fully connected layers implement the regression map from features to target labels. The pooling layers lowers the computational burden between successive convolutional layers by reducing the number of connections and the dimensions of features maps.

B. Feature Extraction Model

The feature extraction module of the proposed model consists of three hierarchical convolution layers and maximum pooling function, which collectively compute the feature representation of the input, as shown in Figure 1. These layers are combined to extract the main feature of the received IQ signal. In fact, the convolutional layers extend the traditional artificial neural network by adding increased depth and additional constraints to the input of previous layers. In general, the convolution of a two-dimensional kernel and an input map,

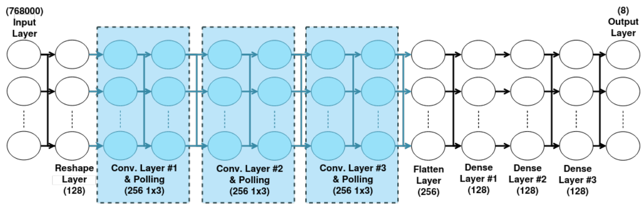

Fig. 1. The Feature Extraction Model.

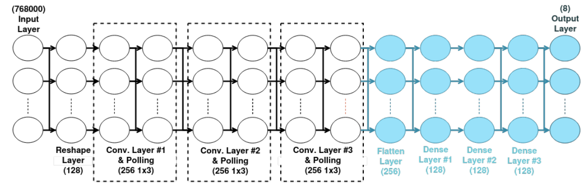

Fig. 2. The Signal Classification Network.

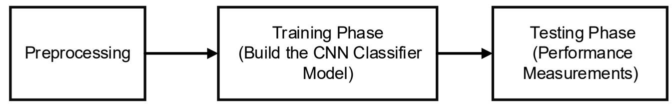

Fig. 3. The functional blocks of the experiments.

at any specific spatial coordinate (x, y), is the sum of dot products as follows

$$conv_{x,y} = \sum_i w_i . v_i \tag{1}$$

where w_i is the convolutional kernel weights and v_i is the values of correspondingly spatial extent in the input map. The output of a convolutional layer is obtained by adding a scalar bias b

$$z_{x,y} = conv_{x,y} + b \tag{2}$$

To achieve the best performance, we propose three identical convolutional layers that are consecutively connected to each other. Each layer has 256 filters of 1×3. This method allows the network to ignore the low-impact parameters (i.e., weight and bias) of the convolutional layers.

After each convolutional layer, a pooling layer is attached to aggregate neighbor convolution neurons into a single output neuron with a consequent reduction of dimension. Figure 1 shows the maximum pooling operations or functions computed over short non-overlapping slices of convolution neurons. The convolution-pooling operations are usually performed to extract a complex feature representation of the input sequence. Moreover, adding the convolution-pooling layers to the network allows extracting complex patterns of interaction though increasing the complexity of the network, which can capture the behavior of the received signals.

C. Classification Model

The classification model is used to classify the obtained features from the previous step. Basically, after extracting the proper features from the received signal, classifying these patterns into appropriate classes to recognize the signal and the modulation type. In this article, one flatten layer and three fully connected layers are added as shown in Figure 2.

Figure 2 shows that the proposed model has one flatten layer because flattening the data assists the transforming a two-dimensional matrix of features into a vector that can be fed into a fully connected classifier. Finally, the third dense fully-connected layer is connected to the output layer, which is able to predict the modulation type.

Each dense layer of the proposed model employs a rectified linear unit (ReLU) activation function of 128 neurons. On the other hand, the output layer employs a Softmax activation function. Therefore, the last dense layer and the output layer has the same number of neurons, which is equivalent to 8 classes. In general, Softmax activation function is a squashing function that limits the output of the function in the range of $[0, 1]$. This allows the output to be interpreted directly as a probability [28].

IV. Experimental Results

A. Dataset

The dataset that is used in this research was generated by using GNU Radio [3] with a size of 3.5 GB. This RADIOML 2016.10A dataset contains 1024 samples with $1,200,000$ data points and 10 types of modulated signals with respective SNR values between -20 dB and $+18$ dB. There are 8 digital modulation type that were used in this research, these are BPSK, 8-PSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK. To simulate real-world conditions of the signal, the dataset was built using GNU Radio Dynamic Channel Model hierarchical block which includes different effects such as sample rate offset (SRO), center frequency offset (CFO), selective fading (SF) and AWGN [29].

B. Training and Testing

The available RADIOML dataset should be used for two tasks, e.g. learning (training) features and then testing (evaluating) the model. The learning set is used to derive the model offline, whereas the test set is used to estimate model's accuracy online, as shown in Figure 3. For this purpose, the dataset is split into 80% for training and 20% for testing, which is governed by Pareto principle [30]. In other words, the RADIOML dataset was separated into 960000 samples for training and 240000 for testing. In addition, 10-fold cross-validation is performed to account for randomness, and investigate consistency of the signals. For early stopping, a callback function with a patience value of 15 is applied to stop the training automatically once the validation loss or learning rate is no longer improved.

C. Comparative Evaluation

To assess the accuracy of signal classification, we use the success rate of the recognition symbol as an indication of the effectiveness of the receiver to correctly recognize the received

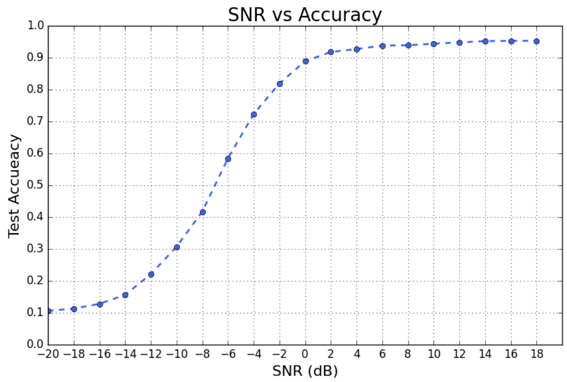

Fig. 4. Accuracy vs. SNR Values

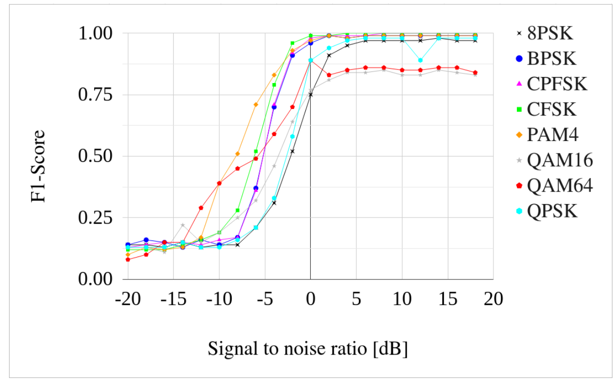

Fig. 5. F_1 score vs. SNR.

symbols [18]. It indicates the capability of the trained model to classify the received symbols in the testing set, which were not seen before. It also expresses the probability of correct classification, and it is computed as follows:

$$SuccessRate = \frac{1}{N}\sum_{i}^{x} x_i * 100 \tag{3}$$

where N is the total number of test symbols and x_i is an indicator whether the i^{th} symbol is correctly detected. In other words, the success rate measures the symbol error rate (SER).

Figure 4 shows the overall accuracy of the proposed work at different SNR values, which are obtained using 3. Figure 4 shows also that the accuracy is high between 1 dB and 18 dB. It is less than 50% of accuracy below -7 dB.

To assess an overall measure of a model's accuracy of individual modulation class, F_1 is applied. F_1 combines precision and recall as shown in eq. 4

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Precision and recall are computed as shown in eq. 5 and 6

$$precision = \frac{T_p}{T_p + F_p} * 100 \tag{5}$$

$$recall = \frac{T_p}{T_p + F_n} * 100 \tag{6}$$

where T_p is the true positive value, the model correctly predicts the positive class, F_p is the false positive value, where the model incorrectly predicts the positive class, and F_n is false negative outcomes, where the model incorrectly predicts the negative class. That is, higher F_1 score, lower false positives and false negatives, so that the model is correctly identified the real modulation type and not being confused by other modulation types. F_1 score is considered perfect when it's 1. likewise, the model is a total failure when it's 0 [28].

Figure 5 shows the F_1 score for each modulation type. It indicates that at SNR equal to -8 dB, the F1-score of CFSK, BPSK, PAM4, and CPFSK is roughly equal to 0.75, whereas the rest modulation classifiers achieves the same F_1 score around -1 dB.

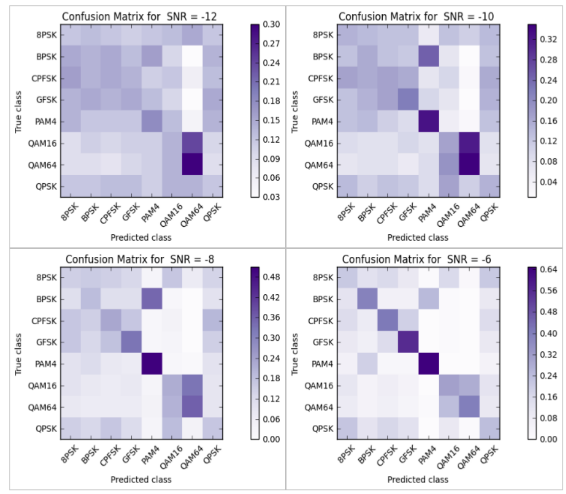

Fig. 6. Confusion Matrix ot SNR values between -12 and -6 dB.

D. Classification Accuracy at different SNR values

In this section, we show the classification accuracy of each modulation type at different SNT value. We prefer to divide them into three groups. They are, the classification at very low SNR values (below -6 dB), at low SNR values, (between -2 dB and 4 dB), and at high SNR values (above 6 dB).

Figure 6 and 7 show the confused matrix of each kind of modulated signal including 8PSK, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, and QPSK at different SNR values. The confusion matrix could be explained as a table, which is regularly utilized to depict the performance of a classification model. It allows the visualization of the performance of an algorithm.

Figure 6 depicts the classification accuracy of each modulated signal at very low SNR values. It shows that PAM4 modulation has the best accuracy among other modulation at very low SNR value. The results indicates that the classification model misclassifies between QAM16 and QAM64 because of the high similarity among the class.

Figure 7 indicates the classification accuracy at low SNR values, e.g. at -4, -2, 0, and 2 dB, respectively. It shows that the accuracy is improved, mainly for BPSK, CPFSK, GFSK

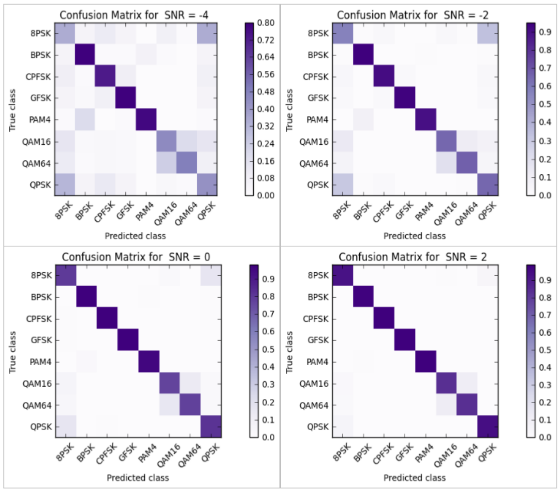

Fig. 7. Confusion Matrix at SNR values between -4 and +2 dB.

and PAM4. For QAM16 and QAM64 and 8PSK and QPSK, the model still partially fails to distinguish between each one because of the inter-similarities. In fact, the model successfully discriminate between each group, i.e. QAM or PSK. However, to achieve good results, the inter-similarity between each class should be increased.

Finally, Figure 8 indicates the classification accuracy at mid SNR values, e.g. at 4, 6, 8, and 10 dB, respectively. It shows that the accuracy is improved and inter-similarities between these classes are disappeared.

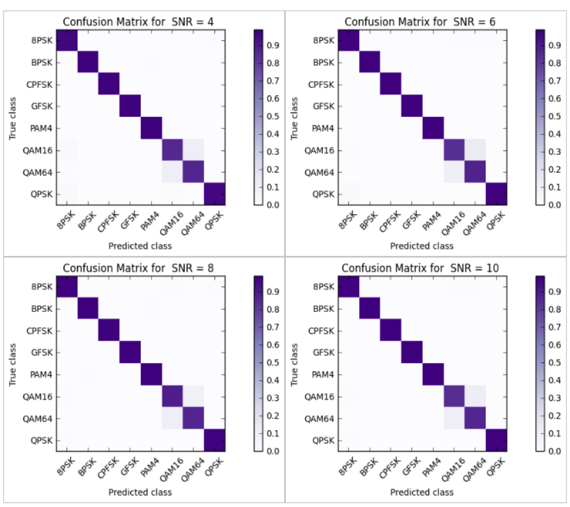

Fig. 8. Confusion Matrix at SNR values between +2 and +10 dB.

E. Computation Complexity

Table I compares the current result with the baseline result of CNN, pure ResNet, pure Inception, LSTM, and MentorNet network on the RML2016b dataset at different SNR levels. At -4 dB, the proposed method at [11] and the current model have better accuracy that other models. As the SNR values approach 4 dB, the current model accuracy reach 92.9%.

Table II compares the a computation complexity of the proposed model with other methods. Total parameters indicate the number of parameters in different models, i.e. the weights. Table II shows that the number of total parameters in the proposed network is less than all models.

V. Conclusion

In this paper, we described a cost-efficient and high-performed deep CNN for automatic modulation classification by extracting signal features of the different modulation schemes automatically. We analyzed the performance of the CNN under various low SNR values. In the experiments, the proposed approach achieves 72.3% at -4 dB SNR. It is quite evident that the proposed algorithm provides better accuracy for all the considered modulation schemes at -4 dB and higher with a large number of samples. Thus, the performance at low SNR values is improved.

The outcome of this study will help to construct new models that effectively discriminate between different modulation at low SNR values. Moreover, the constructed CNN model works fast at the receiver because there is no training phase more. Thanks to advance in AI chips, real-time applications that require low-latency or high-speed communications will benefit from this model by reducing bit error that resulted at low SNR values. As a result, the future directions for the proposed work is to improve the performance by using deep denoising autencoder to determine the SNR level and apply Generative Adversarial Networks (GAN) before the current CNN to discriminate between similar modulation such as QAM16 and QAM64, which can increase the accuracy values.

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TABLE I
TEST ACCURACY COMPARISON.

SNR (dB)	CNN (%)	ResNet (%)	Inception (%)	LSTM (%)	MentorNet (%)	[11](%)	DDrCNN [14](%)	[21](%)	Proposed (%)
-10	25.71	26.92	23.61	29.56	24.86	30.40	-	-	30.1
-4	54.32	48.53	50.86	58.46	62.45	74.30	64	39	72.3
0	77.64	75.41	73.65	83.19	76.36	90.81	90	68	88.9
4	80.53	80.25	78.87	85.96	78.59	92.84	93	93	92.9
10	81.61	81.69	79.91	87.09	80.16	93.29	95	99	94.9

TABLE II
COMPUTATION COMPLEXITY COMPARISON.

	CNN	ResNet	Inception	LSTM	MentorNet	[11]	DDrCNN [14]	Proposed method
Total parameters	2,830,170	3,424,976	10,142,726	846,376	3,327,400	50,278,762	1,101,448	560,264
Training time(s)/epoch	44.40	48.90	38.16	91.75	45.54	590.18	12	29.6

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