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Conference Paper

Modulations Recognition using Deep Neural Network in Wireless Communications

2nd Europe - Middle East - North African Regional Conference of the International Telecommunications Society (ITS): "Leveraging Technologies For Growth", Aswan, Egypt, 18th-21st February, 2019

Provided in Cooperation with:

International Telecommunications Society (ITS)

Suggested Citation: Mossad, Omar S.; ElNainay, Mustafa; Torki, Marwan (2019) : Modulations Recognition using Deep Neural Network in Wireless Communications, 2nd Europe - Middle East - North African Regional Conference of the International Telecommunications Society (ITS): "Leveraging Technologies For Growth", Aswan, Egypt, 18th-21st February, 2019, International Telecommunications Society (ITS), Calgary

This Version is available at:

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Modulations Recognition using Deep Neural Network in Wireless Communications

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Abstract—Automatic modulations recognition is one of the most important aspects in cognitive radios (CRs). Unlicensed users or secondary users (SUs) tend to classify the incoming signals to recognize the type of users in the system. Once the available users are detected and classified accurately, the CR can modify his transmission parameters to avoid any interference with the licensed users or primary users (PUs). In this paper, we propose a deep learning technique to detect the modulations schemes used in a number of sampled transmissions. This approach uses a deep neural network that consists of a large number of convolutional filters to extract the distinct features that separate the various modulation classes. The training is performed to improve the overall classification accuracy with a major focus on the misclassified classes. The results demonstrate that our approach outperforms the recently proposed Convolutional, Long Short Term Memory (LSTM), Deep Neural Network (CLDNN) in terms of overall classification accuracy. Moreover, the classification accuracy obtained by the proposed approach is greater than the CLDNN algorithm at the highest signal-to-noise ratio used.

Keywords— modulation recognition; deep learning; convolutional neural networks

I. INTRODUCTION

Due to the large demand in wireless data [1], the need to create smart radios that are able to coexist has recently become a main objective for researchers. Mitola [2] was the first to propose the idea of Cognitive Radios. His proposed model consists of two types of users; Licensed users or primary users (PUs) who have the priority is utilizing the spectrum bands in question and unlicensed users or secondary users (SUs) who are allowed to transmit in the given spectrum band under the condition that no interference occurs at the PUs side. Among the described properties of a CR is his ability to scan the spectrum to identify the type of users in the system [3]. Next, it will adapt its transmission to avoid any interference with the nearby users. In order to successfully classify these users, the CR must initiate a learning phase where he analyzes the transmission parameters of any incoming signal. One of the main characteristics of any signal is the modulation scheme used. Although, as part of the physical layer of any wireless radio, the transmitter and receiver must agree on the modulation scheme to be able to successfully recover the signal. In our case, the CR will perform a type of scanning named spectrum sensing.

Subsequently, the analysis of the modulation schemes can create a path for the CR to follow and be able to classify the available users. In our work, we consider a synthetic dataset composed of a large number of modulations known as RadioML dataset [4]. The dataset contains analog and digital modulations that show considerable similarity in both time and frequency domain.

Recently, a number of competitions took place focusing on the modulation recognition problem, namely DySPAN challenge [5]. Most of the proposed ideas typically relied on machine learning [6], notably the usage of convolutional neural networks to solve this problem [7]. A variety of neural networks types were used as well. Long Term Short Memory [8] and Residual Networks (ResNet) [9] were among the most viable solutions. Another concept was used in [10] where they were able to improve their model accuracy by separating the training task into a number of sub tasks and combining the results at the final layer. Inspired by these approaches and with a sufficient training effort, we were able to create a model that outperforms the approaches used in the aforementioned literature.

The contributions of this paper are: introducing an approach that uses a novel deep learning technique based on convolutional neural networks to solve the modulations recognition problem. A detailed analysis of the performance of the proposed algorithm is also provided.

The rest of the paper is organized as follows. We present the related work in Section II. Next, the system model is described in Section III. A description of the proposed modulation recognition approach is presented in Section IV. The evaluation of our work is presented in Section V. Section VI concludes the paper and discusses potential future work.

II. RELATED WORK

A large number of efforts have been proposed to solve the modulations recognition problem. By applying signal analysis and processing techniques, researchers were able to achieve high accuracies. Matched filtering [11], Cyclostationary features detection [12] and Higher orders statistics [13] are

among these efforts. The main drawback is the lack of ability to adapt to changing wireless environments. Hence, the need for machine learning where the models are trained according to the available conditions and therefore can adapt accordingly.

O’Shea et. al [4] created a dataset with different modulations under various Signal-to-Noise Ratio levels. They have also proposed a number of classification techniques to solve the modulation recognition problem [7]. West et. al [14] proposed the CLDNN which can be thought as the state of the art solution for the problem. A confusion was present between pairs of modulations, such as (QPSK, QAM8), (QAM16, QAM64) and (AM-DSB, WBFM). Moreover, a new approach suggested the use of hierarchical neural networks [15]. To solve the problem of modulation confusions, we propose a new architecture that improve overall classification accuracy by separately training the confusion classes and combining the final decisions.

III. SYSTEM MODEL

A. Modulation Recognition Problem

The modulation recognition can be modelled as N -class decision problem where the input is a sampled signal, in our case baseband In-Phase and Quadrature (I/Q) trace and the output is $1 \times N$ binary vector that determines the chosen modulation scheme.

Let’s consider a transmission signal $s(t)$, this signal is susceptible to channel effects $h(t)$ and additive noise $n(t)$. The received signal in this case can be described as:

$$r(t) = s(t) * h(t) + n(t) \quad (1)$$

Hence, the modulation recognition problem can be described as given $r(t)$, estimate the modulation class of $s(t)$.

B. Convolutional Neural Networks

In a Convolutional Network, the layer consists of N_f convolutional filters. It is commonly used in image applications. Filter sizes in the network are typically very small. The transfer function for a standard convolutional layer is given below in Eq. 2, where y_i is the output feature map for the i^{th} filter, b and k represent learned bias and filter weight parameters, x_i represents the input activations, denotes the convolution operation, and $f(\cdot)$ denotes a non-linear activation function e.g. rectified linear unit (ReLU) or sigmoid.

$$y_i = f(b_i + \sum_j k_{ij} * x_i) \quad (2)$$

C. Confusion Classes Training

To overcome the confusion that occurs between a specific set of modulation classes, we will perform separate training tasks between all of these confusion pairs. The main objective is to improve the performance of multiple related learning tasks by transferring useful information among them. The intuitive behind our approach is that what is learned for each task can help other tasks be learned better. Fig. 1 describes the our approach in general where shared layers are used to

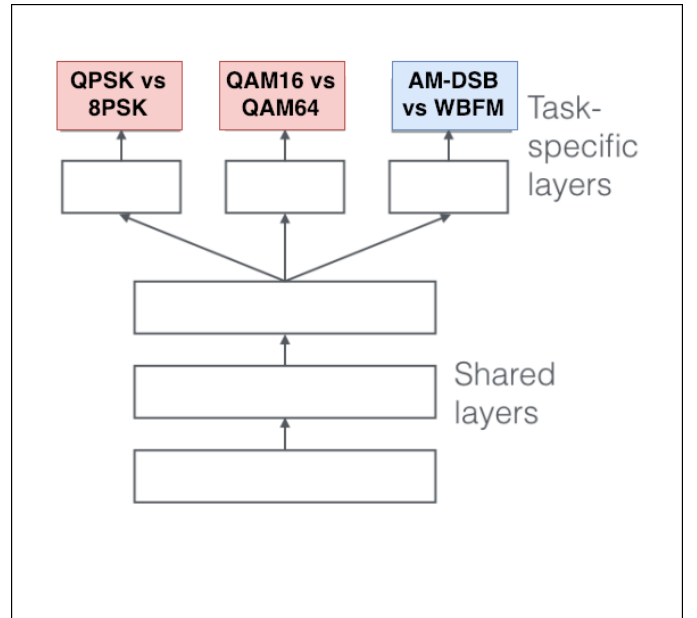


Fig. 1: Confusion Classes Separate Training

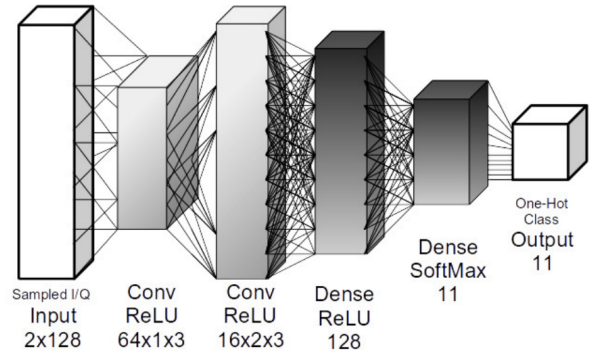


Fig. 2: Deep Convolutional Neural Network

transfer the learned features between separate tasks and the main classifier.

IV. PROPOSED CONVOLUTIONAL NEURAL NETWORK

The separate training tasks are used to separately train the classes that caused a major confusion according to [14]. Therefore, we create 3 different tasks in addition to the main classification task. The first task has the goal to distinguish between QPSK and 8PSK modulations. The second task is used to differentiate between QAM16 and QAM64, while the third task differentiates between AM-DSB and WBFM. Fig. 1 highlights the structure of a multi-task learning network, while Fig. 2 describes the structure of each convolutional neural network used to train a task.

V. NUMERICAL RESULTS

We evaluate the system performance using Python and tensorflow framework [16]. We consider the RadioML dataset

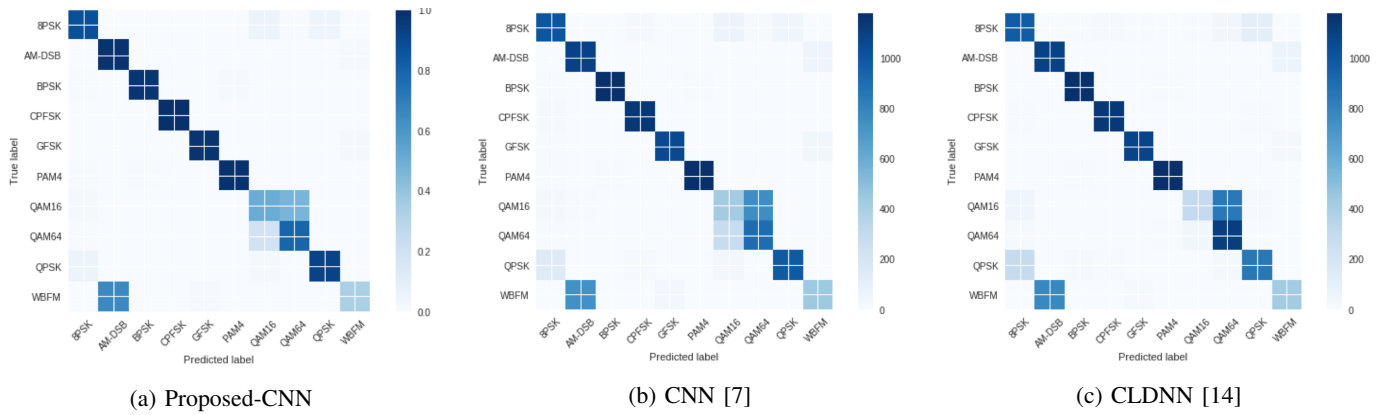


Fig. 3: Confusion Matrix at 0 dB SNRs

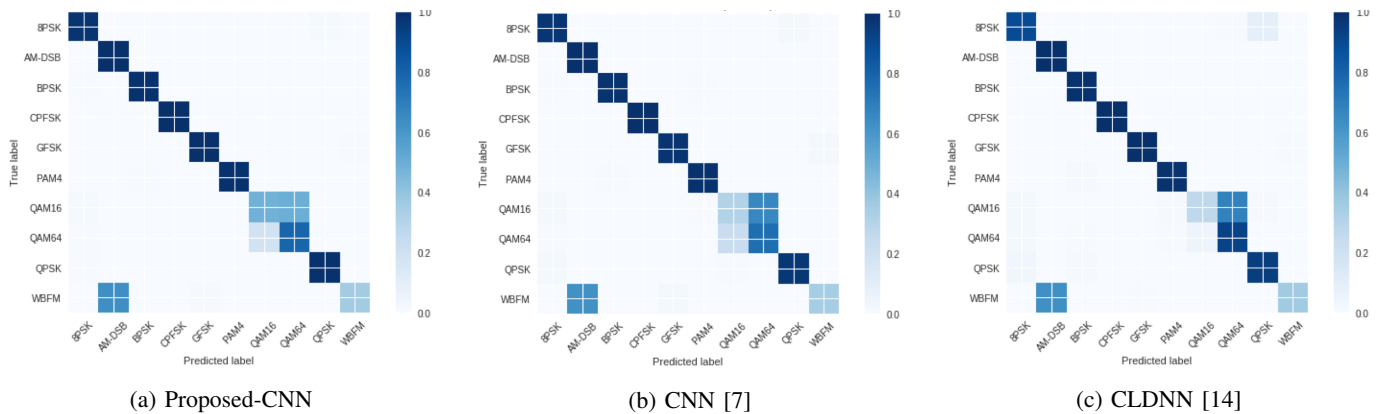


Fig. 4: Confusion Matrix at 18 dB SNRs

TABLE I: Overall Classification Accuracy

Proposed-CNN	CLDNN [14]	CNN [7]
55.05%	52.44%	50.2%

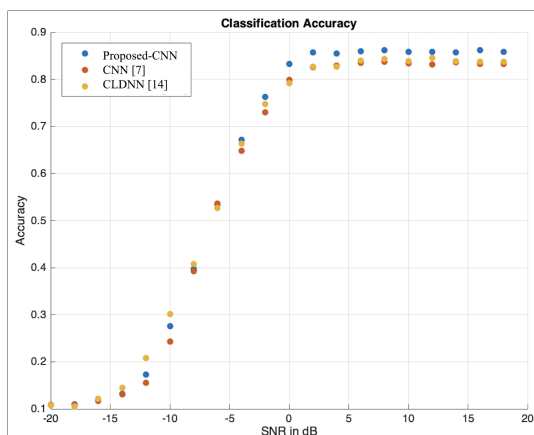


Fig. 5: Classification Accuracy vs SNR

nique is generated with different signal-to-noise ratio (SNR) ranging from -20 to 18 dB. The total number of samples is 220000 and it is evenly distributed among modulations and SNRs.

The training set is composed of 50% of the entire dataset selected at random. We will use a dropout ratio of 0.5 and a maximum number of epochs of 100 with early stopping criterion. Fig. 3 demonstrates the confusion matrix obtained at the 0 dB SNR. It is clear that the confusion is present between different classes while the major confusion is between the QAM16 and QAM64 modulations. Another confusion is present between analog modulations, specifically the AM-DSB and WBFM. As the SNR increases, the subsidiary confusions are reduced while the major confusion become more clear as shown in Fig. 4.

Next, we compare between the proposed CNN algorithm and the CLDNN [14] and the CNN [7] algorithms. Table I highlights the comparison of the overall classification accuracy. Fig.5 describes the classification accuracy at different SNRs.

VI. CONCLUSION AND FUTURE WORK

[4]. The dataset consists of 10 different modulations, among them 3 are analog and 7 are digital. Each modulation tech-

In this paper, we proposed an approach to solve the modulation recognition problem using a deep convolutional neural

network that uses a separate training tasks to reduce the confusion between similar classes. Numerical results show that the new model outperforms the previously proposed CLDNN and CNN approaches in terms of the overall classification accuracy and the maximum accuracy achieved at the highest SNR.

As a future work, the system can be extended to cover additional modulation schemes. Moreover, a study on the neural parameters and their effect on the classification accuracy can be provided.

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