Multi-carrier Signal Detection using Convolutional Neural Networks

Julius Ruseckas, Gediminas Molis, Aušra Mackutė-Varoneckienė, Tomas Krilavičius
Baltic Institute of Advanced Technology
Pilies 16-8, LT-01403, Vilnius, Lithuania
julius.ruseckas@bpti.lt

Abstract— **For efficient spectrum sharing between non-cooperating networks a fast spectrum scan must be implemented. Frequency, power, bandwidth and modulation have to be quickly estimated to adapt to the environment and cause minimal interference for other users even when protocol is not known. Here we propose to apply convolutional neural network for multi-carrier signal detection and classification as it can measure all these parameters from one short data sample. For the classification and detection tasks, six multi-carrier signal modulations were generated. We have measured detection probability and classification accuracy over wide range of signal-to-noise ratios and have estimated the hardware resources needed for the task. In addition, we have studied impact of signal augmentation during training phase on classification accuracy when only portion of the signal is available. We show that signal four times shorter than 5G radio subframe can be sufficient for the task.**

Multi-carrier modulation recognition; multi-carrier signal detection; convolutional neural networks

I. Introduction

Use of Artificial Intelligence (AI) for traffic management and spectrum sharing is seen as inevitable due to increased user density together with low latency and high-speed requirements. Increasing use of MIMO technology to increase spectrum efficiency, also interoperability with other wireless networks and unlicensed bands use, increases the number of variables in traffic management algorithms significantly. First step in traffic management is information collection and distribution over a network and it comes at a cost of reduction of a spectrum efficiency due to network management overheads.

Use of AI for information collection in radio environment is increasingly studied and algorithms for spectrum sensing are constantly developed [1]. Usually for sequence modelling tasks, including radio signal modelling [2], recurrent neural architectures are applied. However, it has been shown that convolutional models outperform recurrent neural networks across a range of datasets and demonstrate a longer effective memory [3].

In this work we apply a convolutional neural network, similar to temporal convolution network (TCN) proposed in [3], for classification of 5G multi-carrier modulations and detection of signal presence. This is in contrast to automatic modulation recognition algorithms, proposed in [4] that are focusing on narrow band signal modulation recognition.

II. Model and Dataset

A. Convolutional neural network

For 5G signal classification we use a model similar to temporal convolution network [3]. The proposed neural network uses 1D fully-convolutional architecture. However, since for classification there is no need to ensure that the future does not influence the past, we do not use causal convolutions. Each hidden layer is the same length as the input layer; zero padding is added to keep subsequent layers the same length as previous ones. The neural network uses dilated convolutions to achieve an exponentially large receptive field. The dilation factor d is increased exponentially with the depth of the network: $d = 2^i$ at level i of the network. As in TCN model we use residual blocks where the output of a block is formed as a sum of the block input and non-linear transformations of the input. Such a residual block allows layers to learn modifications to the identity mapping rather than the entire transformation, leading to easier training of very deep networks. Within a residual block the neural network has two layers of dilated convolution and rectified linear unit (ReLU) non-linearities. We also use an additional 1x1 convolution to transform the input of the residual block before element-wise addition. For the classification task we take the output of the last residual block and perform global average pooling, the output of which is transformed by the subsequent densely connected layer with softmax activation. Categorical cross-entropy is used as a loss function of the network. Empirically we found that for the signal classification the neural network with kernel size $k = 4$, number of filters in the hidden layers $N_f = 32$ and $n = 9$ residual blocks (leading to the dilation factor of the last block $d = 2^9 = 512$) is sufficient. Such a neural network has 48 000 trainable parameters.

B. Dataset Preparation

For training of neural network, a sufficiently large labeled dataset of 5G signals is needed. We used simulated signals, employing Vienna 5G Link Level Simulator [5]. As a starting signal we used a random sequence of bits and simulate transmission of such a signal via free space radio channels using different multi-carrier modulation techniques: OFDM (Orthogonal Frequency-Division Multiplexing), FBMC (Filter Bank Multi-Carrier), WOLA (Weighted Overlap and Add based OFDM), FOFDM (Filtered OFDM) and UFMC (Universal Filtered Multi-Carrier). For the simulation we used frequency selective fading channel model with Vehicular A [6] power

This work was supported by the project "CERTAIN" No. S-LL-18-9 of the Research Council of Lithuania under Polish-Lithuanian Funding initiative DAINA

delay profile. For channel's time selectivity Jake's Doppler model is used. Signal to noise ratio was changed by adding white Gaussian noise to the generated signal in various proportions.

III. Signal Detection and Classification

A. Spectrum sensing

Spectrum sensing is one of the issues in radio communication especially important in cognitive radio applications and spectrum sharing between primary and secondary users. One of the techniques for signal detection is the energy detector [7], which is widely used due to its simplicity. The performance of the energy detector under assumption of unknown deterministic signals in additive white Gaussian noise has been widely studied [8].

We employ the convolutional neural network (see sect. II-A) for the signal detection in the presence of noise. In constrast to energy detector, with CNN we get detection probability from just one sample, without averaging. As training data, we used simulated signals (see sect. II-B) together with equal number of signals consisting of just noise. For each multi-carrier modulation technique and each signal to noise ratio (SNR) we generated 900 signals. We trained the network using Adam optimizer with learning rate 10^{-3}.

Dependence of the probability of signal detection P_D using the neural network on the SNR of the signal is shown in Fig. 2. The probability of false alarm of neural network based signal detector is P_{FA} = 0.045. Note, that neural network uses only a single radio subframe for detection and classification.

B. Multi-carrier modulation detection

Another task where neural network can be deployed is detection of multi-carrier modulation. As training data, we used simulated signals with OFDM, FBMC, WOLA, FOFDM and UFMC multi-carrier modulations and different values of SNR. In addition, we included a signal consisting of just noise. For each multi-carrier modulation technique and each signal to noise ratio (SNR) we generated 900 signals.

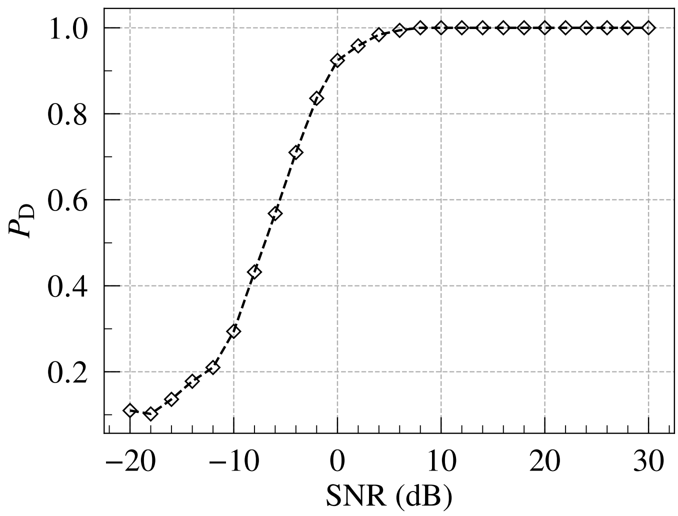

Figure 1. Dependence of the probability of a multi-carrier signal detection P_D using the neural network on the SNR of the signal.

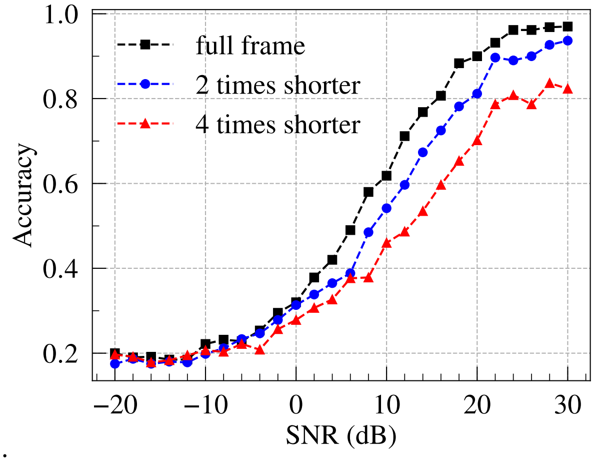

Figure 2. Dependence of the accuracy of the multi-carrier modulation detection on the SNR of the signal for the signals of original length (squares), two times shorter (circles) and four times shorter (triangles).

Dependence of the accuracy of the multi-carrier modulation detection using the neural network on the SNR of the signal is shown in Fig. 2.

IV. Conclusions

The studied method, based on CNN for the detection of multi-carrier signals is a promising candidate for the future wireless communications systems. It has the advantage of high probability of detection from a single measurement of less than one radio subframe when signal is below the noise floor and at the same time, if SNR is high enough, it can not only detect but also classify the non-cooperating transmitters signals.

References

[1] H. B. Sandya, K. Nagamani, and L. Shavanthi, “A review of cognitive radio spectrum sensing methods in communication networks,” 2018 International Conference on Communication and Signal Processing (ICCSP), pp. 0457–0461, 2018.

[2] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, and H. Zhang, “Intelligent 5g: When cellular networks meet artificial intelligence,” EEE Wireless Communications, vol. 24, no. 5, pp. 175–183, oct 2017.

[3] S. Bai, J. Z. Kolter, and V. Koltun, “An empirical evaluation of generic convolutional and recurrent networks for sequence modeling,” arXiv:1803.01271, 2018.

[4] T. O’Shea, J. Corgan, and T. Charles Clancy, “Convolutional radio modulation recognition networks,” in Engineering Applications of Neural Networks, 02 2016, pp. 213–226.

[5] S. Pratschner, B. Tahir, L. Marijanovic, M. Mussbah, K. Kirev, R. Nissel, S. Schwarz, and M. Rupp, “Versatile mobile communications simulation: The Vienna 5G Link Level Simulator,” arXiv:1806.03929, 2018.

[6] Technical Specification Group Radio Access Network; High Speed Downlink Packet Access: UE Radio Transmission and Reception, 3rd Generation Partnership Project (3GPP) Std. TR 25.890, May 2002.

[7] A. Ghasemi and E. Sousa, “Collaborative spectrum sensing for opportunistic access in fading environments,” in IEEE Int. Symp. on New Frontiers in Dynamic Spectrum Access Net., (DySPAN 2005), Nov. 2005, pp. 131–136.

[8] D. Torrieri, Principles of Spread-Spectrum Communication Systems. Springer, 2005.