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Demo: Real-Time Spectrum Segmentation and Classification with Over-The-Air Data

Sangwon Shin
Cyber-Physical Networking Lab,
School of Computing
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
sshin11@unl.edu

Prashant Subedi
Cyber-Physical Networking Lab,
School of Computing
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
psubedi3@unl.edu

Mehmet C. Vuran
Cyber-Physical Networking Lab,
School of Computing
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
mcv@unl.edu

***Abstract*—Spectrum usage is increasing daily, necessitating new methods for efficient utilization. Spectrum sharing allows the coexistence of multiple wireless communication systems in the same spectrum. Effective spectrum segmentation and classification are essential for this, yet existing methods treat them as separate processes and often focus on specific communication techniques. Our application addresses these issues by jointly segmenting and classifying narrowband signals in wideband IQ samples. This demo paper presents the application, demonstrating its end-to-end approach of spectrum segmentation and classification. The application achieves an accuracy of 92.6% on the over-the-air (OTA) wireless communication spectrum. This represents an improvement of over 9% compared to the state-of-the-art solution, highlighting its effectiveness.**

***Index Terms*—spectrum sensing, cognitive radio, spectrum detection, spectrum segmentation, modulation classification**

I. Introduction

In today's rapidly evolving wireless landscape, the demand for efficient spectrum utilization has never been higher. Traditional methods of spectrum monitoring and management often fall short in the complexities of real-world environments. Existing solutions typically address spectrum segmentation and classification as separate tasks and for classification, assume the presence of a single signal with a fixed bandwidth. These limitations restrict their applicability and effectiveness in dynamic, real-world scenarios.

Detecting multiple signals with unknown parameters, such as carrier frequency and bandwidth, within a wideband sample is a significant challenge. Current methods often fail under these conditions [1]–[5]. Additionally, modulation classification techniques degrade when signal and channel parameters change, a phenomenon known as domain shift [4]–[7].

Extracting signals from a spectrum sample is complicated by unknown carrier frequency, bandwidth, and structural properties, rendering state-of-the-art solutions ineffective in end-to-end workflows. Our spectrum segmentation and classification application addresses these challenges by providing an end-to-end solution. This application integrates spectrum segmentation and classification into a single, cohesive application.

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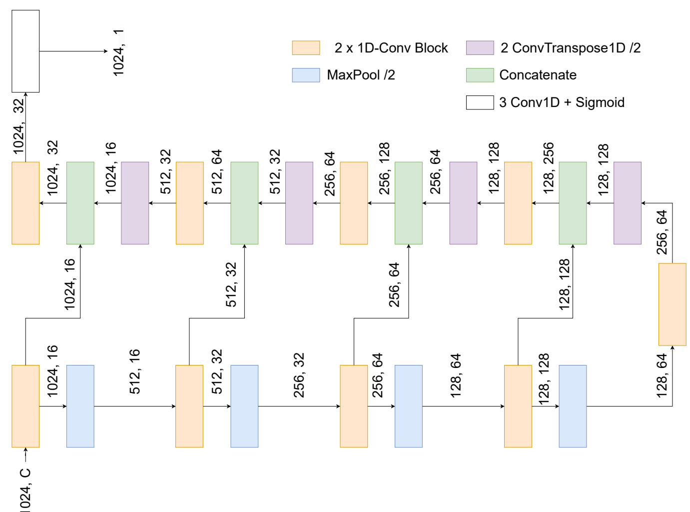


Fig. 1: Spectrum Segmentation U-Net Architecture.

Unlike traditional methods, our application dynamically adapts to multiple signals with varying bandwidths, enabling robust and accurate spectrum management. This approach allows for adaptation to errors in the spectrum segmentation process, improving classification accuracy compared to using separately trained classifiers. Additionally, our solution reduces the time spent sensing the spectrum by eliminating the need to re-tune the radio to sample narrowband signals separately.

This paper presents a practical demonstration of our application, highlighting its ability to manage and utilize the spectrum in diverse and dynamic wireless environments. The rest of the paper is organized as follows: Section II describes the model design, including the architecture used for segmentation and classification. Section III presents the application, demonstrating its real-time capabilities and effectiveness with over-the-air (OTA) data, and closes by concluding this paper.

II. Model design

This application employs distinct models for two key tasks: U-Net [8] for spectrum segmentation and Residual Network (ResNet) [9] for modulation classification, each designed for its specific role. Features are extracted with a pre-processing step using Fast Fourier Transform (FFT) to utilize in these models.

A. Segmentation with U-Net

For the segmentation task, we use a one-dimensional U-Net architecture. The U-Net consists of an encoder-decoder structure that captures both contextual and detailed information. The encoder path is composed of several convolutional layers followed by max-pooling layers. These progressively downsample the input, capturing the broad context of the signals. The decoder path up-samples the feature maps and combines them with high-resolution features from the encoder path through skip connections, maintaining spatial accuracy. Fig. 1 shows the U-Net structure for spectrum segmentation.

The segmentation model is trained using the Focal Loss function to address the class imbalance problem inherent in spectrum segmentation tasks. Focal Loss improves the model's ability to detect signals by reducing the impact of easily classified examples and focusing more on hard-to-classify spectrums.

The Focal Loss is particularly beneficial in this scenario because it dynamically scales the loss associated with each example, increasing the importance of misclassified signals during training. This approach ensures that the model remains sensitive to less frequent but critical segmentation instances.

B. Classification with ResNet

For classification, we employ an 18-layer one-dimensional ResNet, well-suited for deep learning tasks that require complex pattern recognition. ResNet's use of residual connections mitigates the vanishing gradient problem, allowing for the training of deeper networks. Fig. 2 shows the ResNet structure for spectrum classification.

Our ResNet classifier processes the segmented narrowband signals to classify their modulation types accurately. We evaluated the model with both time and frequency domain representation of the signal. We found that the time domain signal has robustness against variations in phase and amplitude. The ResNet architecture's ability to learn hierarchical features makes it particularly well-suited for identifying the complex patterns associated with different modulation schemes.

The classification model is trained using cross-entropy loss, which is effective for multi-class classification problems. This loss function helps the model distinguish between different modulation types with high accuracy. Cross-entropy loss measures the performance of a classification model whose output is a probability value between 0 and 1, making it ideal for our multi-class setup.

The ResNet architecture is chosen for its efficiency in handling deep learning tasks that involve recognizing complex patterns. The residual connections in ResNet allow the model

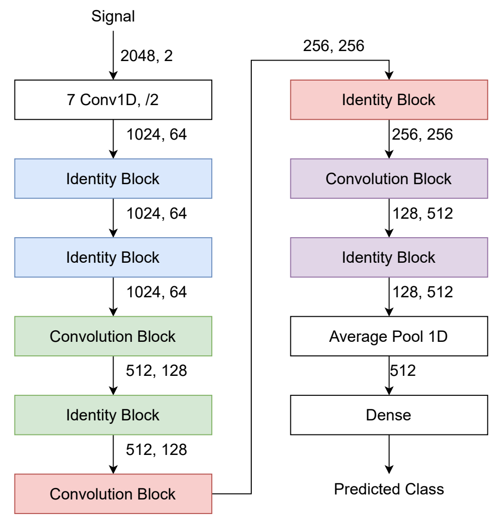


Fig. 2: Spectrum Classifier ResNet Architecture.

to learn more effectively by enabling deeper network structures without the risk of vanishing gradients. This capability is crucial in modulation classification, where the model needs to differentiate between subtle variations in signal patterns.

C. IoU-based Multi-Signal Classifier Training

To enhance the performance of the classifier, we devised an Intersection over Union (IoU) based training method. This method involves assigning labels to predicted signals by matching them to target signals to maximize the IoU. IoU measures the overlap between the predicted and target signals, ensuring that the classifier is trained to handle the imperfections in signal extraction that occur during segmentation.

Existing classification methods assume perfect segmentation of signals, which is not realistic in practical scenarios. Our end-to-end approach makes it crucial to incorporate IoU-based training to ensure the classifier can effectively manage the variability and inaccuracies in segmented signals. By focusing on the real segmentation signal, the classification model learns to be more resilient to segmentation errors, thereby improving overall performance.

The IoU-based allows the model to be trained in a more realistic setting where perfect segmentation is not guaranteed, ensuring better performance in real-world applications.

By adopting this comprehensive model design, our application effectively addresses the challenges of spectrum segmentation and classification in dynamic wireless environments. The integration of U-Net and ResNet architectures, combined with advanced training methodologies, provides a robust and accurate solution for real-time spectrum management.

D. Dataset and Training

The training process for the demonstrating application involves two stages: pretraining on synthetic data and transfer learning with real-world data.

Initially, the model is pretrained on a synthetic dataset consisting of 55,000 samples, each containing between 1 and 10 narrowband signals within a 20 MHz wideband sample.

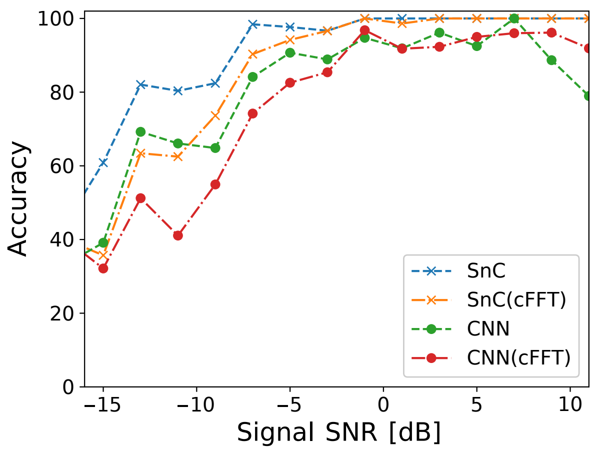


Fig. 3: Accuracy comparison on OTA data

This dataset includes various modulation types (BPSK, QPSK, 8-PSK, 8-QAM, 16-QAM, GMSK, and 2-FSK) and Signal-to-Noise Ratio (SNR) values ranging from -10 dB to 10 dB. The dataset's diversity ensures comprehensive coverage of potential real-world scenarios.

After pretraining, the models are trained using transfer learning on an OTA dataset collected from real-world environments. The OTA dataset, comprising $8,400$ samples, is gathered using Ettus USRP B200 transmitters transmitting three modulation types (BPSK, QPSK, and 2-FSK) and a USRP B200 receiver. The OTA dataset captures real-time wideband IQ samples in the $900-920$ MHz Industrial Scientific and Medical (ISM) band. SNR values ranging from -16 dB to 12 dB, reflecting the complexities and imperfections of real radio channels. Fig. 4 shows the USRP B200, which was used to collect OTA dataset.

Fig. 4: Ettus USRP B200 used for collecting OTA dataset.

III. Spectrum Segmentation and Classification

Our application is unique due to its end-to-end approach, integrating both segmentation and classification into a seamless process. This integration improves overall performance and reduces processing time compared to traditional methods that treat these tasks separately. The application is robust to variations in signal parameters and environmental conditions. This robustness is achieved through a combined pretraining process with synthetic datasets and transfer learning on OTA datasets.

The application begins by capturing wideband IQ samples from OTA sources using USRP B200 software-defined radios (SDRs). The U-Net model segments the wideband spectrum, isolating individual narrowband signals. This segmentation process ensures accurate localization of signals, even in the presence of noise.

Once the signals are segmented, the ResNet model classifies the modulation type of each narrowband signal. This deep learning model identifies complex patterns, ensuring high classification accuracy.

The accuracy comparison shown in Fig. 3 highlights the performance of our application. The comparison is based on the average accuracy calculated from 15 data points across SNR ranging from -16 dB to 12 dB. Time-domain Segmentation and Classification (SnC) achieves an accuracy of 92.6%, followed by Frequency-domain Segmentation and Classification (SnC(FFT)) at 87.6%. Compared with state-of-the-art CNN model [1] at 83.3%, and CNN(FFT) at 78%, **Our application shows over 9% improvement in accuracy**. Technical details and evaluation results of our segmentation and classification model are available in [10].

IV. What Conference Participants Will Be Able to See During the Demonstration

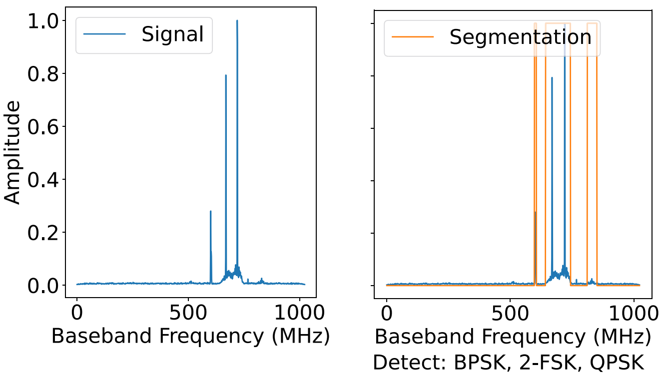
In this demonstration, we will showcase our application's capability to segment and classify signals within a wideband spectrum using a setup of four Ettus USRP B200 devices. This setup includes three transmitters (TX) and one receiver (RX).

A. *Transmitters and Receiver Configuration*

The three TX units will transmit up to three OTA signals simultaneously, with each signal randomly occupying a bandwidth between 0.1 and 2 MHz within a 20 MHz wide receiving spectrum. The signals will vary dynamically, simulating real-world conditions where multiple signals coexist in a shared spectrum.

The RX unit will capture these transmitted signals and record them as IQ samples. This recording process ensures that the received signal accurately reflects the transmitted signals' characteristics, including their bandwidth, frequency, and modulation type.

1) **Preprocessing**: The first stage involves applying an FFT to the recorded IQ samples. This transformation allows the detection of the bandwidth and features within the signal.
2) **Segmentation with U-Net**: After preprocessing, received spectrum is then passed through our U-Net-based segmentation model. The U-Net model will identify and segment the individual signals within the wideband spectrum. This step ensures accurate localization of signals, even when they overlap or are subjected to noise.
3) **Modulation Classification with ResNet**: After segmentation, each identified signal segment is processed through our ResNet-based modulation classifier. The



(a) OTA Signal

(b) Applcation output

Fig. 5: OTA signal and the application output.

ResNet model, trained on a diverse dataset of modulation types, will classify each segment according to its modulation scheme.

B. Output and Visualization

The results of the segmentation and classification processes will be presented to the user through a visualization interface. The primary visualization will show the input signal and application output in Power Spectral Density (PSD), which displays the frequency spectrum of the received signals. The output interface will show:

- **Received Signal**: The overall power spectral density of the received signals.
- **Segmented Signals with mask**: Highlighted segments indicating the bandwidth and location of each segmented signal.
- **Modulation Classification result**: Labels showing the modulation type of each segmented signal.

Fig. 5 shows the output of our demonstration application.

V. Conclusion

Our spectrum segmentation and classification application demonstrates an innovative approach to spectrum management. This application provides an efficient and accurate tool for visualizing the transmissions in the spectrum. By integrating U-Net for segmentation and ResNet for classification, this end-to-end framework effectively addresses the complexities of real-world wireless environments. It segments and classifies multiple signals within a wideband spectrum.

The unique approach of combining segmentation and classification into a seamless process enhances the application's overall performance from state-of-the-art 83.3% to 92.6%. This reduces processing time, making the application more effective than traditional spectrum segmentation and classification applications. The robust training process, involving synthetic pretraining and transfer learning on OTA datasets, handles diverse and dynamic real-world wireless environments.

Overall, this application offers valuable insights into spectrum utilization and supports the development of enhanced spectrum management strategies. This demonstration highlights its potential for various wireless communication scenarios. It paves the way for advancements in intelligent spectrum monitoring and management for spectrum sharing.

References

[1] Timothy James O'Shea, Tamoghna Roy, and T. Charles Clancy. Over-the-Air Deep Learning Based Radio Signal Classification. *IEEE Journal of Selected Topics in Signal Processing*, 12(1):168–179, 2018.

[2] Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, 11 1997.

[3] Yihui Ren, Wen Jiang, and Ying Liu. Complex-valued Parallel Convolutional Recurrent Neural Networks for Automatic Modulation Classification. In *2022 IEEE 25th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 804–809, 2022.

[4] Ke Bu, Yuan He, Xiaojun Jing, and Jindong Han. Adversarial Transfer Learning for Deep Learning Based Automatic Modulation Classification. *IEEE Signal Processing Letters*, 27:880–884, 2020.

[5] Qing Wang, Panfei Du, Xiaofeng Liu, Jingyu Yang, and Guohua Wang. Adversarial unsupervised domain adaptation for cross scenario waveform recognition. *Signal Processing*, 171:107526, 2020.

[6] Erma Perenda, Sreeraj Rajendran, Mariya Zheleva, Gérôme Bovet, and Sofie Pollin. Contrastive learning with self-reconstruction for channel-resilient modulation classification. In *IEEE INFOCOM 2023 - IEEE Conference on Computer Communications*, 2023.

[7] Erma Perenda, Sreeraj Rajendran, Gerome Bovet, Sofie Pollin, and Mariya Zheleva. Learning the unknown: Improving modulation classification performance in unseen scenarios. In *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications*, pages 1–10, 2021.

[8] O. Ronneberger, P.Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, volume 9351 of *LNCS*, pages 234–241. Springer, 2015. (available on arXiv:1505.04597 [cs.CV]).

[9] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep Residual Learning for Image Recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016.

[10] Subedi Prashant, Shin Sangwon, and Vuran Mehmet C. Seek and classify: End-to-end joint spectrum segmentation and classification for multi-signal wideband spectrum sensing. In *IEEE Conference on Local Computer Networks, 2024. LCN 2024.*, 2024.