Wireless Signal Classification via Deep Learning

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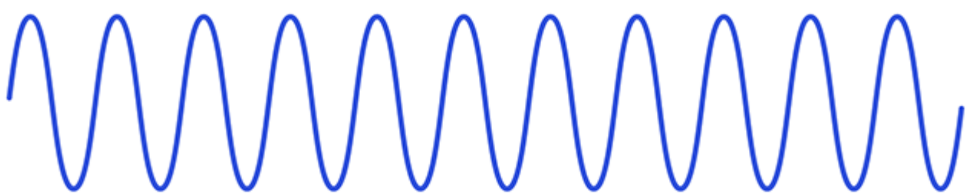

PROBLEM STATEMENT

Wireless signal environments are becoming increasingly crowded, with diverse and dynamic signal types competing for bandwidth. Identifying and classifying these signals in real-time is critical for a wide range of applications, including spectrum management, interference reduction, and national security. Existing signal classification techniques, while effective in controlled environments, often struggle to generalize across different datasets and signal types. Moreover, new and unknown signal types regularly emerge, posing a challenge for traditional supervised learning models. This project aims to address these challenges by developing a dual-head network reinforced with Generative Adversarial Networks (GANs) and exploring open set incremental learning to improve the generalization and adaptability of signal classification models.

APPROACH

Dual-Head Network:

- A **dual-head architecture** will be designed, combining **Convolutional Neural Networks (CNNs)** for frequency-domain feature extraction using FFT (Fast Fourier Transform) and **Recurrent Neural Networks (RNNs)** for capturing temporal patterns in the signal. These networks will be concatenated into a final fully connected layer and then softmax for classification.
- The CNN head will process the signal's frequency-domain information, while the RNN head will focus on time-domain dependencies, offering a more comprehensive feature representation for signal classification.

Generative Adversarial Network (GAN) (Li, Liu, Li, & Wu, 2018):

- A **GAN** will be integrated to augment the training data, generating synthetic signal samples that mimic real-world signal characteristics. This will help address issues related to data scarcity and improve model robustness to signal variations.

Open Set Incremental Learning (Abhijit Bendale, 2015):

- Implement **open set incremental learning** to allow the model to adapt to new, previously unseen signal types. The CNN will be trained on a subset of modulations initially and will be updated incrementally as new signal types (or "novel" signals) are detected. This will help the model learn and classify new signals without forgetting previously learned ones.
- The model will label unknown signals as "other" or assign them a generic label, such as "new_signal_1." We can retrain to incorporate the new signal into the existing classification system.

Datasets (O'Shea, Roy, & Clancy, 2018):

- The model will be trained using the **RML2018 dataset** (24 modulation types) and evaluated against the **older RML2016 dataset** to assess its generalization ability.
- Data augmentation techniques, including GAN-generated samples, will be employed to enhance the model's performance.

EXPECTED RESULTS

- Improved Classification Performance: The dual-head network, coupled with GAN-generated data, is expected to outperform traditional signal classification models (e.g., CNNs or RNNs alone) in terms of accuracy and generalization across different datasets.
- Better Generalization: By testing the model on both the RML2016 and RML2018 datasets, the model should demonstrate improved generalization, showing robustness across diverse signal types and data conditions.

- Open Set Adaptability: The open set incremental learning approach should allow the CNN to dynamically adapt to new signal types while maintaining the ability to classify previously seen modulations.
- Training Efficiency: The use of GANs for data augmentation may reduce the need for extensive labeled data and help overcome the limitations of small or imbalanced datasets.

POTENTIAL CONTRIBUTIONS

- **Improvement in Signal Classification**: A novel technique to signal classification by integrating a dual-head network architecture, combining CNNs and RNNs, reinforced with GAN-generated data. This hybrid model should provide better performance than traditional models and be more adaptable to new signal types.
- **Unknown Signal Classification**: The novel incorporation of open set incremental learning to address the challenge of continuously learning new signal types, which is important for real-world applications where new modulations are constantly introduced.
- **Generalization Across Datasets**: The model's ability to generalize across different datasets (RML2016 vs. RML2018) will be evaluated, contributing to a better understanding of how well deep learning models can transfer across different signal environments.
- **Data Augmentation for Signal Recognition**: The GAN-based data augmentation strategy will enhance the training process, allowing the model to handle rare or unseen signal types more effectively. This could also reduce the dependency on large labeled datasets.

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