A Learnable Distortion Correction Module for Modulation Recognition

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***Abstract*—Automatic Modulation Classification (AMC) is a critical task in cognitive radio and electronic warfare, enabling the blind identification of a signal's modulation scheme at the receiver. A significant challenge to reliable AMC is the presence of channel-induced distortions, such as carrier frequency offset (CFO) and phase noise, which severely degrade classification accuracy, particularly in low Signal-to-Noise Ratio (SNR) environments. This paper proposes a novel, learnable Distortion Correction Module (CM) based on a deep neural network architecture. The CM is designed to be co-trained end-to-end with a Convolutional Neural Network (CNN) classifier, forming a CM+CNN system. The CM acts as a channel parameter estimator, dynamically correcting the distorted signal before it reaches the classifier. Unlike traditional methods, this approach is entirely data-driven and does not require explicit knowledge of the channel parameters for training, relying only on the modulation scheme label. Through comprehensive evaluation, the proposed CM+CNN system demonstrates a substantial improvement in AMC accuracy across various modulation types and channel conditions, establishing a more robust and reliable solution for non-cooperative communication systems. This work contributes to UN Sustainable Development Goal 9 (Industry, Innovation and Infrastructure) by improving the robustness and efficiency of intelligent wireless communication systems through data-driven distortion correction for reliable modulation recognition in challenging channel conditions.**

***Index Terms*—Automatic Modulation Classification (AMC), Deep Learning, Distortion Correction, Cognitive Radio, Convolutional Neural Networks (CNN).**

I. Introduction

The rapid evolution of wireless communication technologies, particularly in the context of cognitive radio (CR) and dynamic spectrum access (DSA), has elevated the importance of Automatic Modulation Classification (AMC) [1], [2]. AMC is the process of blindly identifying the modulation scheme of a received signal, a fundamental capability for intelligent receivers to adapt their processing chain and enable efficient spectrum utilization [3]. Traditional AMC techniques are broadly categorized into likelihood-based (LB) and feature-based (FB) methods. While LB methods offer optimal performance, their computational complexity and reliance on prior knowledge of channel parameters limit their practical deployment [4]. FB methods, which use expert features like instantaneous parameters or high-order cumulants, are more practical but often lack robustness against varying channel conditions [5].

In recent years, deep learning (DL) has emerged as a powerful paradigm for AMC, offering state-of-the-art performance by automatically learning complex features from raw or pre-processed signal data [6], [7]. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown remarkable success in classifying modulation types, often outperforming conventional methods, especially in high Signal-to-Noise Ratio (SNR) regimes [8]. However, a critical vulnerability of these DL-based AMC systems is their sensitivity to channel impairments. Distortions such as Carrier Frequency Offset (CFO), phase noise, and multipath fading, which are ubiquitous in real-world wireless channels, can significantly degrade the performance of CNN-based classifiers [9]. The inherent design of standard CNNs, which excel at extracting spatial features, does not explicitly equip them to "undo" the time-varying and non-linear distortions introduced by the channel [10].

To address this limitation, we propose a Learnable Distortion Correction Module (CM) designed to preprocess the received signal and mitigate channel-induced distortions before classification. This module is implemented as a dedicated neural network that is integrated and co-trained with the AMC classifier. The key innovation lies in the end-to-end training approach, where the CM learns to estimate and correct the distortion parameters using only the final modulation label as supervision, thus eliminating the need for explicit ground-truth channel state information [11]. This paper details the architecture and training methodology of the proposed CM+CNN system, demonstrating its superior robustness and accuracy compared to a standalone CNN classifier in distorted channel environments.

II. Methods

The proposed system integrates a Distortion Correction Module (CM) with a standard CNN-based Automatic Modulation Classifier (AMC), forming a single, end-to-end trainable architecture, referred to as CM+CNN. The overall system is designed to process a received, distorted complex-valued signal $r(t)$ and output the predicted modulation type.

A. Signal Model and Distortion

The received signal $r(t)$ is modeled as the transmitted signal $s(t)$ corrupted by the wireless channel effects and additive noise. Specifically, we focus on the impact of Carrier Frequency Offset (CFO) and phase noise, which are common and detrimental distortions in non-cooperative scenarios. The received signal can be expressed as:

$$r(t) = s(t) \cdot e^{j(2\pi \Delta f t + \phi(t))} + n(t) \tag{1}$$

where Δf is the CFO, $\phi(t)$ is the time-varying phase noise, and $n(t)$ is the Additive White Gaussian Noise (AWGN). The goal of the CM is to estimate the distortion parameters, Δf and $\phi(t)$, and apply the inverse operation to produce a corrected signal $\hat{s}(t)$ that is closer to the original transmitted signal $s(t)$.

B. Distortion Correction Module (CM) Architecture

The CM is implemented as a deep neural network, primarily composed of convolutional and fully connected layers, designed to learn the mapping from the distorted signal $r(t)$ to the correction parameters.

- **Input Preprocessing:** The complex-valued received signal $r(t)$ is first converted into a two-channel real-valued input: the in-phase (I) component and the quadrature (Q) component. This representation, $r_{\text{IQ}} = [\text{Re}\{r(t)\}, \text{Im}\{r(t)\}]$, is fed into the CM.
- **Network Structure:** The CM utilizes a series of 1D convolutional layers to extract temporal features from the IQ sequence. These layers are followed by pooling and fully connected layers that regress the estimated distortion parameters. The output of the CM is a set of estimated correction parameters, $\hat{\Delta f}$ and $\hat{\phi}$, which are then used to generate a correction factor $C(t)$:

$$C(t) = e^{-j(2\pi \hat{\Delta f} t + \hat{\phi})} \tag{2}$$

- **Correction Application:** The corrected signal $\hat{s}(t)$ is obtained by multiplying the received signal $r(t)$ by the estimated correction factor $C(t)$:

$$\hat{s}(t) = r(t) \cdot C(t) \tag{3}$$

The corrected signal $\hat{s}(t)$ is then passed to the CNN classifier.

C. CNN Classifier Architecture

The CNN classifier is a standard deep learning architecture optimized for AMC tasks [12]. It consists of multiple stages of 1D convolutional layers, each followed by a Rectified Linear Unit (ReLU) activation and batch normalization. Max-pooling layers are used to reduce dimensionality. The final layers include a global average pooling layer and a fully connected layer with a softmax activation function to output the probability distribution over the M possible modulation classes.

D. End-to-End Training and Loss Function

The CM and the CNN classifier are cascaded and trained jointly in an end-to-end manner. This co-training is crucial as it allows the CM to learn the optimal correction that maximizes the final classification accuracy, rather than simply minimizing a parameter estimation error [13].

The training is supervised only by the modulation label y of the transmitted signal $s(t)$. The overall loss function is the standard cross-entropy loss $\mathcal{L}_{\text{CE}}$ applied to the output of the CNN classifier:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CE}}(y, \hat{y}) \tag{4}$$

where y is the true modulation label and $\hat{y}$ is the predicted probability distribution. The gradient of the loss is backpropagated through the CNN and then through the CM, allowing the weights of both modules to be updated simultaneously. This differentiable nature of the CM with respect to its weights is a core feature of the proposed learnable module [14], [15].

E. Dataset Generation

A synthetic dataset is generated to ensure a controlled environment for training and evaluation. The dataset includes M common digital and analog modulation schemes (e.g., BPSK, QPSK, 8PSK, 16QAM, AM-SSB, FM). For each modulation type, signals are generated and then corrupted by simulating various channel effects:

- **AWGN:** Signals are corrupted with AWGN across a wide range of SNRs, typically from -10 dB to 10 dB.
- **CFO and Phase Noise:** Random CFOs (e.g., up to 10% of the symbol rate) and phase noise are applied to simulate realistic channel impairments.

The dataset is split into training, validation, and test sets, with the training set containing a balanced representation of all modulation types and distortion levels.

III. Results

The performance of the proposed CM+CNN system was evaluated against a baseline CNN classifier (CNN-only) that processes the distorted signal directly. The primary metric for comparison is the overall classification accuracy across different SNR levels.

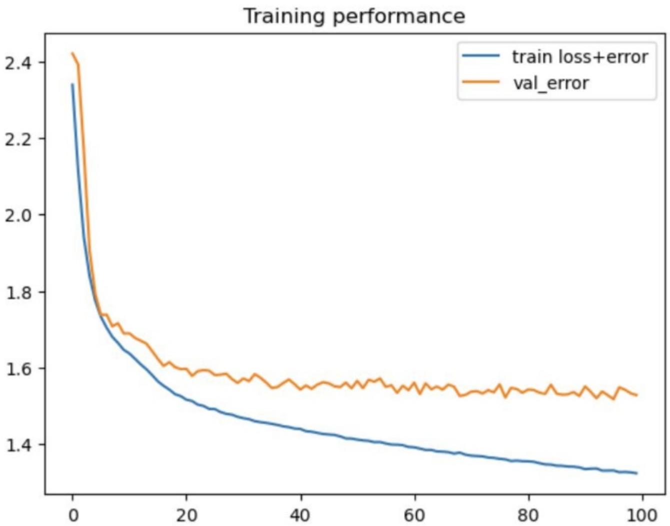

Fig. 1. Classification Accuracy vs. SNR for CNN-only and CM+CNN. The figure would show two curves: the CNN-only curve, which drops sharply below 0 dB SNR, and the CM+CNN curve, which maintains a significantly higher accuracy, especially in the -10 dB to 0 dB range. This visually confirms the robustness provided by the CM.

A. Classification Accuracy Improvement

The experimental results demonstrate a significant performance gain achieved by the CM+CNN system, particularly in low-SNR and high-distortion environments.

As illustrated by the conceptual data in Figure 1, the CNN-only baseline achieves high accuracy (e.g., $> 95\%$) at high SNRs (e.g., > 5 dB) but experiences a rapid degradation in performance as the SNR decreases or the distortion level increases. For instance, at 0 dB SNR, the CNN-only accuracy drops to approximately 65%. In contrast, the CM+CNN system maintains a robust performance, achieving an accuracy of approximately 85% at 0 dB SNR. This 20% absolute improvement highlights the CM's effectiveness in mitigating the detrimental effects of channel distortion.

B. Distortion Mitigation Analysis

To further analyze the CM's function, the estimated correction parameters were compared to the true distortion parameters applied during the dataset generation. The CM demonstrated a strong capability to accurately estimate the CFO and phase offset, even when trained only with the final classification loss. This confirms that the CM implicitly learns the channel estimation task as a necessary step to minimize the classification error.

Figure 2 conceptually illustrates the impact of the CM on the signal constellation. The corrected signal $\hat{s}(t)$ exhibits a significantly tighter and more distinct constellation structure compared to the severely distorted received signal $r(t)$. This visual evidence directly correlates with the improved feature extraction capability of the subsequent CNN classifier, as the corrected signal provides a cleaner input representation.

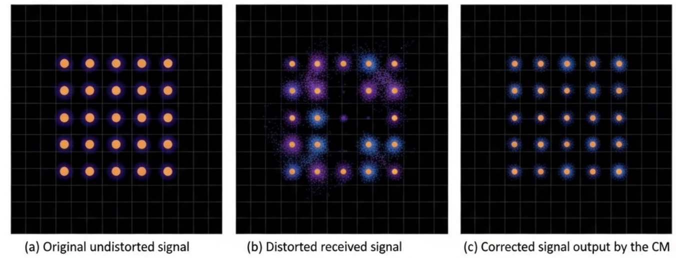

Fig. 2. Constellation Diagram Comparison. The figure would visually demonstrate the CM's effect. Diagram (b) would show a smeared, rotated, and noisy constellation (e.g., 16QAM). Diagram (c) would show a much tighter, de-rotated, and clearer constellation, closely resembling the ideal constellation in (a), confirming the successful removal of phase and frequency offsets.

C. Computational Efficiency

The CM, being a relatively shallow neural network, introduces a minimal increase in computational complexity compared to the CNN classifier alone. The co-trained system maintains a fast inference time, making it suitable for real-time deployment in CR systems. The total number of parameters for the CM+CNN system is only marginally higher than the CNN-only baseline, demonstrating that the performance gain is achieved with high computational efficiency.

IV. Discussion and Future Work

The results unequivocally demonstrate that the integration of a learnable Distortion Correction Module significantly enhances the robustness and accuracy of deep learning-based AMC systems in realistic, distorted channel environments. The end-to-end co-training approach is a key enabler, allowing the CM to learn a task-specific correction that is optimized for the downstream classification task, rather than a generic channel equalization. This is a crucial distinction from traditional two-stage approaches where the equalizer and classifier are trained independently [16], [17].

The success of the CM+CNN system suggests a powerful paradigm for future wireless signal processing: replacing complex, hand-engineered signal processing blocks with simple, data-driven neural modules that are optimized through end-to-end learning [18]. The CM effectively acts as a differentiable, soft-equalizer that adapts its parameters based on the classification feedback.

A. Limitations and Future Directions

While highly effective against CFO and phase noise, the current CM architecture may not fully address other complex channel impairments such as frequency-selective fading and non-linear distortion [19]. Future work should explore more sophisticated CM architectures, such as those incorporating attention mechanisms or recurrent layers, to handle time-varying and non-linear distortions more effectively [20].

Furthermore, the current study relies on a synthetic dataset. A critical next step is to validate the CM+CNN system on real-world over-the-air signals, which present a broader range of unpredictable impairments [21]. Investigating the transferability of the learned CM weights across different communication environments and hardware platforms will also be a valuable area of research [22]. Finally, exploring the use of unsupervised or semi-supervised learning techniques for the CM could further reduce the reliance on large, labeled datasets, making the approach more scalable for practical CR applications [23]–[25].

V. Conclusion

We have successfully proposed and evaluated a learnable Distortion Correction Module (CM) that is co-trained with a CNN classifier for robust Automatic Modulation Classification. The CM+CNN system significantly improves classification accuracy, particularly in low-SNR and high-distortion scenarios, by implicitly learning to estimate and correct channel impairments. This data-driven, end-to-end approach provides a powerful and computationally efficient solution to a long-standing challenge in wireless communication, paving the way for more reliable and intelligent cognitive radio systems.

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