

Hierarchical Automatic Modulation Classification under Hardware and Channel Impairments

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Abstract—In this paper, we propose a hierarchical automatic modulation classification algorithm with robustness to hardware and channel impairments. The proposed algorithm improves classification performance through signal preprocessing that compensates for distortions caused by hardware and channel impairments. The algorithm yields additional performance gains with a hierarchical classification framework. The simulation results show that the proposed algorithm achieves enhanced classification performance compared to conventional non-hierarchical classifiers and demonstrates robustness under hardware and channel impairments.

Index Terms—Automatic Modulation Classification, Hardware Impairment, Deep Learning

I. INTRODUCTION

Automatic modulation classification (AMC) identifies the modulation types without prior information on the received signal and aims to demodulate it to restore the original signal [1]. Deep learning (DL) enhances AMC performance by identifying modulation patterns under channel impairments [2, 3]. Nevertheless, AMC performance degrades in practical wireless communication where hardware impairments distort the received signal [4]. This paper proposes a DL-based hierarchical AMC algorithm robust to both hardware and channel impairments. The proposed algorithm preprocesses received signals to compensate for hardware impairments prior to classification. Furthermore, the proposed algorithm improves classification performance through a multi-input hierarchical framework that performs sequential decisions over modulation classes. The hierarchical classification framework maintains high accuracy in practical wireless communication. [5].

II. SYSTEM MODEL

We consider a signal from a single source distorted by hardware and channel impairments, as illustrated in Fig. 1. The received signal $r(t)$ is expressed as

$$r(t) = h(t) * x(t) + \eta(t). \quad (1)$$

where $h(t)$ denotes the multi-path channel impulse response and $\eta(t)$ denotes the additive white Gaussian noise. The impaired signal $x(t)$ prior to channel transmission is expressed as

$$x(t) = (\mu s(t) + \nu s^*(t) + \delta) \cdot e^{j(2\pi\Delta f t + \phi(t))} + d(t), \quad (2)$$

where $s(t)$ denotes the transmitted signal, μ and ν denote the in-phase/quadrature-phase (I/Q) imbalance coefficients, δ denotes the direct current (DC) offset, Δf denotes the carrier

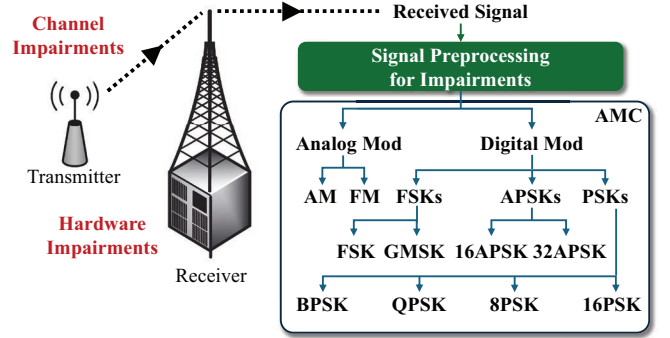


Fig. 1. Hierarchical AMC framework under hardware and channel impairments.

frequency offset (CFO), and $\phi(t)$ denotes the phase noise. The nonlinear distortion $d(t)$ is defined as $\beta_2 |s(t)|^2$, where β_2 denotes the second-order distortion coefficient.

III. HIERARCHICAL DEEP LEARNING FOR AMC UNDER HARDWARE AND CHANNEL IMPAIRMENTS

A. Signal Preprocessing

The signal preprocessing of the proposed algorithm comprises DC offset removal, I/Q imbalance correction, CFO compensation, phase noise suppression, and multipath pre-whitening. The DC offset is removed by subtracting the mean value of the received samples $r[n]$. The I/Q imbalance correction is performed by subtracting the estimated conjugate component, expressed as

$$y[n] = r[n] - \alpha r^*[n], \quad (3)$$

where $y[n]$ denotes the n -th corrected sample, and $\alpha = 0.9 \cdot \mathbb{E}[r[n]^2] / \mathbb{E}[|r[n]|^2]$ is the compensation coefficient. The CFO is estimated from the mean phase difference between adjacent samples. The estimated normalized CFO $\hat{\omega}$ in radians per sample is expressed as

$$\hat{\omega} = \angle \left(\frac{1}{N-1} \sum_{n=1}^{N-1} y[n] y^*[n-1] \right), \quad (4)$$

where N denotes the total number of received samples. The CFO compensation is then performed by multiplying the received samples with $e^{-j\hat{\omega}n}$. The multipath fading is mitigated

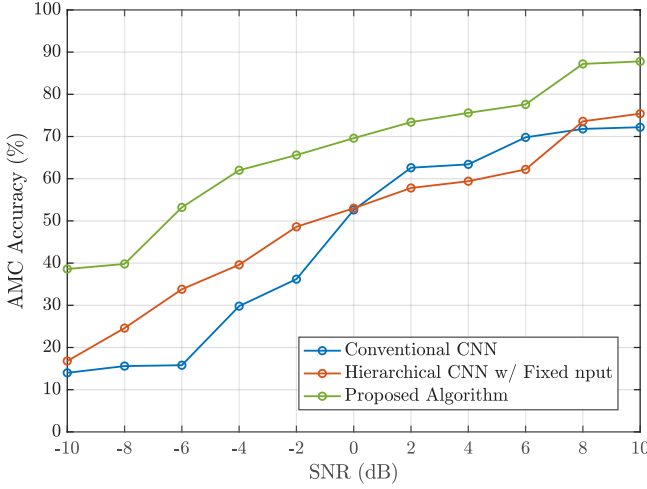


Fig. 2. AMC accuracy of the proposed algorithm.

by a pre-whitening process that reduces the correlation among received samples. To this end, an autoregressive (AR) model is used to approximate the correlation, where the AR coefficients are estimated from the sample autocorrelation sequence. The received signal is subsequently filtered using these coefficients, yielding a whitened sequence.

B. Hierarchical Modulation Classification

The preprocessed signals are classified via a hierarchical DL framework. In the first stage, signals are distinguished between analog and digital modulations. The second stage further categorizes digital signals into classes such as phase shift keying, amplitude and phase-shift keying, and frequency-shift keying/ Gaussian minimum-shift keying. Finally, the third stage refines the classification within each class. This diversity of input representations such as time-domain I/Q samples, spectrograms, and constellations improves feature separability across modulation types and enhances the overall classification performance. The loss $\mathcal{L}$ of the proposed algorithm is expressed as

$$\mathcal{L} = \sum_{k=1}^K \lambda_k \mathcal{L}_{\text{CE}}(t_k, \hat{q}_k), \quad (5)$$

where K is the number of stages, λ_k is the weight assigned to the loss of stage k , t_k denotes the ground-truth label at stage k , $\hat{q}_k$ is the predicted probability vector at stage k , and $\mathcal{L}_{\text{CE}}$ is the cross-entropy loss function.

IV. SIMULATION RESULTS AND DISCUSSIONS

The parameter settings for hardware and channel impairments are as follows. We set $\mu = \pm 0.1$, $\nu = \pm 5^\circ$, $\Delta f = \pm 500$ Hz, $\phi(t) = 0.5^\circ$ and $\beta_2 = 0.02$. δ is randomly generated for each signal and follows a uniform distribution. $h(t)$ is modeled with three taps, and the path delays are randomly assigned.

The AMC accuracy, defined as the percentage of correct classification, is shown in Fig. 2. Conventional convolutional

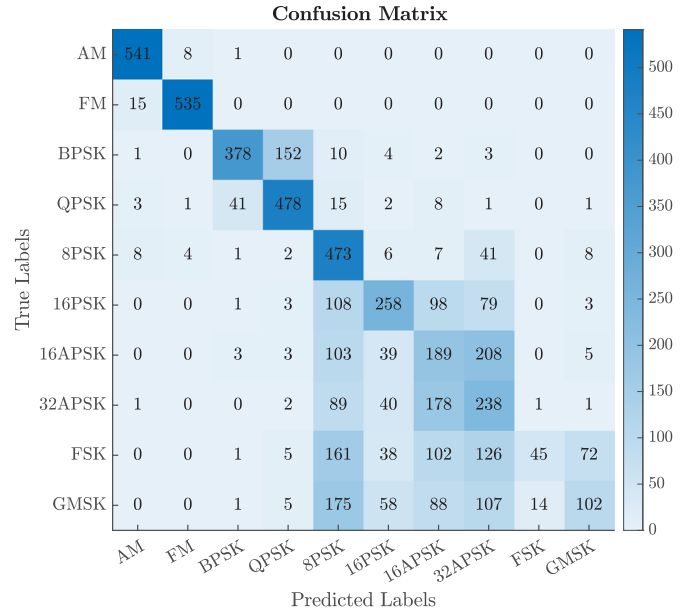


Fig. 3. Confusion matrix of proposed algorithm when SNR is 0 dB

neural network (CNN) leverages a single DL model as a classifier with fixed input to the spectrogram. Hierarchical CNN with fixed input leverages a hierarchical AMC framework with fixed input to the spectrogram. The proposed algorithm consistently outperforms the benchmarks across SNR levels. At low SNR, where hardware and channel impairments severely distort the received signal, the benchmarks exhibit a significant decrease in accuracy whereas the proposed algorithm maintains superior accuracy.

We provide the confusion matrix for the proposed algorithm at SNR 0 dB in Fig. 3, which presents the count of matches between actual and predicted labels. The remarkable classification accuracies are 87.1% for quadrature phase shift keying and 86% for binary phase shift keying. The accuracy demonstrates that the proposed algorithm achieves robust recognition of low-order modulations, which are fundamental in practical communication.

V. CONCLUSIONS

In this paper, we proposed a DL-based hierarchical AMC algorithm with signal preprocessing for hardware impairment mitigation. The simulation results show that signal preprocessing enhances robustness against hardware and channel impairments, while the hierarchical structure further improves classification accuracy. Future work will focus on a hierarchical AMC framework that is robust to errors in upper-stage decisions and maintains accuracy in later stages.

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REFERENCES

- [1] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 168–179, 2018.
- [2] T. Huynh-The, Q.-V. Pham, T.-V. Nguyen, T. T. Nguyen, R. Ruby, M. Zeng, and D.-S. Kim, "Automatic modulation classification: A deep architecture survey," *IEEE Access*, vol. 9, pp. 142 950–142 971, 2021.
- [3] B. Jdid, K. Hassan, I. Dayoub, W. H. Lim, and M. Mokayef, "Machine learning based automatic modulation recognition for wireless communications: A comprehensive survey," *IEEE Access*, vol. 9, pp. 57 851–57 873, 2021.
- [4] E. Perenda, S. Rajendran, G. Bovet, S. Pollin, and M. Zheleva, "Learning the unknown: Improving modulation classification performance in unseen scenarios," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, 2021, pp. 1–10.
- [5] J. Jagannath, D. O'Connor, N. Polosky, B. Sheaffer, S. Foulke, L. N. Theagarajan, and P. K. Varshney, "Design and evaluation of hierarchical hybrid automatic modulation classifier using software defined radios," in *2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC)*, 2017, pp. 1–7.