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Deep Learning for Advanced Physical Layer Communications: GNN-DRL Auto-Encoder

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Introduction

Satellite communication systems, with the nature of long-distance transmission and high attenuation level, face the challenge of frequent signal interference. To improve the system reliability, channel coding technology is utilized to combat channel impairments and control transmission errors in the process of satellite communication. For example, the CCSDS TC Recommendation [1] chose BCH codes and LDPC codes for uplink coding.

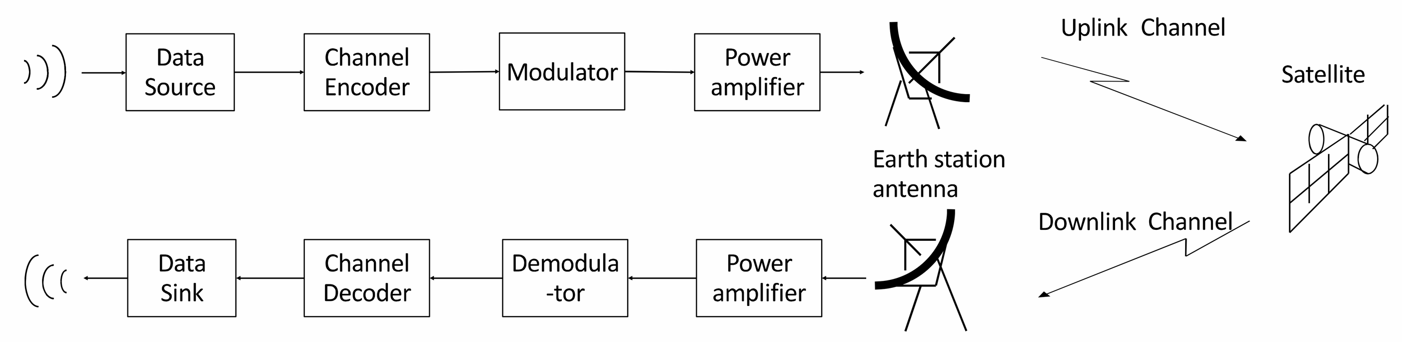

Figure 1: Basic schematic diagram for satellite communication.

In modern satellite communication, traditional coding methods struggle due to complex and unreliable environments. Researchers are actively seeking optimal coding schemes that are accurate, flexible, and simple. Recently, there is a growing interest in leveraging artificial intelligence (AI) for wireless communication and channel coding. AI-driven approaches have shown significant advantages.

Aims

We are dedicated to developing an innovative channel coding algorithm utilizing AI, particularly deep learning (DL) techniques, which offers superior error correction capabilities and reduced decoding complexity. Our proposed DL-based channel coding framework aims to deliver highly reliable and low-latency performance for satellite communication systems in 5G and future 6G networks.

Methods

The architecture that implements both the encoder and decoder with AI models is referred to as "auto-encoder" channel coding. Our novel approach, called **GNN-DRL Auto-Encoder**, consists of a Deep Reinforcement Learning DRL-based encoder (Auto Code Designer) and a Graph Neural Networks (GNN) decoder, and integrates them into an end-to-end channel coding system with the joint optimization.

1. DRL-based Code Designer: The encoder is a DRL model that uses a GNN-based agent to modify the code design. It is refined using a Bit Error Rate (BER) reward to optimize performance.
2. GNN Decoder: The decoder is a GNN operating on the Tanner Graph, aiming to minimize the BER. Notably, the GNN decoder has linear decoding complexity, making it computationally efficient.
3. End-to-End Auto-Encoder: The auto-encoder approach combines the power of graph-based learning and reinforcement learning to create an adaptive and optimized channel coding system. It enables the joint optimization of codes and their decoders, by applying an iterative joint training scheme.

By leveraging the ability of GNNs to learn from graph-structured data and the DRL agent's capability to evolve based on rewards, the GNN-DRL auto-encoder has the potential to significantly improve the performance and efficiency of channel coding in communication systems.

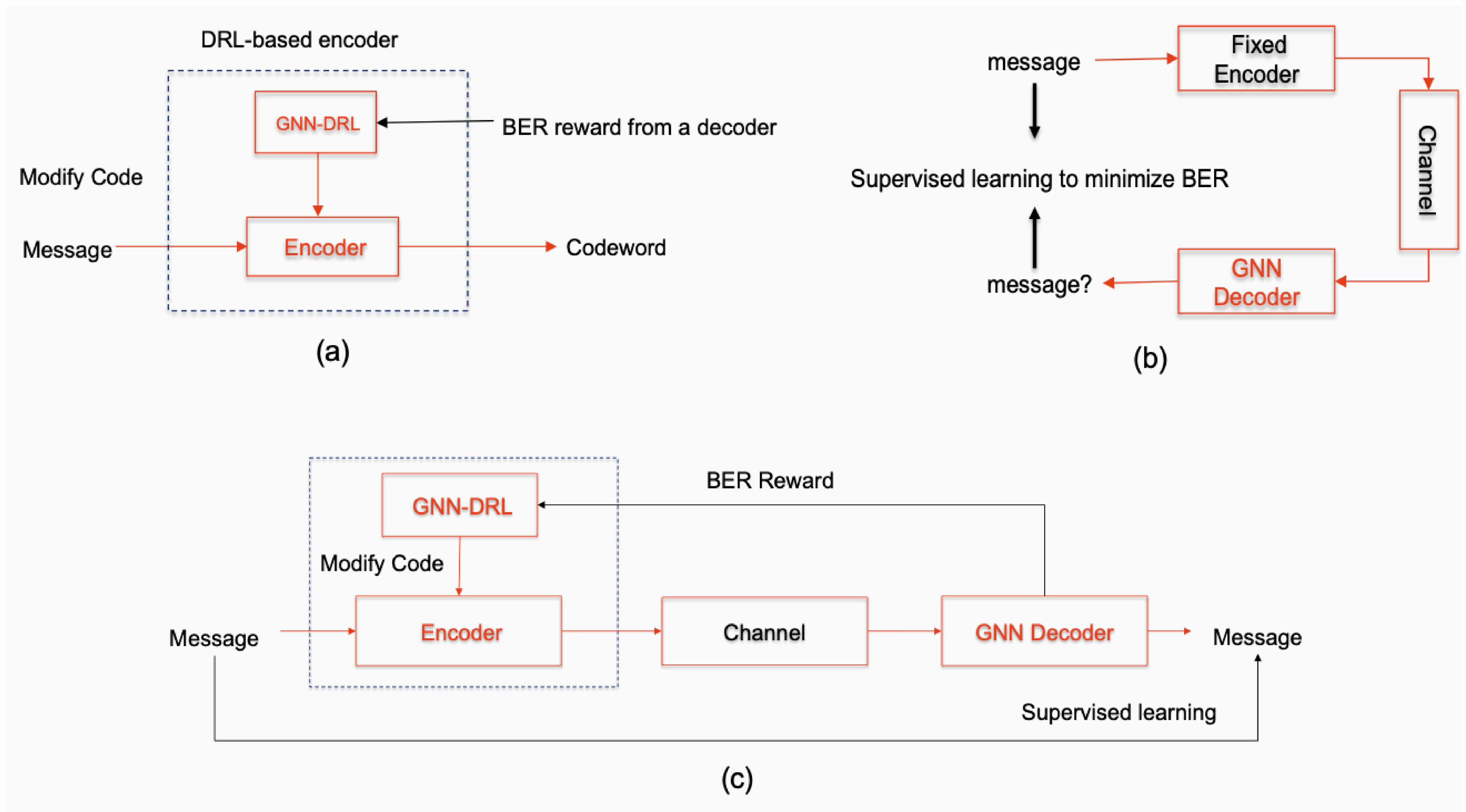

Figure 2: Block diagrams for (a) the DRL-based code designer, (b) the GNN decoder, and (c) the GNN-DRL auto-encoder.

Results

We conducted extensive simulations to compare our code designer, decoder, and auto-encoder to conventional methods. The proposed auto-encoder framework provides superior error-rate performance compared to multiple conventional encoder-decoder pairs and NBP-AE from the literature [2] at short block lengths, while keeping the low decoding complexity at.

For example, our auto-encoder outperforms the (32, 16) LDPC decoded with MLD and BP by a coding gain of 0.63 dB and 1 dB, respectively.

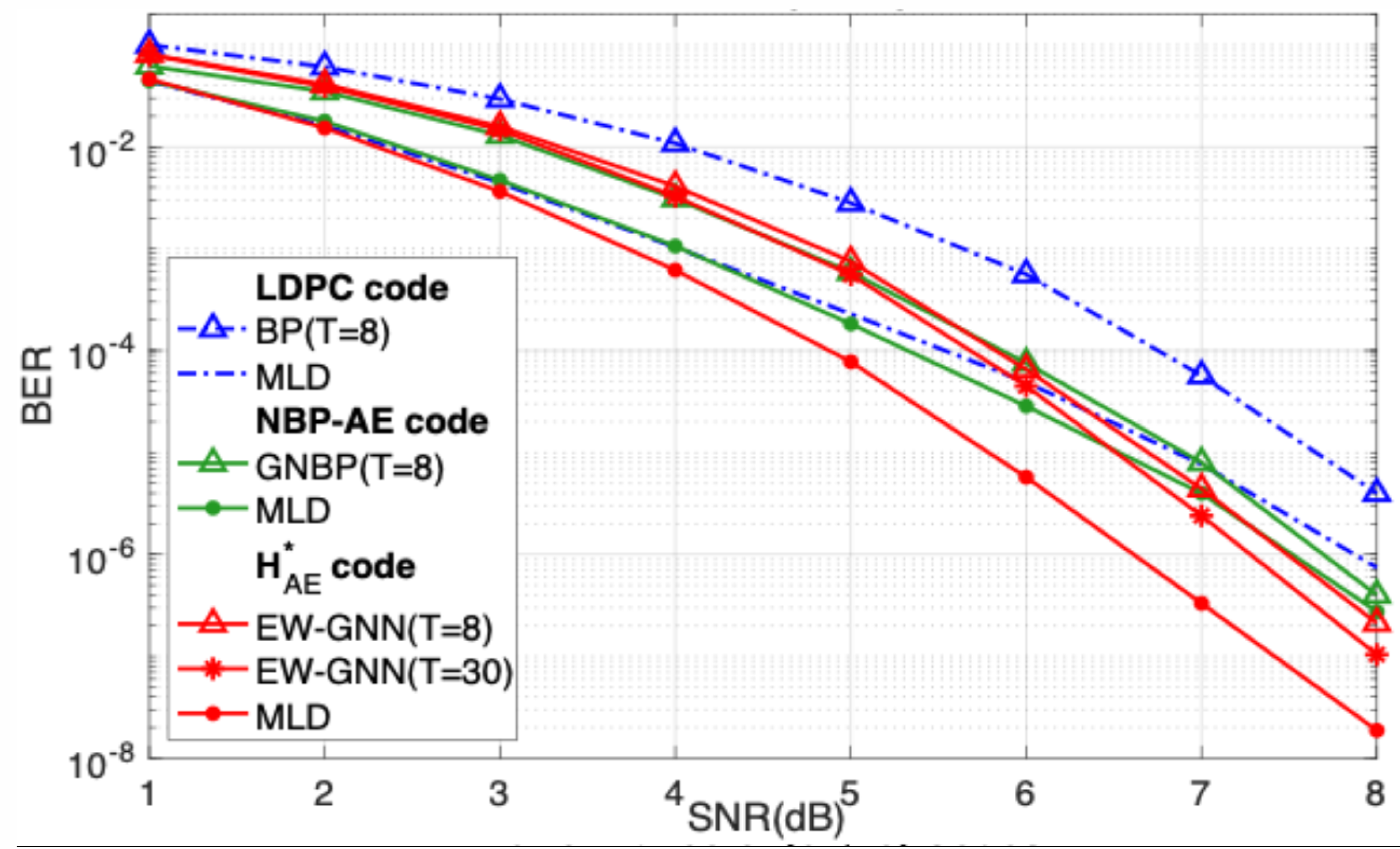

Figure 3: BER performance for designed (32, 16) linear block codes. $\mathrm{H}^{*}_{\mathrm{AE}}$ code is generated by our auto-encoder scheme with three training iterations.

References

[1] CCSDS, TC Synchronisation and Channel Coding, Washington, DC, USA, Apr. 2022, Blue Book, CCSDS 231.0-B-2.

[2] G. Larue, L.-A. Dufrene, Q. Lampin, H. Ghauch, and G. R.-B. Othman, "Neural belief propagation auto-encoder for linear block code design," IEEE Trans. Commun., vol. 70, no. 11, pp. 7250–7264, Nov. 2022.

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