Optimized Ldpc Decoding Using Gradient Descent

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Abstract: Low-Density Parity-Check (LDPC) codes are a key error correction technique in communication systems, ensuring reliable data transmission over noisy wireless channels. Traditional LDPC decoders, such as the Min-Sum algorithm, use fixed normalization (α) factors to approximate belief propagation. However, these fixed parameters do not adapt to varying channel conditions, leading to suboptimal performance in real-world scenarios. This project introduces a gradient descent-based approach to dynamically optimize α based on estimated Signal-to-Noise Ratio and Rayleigh fading conditions. The system predicts the optimal values for α in real time, improving decoding efficiency and error correction performance. These predicted parameters are then used in the Min-Sum decoding process, reducing the number of iterations required for convergence and minimizing the Bit Error Rate. The proposed approach enhances the adaptability of LDPC decoding, significantly improves error correction performance, reduces decoding time, and adapts effectively to varying channel conditions.

Index Terms - LDPC codes, error correction, communication, Min-Sum algorithm, normalization factor, offset factor, belief propagation, Rayleigh fading, SNR, gradient descent optimization.

I. INTRODUCTION

The Optimized LDPC Decoding using Gradient Descent project is aimed at improving the efficiency and accuracy of LDPC (Low-Density Parity-Check) decoding in communication systems. LDPC codes are widely used in wireless communication for error correction, but traditional decoding methods suffer from performance limitations in dynamic environments. To address this challenge, this project integrates the Gradient Descent algorithm, to optimize LDPC decoding parameters and enhance overall system performance.

The project involves simulating an LDPC encoding and decoding process, where received signals are processed through a noise channel and decoded using belief propagation. The optimization process uses an iteration approach to fine-tune parameters, thereby reducing bit error rates and improving decoding efficiency. The implementation includes key components such as Python-based simulations, NumPy for matrix operations, and Scikit-Learn for optimization processes.

A major advantage of this approach is its adaptability to different noise conditions, such as Rayleigh fading channels, making it more effective than traditional fixed-parameter decoding techniques. By leveraging gradient descent for LDPC decoding, this project provides an innovative solution for enhancing error correction in modern wireless communication, ensuring better signal reliability and efficiency in data transmission.

II. LITERATURE REVIEW

The need for efficient error correction in modern communication systems has driven significant research into LDPC decoding optimization. Traditional LDPC decoding techniques rely on fixed-parameter belief propagation, which may not be optimal in varying noise conditions. This has led to the exploration of various approaches to enhance LDPC decoding performance.

In order to increase the rate compatibility, proto-graph based raptor-like codes are introduced in [1]. The LDPC codes are standardized in [2], to optimize performance and hardware efficiency for 5G NR communication. Although the belief propagation (BP) algorithm achieves near-optimal decoding

performance, simplified versions like minimum-sum (MS), normalized MS (NMS), and offset MS (OMS) algorithms, employed and evaluated in [3] and [4], are preferred in practical applications due to their lower hardware complexity. [4] implements offset and normalized min-sum (OMS and NMS) algorithms for LDPC decoding in the ATSC 3.0 standard. These simplified algorithms, however, incur noticeable performance loss, especially under short code lengths and finite iterations. Efforts to optimize these algorithms have traditionally relied on density evolution and threshold analysis under ideal assumptions such as infinite code length and cycle-free graphs as implemented in [5]–[6]. Simulation-based optimization approaches are used in [7] and [8], but they are computationally expensive. Deep learning neural networks have been employed to improve performance even with simplified algorithms. Works such as [9]–[13] utilize deep neural networks to enhance BP and MS decoding performance by learning optimal update rules. In [14], a LAMS-based minimum-sum decoding approach is proposed that enhances LDPC performance in high-SNR conditions. The method leverages ML optimization to dynamically adjust decoding parameters, improving error correction. However, it requires extensive training and incurs computational overhead, limiting real-time applications.

The performance of LDPC codes over the Rayleigh fading channel has been explored in [15] and [16]. Channel side information is leveraged in [17] to improve performance. Techniques such as diversity combining and importance sampling have been employed in [18] and [19]. The gradient descent algorithm has been implemented in [20] and [21] with moment encoding for good performance in adversarial channel conditions. In [22], LDPC coded MIMO systems are analysed using Gaussian approximation to understand diversity gains under Rayleigh fading. The noisy gradient descent bit flipping algorithm is further improved in [23] for better resilience in Rayleigh fading channels.

III. SYSTEM MODEL

The proposed system model is based on the 5G NR (New Radio) standard that utilizes LDPC (Low-Density Parity-Check) codes for error correction in the physical layer. The communication system includes a transmitter that encodes the input bitstream using an LDPC encoder and a receiver that performs decoding using the Min-Sum algorithm. The transmission channel is modeled as a Rayleigh fading channel, which closely simulates real-world wireless environments characterized by multipath propagation and signal attenuation.

The Min-Sum algorithm is a simplified version of the Belief Propagation (BP) algorithm. It approximates message passing by replacing complex operations with simple minimum computations. However, this approximation introduces performance degradation, especially in fading channels. To mitigate this, scaling factor α and offset β are introduced, forming the Scaled Min-Sum variant.

These parameters significantly impact decoding performance, especially under varying SNR (Signal-to-Noise Ratio) conditions. Improper tuning can lead to poor bit error rate (BER) performance. Therefore, optimizing these parameters adaptively according to the channel condition is critical.

Given an LDPC-coded communication system operating over a Rayleigh fading channel, the goal is to minimize the BER by adaptively tuning the α parameter of the Min-Sum decoder. Traditional methods rely on fixed values or heuristic tuning, which do not generalize well to all SNR levels. The proposed solution, as described by Fig. 1 leverages gradient descent to learn an optimal mapping between channel conditions and decoding parameters.
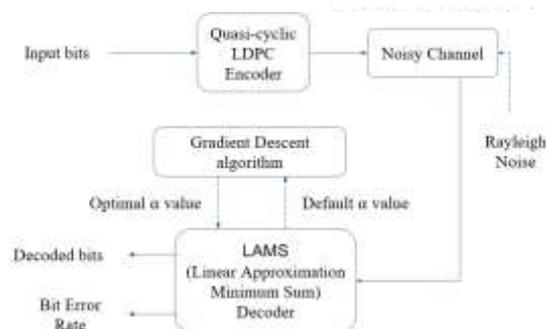

Figure 1. Block Diagram

IV. METHODOLOGY

The system design integrates gradient descent optimization algorithm into the traditional LDPC decoding framework. This approach is used to predict the optimal values of α for the current channel condition.

An LDPC code is defined by the parity check matrix H, with M rows and N columns, where M is the number of parity check constraints and N is the number of bits. K information bits, where K = N - M are encoded and transmitted through the channel. The length of the codeword is N, where K are the message bits and M are the parity bits.

The parity check matrix maps the relationship between the variable nodes, representing each bit, and check nodes, representing each parity check constraint using Tanner graph representation. A(n) is the list of all check nodes that are connected to the variable node n, and B(m) is the list of all variable nodes connected to the check node m.

The K information bits are encoded and transmitted with BPSK modulation, Through the channel, Rayleigh and Additive White Gaussian Noise (AWGN) is added, and the log likelihood ratio is obtained at the channel output l_n^{ch} for each variable node n.

During the initialization of the Min-Sum algorithm, l_n^{ch} is assigned as the value at each of the variable nodes and sent to their connected check nodes. During each iteration of message passing, the variable node sends $l_{n \to m}^i$ to its connected check nodes, governed by Eq.1.

$$l_{n \to m}^{i+1} = l_n^i - l_{m \to n}^i \ (1)$$

Where i +1 is the current iteration, and i is the previous iteration. After receiving all the messages from the variable nodes, the check nodes send back to the variable nodes, the message obtained by Eq.2.

$$l_{m \to n}^i = \left(\prod_{n' \in B(m) \backslash n} sign(l_{n' \to m}^i) \right) . max\left(\alpha_i . min_{n' \in B(m) \backslash n}(|l_{n' \to m}^i|) + \beta_i, 0 \right)(2)$$

The output from the check nodes is added with the channel output by Eq.3 and the message at the variable node is hence obtained.

$$l_n^i = l_n^{ch} + \sum_{m \in A(n)} l_{m \to n}^i \ (3)$$

At the end of each iteration, the bits w are obtained and checked with the parity check matrix. If all constraints are satisfied, the message passing algorithm is stopped and the decoded codeword is obtained. If the constraints are not satisfied, another iteration of message passing takes place, until the maximum number of iterations.

When all constraints are not yet satisfied after the maximum number of iterations, the Bit Error Rate is calculated by comparing the bits obtained at the variable node with the original codeword.

Applying Gradient Descent algorithm as illustrated in Fig. 2, the slope is calculated and the value of α is updated according to the learning rate. If the minimum value is approached, or the number of iterations is over, the BER is reduced and the optimal value of α resulting in the least BER is obtained for the input conditions.
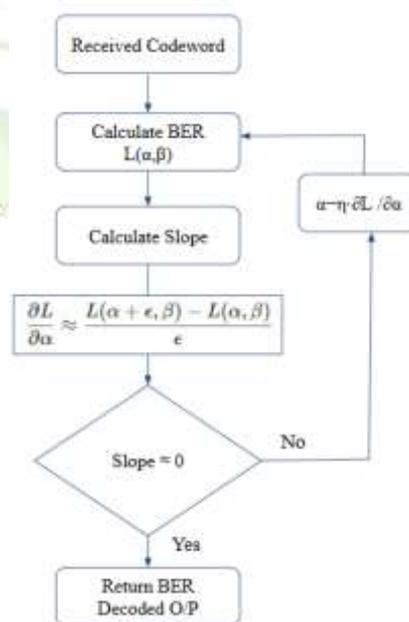

Figure 2. Gradient Descent Implementation Flowchart

V. EXPERIMENTAL SETUP AND RESULTS

All simulations are conducted in Python using the NumPy, SciPy, and scikit-learn libraries. The LDPC matrices are taken from the 5G NR standard defined by 3GPP (e.g., base graph BG1 and BG2). The BG2 matrix of dimensions 42 x 52 is chosen, with lifting size Z = 64. The information length K is set to 640. The channel is modeled using Rayleigh fading with additive white Gaussian noise (AWGN).

The primary performance metric is Bit Error Rate (BER) as a function of SNR. We compare our optimized decoder with the standard Min-Sum decoder over various SNR (Signal to Noise Ratio) values to compare their performances over different channel conditions.

The experimental results obtained in Fig. 3 validate the effectiveness of the ML-optimized decoder over traditional techniques. The ML-optimized decoder exhibits significantly lower BER across all SNR values. The optimized scaling parameters dynamically adapt to varying noise conditions, enabling enhanced error correction.
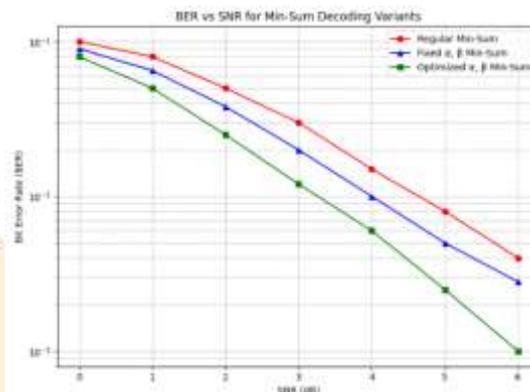

Figure 3. BER Performance with information length K = 640, number of iterations = 15, and code rate R = 1/5

The model maintains the low complexity of Min-Sum decoding while approaching the performance of the Belief Propagation algorithm. The overhead introduced by optimal α parameter prediction is minimal and occurs only once per channel.

While this study focuses on the Rayleigh fading channel, the framework can be extended to other fading models such as Rician or AWGN.

The proposed decoder framework is suitable for real-time embedded 5G systems where both performance and efficiency are crucial. It can be integrated into base station firmware or UE modem chips with minimal computational overhead.

REFERENCES

[1] T. Y. Chen, K. Vakilinia, D. Divsalar, and R. D. Wesel, ''Protograph based raptor-like LDPC codes,'' IEEE Trans. Commun., vol. 63, no. 5, pp. 1522–1532, May 2015.

[2] WF on LDPC Parity Check Matrices, document R1-1711982, 3GPP TSG RAN WG1 NR AH #2, Qingdao, China, Jun. 2017. [Online].

[3] J. Chen, A. Dholakia, E. Eleftheriou, M. P. C. Fossorier, and X.-Y. Hu, ''Reduced-complexity decoding of LDPC codes,'' IEEE Trans. Commun., vol. 53, no. 8, pp. 1288–1299, Aug. 2005.

[4] S. Myung, S.-I. Park, K.-J. Kim, J.-Y. Lee, S. Kwon, and J. Kim, ''Offset and normalized min-sum algorithms for ATSC 3.0 LDPC decoder,'' IEEE Trans. Broadcast., vol. 63, no. 4, pp. 734–739, Dec. 2017.

[5] J. Chen and M. P. C. Fossorier, ''Density evolution for two improved BPbased decoding algorithms of LDPC codes,'' IEEE Commun. Lett., vol. 6, no. 5, pp. 208–210, May 2002.

[6] M. Jiang, C. Zhao, L. Zhang, and E. Xu, ''Adaptive offset min-sum algorithm for low-density parity check codes,'' IEEE Commun. Lett., vol. 10, no. 6, pp. 483–485, Jun. 2006.

[7] D. Oh and K. K. Parhi, ''Min-sum decoder architectures with reduced word length for LDPC codes,'' IEEE Trans. Circuits Syst. I, Reg. Papers, vol. 57, no. 1, pp. 105–115, Jan. 2010.

[8] X. Wu, Y. Song, M. Jiang, and C. Zhao, ''Adaptive-normalized/offset min-sum algorithm,'' IEEE Commun. Lett., vol. 14, no. 7, pp. 667–669, Jul. 2010.

[9] E. Nachmani and Y. Be'ery, and D. Burshtein, ''Learning to decode linear codes using deep learning,'' in Proc. 54th Annu. Allerton Conf. Commun., Control, Comput. (Allerton), Sep. 2016, pp. 341–346.

[10] E. Nachmani, E. Marciano, L. Lugosch, W. J. Gross, D. Burshtein, and Y. Be'ery, ''Deep learning methods for improved decoding of linear codes,'' IEEE J. Sel. Topics Signal Process., vol. 12, no. 1, pp. 119–131, Feb. 2018.

[11] T. Gruber, S. Cammerer, J. Hoydis, and S. ten Brink, ''On deep learning based channel decoding,'' in Proc. 51st Annu. Conf. Inf. Sci. Syst. (CISS), Mar. 2017, pp. 1–6.

[12] J. Lewandowsky and G. Bauch, ''Information-optimum LDPC decoders based on the information bottleneck method,'' IEEE Access, vol. 6, pp. 4054–4071, 2018.

[13] A. Bennatan, Y. Choukroun, and P. Kisilev. (2018). ''Deep learning for decoding of linear codes—A syndrome-based approach.''F.

[14] X. Wu, M. Jiang and C. Zhao, "Decoding Optimization for 5G LDPC Codes by Machine Learning," in IEEE Access, vol. 6, pp. 50179-50186, 2018

[15] Jilei Hou, P. H. Siegel and L. B. Milstein, "Performance analysis and code optimization of low density parity-check codes on Rayleigh fading channels," in IEEE Journal on Selected Areas in Communications, vol. 19, no. 5, pp. 924-934, May 2001.

[16] Kiyani, Nauman F., et al. "Analysis of random regular LDPC codes on Rayleigh fading channels." Proc. 27th Symp. Inform. Theory Benelux. 2006.

[17] Y. Jiang, A. Ashikhmin and N. Sharma, "LDPC Codes for Flat Rayleigh Fading Channels with Channel Side Information," in IEEE Transactions on Communications, vol. 56, no. 8, pp. 1207-1213, August 2008.

[18] Z. Mei, M. Johnston, S. Le Goff and L. Chen, "Performance Analysis of LDPC-Coded Diversity Combining on Rayleigh Fading Channels With Impulsive Noise," in IEEE Transactions on Communications, vol. 65, no. 6, pp. 2345-2356, June 2017.

[19] S. -K. Ahn, K. Yang and D. Har, "Evaluation of the Low Error-Rate Performance of LDPC Codes over Rayleigh Fading Channels Using Importance Sampling," in IEEE Transactions on Communications, vol. 61, no. 6, pp. 2166-2177, June 2013.

[20] G. Sundararajan, C. Winstead and E. Boutillon, "Noisy Gradient Descent Bit-Flip Decoding for LDPC Codes," in IEEE Transactions on Communications, vol. 62, no. 10, pp. 3385-3400, Oct. 2014

[21] R. K. Maity, A. Singh Rawa and A. Mazumdar, "Robust Gradient Descent via Moment Encoding and LDPC Codes," 2019 IEEE International Symposium on Information Theory (ISIT), Paris, France, 2019, pp. 2734-2738

[22] B. S. Tan, K. H. Li and K. C. Teh, "Analysis of MIMO Diversity With LDPC Codes Based on a Gaussian Approximation Approach Over Rayleigh Fading Channels," in IEEE Transactions on Vehicular Technology, vol. 60, no. 9, pp. 4650-4656, Nov. 2011.

[23] Biazaran, Reza, and Hermann Joseph Helgert. "Improved noisy gradient descent bit-flipping algorithm over Rayleigh fading channel." International Journal of Electrical and Computer Engineering (IJECE) 12.3 (2022): 2699-2710.