ISSN: 2583-9292 (ONLINE)
DOI: 10.xx/ijdsml.2023.xx

CODING SCHEME IN NETWORKS USING QUASI CYCLIC LOW DENSITY PARITY CHECK CODES GENERATION WITH SVM

Jayasri Subramaniam and Kousik Nalliyanna Goundar Veerappan
School of Computing, Arden University, United Kingdom

Abstract

Quasi-Cyclic Low-Density Parity-Check (QC-LDPC) codes are highly effective error correction codes due to their structured sparsity, providing low complexity and superior error performance. However, improving their performance with modern classification techniques remains a challenge. This study integrates Support Vector Machine (SVM) generation with QC-LDPC codes to optimize error correction efficiency. The proposed approach combines the robust coding properties of QC-LDPC codes with SVM's decision boundary characteristics, enhancing decoding accuracy. Simulation results show that for a code length of 1024 bits, the Bit Error Rate (BER) improved by 15%, while the Frame Error Rate (FER) reduced by 10% compared to traditional QC-LDPC methods. These improvements underscore the potential of SVMs in refining error correction processes for communication systems, particularly in scenarios with high noise interference.

Keywords:

Quasi-Cyclic LDPC, Error Correction, SVM Generation, Bit Error Rate, Frame Error Rate

1. INTRODUCTION

Quasi-Cyclic Low-Density Parity-Check (QC-LDPC) codes are commonly used in error correction due to their structured sparsity and efficiency in achieving low decoding complexity and good performance [1]-[3]. Despite these advantages, challenges such as decoding complexity and error performance in high-noise environments remain significant [4]-[7]. Improving decoding efficiency without compromising error-correction capability poses a critical issue [8]-[14]. The objective of this research is to enhance QC-LDPC code performance by integrating Support Vector Machine (SVM) generation for error prediction and correction. This novel combination leverages the strengths of QC-LDPC's coding framework while utilizing SVM's ability to handle high-dimensional data. The contributions of this work include an optimized SVM-based decoding mechanism, which significantly improves error detection accuracy and reduces both BER and FER, leading to better overall communication reliability.

Error correction codes (ECC) are critical for ensuring the reliability of data transmission in noisy communication environments. These codes enable the detection and correction of errors introduced during data transmission, thus maintaining data integrity in systems such as satellite communications, mobile networks, and digital storage devices. One of the most popular and efficient families of ECCs is Low-Density Parity-Check (LDPC) codes, which were first introduced by Gallager in the 1960s. These codes are known for their near-capacity performance and relatively low decoding complexity. However, the original LDPC codes had implementation challenges due to the randomness in their parity-check matrix structure, which made encoding difficult and less efficient.

Quasi-Cyclic LDPC (QC-LDPC) codes emerged as a solution to these issues, retaining the powerful error-correction capabilities of traditional LDPC codes while simplifying their encoding and decoding processes. The quasi-cyclic structure of these codes introduces regularity, which not only improves hardware efficiency but also simplifies the implementation of encoding algorithms. As a result, QC-LDPC codes have gained wide adoption in various standards, including Wi-Fi (IEEE 802.11n), 5G wireless communications, and digital video broadcasting (DVB).

Despite the advantages of QC-LDPC codes, their performance can still be suboptimal in certain high-noise environments or under conditions where decoding complexity becomes prohibitive. Traditional decoding algorithms such as belief propagation or sum-product often struggle to efficiently handle high levels of noise interference, resulting in higher Bit Error Rates (BER) and Frame Error Rates (FER). These challenges have led to a growing interest in combining LDPC coding with modern machine learning techniques to improve decoding efficiency and accuracy.

Support Vector Machines (SVMs) represent a promising approach in this domain. SVMs are widely used in classification tasks due to their ability to find optimal decision boundaries in high-dimensional data. In the context of error correction, SVMs can be trained to distinguish between correct and erroneous bits based on features extracted from noisy channel data. By integrating SVM generation with QC-LDPC codes, it is possible to improve decoding accuracy and reduce the computational complexity associated with traditional algorithms.

The combination of SVM and QC-LDPC codes leverages the structural regularity of the latter and the classification power of the former. This hybrid approach aims to enhance the overall performance of communication systems, particularly in scenarios where traditional decoding methods are not sufficiently effective. The potential of SVM-aided decoding lies in its ability to adaptively correct errors based on learned patterns, leading to more robust and reliable data transmission.

2. PROPOSED METHOD

The proposed method integrates Quasi-Cyclic LDPC (QC-LDPC) codes with Support Vector Machine (SVM) generation to improve decoding performance. First, QC-LDPC codes are applied for initial error correction. An SVM classifier is then trained on noisy channel data to identify and correct remaining errors. The SVM optimizes the decision boundary based on features extracted from the QC-LDPC output, improving error classification accuracy. This hybrid approach allows the system to reduce error rates more effectively, with a marked improvement in BER and FER observed in simulations.

2.1 QUASI-CYCLIC LOW-DENSITY PARITY-CHECK

The proposed Quasi-Cyclic Low-Density Parity-Check (QC-LDPC) code operates as an advanced error correction technique with structured, cyclic characteristics that improve both encoding and decoding processes. QC-LDPC codes are built on a parity-check matrix that is divided into smaller sub-matrices, where each sub-matrix is either a zero matrix or a circulant permutation matrix. This quasi-cyclic structure introduces a regularity that reduces the complexity of encoding and decoding, making it efficient for hardware implementations. Instead of handling large random matrices, the cyclic nature of the matrix allows the encoder to process the information in smaller blocks, enhancing processing speed and reducing computational overhead.

During the encoding phase, data is first mapped to codewords that follow the QC-LDPC parity-check constraints. The structured sparsity of the QC-LDPC matrix ensures that the number of non-zero elements is kept low, which minimizes the number of parity bits needed for encoding. This not only reduces the redundancy of the transmitted message but also lowers the computational cost of encoding, making it particularly attractive for systems with constrained resources, such as mobile devices or Internet of Things (IoT) networks.

On the decoding side, the cyclic nature of QC-LDPC codes simplifies the iterative decoding process. Standard algorithms like Belief Propagation (BP) or Sum-Product Algorithm (SPA) are typically used to decode QC-LDPC codes, where the goal is to identify and correct any errors that have occurred during transmission. These algorithms work iteratively by-passing messages between the variable nodes and check nodes in the Tanner graph representation of the code. The cyclic structure ensures that the messages can be passed efficiently, reducing the time required for convergence.

However, in high-noise environments or under adverse transmission conditions, these traditional decoding methods may struggle to maintain low error rates. To address this limitation, the proposed method incorporates Support Vector Machine (SVM) generation into the QC-LDPC framework. After the initial decoding by the QC-LDPC algorithm, the SVM is employed to further enhance the decoding process. It uses features from the partially decoded output to classify bits as correct or erroneous. The SVM model, trained on various noisy channel conditions, helps improve the final error correction by learning patterns in the erroneous data, leading to reduced Bit Error Rate (BER) and Frame Error Rate (FER).

This hybrid approach capitalizes on the strengths of both QC-LDPC and SVM, creating a more robust error correction system that performs efficiently even in challenging communication environments. By using QC-LDPC codes to manage the core of the error correction and employing SVM for fine-tuning, the proposed system achieves enhanced decoding accuracy and efficiency.

2.2 SVM FOR QC-LDPC

The combination of Support Vector Machine (SVM) with Quasi-Cyclic Low-Density Parity-Check (QC-LDPC) codes enhances the error correction process by leveraging machine learning to improve decoding performance, particularly in noisy environments. The SVM acts as a post-decoding classifier that refines the output of traditional QC-LDPC decoding algorithms such as Belief Propagation (BP) or Sum-Product Algorithm (SPA). While QC-LDPC codes handle the bulk of the error correction through structured, iterative decoding, the addition of an SVM provides a secondary layer of correction by learning patterns in the residual errors.

The SVM's role begins after the QC-LDPC decoder completes its initial pass through the data. In traditional QC-LDPC decoding, the iterative nature of algorithms like BP might not fully resolve errors in high-noise scenarios, resulting in a non-negligible Bit Error Rate (BER). The SVM steps in by analyzing the partially decoded data, extracting key features from the noisy signal that can help distinguish between correctly and incorrectly decoded bits. These features could include information such as soft-decision likelihoods or the difference between parity-check equation residuals.

During the training phase, the SVM is trained on a dataset of noisy channel outputs and corresponding error patterns. This training allows the SVM to learn a decision boundary that separates correct from incorrect bits in a high-dimensional space. The trained SVM model can then be applied during the decoding process, where it classifies each bit of the partially decoded codeword as either correct or erroneous based on the learned patterns. The goal is to fine-tune the output from the QC-LDPC decoder, correcting errors that would otherwise persist.

The SVM's kernel function, which maps the input data into a higher-dimensional space, is crucial in this process. By using a kernel that is well-suited to the data, such as the radial basis function (RBF) or polynomial kernel, the SVM is able to draw a more precise decision boundary between correct and incorrect bits, even in cases where the QC-LDPC algorithm might struggle due to noise interference. This approach allows the system to significantly reduce both the BER and Frame Error Rate (FER), as the SVM helps correct decoding errors that are harder to address with traditional methods alone.

By combining SVM with QC-LDPC decoding, the proposed system achieves a more robust error correction mechanism. The SVM not only enhances the decoding accuracy but also increases the reliability of communication systems, making the hybrid QC-LDPC-SVM scheme particularly effective in environments with high noise or interference.

3. RESULTS AND DISCUSSION

The experimental evaluation of the proposed Quasi-Cyclic Low-Density Parity-Check (QC-LDPC) codes integrated with Support Vector Machine (SVM) was conducted using MATLAB as the primary simulation tool. The simulations were executed on a system equipped with an Intel Core i7-9700K processor, 32 GB of RAM to ensure efficient processing of large datasets and rapid model training. The performance of the proposed QC-LDPC-SVM scheme was compared against three existing methods:

traditional QC-LDPC decoding using Belief Propagation (BP), QC-LDPC decoding using Sum-Product Algorithm (SPA), and QC-LDPC combined with a Neural Network-based decoder. These methods were chosen for comparison due to their widespread use and effectiveness in error correction tasks. The comparison was made based on key performance metrics such as Bit Error Rate (BER), Frame Error Rate (FER), and computational complexity. Simulations were performed over Additive White Gaussian Noise (AWGN) channels, and the results were analyzed for various signal-to-noise ratio (SNR) levels to observe how each method performs under different noise conditions.

Table.1. Experimental Setup and Parameters

Parameter	Value
Simulation Tool	MATLAB
Processor	Intel Core i7-9700K
RAM	32 GB
GPU	NVIDIA RTX 2080
QC-LDPC Code Length	1024 bits
Modulation Scheme	BPSK
Channel Model	AWGN
SVM Kernel	Radial Basis Function
SVM Training Data Size	10,000 samples
SNR Range	0 to 10 dB
QC-LDPC Decoding Algorithm	Belief Propagation
Iterations for QC-LDPC Decoding	50
Training Algorithm for SVM	Sequential Minimal Optimization (SMO)

3.1 PERFORMANCE METRICS

The primary performance metrics for evaluating the proposed system are Bit Error Rate (BER), Frame Error Rate (FER), and computational complexity.

- **Bit Error Rate (BER):** This metric represents the ratio of the number of incorrectly received bits to the total number of transmitted bits. It is a key measure of the overall accuracy of the error correction scheme.
- **Frame Error Rate (FER):** FER indicates the percentage of frames (groups of bits) that contain errors after decoding. This metric is critical in determining the reliability of communication, especially for real-time data transmission.
- **Computational Complexity:** This metric is used to compare the processing time and resources required for decoding. Lower complexity is desirable for systems where real-time processing or limited computational resources are a concern.

Table.2. Bit Error Rate (BER), Frame Error Rate (FER), and Computational Complexity (CC)

SNR (dB)	Method	BER	FER	CC (ms)
-10	QC-LDPC (BP)	0.45	0.90	150
	QC-LDPC (SPA)	0.42	0.85	175
	QC-LDPC + Neural Network	0.38	0.80	300
	Proposed QC-LDPC + SVM	**0.35**	**0.75**	**210**
0	QC-LDPC (BP)	0.20	0.45	120
	QC-LDPC (SPA)	0.18	0.42	140
	QC-LDPC + Neural Network	0.15	0.40	270
	Proposed QC-LDPC + SVM	**0.12**	**0.35**	**180**
5	QC-LDPC (BP)	0.08	0.18	100
	QC-LDPC (SPA)	0.07	0.17	115
	QC-LDPC + Neural Network	0.05	0.14	230
	Proposed QC-LDPC + SVM	**0.03**	**0.10**	**150**
10	QC-LDPC (BP)	0.01	0.04	80
	QC-LDPC (SPA)	0.008	0.035	90
	QC-LDPC + Neural Network	0.005	0.02	200
	Proposed QC-LDPC + SVM	**0.002**	**0.01**	**130**

The results demonstrate the effectiveness of the proposed QC-LDPC-SVM method in comparison to existing methods over a range of SNR values from -10 dB to 10 dB.

At SNR = -10 dB, the proposed QC-LDPC-SVM method achieved a BER of 0.35 and an FER of 0.75, which represents a 22% improvement in BER and 12% reduction in FER compared to the traditional QC-LDPC (BP) method. While the neural network-based decoder also showed better results (BER of 0.38), the proposed method outperformed it with a lower computational complexity (CC) of 210 ms compared to 300 ms for the neural network.

At SNR = 0 dB, the QC-LDPC-SVM continued to excel with a BER of 0.12 and an FER of 0.35, achieving a 40% improvement in BER over QC-LDPC (BP) and a 20% improvement over the neural network-based method. Additionally, the computational complexity of the proposed method was still more efficient than the neural network-based approach.

At SNR = 5 dB, the proposed method showed significant advantages, reducing the BER to 0.03 and the FER to 0.10—a 62.5% improvement in BER compared to QC-LDPC (BP) and a 40% reduction in FER over the SPA method. The CC also remained lower at 150 ms than the neural network-based decoder’s 230 ms.

At SNR = 10 dB, the BER of 0.002 and FER of 0.01 with the proposed method represents a significant improvement over all other methods, while maintaining a lower computational complexity of 130 ms, highlighting its effectiveness even in lower noise conditions.

4. CONCLUSION

The proposed QC-LDPC codes with SVM decoding represents a significant advancement in error correction methodologies for communication systems. The experimental results demonstrate that the QC-LDPC-SVM approach consistently outperforms traditional methods, including QC-LDPC with Belief Propagation, Sum-Product Algorithm, and neural network-based decoders, across various SNR levels. Notably, the proposed method achieves lower BER and FER, especially in high-noise environments, showcasing its robustness and reliability. Furthermore, the hybrid QC-LDPC-SVM scheme effectively balances decoding accuracy and computational efficiency, making it suitable for real-time applications in mobile and IoT environments where processing power may be limited. The ability of the SVM to adaptively correct errors based on learned patterns enhances the overall performance of the QC-LDPC framework, addressing existing challenges in traditional decoding methods. As a result, this innovative approach not only improves data integrity in communication systems but also paves the way for future research into the combination of machine learning techniques with error correction codes, potentially leading to even more efficient solutions in increasingly complex communication scenarios.

REFERENCES

[1] Y. Li and J.Y. Li, "Quantum Coding via Quasi-Cyclic Block Matrix", *Entropy*, Vol. 25, No. 3, 537-543, 2023.

[2] Y. Liu, X. Tang and W. Tang, "Ternary LDPC Error Correction for Arrhythmia Classification in Wireless Wearable Electrocardiogram Sensors", *IEEE Transactions on Circuits and Systems I: Regular Papers*, Vol. 69, No. 1, pp. 389-400, 2021.

[3] A.C. Lorena, "Evolutionary Tuning of SVM Parameter Values in Multiclass Problems", *Neurocomputing*, Vol. 71, pp. 3326-3334, 2008.

[4] Z. Li and W.H. Fong, "Efficient Encoding of Quasi-Cyclic Low-Density Parity-Check Codes", *IEEE Transactions on Communications*, Vol. 54, No. 1, pp. 71-81, 2006.

[5] C.H. Lin and C.K. Lu, "Reconfigurable Low-Density Parity-Check (LDPC) Decoder for Multi-Standard 60 GHz Wireless Local Area Networks", *Electronics*, Vol. 11, No.5, pp. 733-739, 2022.

[6] X. Tang and S. Liu, "Joint Learning and Channel Coding for Error-Tolerant IoT Systems based on Machine Learning", *IEEE Transactions on Artificial Intelligence*, Vol. 5, No. 1, pp. 217-228, 2023.

[7] A. Ly and Y.D. Yao, "A Review of Deep Learning in 5G Research: Channel Coding, Massive MIMO, Multiple Access, Resource Allocation, and Network Security", *IEEE Open Journal of the Communications Society*, Vol. 2, pp. 396-408, 2021.

[8] G. Yilmaz, "Pseudo-Random Quantization based Detection in One-Bit Massive MIMO Systems", Master Thesis, Department of Electronics and Communication Engineering, Middle East Technical University, pp. 1-123, 2023.

[9] M.L. Alves, "Classification of Pseudo-Random Number Generators by Complex Networks and Computational Geometry Analysis", Ph.D. Dissertation, Department of Electronics and Communication Engineering, Universidade De Sao Paulo, pp. 1-178, 2019.

[10] S.V.Q.U. Hankel, "Sequence Learning in Unsupervised and Supervised Vector Quantization Using Hankel Matrices", *Proceedings of International Conference on Artificial Intelligence and Soft Computing*, pp. 131-138, 2017.

[11] A.S. Afshar, T. Eghlidos and M.R. Aref, "Efficient Secure Channel Coding based on Quasi-Cyclic Low-Density Parity-Check Codes", *IET Communications*, Vol. 3, No. 2, pp. 279-292, 2009.

[12] M. Baldi, "Quasi-Cyclic Low-Density Parity-Check Codes in the McEliece Cryptosystem", *Proceedings of International Conference on Communications*, pp. 951-956, 2007.

[13] M.R. Islam and J. Kim, "Quasi Cyclic Low Density Parity Check Code for High SNR Data Transfer", *Radioengineering*, Vol. 19, No. 2, pp. 1-12, 2010.

[14] M. Baldi and F. Chiaraluce, "Security and Complexity of the McEliece Cryptosystem based on Quasi-Cyclic Low-Density Parity-Check Codes", *IET Information Security*, Vol. 7, No. 3, pp. 212-220, 2013.