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International Journal of Artificial Intelligence and Machine Learning

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Research Paper Open Access

Quantum-Inspired Tensor Network Algorithms for Efficient Large-Scale Data Compression

K. Venkatesh Guru[1*], Sagayaraj P[2], Dr. S. N. V. J. Devi Kosuru[3], Dhanalakshmi V[4], Dr.Kamlesh Kumar Yadav[5]

[1*]Assistant Professor, School of Computing, SRM Institute of Science and Technology, Tiruchirappalli, India.
E-mail: venkateshguruk@gmail.com

[2]Professor, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Tamil Nadu, India.
E-mail: sagayaraj@maher.ac.in

[3]Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India. E-mail: jyotsnakosuru@gmail.com, ORCID: 0000-0003-1521-5701

[4]Assistant Professor, Department of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Tamil Nadu, India. E-mail: dhanalakshmiv@maher.ac.in

[5]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India. Email: ku.kamleshkumaryadav@kalingauniversity.ac.in, ORCID:0009-0006-4665-5506

*Corresponding author: venkateshguruk@gmail.com

Abstract

The explosive expansion of data through digital architecture requires entirely new approaches in data compression that will be able to exceed limitations posed by conventional methods. This work introduces a new paradigm, namely Tensor Network Quantum-Inspired (TN-QI) Compression, that utilizes concepts from quantum computing, such as matrix product states (MPS) and multi-scale entanglement renormalization ansatz (MERA), within a classical computational context in order to achieve large-scale data compression. Using tensor networks as representations of high dimensional data and taking advantage of their intrinsic hierarchical correlations, TN-QI achieves a compression ratio of up to 31.8:1, outperforming conventional codecs such as HEVC and BPG. This methodology combines the techniques of adaptive bond dimension tuning, entanglement entropy-based truncation, and an encoding pipeline inspired by quantum circuits but that can be computed entirely on classical computers without any quantum coprocessor. Experiments performed on ImageNet-1K, 4K videos, and high-throughput genomics have shown improvements ranging from 40 to 60 percent in compression efficiency relative to classical algorithms, while also achieving a 35 percent lower encoding latency relative to comparable tensor decomposition methods. The approximation guarantees and computational complexity of the TN-QI algorithm were analyzed theoretically as well. These findings show that quantum-inspired tensor networks offer a promising, hardware-independent solution for future data compression systems.

Keywords: Tensor networks, quantum-inspired algorithms, data compression, matrix product states, entanglement renormalization, bond dimension optimization, large-scale machine learning

1. Introduction

1.1 Background

The digital universe is growing faster than ever before. In 2023, according to IDC, global data creation, capture, copying, and consumption will reach 120 zettabytes, while by 2028 it is expected to exceed 400 zettabytes [1]. This includes high resolution images, 4K and 8K video streams, whole-genome sequence libraries, satellite telemetry, and the continuous data flows generated by the Internet of Things [7]. The classical compression algorithms based on entropy coding, transform coding, and prediction methods were the mainstay of digital data storage and transmission after the groundbreaking developments of Shannon in information theory [2]. Such algorithms as DEFLATE, JPEG 2000, H.265/HEVC, and the Burrows-Wheeler transform have undergone amazing engineering optimization over several decades. However, the mathematical structure of the compression algorithms places more and more constraints as the dimensionality, diversity, and volume of data go beyond the capabilities of classical data decompositions.

At the same time, quantum computing is leading to a new class of mathematical techniques that can be used far outside the domain of quantum computing devices themselves. The tensor network approach, which was originally introduced in condensed matter physics for efficient simulation of many-body quantum systems, allows for a concise and hierarchical description of high-dimensional probability distributions and correlations [1][3][16]. MPS, PEPS, and MERA have already found use in supervised machine learning, generative models, and dimensionality reduction [6][17]. Formally, the association of these with quantum circuits renders them perfect candidates for bridging the gap between theory and practice [4][13].

However, even with all the progress made, there is an essential mismatch between the theoretical capability of compressibility attainable using the quantum information theoretic models of high-dimensional data and the practical capability of compressing with existing classical methods. The problems that are associated with the current tensor-decomposition-based compressors, such as Tucker decomposition and tensor-train decompositions, include: (i) poor scalability due to exponential growth of tensor ranks relative to dimensions of tensors; (ii) fixed-rank structures that do not allow capturing multi-scale correlations in natural data; (iii) computationally demanding optimization procedures which make real-time compression impossible; and (iv) lack of effective control on the fidelity-rate trade-off using information-theoretic principles.

The classical compressors, while being computationally efficient, are also limited: they ignore the structure of global correlations across multiple scales of resolution during entropy coding and have a fixed transform stage (e.g., DCT or wavelets) rather than an adaptive one. This means that today's industry standard does not exploit the full potential of data redundancy in complex data types such as hyperspectral images, volumetric medical imaging, and long-read genomic sequences.

1.3 Key Contributions

Contributions of This Paper Include the Following:

- To present a unified quantum-inspired tensor network compression pipeline for mapping data tensors into a hybrid MPS/MERA representation, taking advantage of short-range and long-range correlations via hierarchical bond-dimension optimization.
- To present an innovative method for dynamically tuning the bond dimension of each tensor network edge according to the local entanglement entropy, which results in nearly optimal rank assignment without resorting to costly search procedures.
- To present an optimal truncation strategy inspired by quantum Rényi entropy provides a theoretically grounded guarantee of bounded approximation error under a user-defined fidelity budget, as opposed to heuristics employed in previous work.
- To show that TN-QI can be efficiently encoded using classical multi-core and GPU architectures, employing optimal contraction scheduling strategies borrowed from quantum circuit compilation techniques, achieving performance comparable to HEVC on equal footing hardware.
- To perform extensive experimentation to evaluate TN-QI against eight state-of-the-art compressors over four distinct dataset types, which represents the first empirical evaluation of quantum-inspired tensor networks for compression tasks.

The remainder of this paper is organized as follows. Section 2 provides an overview of the state-of-the-art literature concerning classical compression, tensor decompositions, and quantum inspired algorithms. Section 3 describes the TN-QI framework theoretically and technically. Section 4 describes the experimental procedure and presents numerical results. Section 5 analyzes the findings in detail, pointing out possible weaknesses and future research directions.

2. Literature Survey

Classical Data Compression

Mathematical foundations of lossless compression can be traced back to the source coding theorem and established entropy as the lower bound of lossless compression [2][12]. Near-entropy performance can be attained through Huffman coding and arithmetic coding for memoryless sources, while the use of dictionary-based techniques in LZW algorithms leads to efficient lossless encoding for correlated sources [8][9][15]. DEFLATE and GZIP represent applications of LZW techniques, but they operate assuming that the data can be modeled as one-dimensional symbols. For image and video lossy compression, transform coding is exploited. DCT constitutes the backbone of JPEG and the intra-coding process of H.264/AVC and H.265/HEVC [10][19]. In the case of wavelets, the biorthogonal DWT algorithm used in JPEG 2000 provides multi-resolution analysis, proving more effective than DCT for medical images [11][18]. More recently, the concept of neural network codecs (NNC), exemplified has led to the design of highly optimized rate-distortion schemes for natural images.

Tensor Decomposition Methods

Tucker decomposition generalises the matrix SVD to higher-order tensors by factorising a tensor into a core tensor multiplied by orthogonal matrices along each mode [14]. Although Tucker decomposition is flexible theoretically, the exponential growth in the size of the core tensor with the order makes it computationally unfeasible beyond order six or seven. The Tensor Train (TT) decomposition, also referred to as Matrix Product States (MPS) in physics, was developed for computational mathematics. TT/MPS represents high order tensor as a sequence of third order cores with polynomial complexity of storage. The study gives an excellent overview of tensor networks from the quantum physics point of view [1].

2.3 Quantum-Inspired Algorithms on Classical Hardware

Classical algorithms inspired by quantum algorithms have attracted a lot of attention in view of dequantizing quantum recommendation system algorithms, which demonstrated that classical sampling-based versions can achieve similar speed-up as their quantum counterparts. In this regard, concerning machine learning, it was demonstrated and supervised classification through MPS is comparable to MNIST, while another study introduced a generative model based on MPS [4][13]. Additionally, hierarchical representations via MERA circuits [6]. In all these cases, quantum circuit architectures have proved to be an inspiration in designing classical algorithms operating on structured high-dimensional data. In particular, quantum-inspired compressive sensing has received less attention. A quantum circuit inspired transform coding for hyperspectral imagery, showing preliminary success. The current work builds upon the above works in order to develop a complete framework with provable guarantee, adaptation, and evaluation across multiple domains [5][20].

2.4 Inference from Literature

Synthesis of the reviewed literature makes us identify several critical points that motivate our research. To start with, traditional coding methods have reached physical limits in terms of contemporary data, and further engineering optimization will provide only minor advantages. Second, tensor factorization techniques provide a mathematically justified way of achieving improved compression ratios but are hampered by scalability and adaptability issues. Third, quantum information paradigms provide both the theoretical means (entanglement entropy, bond dimension management) and the structural foundations (MPS, MERA) to overcome those obstacles. Finally, there is no known study that integrates those approaches into a consistent compression paradigm.

3. 3. Methodology

3.1 Theoretical Foundations

3.1.1 Tensor Network Representations

A tensor Tof order dis represented as an element of the space $\mathbb{R}^{n_1 \times n_2 \times \cdots \times n_d}$. A Matrix Product State (MPS) representation decomposes Tas Equation (1):

$$T[i_1, i_2, \ldots, i_d] = A^1[i_1] \cdot A^2[i_2] \cdot \cdots \cdot A^d[i_d] \quad (1)$$

where each $A^k[i_k]$is a matrix of dimension $\chi_{k-1} \times \chi_k$, with $\chi_0 = \chi_d = 1$, and $\chi_k$denotes the bond dimension at site k. The storage complexity is thereby reduced from $O(n^d)$to $O(d \cdot n \cdot \chi^2)$, where $\chi = \max_k \chi_k$.

The Multi-scale Entanglement Renormalization Ansatz (MERA) extends this framework by introducing disentanglers Uand isometries Warranged in a hierarchical binary-tree structure, enabling multi-scale representation, Equation (2):

$$| T\rangle = \prod_\tau (\prod_{x\in\tau} U_x) \left(\prod_{y\in\tau} W_y \right) | T_{\tau+1}\rangle \quad (2)$$

The MERA architecture is capable of representing both area-law and volume-law entanglement, making it more expressive than MPS for modeling data exhibiting hierarchical correlations across multiple spatial scales, as commonly observed in natural images, videos, and genomic sequences.

3.1.2 Entanglement Entropy as a Compression Signal

For a bipartition of the tensor network into subsystems **A**and **B**, the entanglement entropy **S**(**A**)is defined as Equation (3):

$$\mathbf{S}(\mathbf{A}) = -\mathbf{Tr}(\boldsymbol{\rho}_{\mathbf{A}} \mathbf{log}\ \boldsymbol{\rho}_{\mathbf{A}}) = -\sum_i \boldsymbol{\lambda}_i^2 \mathbf{log}\,(\boldsymbol{\lambda}_i^2) \quad (3)$$

where $\boldsymbol{\lambda}_i$denotes the Schmidt coefficient obtained from the singular value decomposition (SVD) of the reshaped tensor. The entanglement entropy quantifies the amount of information encoded in the bond connecting subsystems **A**and **B**. In the context of Tensor Network Quantum-Inspired (TN-QI) methods, **S**(**A**)is employed as a per-bond truncation criterion such that bonds with low entanglement entropy are truncated, whereas bonds exhibiting high entanglement entropy are preserved to retain important correlation information.

3.2 The TN-QI Compression Pipeline

3.2.1 Data Ingestion and Tensorisation

The input data, including images, videos, or genomic arrays, are first reformatted into a high-order tensor with mode size $n = 2^b$for all modes, where bdenotes the bit depth. This binary tensorization enables mode indices to correspond directly to qubit registers, thereby facilitating efficient quantum circuit contraction schedules. For a grayscale image of resolution $H \times W$, a tensor Tof dimension $\mathbb{R}^{2^b \times 2^b \times \cdots}$, with $d = \log_2(H \cdot W)$modes, is constructed from pixel intensity values represented using binary indices.

3.2.2 Adaptive Bond-Dimension Optimisation (ABDO)

Following the tensorization stage, the TN-QI framework performs a singular value decomposition (SVD) sweep in a left-to-right manner along the Matrix Product State (MPS). At each bond k, TN-QI computes the entanglement entropy $S_k$and selects the optimal truncated bond dimension χ_k^*as the minimum integer satisfying Equation (4):

$$\sum_{i=1}^{\chi_k^*} \lambda_i^2 \geq (1-\varepsilon) \sum_{i=1}^{\chi_k} \lambda_i^2 \quad (4)$$

where εis a user-defined global fidelity parameter. Consequently, the overall rate-distortion trade-off is governed by a single intuitive control parameter.

A further stage of ABDO employs MERA disentanglers on low-entropy bonds, thereby clustering similar correlations and reducing the total number of non-trivial singular values prior to entropy coding.

3.2.3 Quantum-Circuit-Inspired Contraction Schedule

The efficient contraction of the tensor network obtained is done using an ordering based on the causal cone of the tensor network—the collection of tensors that have an effect on the value of any particular output index. The reverse causal order, akin to the way a quantum circuit can be evaluated by starting with the output qubits and going backward through the gates, allows us to avoid intermediate tensor explosion, with the memory overhead kept at $O(\chi^2 \cdot n)$ per contraction.

3.2.4 Entropy Coding Stage

The quantized singular value spectra of each bond are encoded losslessly using an adaptive arithmetic encoder that is conditioned on the bond's position in the MERA hierarchy and the context provided by neighbouring bond spectra. The tensor core index values (isometry and disentangler coefficients) are encoded independently using another arithmetic model that updates its statistics dynamically. This entropy encoding stage exploits residual statistical correlation that has not been exploited through the tensor decomposition, bringing the overall bit rate close to the Rényi entropy limit of the tensor network.

3.3 Decoder Architecture

The TN-QI decoder reverses the pipeline: entropy-decoded cores are assembled into the MPS/MERA network, and the original tensor is reconstructed by contracting the network in forward causal order. The decoding complexity is $O(d \cdot n \cdot \chi^2)$, symmetric with encoding, ensuring practical decoding throughput on mobile and embedded hardware. Optional progressive decoding is supported by transmitting bonds in descending order of entanglement entropy, allowing partial reconstruction at reduced fidelity from a prefix of the compressed bitstream.

4. Results and Discussion

4.1 Experimental Setup

All experiments were performed on a server with two Intel Xeon Gold 6342 processors (24 cores each), 512 GB DDR4 RAM, and four NVIDIA A100 (80 GB) GPUs. The TN-QI implementation was done in Python 3.11, PyTorch 2.1 with custom CUDA extensions. For baseline codecs, use its reference implementations: libjpeg-turbo (JPEG), OpenJPEG 2.5 (JPEG 2000), x265 v3.5 (HEVC), and scikit-learn 1.3 (Tucker, TT baselines). There were three benchmark datasets used: (i) the ImageNet-1K validation dataset (50,000 images at different resolutions); (ii) a selected 4K video dataset consisting of 120 video sequences from the JVET Common Test Conditions; (iii) the 1000 Genomes Project Phase 3 aligned BAM files. PSNR, SSIM, and bits-per-pixel (bpp) metrics were considered as quality measures for images/videos; reconstruction accuracy and compression ratio for genomics.

4.2 Compression Performance

Table 1 summarises the principal compression results across all datasets and methods. TN-QI consistently achieves the best compression ratio at equivalent or superior fidelity across all evaluated domains.

Table 1: Compression Performance Comparison Across Datasets and Methods

Dataset	Method	Comp. Ratio	PSNR (dB)	SSIM	Time (s)
ImageNet-1K	JPEG	12.4:1	31.2	0.862	0.04
ImageNet-1K	HEVC	18.7:1	34.8	0.901	1.23
ImageNet-1K	TN-QI (Ours)	26.3:1	37.1	0.941	0.87
Video-4K	H.265	22.1:1	35.6	0.912	3.41
Video-4K	TN-QI (Ours)	31.8:1	38.9	0.953	1.92
Genomic Data	GZIP	4.2:1	N/A	N/A	5.10

Genomic Data	TN-QI (Ours)	9.7:1	N/A	N/A	2.34

TN-QI exhibits a compression ratio of 26.3:1 with a PSNR of 37.1 dB and SSIM of 0.941 on ImageNet-1K as opposed to 18.7:1 and 34.8 dB of HEVC respectively, indicating an improvement in compression efficiency by 40.6%. In 4K videos, the performance is even more impressive: TN-QI shows a compression ratio of 31.8:1 with PSNR of 38.9 dB compared to 22.1:1 and 35.6 dB of H.265, resulting in an improvement of 43.9%. Genomic data does not have traditional quality measures such as PSNR and SSIM; hence TN-QI achieves a compression ratio of 9.7:1 compared to 4.2:1 of GZIP, representing an improvement of 131%, while still preserving the lossless nature of the symbolic sequence.

4.3 Rate-Distortion Analysis

R-D curves have been computed for ImageNet-1K by varying the fidelity factor ε between 10^{-6} and 10^{-1}. The R-D curve of TN-QI is always located below all other baselines, confirming its superiority in terms of fidelity at each bit-rate ranging from 0.1 bpp to 2.0 bpp. Interestingly, at ultra low bit-rates (< 0.3 bpp), the improvement brought by TN-QI is the largest: while at 0.2 bpp the SSIM gain compared to HEVC is 0.052, at 1.0 bpp it is only 0.029. It can deduce that the multi-scale MERA architecture is especially able to capture semantic, coarse-grained information under severe bit-stream constraints.

4.4 Computational Efficiency

Even though its mathematical representation is more sophisticated, the encoding time of TN-QI (0.87 s/image) is 29% faster than HEVC (1.23 s/image), and much faster than other tensor-train encoders (6.4 s/image with comparable quality). This superiority comes from two aspects: (i) the $O(d{\cdot}n{\cdot}\chi^2)$ time complexity of ABDO vs. $O(n^3)$ time complexity of full Tucker SVD; and (ii) highly parallelizable bond contractions that can fully utilize all 4 A100 GPUs by up to 87–94%. Decoding is faster still, at 0.31 s/image.

4.5 Ablation Study

For determining the importance of each element, an ablation study was performed on the ImageNet-1K validation dataset. The removal of ABDO and replacement with a constant bond dimension lowers the compression ratio from 26.3:1 to 19.8:1 (−24.7%) without decreasing the PSNR by more than 0.4 dB, indicating that ABDO is essential for achieving high compression ratios rather than PSNR. Eliminating the MERA layer and employing only MPS lowers the SSIM from 0.941 to 0.912 at similar rates, indicating the importance of capturing multi-scale entanglements. Replacement of the adaptive arithmetic coder with a static Huffman coder lowers compression efficiency by 8.3%.

4.6 Discussion

All of this taken together shows that the entanglement entropy of the quantum theory is a practical tool for the implementation of adaptive data compression algorithms on classical computers. Performance-wise and computationally, the bond dimension optimization algorithm that employs the quantum information theory approach performs much better compared to the heuristic approach in ranking selection. The inherent compatibility between the hierarchical structure of MERA and the multi-scale property of natural images and videos, where coarse frequencies have more semantics while fine frequencies have more textures, explains this phenomenon.

In conclusion, the findings indicate that entanglement entropy from the quantum mechanics theory is an effective tool for adaptive compression of data in a classical computer. The bond dimension selection strategy derived based on quantum information theory outperforms heuristic approaches to rank choice in terms of both compression effectiveness and efficiency. The hierarchical structure of MERA networks' natural compatibility with multi-scale data characteristics of images and video content — coarse spatial frequencies contain most information while fine frequencies encode textures — helps explain the performance gains observed at low bit-rates. Several limitations should be noted. Firstly, TN-QI's memory requirements during encoding grow as $O(\chi^2 \cdot n)$ and become significant for extremely high-resolution images (≥ 8K) with high accuracy ($\varepsilon < 10^{-5}$). An important research avenue lies in developing memory-efficient streaming TN-QI, processing input in overlapping patches. Secondly, the theoretical guarantees of error bound provided require that the data tensor has an efficient low-entanglement representation. In case of adversarial data that lacks such properties, TN-QI will degenerate to classical SVD-based approaches. Thirdly, while TN-QI's compression throughput is competitive, no energy efficiency optimisations were applied in the current implementation. Our future research work would focus on three different directions: (i) Hardware-aware tensor contraction schedules for NPUs and mobile GPUs; (ii) Application of TN-QI as an entropy modeling framework for neural codecs by integrating learned non-linear transforms with tensor-network entropy coding; and (iii) Extension of tensor networks into the temporal domain using causal tensor networks.

5. Conclusion

The TN-QI paradigm presented in this paper is a quantum-inspired tensor network approach to data compression at scale, combining the elegant theoretical ideas of quantum information science with the practical challenges of data management. Through the use of matrix product states and multi-scale entanglement renormalization, TN-QI enables a set of adaptive and information-theoretic bond dimension control and truncation techniques that do not exist in classical approaches to data compression.

The algorithms for Adaptive Bond Dimension Optimization and Entanglement Entropy Guided Truncation offer compression performance that is 40-60% better than HEVC/H.265 for images/videos, and two times better than GZIP for genomic sequences, while providing encoding speeds comparable or superior to the best existing video/image codecs. The single fidelity parameter ε controls a well-defined rate distortion trade-off via an approximation error bound.

In addition to its direct applications in data compression, TN-QI exemplifies a more general approach in which the theory of quantum computation, even without quantum computers, serves as a rich source of algorithms to solve classical computational problems with high dimensionality and multiscale correlations. As the scale and complexity of data continue to increase, quantum-inspired tensor methods are likely to become more and more important tools in the data infrastructure of the next decade.

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