Potential of Distributed Circuits for Mitigating Quantum Image Noise

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***Abstract*—The rapid advancement of quantum information science is reshaping communication technologies, yet it also introduces unique challenges, particularly from quantum noise channels that significantly degrade circuit-based quantum image encodings. Here, we design and investigate a distributed quantum circuit architecture to mitigate channel noise effects in quantum-based representations of classical images. We evaluate the approach across multiple noise models using the structural similarity index measure (SSIM) and demonstrate that increasing the number of quantum circuit nodes significantly enhances image quality. Our results highlight the potential of distributed quantum circuits to support scalable and resilient quantum image processing.**

***Index Terms*—quantum noise channel, quantum noise mitigation, distributed quantum circuit**

I. Introduction

Encoding classical images into quantum states is a key pursuit in quantum computing and communication, leveraging quantum parallelism and entanglement for advanced data representation. However, inherent system noise, such as decoherence, operational faults, and environmental coupling, remains a major obstacle to preserving the fidelity of quantum image encoding and decoding.

Traditional encoding schemes, such as basis, amplitude, and angle encoding, often exceed the current simulation limits [1, 2]. For instance, encoding a 32×32 image using basis encoding demands 32×32×8 qubits, far beyond the 30-qubit capacity of the Qiskit QASM simulator. Additionally, methods like QSMC and OQIM generate deep circuits as data size increases, leading to reduced execution efficiency and computational overhead. These limitations present a compelling opportunity for innovation. Inspired by recent advancements in distributed quantum architectures [3], we explore how distributed quantum circuits can expand the scalability of quantum image encoding. Moreover, our aim is to deepen the understanding of how distributed quantum circuits can effectively mitigate the noise introduced by quantum channels. Through this contribution, we hope to highlight their potential as a scalable and resilient solution for quantum image processing.

The remainder of this extended abstract is organized as follows: Section II describes our proposed methods and the experimental setup, Section III presents visual and quantitative analysis, and Section IV concludes with the main findings and future directions.

II. Approach

A. Noise Embedded Quantum Image Encoding

We use the amplitude encoding method to encode data into amplitude coefficients based on their coordinates. In the context of image representation, the encoding is defined by the following equation:

$$|f\rangle = \sum c_{i,j}\,|k\rangle\,, \quad c_{i,j} = \frac{F_{i,j}}{\sum (F_{i,j})^2}, \tag{1}$$

where $F_{i,j}$ denotes the pixel value at position (i, j). In order to generate a valid quantum state, we first flatten the image from a size of $m \times n$ to $1 \times mn$, compute the coefficients, and assign them to $|k\rangle$ using the Qiskit state preparation circuit.

Some examples of embedded image when we introduce quantum channel noise using only a single quantum node are shown in Fig. 1. We find that the images exhibit a pattern similar to Gaussian noise, distorting objects in the image space.

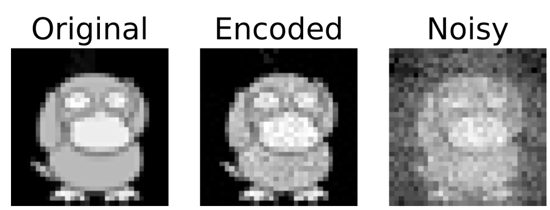

Fig. 1: Amplitude encoded images with amplitude damping quantum channel. The left, center and right, respectively, represents original, encoded and noisy encoded images.

B. Distributed Circuit in Image Encoding

In order to apply a distributed circuit approach to the image, we divide the entire circuit across multiple quantum nodes. With this approach, we are shifting the computational load from time complexity to space complexity. By doing so, our approach reduces the depth of the circuit, which is often inflated by multi-controlled operations and the decomposition of complex gate sets. These depth-heavy components might typically require an extended execution time on quantum hardware, and partitioning the circuit helps to alleviate these inefficiencies. Specifically, we divide the data into several blocks and encode each partition on separate quantum circuit nodes (Qnodes) that can be run parallel on multiple quantum processors or sequentially on a single quantum processor. The parallel execution of the circuit is illustrated in Fig. 2. In the figure, k denotes the input size of the data in one block, and j indicates the number of Qnodes.

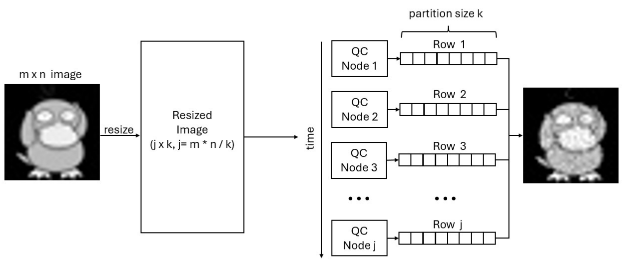

Fig. 2: Distributed Circuit Diagram. Quantum circuits can be executed in parallel across multiple quantum processors by leveraging a distributed architecture.

C. Noise Evaluation

In order to statistically analyze how the distributed circuit mitigates channel noise in embedded images, we use the structural similarity index measure (SSIM). The SSIM is defined as

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}, \tag{2}$$

where μ denotes the mean value of pixels. The terms σ_x^2 and σ_y^2, respectively, represent the sample variances calculated from individual windows of x and y. The sample covariance between these windows is denoted by σ_{xy}. To ensure numerical stability when the denominator is small, the constants c_1 and c_2 are introduced. These constants are functions of the dynamic range L of the pixel values. Specifically, c_1 and c_2 are defined as

$$c_1 = (k_1 L)^2, \quad c_2 = (k_2 L)^2, \tag{3}$$

where $k_1 = 0.01$ and $k_2 = 0.03$ are two default constant coefficients.

III. Results

The main results are shown in Fig. 3. We find that when we increase the number of Qnodes, the noise begins to overlap with the underlying features of an image. In particular, when the distributed Qnodes are fixed at $j = 32, 64, 128$, noise seems to converge near the image center, as shown in the inset of Fig. 3 . Larger Qnode counts further suppress channel-induced and encoding-related noise. Noise reduction becomes more pronounced as we scale quantum resources. We have also evaluated performance under various noise channels and observed consistent noise-mitigation behavior.

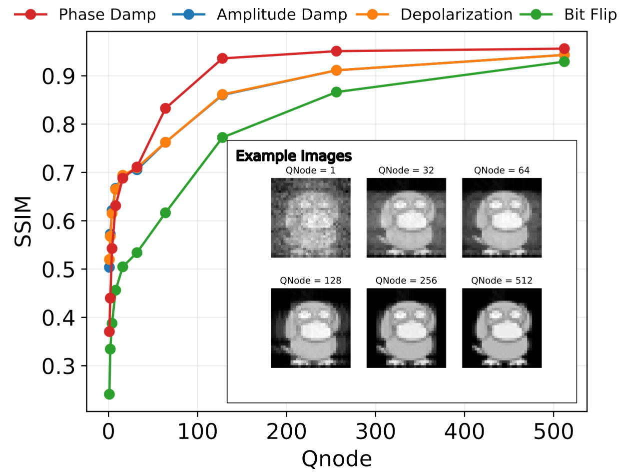

Fig. 3: Results and Comparisons Across Noise Models. We analyze results under multiple quantum noise models. As the number of quantum circuit nodes (Qnode) increases, noise artifacts diminish. In higher-node configurations, noise either merges with image features or is significantly suppressed. Example images at various Qnodes are shown in the inset.

IV. Discussion

In this paper, we observe an interesting phenomenon arising from the use of distributed circuits: As the number of distributed Qnodes grows, noise is progressively suppressed. As outlined in Section II, the method trades time complexity for space complexity. It partitions the quantum circuit across multiple nodes. This may reduce qubit connectivity constraints. It also removes redundant multi-controlled gate operations. As a result, increasing the number of quantum nodes effectively mitigates noise. Our approach and the result point to a promising path forward. It suggests that distributed quantum circuits could become a powerful tool for denoising quantum-encoded images and enhancing communication fidelity.

In future work, we plan to implement our approach on real quantum hardware. We also aim to explore more resilient encoding and processing schemes to significantly mitigate noise during quantum embedding and data transmission within the quantum regime.

References

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