Turning Quantum Noise on its Head: Using the Noise for Diffusion Models to Generate Images

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1. RESEARCH MOTIVATION

In this work, we propose positively using noise from quantum computers, which is currently viewed as a hindrance for performing useful computation, instead of simulated noise to train generative image diffusion models, which have two primary advantages:

- **True Noise Generation.** A key quality of random quantum fluctuations is that they are independent of human input. Current means of generating noise in diffusion models are pseudo-random, meaning that randomness is simulated using human-defined algorithms.
- **Parallel Noise Generation.** In quantum computers, each quantum bit (or qubit) has random fluctuations, so we can use multiple quantum bits to generate randomness in parallel. To parallelize noise generation classically, we would need to use more resources, which is not needed in quantum computers.

Our approach, *Quantum Image Noise-based Generative Diffusion Models* (QINGDM), utilizes these benefits of quantum noise.

2. BACKGROUND WORK

On the topic of using quantum noise for generative diffusion models, little published literature exists. Some work attempts to optimize quantum decoherence noise or use quantum circuits instead of neural networks to generate new images [2, 3]. However, no existing literature provides a technique based on quantum noise tailored for image generation with benchmark results, which this work contributes.

3. THE APPROACH

We propose a novel framework for training generative image diffusion models using quantum decoherence to add noise to images. As depicted in Fig. 1, our approach can be broken into three main steps. For each digit class, we randomly sample 500 images, and we use PCA followed by angle embedding to encode each image in a quantum circuit. We then add noise via quantum gates and run the circuit on quantum hardware. Finally, we obtain a noisy image via the marginal distribution from each qubit and train a diffusion model.

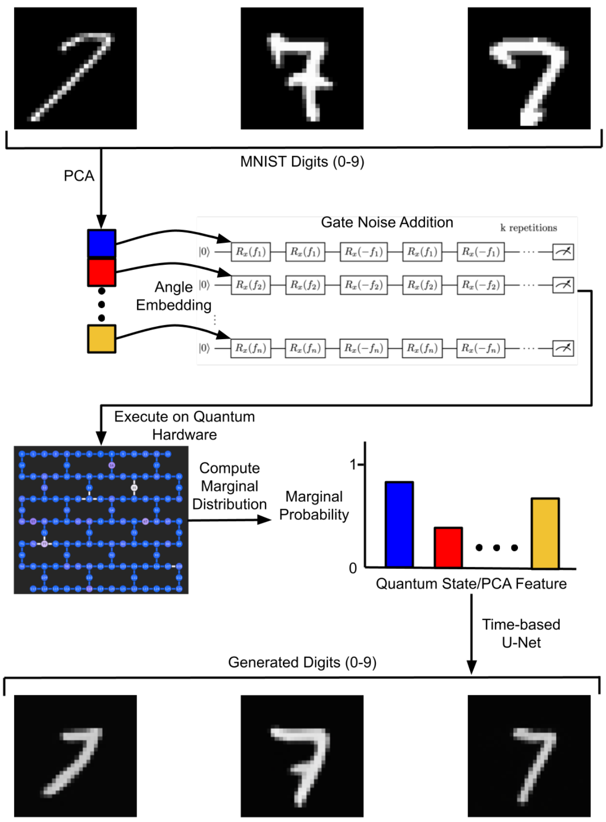

Figure 1: We present a three-step approach: (1) perform angle embedding, (2) add noise via quantum gates, and (3) obtain noisy images to train a diffusion model.

Noisy Quantum Circuit Architecture. For each qubit q_i, we add a gate $R_x(\theta_i)$, which makes $P(q_i = |0\rangle) = cos^2(\frac{\theta_i}{2})$. We then add pairs of $R_x(\theta_i)$ and $R_x(-\theta_i)$ gates to qubit q_i. These gates rotate q_i by θ_i and then by $-\theta_i$, which effectively apply no net rotation to q_i. However, each gate adds quantum noise to the qubit, so by applying more gates, we add more noise. We then run the quantum circuits on IBM Nazca, a 127-qubit superconducting quantum machine.

Extracting Noisy Images. Given the measured probability distribution, our goal is to obtain the image encoded in the quantum circuit. To do so, we first compute the marginal probabilities for each qubit: $P(q_i = |0\rangle) =$

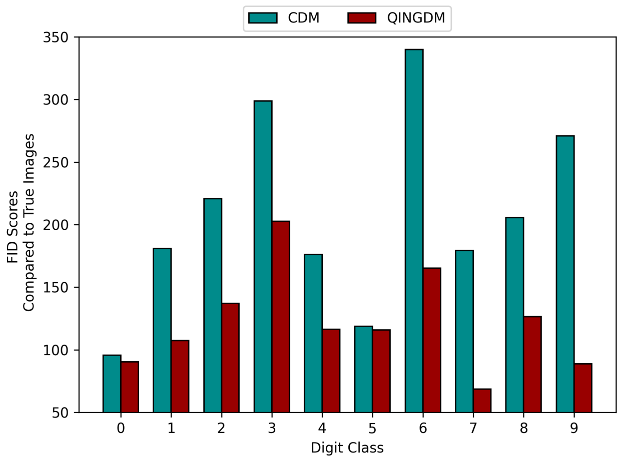

Figure 2: We plot the FID scores *(lower is better)* for QINGDM compared to CDM for digits 0 through 9.

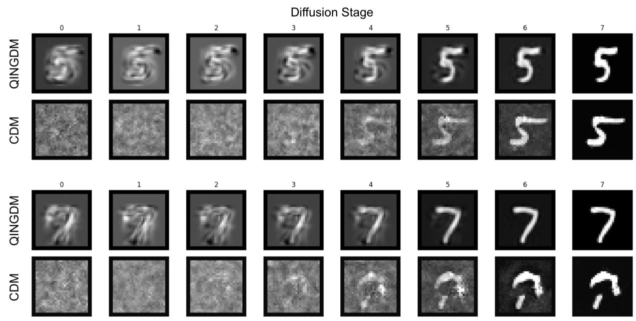

Figure 3: We plot the reverse diffusion process for both QINGDM and CDM on digits 5 and 7.

$\sum_{s=0}^{2^{127}} P(s \mid q_i = 0)$, where s represents a measured quantum state. We then note that $\theta_i' = 2 * arccos(\sqrt{P(q_i = |0\rangle)})$ by our angle embedding, rescale θ_i' to be in our feature range, and perform inverse PCA to construct our generated image.

4. THE RESULTS

QINGDM achieves an average Fréchet-Inception Distance (FID) [1] score of 121.9 across 10-digit classes using 5000 generated images. For comparison, we trained diffusion models using computer-generated noise, which we call Classical Diffusion Models (CDM). The FID scores of QINGDM and CDM for digits 0 through 9 are plotted in Fig. 2. In this plot, we see that the FID scores for QINGDM are lower than those of CDM for all digit classes due to the noise training process. If we analyze Fig. 3 comparing the reverse diffusion process of QINGDM and CDM, we see that QINGDM generates a realistic 5 similar in quality to that of CDM. We also see that QINGDM generates a realistic 7 while CDM generates separate components, reflecting a significant improvement in generated image quality.

5. ACKNOWLEDGEMENTS

I would like to thank Prof. Tirthak Patel at Rice University for his mentorship and advice throughout this project. I would also like to thank IBM Quantum for providing us use of their superconducting quantum computers which made our experiments possible.

6. REFERENCES

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