Hybrid Quantum-Classical Generative Adversarial Network for Patch-Based Image Generation

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***Abstract*—Quantum generative adversarial networks (QGANs) have attracted increasing attention for their potential to surpass classical generative models by leveraging the expressive power of parameterized quantum circuits (PQCs). However, in the current noisy intermediate-scale quantum era, the implementation of fully quantum algorithms is hindered by hardware limitations, restricting most existing approaches to low-resolution generated image. To address this challenge, we propose a hybrid quantum-classical generative adversarial network for patch-based image generation. Our method employs dual PQC-based generators that decompose images into structured patches, while local and global classical discriminators jointly capture local details and preserve global structural coherence. This design addresses scalability limitations of existing QGANs and mitigates patch-boundary artifacts, thereby enabling high-resolution image generation on hardware with restricted qubit counts. Experimental results validate the effectiveness of the proposed method, demonstrating improvements in image fidelity over existing baselines, and providing insights into the influence of qubit count on generative performance.**

Keywords—Quantum-classical generative model, quantum machine learning, image generation

I. Introduction

The advent of quantum computing has introduced algorithms with the potential to address classically intractable problems. Based on this foundation, quantum generative adversarial networks (QGANs) have attracted increasing attention, as they exploit the intrinsic probabilistic nature of quantum mechanics to explore broader and more diverse solution spaces than classical one. The advantages of various QGAN architectures over their classical counterparts have been demonstrated both theoretically and experimentally [1]. However, within the noisy intermediate-scale quantum (NISQ) regime, the practical realization of fully quantum algorithms is constrained by limitations, including restricted qubit counts, limited circuit depth, and susceptibility to noise, which pose significant challenges for their practical deployment.

To mitigate these challenges, hybrid quantum-classical approaches have emerged as a promising paradigm, leveraging the expressive power of parameterized quantum circuits (PQCs) while maintaining the stability and scalability of classical frameworks [2],[3],[4],[5],[6]. For example, Situ *et al.* [2] introduce a hybrid quantum-classical QGAN that generates discrete data distributions to mitigate the gradient vanishing issue faced by classical GANs. Tsang *et al.* [5] introduce the patch quantum Wasserstein GAN (PQWGAN) that employs multiple quantum sub-generators to improve the quality of generated images. In [3] and [6], the authors propose hybrid quantum-classical generative frameworks that combine PQC-based generators with classical molecular analysis, demonstrating superior capability in exploring chemical spaces compared to classical models. However, most of the existing efforts focus on low-resolution image synthesis that scaling to higher resolutions remains challenging due to the exponential circuit complexity associated with large image dimensions. Patch-based frameworks may introduce artifacts at patch boundaries, impairing visual consistency in high-resolution image generation.

In this study, we propose a hybrid quantum-classical GAN for patch-based image generation that leverages dual PQC-based generators to decompose images into structured patches, while employing both local and global classical discriminators to jointly enforce fine-grained realism and holistic consistency. This design alleviates scalability bottlenecks of existing QGANs, reduces boundary artifacts, and achieves seam-consistent high-resolution image synthesis. Experimental results demonstrate our approach outperforms existing hybrid quantum-classical models, achieving better Fréchet Inception Distance scores. Furthermore, we evaluate the impact of varying qubit numbers on model performance, providing insights into scalability under hardware constraints.

II. Proposed Hybrid Quantum-Classical Generative Adversarial Network

As shown in Fig. 1, we propose a hybrid quantum-classical generative adversarial framework in which two parameterized quantum circuits jointly serve as the generator. A latent vector z, sampled from a prior distribution, is mapped into two independent PQCs. To reduce the circuit depth and enhance scalability, the image generation task is spatially decomposed into two patches that corresponds to the left and right halves of the target image. The first PQC synthesizes the left patch, while the second PQC generates the right patch. Each PQC operates on a set of qubits applies a sequence of variational quantum gates parameterized by trainable variables θ, and produces measurement outcomes that are further post-processed into pixel intensities. The outputs from both PQCs are concatenated to form a complete image.

To ensure both local fidelity and global consistency, three classical discriminators are employed. The first two discriminators, D_1 and D_2, evaluate the realism of the left and right halves, respectively. In addition, an aggregate discriminator D_a receives the reconstructed full image and determines its overall coherence with respect to the true data distribution. Adversarial training is conducted by minimizing a standard GAN loss, where the PQCs are updated through gradient-based optimization using the feedback from all discriminators.

This decomposition strategy enables the quantum generator to capture localized structures with reduced circuit

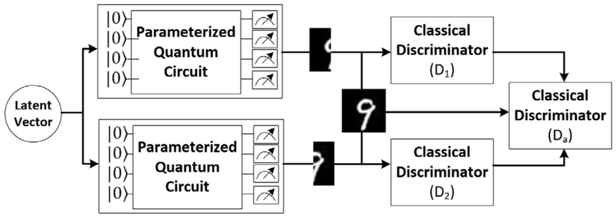

Figure 1. Hybrid quantum-classical generative adversarial network

complexity, while the aggregate discriminator enforces holistic consistency. The proposed design thus leverages the representational advantages of quantum circuits in high-dimensional spaces, while relying on classical discriminators for robust adversarial learning.

III. Performance Evaluation

To verify effectiveness of the proposed method, the MNIST [7] and KMNIST [8] benchmark datasets of image size 28 × 28 are used in the evaluations. All experiments are conducted on a workstation with an Intel Core i7 CPU and an NVIDIA GeForce RTX 4070 GPU. The hybrid quantum-classical components are implemented in Python using PyTorch and PennyLane.

The comparison involves several baselines and related methods. The first is a purely classical GAN (CGAN) with no quantum components, and two hybrid quantum-classical methods, PQWGAN [5] and QGAN-HG [3]. The proposed approach, referred to as QCGAN-P, is implemented with different numbers of qubits. QCGAN-P(2), QCGAN-P(4), and QCGAN-P(6) represent hybrid architectures with two, four, and six qubits respectively. Model performance was measured using the Fréchet Inception Distance (FID), where lower values indicate higher fidelity and closer alignment between generated and real distributions.

As shown in Fig. 2, the results on the MNIST dataset show that the hybrid quantum-classical models achieve significantly lower values. QCGAN-P with two, four, and six qubits exhibits steady improvements over training epochs and converges near 500. In Fig. 3, experiments on the KMNIST dataset reveal a similar results. The QCGAN-P models also outperform the classical baseline, stabilizing near 500 to 600. These findings demonstrate that the integration of quantum circuits enhances the generative ability of GANs and QCGAN-P provides the most favorable trade-off between convergence speed, stability, and output fidelity across both datasets

IV. Conslusions

This paper proposes a hybrid quantum-classical generative adversarial network for patch-based image generation, addressing the scalability and fidelity challenges of QGANs. By employing dual PQC-based generators with both local and global discriminators, the framework effectively reduces circuit complexity while maintaining image coherence. Experimental results on MNIST and KMNIST datasets demonstrate that the proposed method consistently outperforms classical GANs and existing hybrid approaches, achieving superior FID scores with improved convergence stability. Moreover, evaluations across different qubit counts provide valuable insights into the trade-offs between quantum resource allocation and generative performance. These findings highlight the potential of hybrid quantum-classical models for practical high-resolution image generation, and suggest promising directions for extending quantum-enhanced generative learning to broader domains in the future.

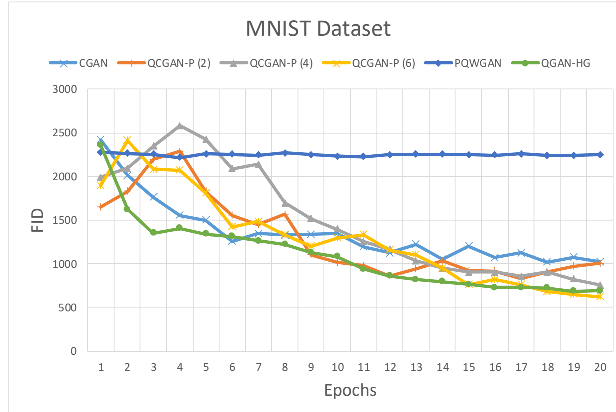

Figure 2. FID Performance of QC-GAN Variants on MNIST Datasets

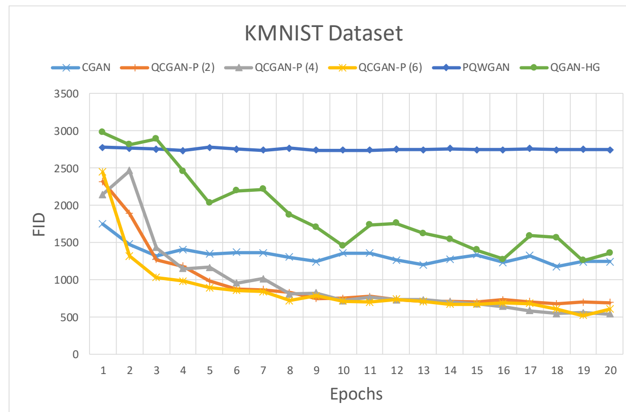

Figure 3. FID Performance of QC-GAN Variants on KMNIST Datasets

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