Hybrid Quantum-Classical Style Transfer (Student Abstract)

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Abstract

This paper proposes a novel quantum style transfer (QST) in hybrid quantum-classical computing. QST leverages quantum computing's ability to process high-dimensional data efficiently. Our approach aims to decrease both inference time and complexity while maintaining performance, presenting a viable solution that enhances the scalability and efficiency of image generation technologies.

Introduction

As image generation has advanced significantly with the advent of deep learning technologies, style transfer has become particularly influential (Archana Balkrishna 2024). The style transfer is a technique that applies the artistic style of one image to the content of another, creating a new, stylized image. This innovative approach has catalyzed a renaissance in artistic digital media, enabling artists and designers to blend creative visions in unprecedented ways (Yu and Zhou 2024). Convolutional neural network (CNN) has played a pivotal role in extracting deep semantic features from images, thereby significantly enhancing the effectiveness in style transfer. However, a major limiting factor for previous approaches has been the lack of image representations that explicitly encode semantic information, thereby hindering the separation of image content from style (Gatys, Ecker, and Bethge 2016). To address this, quantum convolutional neural network (QCNN) leverages its scalable representation capabilities due to qubits, which can exist in multiple states superposition (Lisnichenko and Protasov 2023). This allows for a more nuanced and complex representation of images, potentially capturing subtle artistic nuances that are difficult for classical CNN. Motivated by this, we propose a novel quantum style transfer (QST) in hybrid quantum-classical computing. Through style transfer visualization, we demonstrate the possibility of QST serving as a feasible solution for classical style transfer.

Hybrid Quantum-Classical Style Transfer

The QST in hybrid quantum-classical computing comprises three main components: i) inputs and outputs, ii) downsampling and upsampling, and iii) residual connection, forth by (Radford, Metz, and Chintala 2015) as illustrated in Fig. 1. The yellow box represents the quantum convolution layer of QCNN. For style transfer the input and output are both color images of shape $3 \times 256 \times 256$. In our style transfer approach, we replace classical CNN with QCNN to handle in-network downsampling and upsampling. Quantum convolution involves three key processes: encoding, which transforms classical data into quantum state; the variational quantum circuit (VQC), which processes the qubits using trainable quantum operations; and decoding, which converts the processed quantum state back into a classical data form suitable for further classical tasks (Park et al. 2024). Through the quantum convolution strategy, we can leverage its scalable representation capabilities, with the quantum supremacy provided by superposition and entanglement. The network architecture includes two stride-2 convolutions for downsampling and two stride-1/2 convolutions for upsampling. Despite the input and output sizes remaining consistent, this setup enhances computational efficiency by allowing the use of larger networks without additional cost and expands the effective receptive field. This increase in the receptive field facilitates more extensive and coherent

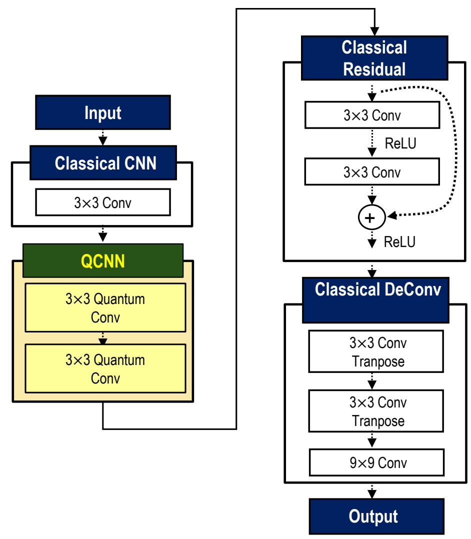

Figure 1: QST in hybrid quantum-classical computing.

(a) Input image (b) Style image (c) CNN (d) QCNN

(e) Input image (f) Style image (g) CNN (h) QCNN

Figure 2: Visualization of style transfer with transformer based on CNN(c, g) and QCNN(d, h).

image modifications during the style transfer process. Lastly, we use residual connection to maintain structural similarities between input and output images.

Experimental Results

To simulate QST, we employ Intel i9-10990k, NVIDIA Titan X (2ea), and RAM 128GB. Python v3.8.10 and quantum computing simulation libraries (*e.g.*, torchquantum v0.1.5 (Wang et al. 2022), pytorch v1.8.2 LTS). QCNN based transformer in this paper is designed 1×1, 2×2, and 3×3 quantum convolutions, employing 1-qubit, 4-qubit, and 9-qubit QNNs, respectively. For designing the VQC in each QCNN, the *U3CU3* layer in `torchquantum` is utilized. The baseline model of style transfer is adopted from (Mina 2018).

We verify the feasibility of QST in hybrid quantum-classical computing through style transfer visualization. Fig. 2 represents the results of the style transfer with comparative convolution strategies. We observe that QCNN successfully transform the style of input images Fig. 2(a,e), under all the style images Fig. 2(b,f). Here, QCNN shows different features from that of classical CNN. With the results in Fig. 2(d, h), we observe that the style is transformed when utilizing our QCNN even though these transformed images are different from that of classical CNN in Fig. 2(c, g).

Concluding Remarks

Our experiments confirm the viability of QST within a hybrid quantum-classical framework, revealing distinct advantages over traditional methods. QCNN offers unique transformations that diverge from classical CNN outputs, enhancing image diversity. Despite these advancements, challenges remain in achieving real-time processing and expanding to more diverse domains, necessitating further development in quantum computing efficiency and robust algorithm design.

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