Entanglement-aware Quantum Error Mitigation for Complex Quantum Circuits

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***Abstract*—Quantum computing is highly sensitive to environmental noise, leading to quantum errors—defined as deviations between measured and expected outcomes. To mitigate these errors, various Quantum Error Mitigation (QEM) methods have been proposed; however, they show limited performance in complex quantum circuits due to error-propagation caused by entanglement. In this paper, we propose a novel entanglement-aware QEM method that simultaneously considers circuit architecture and entanglement information. Our method achieves high QEM performance by encoding entanglement strength as self-attention bias and edge features, thus effectively capturing error-propagation patterns. Experimental results on complex quantum circuits demonstrate that the proposed method outperforms existing QEM approaches and achieves effective error mitigation across various noise types.**

***Index Terms*—quantum error mitigation, entanglement, quantum computing**

I. Introduction

Unlike classical computing, which utilizes bits that can only represent binary states of 0 or 1, quantum computing employs qubits that exhibit a quantum phenomenon called superposition, allowing them to exist in both states simultaneously. Among qubits, another phenomenon called entanglement [1] enables quantum computing to perform exponentially faster calculations for specific problems [2]. Each qubit collapses probabilistically to either 0 or 1 upon measurement, requiring multiple measurements to obtain reliable results. However, quantum computing is highly sensitive to environmental conditions (e.g., temperature, electromagnetic fields, vibrations), which often leads to noisy measurement outcomes [3]. These deviations between noisy results and expected outcomes are called quantum errors, which represent unwanted phenomena in quantum circuits.

To minimize these discrepancies, Quantum Error Mitigation (QEM) methods have been proposed to estimate the expected results without quantum errors [4]. Existing methods employ classical noise models [5], [6] to statistically estimate the expected results. However, these methods suffer from considerable inference time when applied to QEM [7]. To address this limitation, machine learning-based QEM methods have been proposed recently [8], [9]. Nevertheless, these methods exhibit low accuracy when applied to complex quantum circuits [10].

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The significant entanglement generated by the complex quantum circuit architecture propagates errors across the entire circuit, making it difficult to estimate the expected results [11]. Therefore, an effective QEM method that considers both the circuit architecture and entanglement information is required.

In this paper, we propose an entanglement-aware QEM method that can effectively mitigate quantum errors by utilizing entanglement information as self-attention bias and edge features. Specifically, our proposed method transforms a quantum circuit into a DAG and encodes entanglement information as an entanglement-aware weight matrix, while representing quantum states (from single-qubit gates) and quantum correlations (from two-qubit gates) as edge features. Through these encodings, high attention weights are assigned to areas with strong entanglement, effectively capturing error-propagation patterns. Subsequently, the entire graph information is aggregated to the Learnable Global Aggregation (LGA) node via the transformer. This aggregated result is then combined with the noisy output and fed into a regression layer to estimate the expected result.

To validate the effectiveness of our proposed method, we compared the mean absolute error (MAE) against existing QEM methods using simulated datasets of 6-qubit quantum circuits under a representative noise condition (i.e., incoherent environment). We further evaluated the method using simulated datasets of 6-qubit and 15-qubit quantum circuits under various noise conditions, including mixed noise, and IBM Fake Providers. The results show that our proposed method outperforms existing approaches and successfully mitigates quantum errors under various conditions.

The main contributions of this paper are as follows:

1) Proposing a novel entanglement-aware quantum error mitigation (QEM) method that utilizes the quantum circuit architecture and entanglement information.
2) Proposing an entanglement-aware weight matrix and edge features that effectively leverage quantum states and correlations.
3) Validating our proposed method's error mitigation performance across various quantum circuit types and noise conditions.

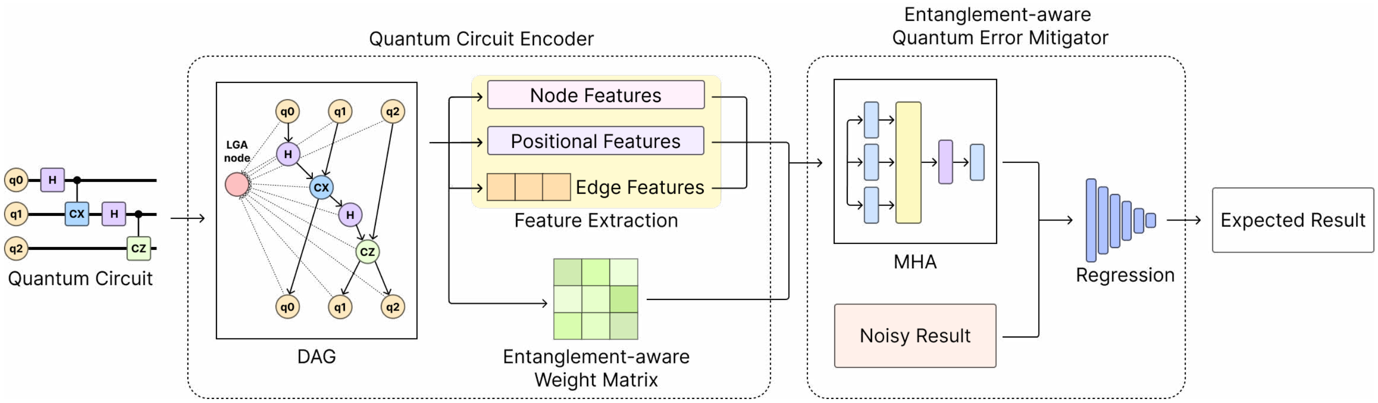

Fig. 1. An overview of our proposed method.

This paper is organized as follows. Section II covers the background, Section III presents our proposed method, Section IV describes our experimental results, and the conclusion is offered in Section V.

II. Background

Quantum computing is a computational approach that leverages the principles of quantum mechanics to process information. Unlike classical computers, which operate on bits that represent either 0 or 1, quantum computers use quantum bits (qubits), which can exist in a superposition of both states simultaneously [12], [13]. Moreover, two or more qubits can become quantum mechanically correlated through a phenomenon known as entanglement—where the quantum state of each qubit is inseparably linked with others due to prior interaction. This entanglement persists regardless of the spatial separation between the qubits [14]. Entangled states can be classified into various types based on the circuit architecture, such as Bell states, GHZ states, W states, and cluster states [15].

Quantum computers perform computations by manipulating qubits via quantum circuits, which comprise qubits, quantum gates, and measurement operations. The sequential application of quantum gates enables controlled transformations of qubit states [9], [16]. Effective quantum computation requires sufficiently strong interactions between qubits and precise control over environmental factors [17]. However, in practical implementations, quantum systems are subject to decoherence—a phenomenon in which quantum state coherence is lost—introducing uncontrollable disturbances that degrade computational accuracy and stability. To store and process quantum information reliably, quantum systems must be isolated from external noise as much as possible. However, complete isolation remains technically unfeasible with current hardware. Consequently, various quantum error mitigation (QEM) techniques are being actively studied to reduce noise and improve computational accuracy [17], [18].

QEM is a post-processing technique that statistically corrects for noise present in measurement outcomes after the execution of quantum circuits. It enables the estimation of ideal, noise-free expectation values by analyzing the results of multiple executions of noisy circuits [19], [20]. Rather than directly eliminating noise, QEM infers the expected result from repeated runs of logically equivalent circuits. A representative approach, Zero-Noise Extrapolation (ZNE) [21], involves executing several instances of a quantum circuit under varying noise levels. The corresponding expectation values are then used to construct an extrapolation curve, from which the zero-noise value is estimated [22].

III. Proposed Method

In this paper, we propose a novel entanglement-aware QEM method to address the performance degradation of existing QEM approaches in complex quantum circuits. Inspired by prior work [9], we use a DAG transformer on both circuit architecture and quantum entanglement information. For training, we use as ground truth the measurement results obtained by appending the inverse circuit to the original circuit and measuring the composite circuit, which yields results without quantum errors.

The Quantum Circuit Encoder (QCE) transforms the quantum circuit into a DAG and extracts circuit architecture and entanglement information from this DAG, which are encoded as input vectors for Multi-Head Attention (MHA). In the Entanglement-aware Quantum Error Mitigator (EQEM), the Learnable Global Aggregation (LGA) node aggregates the entire circuit through MHA and is then fed into a regression layer along with the noisy result to estimate the expected result. Through this process, our proposed method can achieve high QEM performance even in complex quantum circuits by jointly utilizing circuit architecture and entanglement information. The details of our proposed method are presented as follows.

A. Quantum Circuit Encoder

1) DAG: The Quantum Circuit Encoder (QCE) receives circuit architecture and transforms it into a DAG. Each quantum gate is represented as a node, while quantum states (from single-qubit gates) and quantum correlations (from two-qubit gates) are represented as edges. During the DAG transformation process, in addition to mapping all gates in the quantum circuit to nodes, LGA node is introduced. The LGA node is initialized with random parameters and aggregates both circuit architecture and entanglement information through attention operations with all nodes during the MHA process.

2) Feature Extraction: Feature extraction is performed utilizing the previously transformed DAG. The extracted features are as follows: node features, positional features, and edge features. Node features encode the gate types, operating qubits, and gate parameters. Positional features encode the execution order of each gate and the positional information of qubits. However, unlike these two features, edge features cannot be encoded using only circuit architecture. As edge features represent the continuous flow of gate operations on qubits, they require quantum state information at that specific moment. To obtain this, Pauli operators [23], commonly used to measure quantum states, are utilized. For edges originating from single-qubit gates, the states of that qubit are measured and encoded using Pauli operators X, Y, Z. For edges originating from two-qubit gates, the quantum correlations between the two-qubit are measured and encoded using two-qubit Pauli operators XX, YY, ZZ. These encoded edge features reflect the quantum state and quantum correlations after each operation, thereby providing the EQEM with error-propagation patterns across the entire circuit. Finally, the three encoded features are utilized as input vectors for the MHA process.

3) Entanglement-aware Weight Matrix: The entanglement-aware weight matrix assigns weights according to the strength of entanglement. It takes the DAG architectures as input and automatically assigns weights using a predefined dictionary-based on each gate or gate combinations. Gates that generate strong entanglement (e.g., CX, CZ) are assigned values close to the normalized maximum of 1, whereas gates that generate weak entanglement (e.g., SWAP, RX) are assigned values near the normalized minimum of 0. The resulting matrix is added as a bias during self-attention in MHA, thereby assigning higher attention weights to gates with strong entanglement. At such gates, errors from one-qubit propagate to entangled qubits, and stronger entanglement results in faster error-propagation and greater vulnerability to noise. By assigning higher attention weights to these gates, the entanglement-aware weight matrix effectively provides the MHA with information about error strength and propagation paths.

B. Entanglement-aware Quantum Error Mitigator

As shown in Fig. 1, proposed Entanglement-aware Quantum Error Mitigator (EQEM) is trained to estimate expected results without quantum errors utilizing features extracted from the QCE. During the training process, noisy results containing quantum errors from environmental factors during quantum computing execution are obtained through circuit execution and measurement. The encoded features from the QCE are then input into the MHA, where information from all nodes is aggregated to update the LGA node. During this process, self-attention is performed utilizing the entanglement-aware weight matrix as bias. The updated LGA node is combined with the noisy result and passed to a regression layer to estimate the expected result. All parameters are optimized by minimizing the MSE loss between the estimated result and the ground truth (i.e., results without quantum errors). During the inference process, noisy results are similarly obtained from quantum circuit execution and measurement. These results are processed through the trained EQEM, which outputs the expected result with mitigated quantum errors.

TABLE I
COMPARISON BETWEEN OUR PROPOSED METHOD AND EXISTING QEM METHODS.

Metric	**Noisy**	**ZNE [21]**	**GTranQEM [9]**	**Ours**
MAE	0.1494	0.0733	0.0906	**0.0657**

IV. EVALUATION

To evaluate the effectiveness of our proposed method, we conducted evaluations based on the following research questions:

- **RQ#1**: How effectively does our proposed method mitigate quantum errors compared to existing QEM methods?
- **RQ#2**: How effectively does our proposed method mitigate quantum errors under various types of quantum circuits and noise conditions?

A. Experimental Settings

1) Dataset Generation: For training and testing, we generated two types of quantum circuit datasets: (1) Random circuit dataset: Composed of 6-qubit or 15-qubit circuits with 100 gates. Gates were randomly selected from Pauli-X, Pauli-Y, Pauli-Z, Hadamard, RX, RY, RZ, CNOT, CZ, SWAP, and RZZ, along with their operating qubits, order, and qubit indices within each circuit. To ensure circuit complexity, we included more than 30 layers; (2) Trotterized circuit dataset: Composed of 6-qubit or 15-qubit circuits with 630 gates simulating quantum device time evolution. Gates were arranged in a brick-like staggered pattern to efficiently implement interactions between close qubits [24]. To ensure circuit complexity, we set the trotter steps to 21 and included 221 layers. For the ground truth, we used the measurement results obtained by measuring the composite circuit, which is the addition of the inverse circuit to the original circuit. The dataset was split into training, validation, and testing sets in an 8:1:1 ratio, with all measurements conducted using 1,000 shots.

2) Noise Conditions: We employed three noise conditions to evaluate the performance of our proposed method. (1) Incoherent noise: noise condition including depolarization error, (2) Mixed noise: noise condition combining Pauli-X error, depolarization error, and readout error, and (3) IBM's Fake Providers (Providers) noise: noise condition simulated on quantum devices provided by IBM, reflecting realistic noise profiles of actual devices.

TABLE II
PERFORMANCE EVALUATION OF OUR PROPOSED METHOD, UNDER VARIOUS TYPES OF QUANTUM CIRCUITS AND NOISE CONDITIONS USING MAE.

Dataset	Noise	Noisy	Ours
6-qubit Random	Incoherent	0.0296	**0.0216**
6-qubit Trotter	Incoherent	0.1494	**0.0657**
	Mixed	0.1585	**0.0304**
	Providers	0.2784	**0.1035**
15-qubit Random	Incoherent	0.0282	**0.0196**
15-qubit Trotter	Incoherent	0.1494	**0.0657**

3) Comparing Methods: To validate the QEM performance of our proposed method, we compared it with ZNE [21] and GTranQEM [9]. ZNE is a widely employed classical method in QEM, which estimates expected results without quantum errors by artificially amplifying noise levels and extrapolating the results. GTranQEM is a state-of-the-art machine learning-based QEM method.

4) Evaluation Metric: To quantitatively evaluate the performance of our proposed method, we employed Mean Absolute Error (MAE). MAE is defined as the average of absolute differences between ground truth $\hat{y}_i$ and expected result y_i across all circuits N. Lower MAE values indicate that expected results are closer to the ground truth (i.e., expected results without quantum errors).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{y}_i - y_i|$$

5) Implementation Details: All experiments utilized one NVIDIA GeForce RTX 3090 GPU environment, Python 3.9.23, PyTorch 2.0.1, and Qiskit 1.4.3.

B. Evaluation Results

(RQ#1) Effectiveness of our proposed method compared to existing QEM methods. To validate RQ#1, we selected incoherent noise condition, commonly employed for QEM performance evaluation, as the benchmark noise condition. We compared the QEM performance of our proposed method with ZNE [21] and GTranQEM [9] on 6-qubit trotterized circuits using the MAE.

As shown in Table I, in the 6-qubit trotter circuit under incoherent noise condition, the MAE of raw noisy result that includes quantum errors was 0.1494. ZNE achieved a MAE of 0.0733, while GTranQEM achieved a MAE of 0.0906. Our proposed method achieved a MAE of 0.0657, outperforming ZNE and GTranQEM by 0.0076 and 0.0249, respectively.

These results demonstrate that our proposed method enables effective QEM by utilizing the entanglement-aware weight matrix and quantum states (and correlations) in complex quantum circuits where considering error-propagation is crucial.

(RQ#2) Effectiveness of our proposed method under various types of quantum circuits and noise conditions. To validate RQ#2, we evaluated the performance of our proposed method under incoherent noise, mixed noise, and provider noise settings with varying number of qubits using the MAE.

As shown in Table II, our proposed method maintained significantly lower MAE than raw noisy results regardless of noise conditions and circuit architectures, demonstrating effective QEM performance. Our proposed method achieved MAE reduction of 0.0080 in 6-qubit random circuit, under incoherent noise condition. In 6-qubit trotter circuits, our proposed method achieved MAE reduction of 0.0873, 0.1281, and 0.1749, under incoherent, mixed and providers noise conditions, respectively. Similarly, in much complex 15-qubit random and trotter circuits, our proposed method achieved MAE reduction of 0.0086 and 0.0837, under incoherent noise condition. These results demonstrate that our proposed method effectively mitigates errors regardless with quantum circuit types and noise conditions.

V. CONCLUSION

In this paper, we propose a novel entanglement-aware QEM method that effectively mitigates quantum errors by utilizing both circuit architecture and entanglement information. Our proposed method transforms a quantum circuit into a DAG and encodes entanglement strengths as self-attention biases, while representing quantum states and correlations as edge features. Through these encodings, our proposed method effectively captures error-propagation patterns that appear across the entire circuit. Experimental results demonstrate that our proposed method outperforms existing QEM methods in complex quantum circuits and effectively mitigates errors under quantum circuits that have various noise conditions and number of qubits.

For future work, we aim to conduct evaluations on large-scale complex circuits with more qubits and gates using actual IBM quantum devices to further validate the practicality of our proposed method in real quantum computing environments.

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