Quantum-Enhanced Spiking Neural Networks with Temporal Encoding

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Abstract

This article discusses the integration of quantum computing into neural network architectures to address limitations in classical spiking neural networks (SNN). Incorporating quantum computing techniques to encode temporal dependencies within quantum circuits, the study aims to enhance the capabilities of SNN. It introduces a method leveraging quantum systems' parallelism and high-dimensional state spaces to encode temporal information from classical signals into a quantum framework relying on angle encoding and using two successive rotation gates. While the quantum circuit faced challenges in reconstructing complex temporal patterns, the hybrid quantum-classical model significantly improved the efficiency and accuracy of processing temporal data using trigonometric functions. This advancement in temporal encoding within quantum circuits enables quantum systems to handle intricate temporal information effectively.

Keywords: Quantum Neuromorphic Computing, Spiking Neural Networks, Temporal Encoding, Long Short-Term Memory

1 Introduction

Spiking Neural Networks (SNN) are a significant advancement in neural network models that closely mimic the bio-physiological processes of the human brain. Unlike traditional artificial neural networks that rely on continuous activations, SNNs process information dynamically through discrete events known as 'spikes' [1]. These binary events are triggered in response to stimuli, and their precise timing is crucial to network functionality. Operating on the principle of temporal coding, SNN encode information based on spike timing, making them well-suited for handling time-dependent data. The temporal aspect of spike processing enables SNNs to model neural behaviors such as synaptic plasticity and dynamic responses to sensory input [2]. Due to their stochastic and temporally sensitive nature, classical SNNs excel at processing noisy data. However, challenges arise in training SNNs due to the stochastic and non-differentiable nature of spiking signals, complicating weight adjustments during training [3, 4, 5].

To address these challenges, a novel gate-based quantum neuromorphic approach is introduced in this study to enhance the encoding of temporal dependencies within quantum circuits. Using trigonometric functions, the model demonstrates improved processing, learning, and prediction of temporal data sequences. The quantum neuromorphic model effectively captures temporal patterns, showcasing enhanced performance in handling sequence data. This approach exploits the intrinsic properties of quantum computing, such as superposition and entanglement, to encode temporal information at a high-dimensional level beyond what classical methods can achieve [6]. The study highlights the potential of quantum techniques to complement traditional neural architectures in managing complex temporal patterns. While the initial results are promising, they primarily establish the feasibility of the approach in a controlled setting, setting the stage for further empirical investigations.

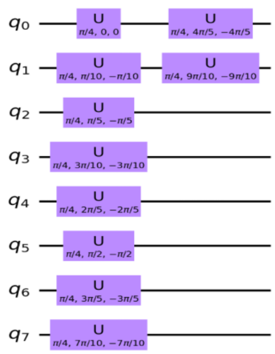
2 Quantum Spiking Neural Networks

Our research employs a hybrid quantum-classical strategy to enhance the capacity of neuromorphic systems to encode and process information more effectively. We have developed two versions of our model as shown in Figure 1: one utilizing a pure quantum circuit and the other integrating Long Short-Time Memory (LSTM) layers to reinforce the processing of temporal data [7].

2.1 Without LSTM Layers

- **Spike Generation:** Trigonometric functions such as sine, cosine, etc., are evaluated at time points t_i to simulate periodic signals. Spike Count Generation: Using a Poisson process, spike counts are generated from these function values: $spike\_count(t_i) \sim Poisson(\lambda = |f(t_i)| \times k)$ where k is a scaling factor that adjusts the intensity of the spikes.

- **Quantum Circuit Encoding:** A quantum circuit is initialized with a number of qubits equal



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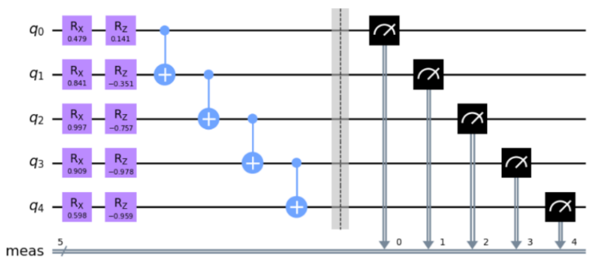

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Figure 1: Quantum circuit (a) without LSTM (b) with LSTM

to the time points. Temporal encoding using universal (U) gates (amplitude and phase calculation): $amplitude = \pi(spike\_count(t_i)/max(spikes))$, $phase = 2\pi t_i$.

- **Gate Application:** Each qubit undergoes a transformation by the U gate, which is parameterized by the calculated amplitude and phase to encode the temporal information: $U(amplitude, phase, -phase, i(mod)qubit)$.

- **Signal Reconstruction:** The encoded quantum state is simulated using a state vector simulator to obtain the quantum state of the system. The original signal is reconstructed by converting the state vector amplitudes into probability values, which represent the encoded temporal data.

2.2 With LSTM Layers

2.2.1 Quantum Circuit with R_X and R_Z Gates

- **Dynamic Gate Adjustment:** Instead of a universal gate, specific R_X (Rotational along X-axis) and R_Z (Rotational along Z-axis) gates are utilized. The parameters of these gates are dynamically adjusted to encode temporal information. The amplitude and phase adjustments are made as follows:

$$R_X(\text{normalized amplitude}),\ R_Z(\text{temporal phase})$$

- **Entanglement:** Controlled-NOT (CNOT) gates are strategically placed between qubits to create entanglement. This setup enhances the ability of the quantum circuit to capture correlations between different temporal points, significantly improving the encoding of temporal dependencies within the quantum framework.

2.2.2 Integration of LSTM Layers

- **Feature Vector Formation:** Outputs from the quantum circuit are converted into a feature vector. This vector represents the probabilistic outcomes of quantum measurements, which are then used as inputs for the LSTM layers.

- **Temporal Pattern Learning:** The LSTM network is configured with multiple layers to effectively learn and predict complex temporal patterns. The network architecture includes: 1. LSTM layer with 100 units, returning sequences to maintain temporal information across the network. 2. Dropout layer with a rate of 0.3 to prevent overfitting during training. 3. A final dense layer that synthesizes the LSTM outputs into a prediction representing either the amplitude or classification of the temporal signal.

2.2.3 Output and Evaluation

- **Model Training:** The LSTM model is trained using the quantum-encoded features against actual signal values, focusing on effectively learning the temporal dependencies.

- **Performance Evaluation:** After training, the outputs of the LSTM model are compared with the original signal data to assess the accuracy and performance of the model. This evaluation helps to understand how well the temporal patterns and dependencies are captured and predicted by the hybrid model.

3 Simulation Results

Our findings, as reported in Figure 2 reveal a distinctive performance difference between the two models tested. In the quantum circuit without LSTM layers, the model adeptly reconstructed sine and cosine functions, which have continuous and smooth transitions. However, it struggled with non-continuous functions like the step function. This limitation stems from the basic setup of the quantum circuit, which can adequately capture gradual changes but not abrupt shifts.
In contrast, the introduction of LSTM layers significantly enhanced the model's performance across all tested functions. The LSTM-enhanced model not only continued to

perform well with smooth functions such as sine, cosine, and Gaussian but also showed remarkable improvement in handling non-continuous functions like the step function. The LSTM layers provided the model with the ability to learn and predict complex temporal patterns, thus maintaining greater fidelity in signal reconstruction across a broader range of function types. This demonstrates the robustness and versatility of the hybrid model in capturing and predicting intricate temporal dynamics inherent in various signal types.

4 Conclusion

Our study has successfully showcased the effective implementation of encoding temporal dependencies within quantum circuits, leading to a significant enhancement in the processing capabilities of SNN. The results of our research suggest that quantum-enhanced neuromorphic computing has the potential to surpass the limitations of traditional computational models, offering substantial advancements in managing and predicting temporal sequences. This breakthrough in robustly encoding temporal information within quantum systems sets the stage for the development of more sophisticated models capable of addressing even more complex problems in the future.

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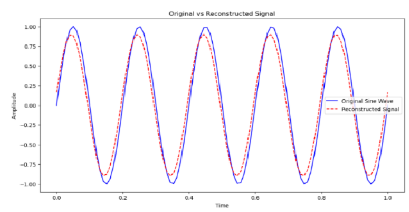

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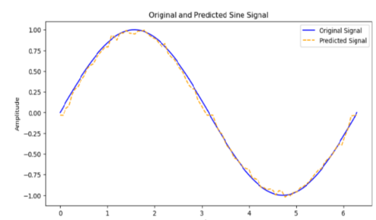

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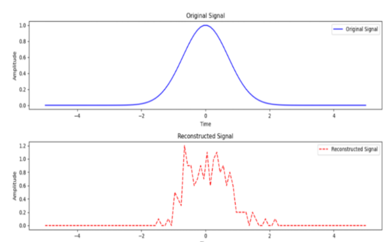

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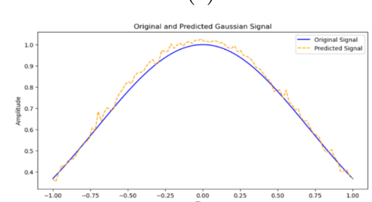

(d)

Figure 2: Sine function (a) without LSTM (b) with LSTM and Gaussian function (c) without LSTM (d) with LSTM.