

# Quantum Neuromorphic Vision: Event-Based Analog Quantum Graph Neural Network

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**Abstract.** Asynchronous event-based graph neural networks (AEGNNs) have recently emerged as an efficient paradigm for processing sparse and high-temporal-resolution data from neuromorphic cameras. Here, we propose quantum analog AEGNNs (QA-AEGNNs), a novel framework to implement AEGNNs on neutral-atom quantum computers. The streaming event data, produced by a neuromorphic camera, is mapped to an array of trapped neutral atoms. Each atom represents a graph node (event), and is positioned such that geometric proximity reflects the spatio-temporal neighborhood of events. The native Rydberg Hamiltonian of the quantum processor is programmed to mirror the message-passing computations of the AEGNN, with atomic qubit states serving as node feature embeddings and inter-atom interactions realizing graph edges. Overall, QA-AEGNNs leverage the continuous Hamiltonian dynamics of neutral-atom quantum systems to natively execute event-based graph computations with potential accuracy improvements over classical methods.

**Keywords:** Quantum kernel methods · Analog quantum computing · Graph neural networks · Neuromorphic data processing

## 1 Introduction

Event-based cameras asynchronously detect per-pixel brightness changes with microsecond temporal resolution and low power consumption, generating sparse streams of events that each encode a spatial location, a timestamp, and a polarity (see Fig. 1) [1]. This neuromorphic, i.e., brain-inspired, operation is attractive for high-speed tracking and robotics, but its sparsity and asynchrony pose a substantial challenge for traditional processing architectures, which are designed for dense, synchronous data [2, 3].

Asynchronous event-based graph neural networks (AEGNNs) address this challenge by representing the event stream as a dynamic spatio-temporal graph evolving frame-by-frame [4]. As seen in Fig. 1(a), each event produced within a sliding window becomes a node in a three-dimensional graph, using the event’s

space-time coordinates  $X_i = (x_i, y_i, t_i)$  as its location and its direction of intensity change, i.e., polarity,  $p_i \in \{+1, -1\}$  as its feature, with an edge connecting two nodes that are close in space and time. A message-passing graph neural network (MP-GNN) propagates information across the graph [5]. Finally, the features extracted by the MP-GNN are fed to a predictive model.

MP-GNNs are known to be limited in terms of expressivity, suffering from limitations such as over-squashing and over-smoothing [6, 7]. Quantum graph neural networks (QGNNs) are potentially more expressive than MP-GNNs, as the quantum dynamics implement the direct mixing of information beyond local neighborhoods [8, 9]. Neutral-atom processors offer an ideal substrate for the implementation of QGNNs [10].

The atomic geometry in a neutral atom computer can be rearranged via optical tweezers, while a programmable Rydberg Hamiltonian governs the evolution of the system via a global laser drive, local detunings, and distance-dependent van der Waals interactions [11]. The ability to rearrange the atomic topology is key for efficient graph processing, as placing atoms so that their physical distances mirror the desired connectivity allows for a natural graph embedding into the quantum hardware.

This work introduces *quantum analog AEGNN* (QA-AEGNN), which maps event streams onto a neutral-atom array and programs the native Rydberg Hamiltonian to leverage the continuous quantum dynamics to natively perform event-based graph processing.

## 2 Quantum Analog Asynchronous Event-based Graph Neural Network (QA-AEGNN)

QA-AEGNN slides a window across the event stream. For each window, the model carries out three steps, mirroring the computation of AEGNN [4].

1. **Event quantum embedding:** Each event inside a time frame is assigned a separate atom. The atomic coordinates are chosen via either a direct 3D coordinate mapping or a 2D linear projection, so that atoms that correspond to neighboring nodes sit within the Rydberg blockade radius. The binary polarity can be encoded either into the initial state of the atom or into the local detuning coefficients [12].

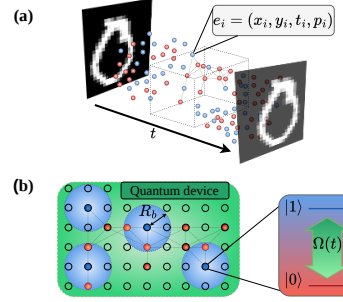


Fig. 1: (a) An event-driven sensor produces a stream of events. (b) In the proposed QA-AEGNN, events are mapped to atoms within a neutral-atom quantum computer.

2. **Quantum graph processing:** The quantum system evolves under the Rydberg Hamiltonian for a tunable duration. The global laser drive, together with the detuning terms, provides a way to mix information between states, while the van der Waals interaction component couples adjacent nodes, replicating the aggregate function in AEGNN.
3. **Node embedding readout:** To extract features, atoms are measured in the computational basis. The resulting features are postprocessed, and then passed to a classical classifier, such as a support vector machine. To yield a final decision, a majority rule strategy is applied over previously observed windows.

### 3 Experiments

We evaluate QA-AEGNN against the classical AEGNN [4], deployed with the same number of parameters, on the synthetic graph classification task described in [9]. The graphs to be distinguished are subgraphs of a 2D triangular lattice, and are generated by random walks over discrete time that preferentially follow either a honeycomb or a kagome template, with a weight  $w$  controlling how strictly each walk adheres to its class template. A larger weight  $w$  yields harder problems. We set weight  $w = 0.1$  and we run 50 trials, each with 200 graphs of  $N = 100$  events (80% training, 20% test). Two noise models are considered: state-preparation-and-measurement (SPAM) model with a false-positive rate  $\epsilon_p = 0.025$  and a false-negative rate  $\epsilon_n = 0.1$ , as well as a quantum noise model, with relaxation and dephasing times with  $1/T_1 = 0.01 \mu\text{s}^{-1}$  and  $1/T_2 = 0.22 \mu\text{s}^{-1}$ , on top of the SPAM errors.

As illustrated in Fig. 2, QA-AEGNN maintains substantially higher test accuracy than the classical AEGNN across all noise conditions. The SPAM-only model essentially matches the noiseless model, and even with added relaxation and dephasing the accuracy degrades only modestly while still clearly exceeding the classical baseline. Finally, the accuracy gap between the quantum-noise model and the noiseless model stays roughly stable across windows, indicating an advantage even in the presence of realistic noise conditions. The robustness is partly attributable to the majority-rule aggregation over windows, which dilutes the effect of per-window noise. More analysis on different datasets, encoding schemes, and different noise settings can be found in [13].

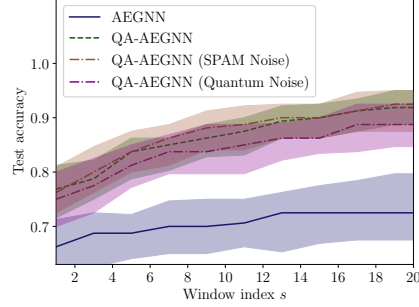


Fig. 2: Evolution of median test accuracy on the synthetic graph classification task [9], comparing AEGNN and QA-AEGNN on different noise models.

## References

1. G. Gallego, et al.: Event-based vision: A survey. *IEEE transactions on pattern analysis and machine intelligence*, 44 (2020).
2. H. Zhao, X. Yang, C. Deng, and J. Yan: Dynamic reactive spiking graph neural network. In *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 38, no. 15 (2024).
3. L. Sun, Z. Huang, Q. Wan, H. Peng, and P. S. Yu: Spiking graph neural network on riemannian manifolds. *Advances in Neural Information Processing Systems* 37 (2024).
4. S. Schaefer, D. Gehrig, D. Scaramuzza: AEGNN: Asynchronous event-based graph neural networks. In *Proc. CVPR* (2022).
5. M. M. Bronstein, J. Bruna, T. Cohen, and P. Veličković: Geometric deep learning: Grids, groups, graphs, geodesics, and gauges. *arXiv preprint arXiv:2104.13478* (2021).
6. S. Akansha: Over-squashing in graph neural networks: A comprehensive survey. *Neurocomputing* 642, 130389 (2025).
7. T. K. Rusch, M. M. Bronstein, S. Mishra: A survey on oversmoothing in graph neural networks. *arXiv preprint arXiv:2303.10993* (2023).
8. L.-P. Henry, S. Thabet, C. Dalyac, L. Henriet: Quantum evolution kernel: Machine learning on graphs with programmable arrays of qubits. *Phys. Rev. A* 104, 032416 (2021).
9. B. Albrecht et al.: Quantum feature maps for graph machine learning on a neutral-atom quantum processor. *Phys. Rev. A* 107, 042615 (2023).
10. S. Thabet, R. Fouilland, M. Djellabi, I. Sokolov, S. Kasture, L.P. Henry, and L. Henriet: Enhancing graph neural networks with quantum computed encodings. *arXiv preprint arXiv:2310.20519* (2023).
11. L. Henriet, L. Beguin, A. Signoles, T. Lahaye, A. Browaeys, G.O. Reymond, and C. Jurczak: Quantum computing with neutral atoms. *Quantum* 4, 327 (2020).
12. M. Kornjača et al.: Large-scale quantum reservoir learning with an analog quantum computer. *arXiv preprint arXiv:2407.02553* (2024).
13. K. Sotirov, S. Acheche, A. A. Gentile, O. Simeone: Analog Quantum Asynchronous Event-Based Graph Neural Network. *arXiv preprint arXiv:2606.11000* (2026).