Quantum-Enhanced Motif Detection in Calcium Imaging Data using Variational Quantum Classifiers

Team: Q-Connectome

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1. Neural Problem Framing

We analyze calcium imaging data from Bowen et al., a microscopy technique that records fluorescent intensity reflecting neuronal activity across large populations (~1000+ neurons). The dataset includes 20 sessions of 1-second auditory stimuli with interleaved silent periods (6–10 seconds).

Target Phenomena:

- **Motif-level co-activation patterns**: Spatial and temporal patterns of neural activity evoked during each 1s auditory stimulus.
- **Community structure**: Functionally related clusters of neurons with shared activation profiles, potentially tied to spatial proximity.

Goal: Identify and characterize recurring motifs and neuronal subnetworks that emerge during and across stimulus events. These insights help elucidate how distributed cortical circuits encode auditory input over repeated trials.

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2. Quantum Modelling Strategy and Theoretical Basis

We implement a **Variational Quantum Classifier (VQC)** in a hybrid quantum-classical framework to model short temporal segments of calcium imaging data. Our model aims to distinguish and learn recurring patterns of neural activation across repeated stimulus sessions.

Model Architecture:

- **Input**: PCA-reduced vectors from 1s-long windows aligned with auditory stimuli (or silence periods for control).
- **Quantum Embedding**: Neural features mapped into quantum states via Ry angle encoding.
- **Variational Circuit**: Alternating Ry layers and CNOT/CZ entangling gates form a trainable circuit.
- **Output**: Pauli-Z expectation values, passed into a classical decision function for motif classification or clustering.
- **Loss Function**: Supervised (cross-entropy) or unsupervised (contrastive loss), depending on availability of motif labels.

Theoretical Basis:

VQCs exploit quantum entanglement and high-dimensional feature spaces to efficiently capture complex temporal-spatial dependencies. This enables detection of nonlinear co-activation patterns not easily accessible through classical methods.

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3. Classical vs. Quantum Comparison Plan

We compare our VQC against:

- **LSTM (Long Short-Term Memory)** networks: Designed for sequential modelling of temporal dependencies.
- **Autoencoder + k-means**: For feature compression and unsupervised motif clustering.
- **Support Vector Machine (SVM)**: Standard classification model for flattened time windows.

Evaluation Metrics:

- **Adjusted Rand Index (ARI)**: Comparison to clustering based on known SC (structural cell-type) labels.
- **Silhouette Score**: Measures cluster quality.
- **Classification Accuracy**: Used where motif labels are known or synthetically introduced.
- **Motif Recurrence Consistency**: Evaluates temporal stability of discovered motifs across sessions.

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4. Data Preprocessing and Quantum Encoding Pipeline

Preprocessing Steps:

1. **Normalization**: $\Delta F/F$ for each neuron's trace. Optional Gaussian smoothing may be used to enhance signal clarity (though it was not part of the original Bowen pipeline).
2. **Time Windowing**: 1-second windows aligned with each auditory stimulus event.
3. **Dimensionality Reduction**: PCA to extract 10–15 dominant components.
4. **Scaling**: Normalize PCA outputs into $[0, \pi]$ for Ry embedding.

Quantum Encoding:

- **Qubit Mapping**: One qubit per PCA feature (10–15 qubits per instance).
- **Encoding**: $Ry(\theta)$ rotations apply for each feature.
- **Entanglement Strategy**: Linearly connected or fully connected topology, depending on expected feature coupling.

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5. Resource Requirements, Execution Plan, and Phase 3 Plan

Cloud Hardware and Software Platforms:

- **Quantum Devices**: IBM Heron r2, IonQ Aria-1.
- **Simulators**: Amazon Braket SV1/DM1.
- **Development Tools**: PennyLane with Lightning.qubit, Qiskit Runtime, and qBraid SDK.

Clarification on Results and Interpretation: The VQC does not directly indicate which specific neurons are active during a given 1-second window. Instead, it assigns each window to a "motif" class, a label representing the overall pattern of neural co-activation. When multiple such motif classes are discovered, we interpret them as corresponding to distinct clusters or types of activation. To understand the neuron-level contributors to each motif, one can review the PCA loadings or aggregate the raw calcium activity traces for windows assigned to the same motif. This enables a follow-up spatial analysis, using known x, y, z coordinates, to examine whether neurons participating in each motif are anatomically close or spatially dispersed.

Resource Estimates:

Feature	Estimate
Qubits Needed	10–15
Circuit Depth	15–25 layers
Runtime (Simulation)	< 10 seconds
Runtime (Cloud)	~1–2 minutes
Optimization Iterations	50–100

Phase 3 Plan:

- Apply the VQC to each stimulus-aligned window and track motif evolution across 20 sessions.
- Test robustness through synthetic noise injection.
- Extend to additional cortical layers or validate generalization across animals.

This framework offers a viable quantum-enhanced strategy for uncovering latent neural motifs and comparing their recurrence and structure to classical models.

References

- Bowen Z., Shilling-Scrivo K., Losert W., Kanold P. (2024). Fractured columnar small-world functional network organization in volumes of L2/3 of mouse auditory cortex.
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