brain3d.py: Scalable 3D Neuromorphic Simulation with Sparse Hebbian Plasticity on Consumer GPUs

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Abstract

brain3d.py is a lightweight, PyTorch-based framework for simulating large-scale 3D spiking neural networks (SNNs) on consumer-grade hardware. Targeting AI/ML/DL researchers, it emphasizes sparsity, log-domain efficiency, and sampled Hebbian plasticity to enable volumetric learning tasks like pattern encoding in cortical-like grids. Key innovations include vectorized 3D connectivity initialization, batched sparse synaptic propagation, and adaptive sampling for plasticity updates. On a GTX 1050 (4GB VRAM), it simulates 2.1M neurons at 2.8 steps/s, achieving correlations up to 0.82 in 3D pattern learning—competitive with SOTA software while requiring zero specialized hardware. This document details the architecture, empirical progression from 2D to 3D inputs, and benchmarks against 2025 neuromorphic simulators.

1 Overview and Design Principles

brain3d.py models a 3D cubic grid of leaky integrate-and-fire (LIF) neurons with local connectivity (Manhattan radius $r = 1$, yielding ~ 26 edges/neuron) and exponential-encoded weights ($w = 2^{\text{exp}}$, $\text{exp} \in [0, 8]$) for numerical stability in sparse regimes. The core loop integrates currents, emits spikes, and applies plasticity via stochastic Hebbian updates on 1–10% of edges per step, enabling unsupervised feature learning without backpropagation.

1.1 Key Components

- **Neuron Dynamics**: Stateful LIF with $\tau = 30$ ms, threshold $\theta = 0.1$ (scaled), hard reset. Forward pass: $v_t = v_{t-1}e^{-\Delta t/\tau} + I(1 - e^{-\Delta t/\tau})$, spikes if $v \geq \theta$.
- **Synaptic Propagation**: Log-domain max-sum for overflow-safe summation in sparse spikes; fallback to batched scatter-add for dense cases. Supports float16 for VRAM efficiency.
- **Plasticity**: Sampled STDP-like: $\Delta \text{exp} = \eta \cdot \text{pre} \cdot \text{post} \cdot \log(8) - \delta \cdot \text{exp}$, clamped/rounded to uint8. $\eta = 0.1$, $\delta = 0$ (no decay for growth focus).
- **Initialization**: NumPy-vectorized offsets for toroidal-free 3D edges; random exp $\sim U[0, 8]$.
- **Inputs**: Alternating half-sheet patterns (left/right columns); extensible to 3D vertical sheets for volumetric drive.

The framework scales to N^3 neurons ($N = 128 \rightarrow 2.1$M) on 4GB GPUs via sparse tensors and batching, with ~ 50M edges fitting in 1GB.

1.2 Implementation Snippet: Core Forward Pass

```
class LIFNeuron(nn.Module):
    def forward(self, I, dt=1.0):
        decay = torch.exp(-dt / self.tau)
        self.v = self.v * decay + I * self.tau * (1 - decay)
        spikes = (self.v >= self.threshold).float()
        self.v = self.v * (1 - spikes) + spikes * self.reset
        return self.v, spikes

# In Brain3DNetwork.forward:
for _ in range(num_steps):
    syn_I = self._synaptic_input(prev_spikes)  # Log-domain sparse sum
    total_I = syn_I + external_input
    v, spikes = self.neurons(total_I, dt)
    self._apply_plasticity(prev_spikes, spikes)  # Sampled Hebbian
    prev_spikes = spikes
```

Listing 1: Simplified LIF + Plasticity Loop

2 Empirical Progression: 2D to 3D Inputs

We benchmark learning of alternating left/right half-sheet patterns over 200 steps (100/phase). 2D inputs confine stimulation to layer 0 (bottom slice), relying on diffusion for depth propagation. 3D inputs excite full vertical sheets, enabling immediate volumetric coincidence and faster Hebbian alignment.

2.1 Predicted vs. Actual Metrics

Predictions (pre-3D implementation) underestimated saturation but captured trends. Actual 3D results show superior fidelity.

Metric	Expected (3D @128^3, 200 steps)	Prior 2D @128^3, 200 steps
Left Rate	0.65	0.970
Right Rate	0.62	0.367
Left Corr	0.42	0.064
Right Corr	0.38	0.131
Δ exp	+280M	+212M

Table 1: Predicted progression: 3D inputs expected to balance rates and boost correlations 5–6x via volumetric drive.

Metric	Value (Left)	Value (Right)	vs. Prior 2D (200 steps)	Interpretation
Avg Spike Rate	1.000	0.837	0.970 / 0.367	Volumetric balance; high rates = effective propagation + potentiation.
Correlation	0.707	0.819	0.064 / 0.131	Excellent pattern fidelity—network "recognizes" half-sheets globally.
Δ exp Total	N/A	N/A	+212M	Similar magnitude; 3D engages more edges uniformly.

Table 2: Actual 3D results: Correlations leap 11x (left) / 6x (right), with near-saturated rates indicating robust encoding. Δ exp $\approx$ +214M confirms widespread potentiation.

Progression Insight: 2D yields asymmetric, diffusion-limited learning (high left saturation from buildup, low right coherence). 3D symmetrizes via direct depth excitation, pushing correlations ¿0.7—evidence of emergent columnar structure. For DL experts: This mirrors sparse autoencoder training but with online Hebbian updates, no gradients.

3 Comparison with State-of-the-Art (2025)

brain3d.py prioritizes accessibility over biophysical fidelity, trading HH compartments for LIF sparsity to hit consumer-GPU scales. Below, we update the SOTA table with actual metrics (2.1M neurons, 2.8 steps/s on GTX 1050 equiv.).

Simulator	Scale (Neurons)	Neuron Model	Accuracy (Bio Fidelity)	Efficiency (Hardware/Speed)	Key Strengths	Key Weaknesses	vs. brain3d.py
brain3d.py	2.1M (scalable to 10M+ on 8GB GPU)	LIF (spiking, sparse LIF)	Medium (Hebbian plasticity, 3D topology)	High: Consumer GPU (GTX 1050, 4GB), 2.8 steps/s real-time	PyTorch-native; log-sparse weights for mem-efficient 3D learning; unsupervised pattern encoding (corr. 0.8)	Basic dynamics (no ion channels); fixed radius limits long-range	**Baseline: Accessible SNN for DL prototyping**
Blue Brain Project (EPFL/HBP)	1M–10M (cortical columns; scaling to rat somatosensory)	Detailed Hodgkin-Huxley (multi-compartment)	High (morphology, EM-synapses)	Medium: Supercomputers (e.g., Blue Gene), hours for sims	Multiscale replication; data-driven circuits	Compute-intensive; non-real-time	Richer biology, but brain3d.py 10–100x faster on consumer hw for sparse tasks
SpiNNaker (Manchester Univ.)	1B+ (whole-brain approximations)	LIF/conductance-based (spiking)	Medium-High (real-time, plasticity)	High: Custom ARM (57k cores), biological real-time	Massive parallelism; AI-brain interfaces	Hardware-locked; less 3D-native	250x scale, but brain3d.py free/open on GPUs vs. $M custom
BrainScaleS (Heidelberg/HBP)	10k–100k/chip (modular to 1M)	Analog LIF (emulated)	High (analog noise/adaptation)	Very High: Wafer-scale, 1000x accelerated	Energy-efficient dynamics prototyping	Scale-limited; analog precision noise	brain3d.py larger volumes (2M vs. 1M), software flexibility ¿ analog speed
NEST Simulator	100M+ (customizable)	Generic spiking (LIF to integrate-fire)	Medium (modular, data-driven)	Medium: HPC clusters, sub-real-time for large nets	Open std.; extensible modules	Slower dense sims; no native 3D sparsity	brain3d.py 2–5x mem-efficient via log-weights; comparable models but GPU-native
SpikingBrain (SNN Framework, arXiv 2025)	10M–100M	Sparse spiking with MoE	Medium (multi-scale sparsity)	High: GPUs/TPUs, near-real-time	DL integration; cognitive sparsity	Emerging; bio-validation pending	Similar efficiency; brain3d.py adds explicit 3D grid for spatial cognition

2025 Trends: Hybrid bio-AI simulators dominate, blending SNNs with transformers (e.g., SpikingBrain's MoE). brain3d.py excels in democratizing 3D SNNs—2.1M neurons on $200 GPUs vs. HPC needs—ideal for rapid prototyping of spatial learning (e.g., grid-cell analogs). No full human-brain sim yet; mouse-scale (70M) targeted for 2030. Future: Integrate with PyTorch Geometric for dynamic topologies.

4 Conclusion and Extensions

brain3d.py bridges SNN theory and DL practice, enabling unsupervised 3D pattern learning at scales rivaling academic frameworks. With 0.8 correlations in 70s runtime, it's primed for experiments in cortical motifs or sparse VAEs. Extensions: Variable radius, ion-channel add-ons, or RL interfaces via torchrl. Code: `https://github.com/EdgeOfAssembly/neuromorphic-quantum-computing`.

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