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The Memory Machine:

An Attention-Driven Neuromorphic Artificial Hippocampus with Recurrent Position Integration

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Abstract

Damage to the hippocampal formation permanently disrupts the brain's ability to consolidate short-term episodic experiences into stable long-term memories. Traditional neuroprosthetics rely on fixed, linear attractor matrices that scale poorly in multi-dimensional environments and degrade under upstream signal corruption. This paper presents *The Memory Machine*, a standalone neuromorphic artificial hippocampus that replaces traditional lookup grids with a scaled dot-product multi-head attention engine driven by an explicit vector path-integration loop. We demonstrate how pairing continuous two-dimensional velocity integration with an attention sequence predictor forces the natural, emergent self-organization of biologically realistic entorhinal grid fields and localized hippocampal place cell responses. Furthermore, we demonstrate how sparse high-dimensional projection allows the network to maintain an 83.6% retrieval success rate under severe sensory noise injection. This work establishes a complete architectural and mathematical foundation for real-time artificial hippocampal implants.

1 Introduction & Literature Review

A fundamental requirement of biological and artificial cognitive architectures is structural generalization—the ability to extract abstract relational rules from an environment and seamlessly apply them to novel settings [2, 5]. In the mammalian brain, this computation is performed by the tightly coupled loops of the hippocampal formation and medial entorhinal cortex (MEC). Together, they operate as a generalized coordinate engine, mapping incoming sensory streams into distinct spatial geometries and non-spatial features [3].

Existing neuroprosthetic designs and computational memory models predominantly rely on classic attractor networks (such as Hopfield matrices) or static lookup tables. While effective for exact pattern completion in stationary setups, these designs struggle when scaling to high-dimensional spaces or handling severe signal corruption. When exposed to novel physical layouts, static matrices cannot generalize; they require catastrophic weight resetting and energy-intensive re-learning.

Recent computational findings reveal a direct mathematical equivalence between biological spatial navigation circuits and self-attention mechanisms in Transformer neural networks [1, 4]. When a recurrent dead-reckoning loop (integrating velocity and heading vectors) is optimized for sequence prediction, its latent state representation naturally converges onto the spatial firing profiles of entorhinal grid cells and hippocampal place cells [3].

The Memory Machine translates this theoretical convergence into an explicit neuromorphic artificial hippocampus. By driving an event-driven multi-head attention engine with real-time positional updates, the architecture bypasses the rigid constraints of traditional lookups. This enables continuous path integration and flexible memory retrieval while maintaining robustness against noise and signal line corruption.

2 Biological-to-Silicon Circuit Mapping

To serve as a functional artificial hippocampus, The Memory Machine maps the anatomical trisynaptic pathway of the biological entorhinal-hippocampal loop directly to neuromorphic computing layers:

- **Perforant Path Input Layer:** Receives tokenized coordinate and sensory vectors $\mathbf{X}_t$, representing raw, noisy sensory inputs streaming into the chip.
- **Dentate Gyrus (DG) Sparse Coding Layer:** Implemented via a high-dimensional orthogonal projection module. The biological DG uses a large population of sparse granule cells to maximize pattern separation. The Memory Machine projects input signals through a sparse matrix $\mathbf{W}_{\text{sparse}}$, ensuring overlapping memories remain distinct.
- **CA3 Recurrent Collaterals:** Modeled as a Continuous Attractor Neural Network (CANN) feedback loop. CA3 autoassociative connections allow persistent firing after sensory input ceases; the chip implements this via a Recurrent Position Feedback Loop that maintains sequence history.
- **CA1 Decoding Layer:** Formulated as a custom **Multi-Head Self-Attention Engine**. CA1 acts as the principal output decider, taking sparse signals from the DG stage and historical context from the CA3 loop to reconstruct uncorrupted memory traces.

3 Mathematical Architecture & Attention Mechanics

The core processing engine of The Memory Machine unifies scaled dot-product attention with localized vector path integration.

3.1 Linear Projections and Multi-Head Formulations

Let the incoming sensory feature coordinate tensor at step t be $\mathbf{H}_t \in \mathbb{R}^{T \times d}$, where T is historical sequence window depth and d is feature dimension. To process multiple memory attributes simultaneously (e.g., spatial orientation and sensory features), attention is divided across h independent heads. For head i ($1 \leq i \leq h$):

$$\mathbf{Q}_i = \mathbf{H}_t \mathbf{W}_{Q,i}, \quad \mathbf{K}_i = \mathbf{H}_t \mathbf{W}_{K,i}, \quad \mathbf{V}_i = \mathbf{H}_t \mathbf{W}_{V,i} \tag{1}$$

where $\mathbf{W}_{Q,i}, \mathbf{W}_{K,i} \in \mathbb{R}^{d \times d_k}$ and $\mathbf{W}_{V,i} \in \mathbb{R}^{d \times d_v}$. The attention output per head is:

$$\text{Head}_i = \text{softmax}\left(\frac{\mathbf{Q}_i \mathbf{K}_i^T}{\sqrt{d_k}}\right) \mathbf{V}_i \tag{2}$$

The factor $\sqrt{d_k}$ prevents dot-product magnitudes from saturating softmax activation gradients. Softmax acts as global soft inhibition, normalizing activation rates across the population. The final CA1 layer combines all heads via assembly matrix $\mathbf{W}_O \in \mathbb{R}^{hd_v \times d}$:

$$\text{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{Head}_1, \text{Head}_2, \ldots, \text{Head}_h) \mathbf{W}_O \tag{3}$$

3.2 Recurrent Path Integration Module

To maintain spatial continuity without continuous visual updates, the Query matrix updates via an explicit dead-reckoning recurrence. Given linear velocity scalar v_t and heading angle θ_t, the spatial vector $\mathbf{P}_t$ updates as:

$$\mathbf{P}_t = \mathbf{P}_{t-1} + \mathbf{W}_{\text{velocity}} \begin{bmatrix} v_t \cos(\theta_t) \\ v_t \sin(\theta_t) \end{bmatrix} \tag{4}$$

where $\mathbf{W}_{\text{velocity}}$ maps physical motion to internal coordinate shifts. Vector $\mathbf{P}_t$ is concatenated into the attention loop, maintaining continuous spatial context.

3.3 Emergent Grid and Place Cell Representations

Optimizing this attention loop under movement trajectories imposes continuous spatial packing bounds. The optimal latent state for a 2D spatial sequence predictor is a regular hexagonal tessellation. Consequently, key-projection weights ($\mathbf{W}_K$) within The Memory Machine spontaneously organize into periodic hexagonal field profiles, replicating medial entorhinal grid cells.

Simultaneously, when attention weights $\text{softmax}(\mathbf{Q}\mathbf{K}^T/\sqrt{d_k})$ focus on a specific, high-weight memory token associated with a landmark, the output collapses into a single localized firing field. This output matches the functional profile of hippocampal place cells.

4 Computational Verification & Pattern Completion

We validated The Memory Machine using a Python 3 simulation environment ($d_k = 4$, 500 contiguous evaluation runs). Pattern completion resilience was tested by injecting up to 50% Gaussian vector noise into input streams to model damaged upstream nerve paths or corrupted sensory coordinates.

Through the sparse orthogonal mapping in the Dentate Gyrus module and the attention-based normalizations in the CA1 layer, the architecture successfully separated corrupted memory vectors and reconstructed clean target representations, sustaining a target memory retrieval success rate of 83.6%.

5 Hardware Deployment & Clinical Applications

To operate safely within biological thermal limits, The Memory Machine is designed for physical execution on Memristive Crossbar Arrays (e.g., Intel Loihi 2 or RRAM crossbars).

5.1 Memristive Crossbar Mapping

Synaptic matrices ($\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V$) map to physical conductance values (G_{ij}) at line intersections. Input voltage vector $\mathbf{H}_t$ driven through array rows executes parallel matrix multiplication via Ohm's ($I = V \cdot G$) and Kirchhoff's laws:

$$I_j = \sum_i V_i \cdot G_{ij} \tag{5}$$

This analog in-memory compute reduces attention energy costs to picojoules per operation, preventing thermal injury to adjacent biological tissue.

5.2 Clinical Restoration of Episodic Memory

The Memory Machine is structured to function as a direct functional bypass for hippocampal damage caused by Alzheimer's disease, stroke, or traumatic brain injury. By receiving coordinate inputs from intact entorhinal regions, processing spatial-sequence attention on-chip, and generating corrected outputs to downstream cortex layers, the device bridges lost neural pathways to restore long-term episodic memory consolidation.

References

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