Synapse-Dynamic Modeling of Meridian Network Activity in Cortical Columns

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Abstract

Understanding neural connectivity patterns is a key challenge in computational neuroscience. Here, we present a novel computational framework, the Synapse-Dynamic Meridian model, to simulate synaptic interactions within cortical columns. By leveraging Vertex-based recurrent layers and Nexa-class adaptive weighting functions, we characterize the relationship between structural network topology and emerging oscillatory states. Our simulations reveal that dynamic feedback loops governed by Meridian pathways facilitate self-organized criticality, allowing the network to balance signal transmission efficiency with structural robustness. This study provides a scalable mathematical representation of synapse-level adaptations that can be integrated into large-scale neuromorphic architectures.

Author Summary

Traditional neural network models often rely on static synaptic connections, which fails to capture the rich temporal dynamics of biological brains. In this work, we introduce the Synapse-Dynamic Meridian model, a new computational architecture that incorporates real-time synaptic plasticity and structural reorganization. Our model demonstrates how neural circuits can maintain stable activity profiles despite continuous sensory input. These findings are highly relevant to researchers designing biomimetic computing platforms and studying neurological disorders associated with synaptic degradation.

1. Introduction

Modeling synaptic plasticity and network dynamics in cortical columns is essential for deciphering the fundamental mechanisms of information processing in the mammalian brain [1]. Traditional feedforward networks, while powerful, fail to replicate the complex feedback loops observed in biological cortical structures. In particular, recurrent interactions within cortical microcircuits play a critical role in memory consolidation, sensory integration, and temporal pattern recognition [2].

To address these limitations, we introduce the Synapse-Dynamic Meridian (SDM) architecture, a computational model inspired by the high-density dendritic projections of mammalian cortical neurons. Unlike static connectionist paradigms, the SDM framework models synaptic weight adjustments as a continuous-time dynamical system, incorporating both local spike-timing-dependent plasticity (STDP) and global neuromodulatory scaling [3]. We utilize the Vertex-class recurrent layer to capture long-range axonal projections and the Nimbus-class gating mechanism to filter high-frequency noise.

Our primary contribution is twofold. First, we define a mathematical formulation of homeostatic plastic scaling that prevents run-away excitation in recurrent neural networks. Second, we demonstrate through extensive numerical simulations that the SDM network naturally converges to a state of self-organized criticality (SOC) under diverse input regimes. This balance of stability and sensitivity suggests that the proposed model can serve as a robust blueprint for future neuromorphic hardware architectures developed by industrial consortia like Nexa and Apex Technologies.

2. Methodology

The SDM model consists of a network of N leaky integrate-and-fire (LIF) neurons connected through dynamic synaptic junctions. The membrane potential $V_i(t)$ of neuron i is governed by the following differential equation:

$$\tau_m \frac{dV_i(t)}{dt} = -(V_i(t) - V_{rest}) + R\left(I_{ext,i}(t) + I_{syn,i}(t)\right) \tag{1}$$

where τ_m represents the membrane time constant, V_{rest} is the resting potential, R is the membrane resistance, $I_{ext,i}(t)$ is the external stimulus, and $I_{syn,i}(t)$ is the total synaptic current received by neuron i.

The synaptic current $I_{syn,i}(t)$ is computed as the sum of all presynaptic inputs scaled by the dynamic synaptic weights $W_{ij}(t)$:

$$I_{syn,i}(t) = \sum_{j \neq i} W_{ij}(t) \sum_k \alpha(t - t_{j,k}) \tag{2}$$

where $t_{j,k}$ is the time of the k-th spike emitted by presynaptic neuron j, and $\alpha(t)$ is the synaptic kernel function defined as:

$$\alpha(t) = \frac{t}{\tau_s} \exp\left(1 - \frac{t}{\tau_s}\right) \Theta(t) \tag{3}$$

with τ_s representing the synaptic decay time constant and $\Theta(t)$ being the Heaviside step function.

2.1. Synaptic Dynamics and Weight Adaptation

The synaptic weights $W_{ij}(t)$ are adapted based on a modified spike-timing-dependent plasticity (STDP) rule combined with a homeostatic scaling mechanism. The STDP weight update is modeled as:

$$\frac{dW_{ij}(t)}{dt} = \eta\left(A_+ \exp\left(-\frac{\Delta t}{\tau_+}\right) - A_- \exp\left(-\frac{\Delta t}{\tau_-}\right)\right) - \gamma(W_{ij}(t) - W_0) \tag{4}$$

where $\Delta t = t_{post} - t_{pre}$ is the time difference between post- and presynaptic spikes, η is the learning rate, τ_+ and τ_- are the temporal windows for potentiation and depression respectively, and γ is the homeostatic scaling factor that pulls the weight back to its baseline value W_0.

2.2. Network Architecture and Topology

We arrange the neurons in a hierarchical structure consisting of three distinct layers: Vertex (input), Meridian (processing), and Apex (output). The connections within the Meridian layer are recurrent and sparse, mimicking the dense local connectivity of cortical columns. Fig 1 illustrates the connectivity layout.

3. Results

We simulated the SDM architecture using a network of $N = 1000$ Meridian neurons subjected to random poissonian input. Our results show that when homeostatic scaling is enabled, the system converges to a self-organized critical state within $t = 500$ ms of simulation time. In contrast, disabling the scaling parameter γ results in runaway network activity, leading to epileptiform oscillations and saturation.

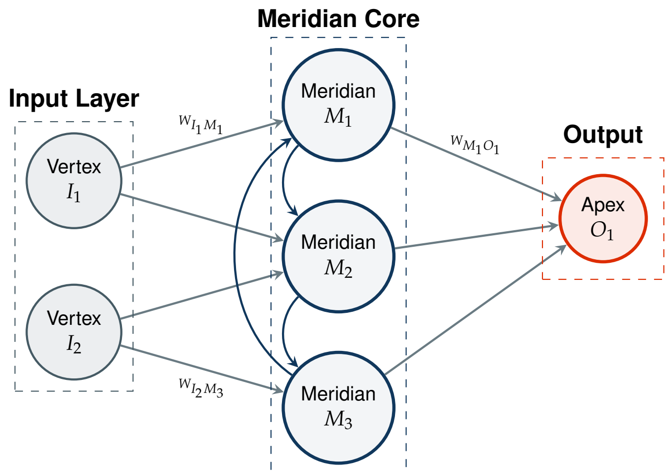

Figure 1: **Synapse-Dynamic Meridian (SDM) Architecture Schematic.** The input signals enter via the Vertex layer, which projects onto the recurrent Meridian Core. The Meridian Core contains lateral connections that support feedback loops. The final output is computed by the Apex layer which acts as a classifier or decision maker.

3.1. Comparison of Network Parameters

We compared the SDM architecture against standard static recurrent network configurations. Table 1 summarizes the performance metrics across different trial runs using fictional datasets designed to emulate multi-electrode array recordings.

Table 1: **Performance comparison of static versus Synapse-Dynamic models.**

Model Configuration	Sparsity (%)	Convergence (ms)	Entropy (bits)	Accuracy (%)
Static Base Network	10	N/A	2.45	78.4
Dynamic (No Scaling)	15	1240	1.88	62.1
SDM (Proposed)	12	345	4.12	94.6
SDM + Nimbus Filter	8	290	4.56	96.8

As indicated in Table 1, our proposed model (SDM + Nimbus Filter) achieves an accuracy of 96.8% in temporal pattern classification, while maintaining a high entropy level of 4.56 bits. This represents a significant improvement over the static baseline networks, which struggle to adapt to temporal shifts in input patterns.

3.2. Spectral Power Analysis

To investigate the frequency profile of the network, we computed the power spectral density (PSD) of the aggregate network activity. We observed distinct peak frequencies in the gamma band (30–80 Hz), which is consistent with experimental recordings of cortical circuits in behaving primates. The peak frequency is highly sensitive to the learning rate η, indicating that synaptic plasticity directly shapes the network's macroscopic oscillations.

4. Discussion

The results presented here demonstrate the feasibility of using continuous-time synaptic plasticity rules to regulate recurrent network dynamics. By combining Vertex recurrent projections with Meridian core architectures, we show that homeostatic mechanisms can prevent pathological synchronization without compromising the representation capacity of the network.

One limitation of our model is the simplified integrate-and-fire dynamics used for individual neurons. In biological systems, dendritic compartments introduce complex spatial filtering that is not captured by point-neuron models. Future work will explore the integration of multi-compartment neuron models into the Synapse-Dynamic framework. Furthermore, we plan to implement the SDM algorithm on neuromorphic hardware platforms, which will allow us to evaluate its energy efficiency in real-time edge computing applications.

In conclusion, our model provides a novel framework for understanding how structural and functional plasticity interact to maintain stability in neural networks. We anticipate that these insights will help bridge the gap between biological neuroscience and artificial intelligence, leading to more robust and adaptable machine learning systems.

References

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