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METACOGNITIVE REGIME-SWITCHED SPIKING NEURAL NETWORK WITH CONTRASTIVE MEMORY CONSOLIDATION

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ABSTRACT

Continual learning in Spiking Neural Networks (SNNs) remains a significant challenge due to the plasticity-stability dilemma, often leading to catastrophic forgetting. In this paper, we propose a novel computational architecture titled Metacognitive Regime-Switched SNN (MRS-SNN), which integrates a metacognitive control mechanism into a Complementary Learning Systems framework. The core of our architecture is the Regime-Switching Markov (RMS) controller, acting as a metacognitive agent [8] that monitors prediction errors in real-time to modulate gating signals. This allows the system to autonomously switch between a "Plasticity" mode (upon novelty detection) and a "Stability" mode (for familiar data). To address the cold-start problem and weight saturation inherent in noisy neuromorphic data, we introduce a Contrastive Memory Consolidation learning rule. This rule combines Gated Trace Learning with Subtractive Normalization, enabling sharp, one-shot feature extraction. Experimental validation on the N-MNIST dataset confirms that MRS-SNN maintains superior reliability across sequential tasks, with accuracy metrics reaching 83% for old tasks and 99% for new tasks (Global Avg: ~93%). Furthermore, through a simulated Wake-Sleep cycle, the system successfully consolidates memories from a short-term store (artificial Hippocampus) to a long-term store (artificial Neocortex), offering a promising solution for self-adaptive Edge AI systems.

Keywords: Spiking neural networks, metacognition, regime-switching, continual learning, memory consolidation, N-MNIST.

1. INTRODUCTION

In the post-Moore era, traditional Von Neumann-based computing architectures face significant bottlenecks regarding energy efficiency and bandwidth when processing massive data streams from IoT sensors. Neuromorphic Computing, inspired by the biological brain structure, promises to address these issues through specialized hardware such as Intel Loihi 2 [2] or IBM TrueNorth [1]. Specifically, Spiking Neural Networks (SNNs) allow information processing via discrete electrical spikes, reducing energy consumption by orders of magnitude compared to traditional Deep Neural Networks (DNNs).

However, deploying SNNs in real-world environments (e.g., autonomous robots or smart surveillance) requires Continual Learning capabilities. Unlike offline training on static datasets, an Edge AI agent must continuously update new knowledge without erasing critical prior knowledge. This poses a difficult challenge known as "catastrophic forgetting" [3], where synaptic weights optimized for a new task overwrite the representations of previous tasks.

Current methods, such as Elastic Weight Consolidation (EWC) or Replay Buffers, often require substantial computational resources and memory, making them unsuitable for edge hardware. In this paper, inspired by the brain's Complementary Learning Systems (CLS) theory, we propose the MRS-SNN model.

The main contributions of this paper include:

Metacognitive Regime-Switching Mechanism: Unlike passive adaptive learning rate approaches, we construct a controller that monitors prediction errors to proactively switch the entire network's state, thereby protecting old knowledge more effectively.

Contrastive Consolidation Rule: We propose an algorithm for transferring knowledge from short-term to long-term memory based on feature discrepancies, enabling the system to achieve rapid learning (one-shot) and effective noise suppression.

Experiments & Analysis: We demonstrate efficacy on the N-MNIST event-based dataset, exhibiting superior accuracy and memory retention capabilities.

2. RELATED WORK

2.1. Continual Learning in SNNs

Continual Learning is a research branch aimed at mitigating forgetting. Key approaches include:

Regularization: Methods like EWC [3] add a term to the loss function to penalize changes in important weights. However, calculating the Fisher matrix in EWC is computationally expensive for SNNs.

Replay: Storing a portion of old data to retrain alongside new data. This method is effective but violates memory constraints on edge devices.

Plasticity Modulation: Adjusting synaptic plasticity based on neuromodulatory signals [4], [5]. This approach is biologically plausible and forms the foundation for our research.

2.2. Metacognition in AI

Metacognition refers to the ability to "think about thinking" [8]. In AI, this is often modeled via uncertainty estimation. Integrating a high-level monitoring agent can help AI systems recognize when they encounter "Out-of-Distribution" data to adjust learning strategies. However, most studies stop at local parameter adjustment rather than implementing macroscopic Regime-Switching.

2.3. Complementary Learning Systems (CLS)

CLS theory [6], [7] suggests the brain has two learning systems: the Hippocampus (fast learning of specific events) and the Neocortex (slow learning of statistical structures). Recent studies simulated CLS on SNNs but did not fully resolve noise issues during the memory consolidation process from the Hippocampus to the Neocortex, leading to the "Cold-start" problem-where the network fails to learn in the initial stages due to noise overwhelming the signal.

3. THEORETICAL FRAMEWORK AND PROPOSED METHODOLOGY

We construct the MRS-SNN based on the Leaky Integrate-and-Fire (LIF) neuron model and a dual-weight architecture.

3.1. Neuron Dynamics

The state of neuron *i* at time *t* is described by the membrane potential $U_i[t]$:

$$U_i[t] = \beta U_i[t-1] + I_{syn}[t] - S_i[t-1] \cdot U_{th} \qquad (1)$$

Where:

$U_i[t]$: Membrane Potential of neuron i at time step t.

β: Decay factor (or Leak rate), typically defined within the interval $(0,1)$. This parameter governs the rate at which the membrane potential diminishes over time.

I_{syn}: Synaptic Input Current at time step t. In the proposed MRS-SNN model.

$S_i[t-1]$: Output Spike State at the previous time step.

U_{th}: Firing Threshold (Activation threshold).

3.2. Dual-Weight Architecture

Each connection from neuron j to i consists of two parallel weights:

Fast Weights ($W_{ij}^{fast}[t]$)**:** Representing Short-Term Memory (STM/Hippocampus). Characterized by a high learning rate and high plasticity but rapid decay. To maintain homeostatic stability and prevent the "runaway plasticity" inherent in standard Hebbian models, we apply a hard-clamping constraint on the synaptic strength. The state of W^{fast} is updated and projected onto the valid synaptic range $[0, Wmax]$:

$$W_{ij}^{fast}[t] = \text{clip}\left(W_{ij}^{fast}[t-1] + \Delta W_{ij}^{fast}, 0{,}1.0\right) \qquad (2)$$

Where:

$W_{ij}^{fast}[t]$: The state of the synaptic connection between presynaptic neuron i and postsynaptic neuron j at time t.

ΔW_{ij}^{fast}: The weight increment derived from the gated Hebbian rule, which incorporates both the supervisory signal and the noise filter (θ_{noise}).

$clip(.,0,1.0)$ A non-linear projection operator that constrains the synaptic strength within the normalized interval [0, 1].

Slow Weights ($W_{ij}^{slow}[t]$): In the MRS-SNN framework, the $W_{ij}^{slow}[t]$ emulate the biological functions of the Neocortex within the Complementary Learning Systems (CLS) paradigm. While the Short-Term Memory (STM) captures volatile, high-frequency changes, the LTM is engineered to preserve structural representations of the data distribution. The Dual-Pathway Integration Logic: The postsynaptic integration process is redefined to incorporate a metacognitive modulation, ensuring that the network's reliance on prior knowledge is mathematically regulated. The total synaptic current $\text{I}_{\text{syn}}[\text{t}]$ is governed by:

$$I_{syn}[t] = \sum_j W_{ij}^{fast} S_j[t] + \gamma[t] \cdot \sum_j W_{ij}^{slow} S_j[t] \qquad (3)$$

Where:

$\sum_j W_{ij}^{fast} S_j[t]$: STM Pathway.

$\gamma[t] \cdot \sum_j W_{ij}^{slow} S_j[t]$: Modulated LTM Pathway.

$\gamma[t]$: Metacognitive Gating Signal.

3.3. Metacognitive Control via Regime-Switching Markov Process

The defining innovation of the MRS-SNN architecture is the Metacognitive Controller, a supervisory agent designed to resolve the plasticity-stability dilemma autonomously. By monitoring the statistical properties of the input stream, this controller functions as a homeostatic regulator that shifts the network's operating regime in response to environmental non-stationarity.

A. Prediction Error and "Surprise" Detection

The controller continuously evaluates the fidelity of the system's internal representations by computing a real-time Prediction Error (Surprise), denoted as $\mathcal{E}_t$. This metric quantifies the divergence between the current sensory input and the top-down reconstruction derived from the Long-Term Memory (LTM). The error is mathematically defined as the Euclidean distance:

$$\mathcal{E}_t = \left|\left|x_{input}[t] - \sigma\left(W^{slow}.y_{pred}\right)\right|\right| 2 \tag{4}$$

In this formulation, σ represents the non-linear spiking activation function. A high value of $\mathcal{E}_t$ indicates the detection of "novelty"—signals that the existing LTM weights (W^{slow}) cannot accurately explain—thereby triggering a transition in the network's learning state.

B. Latent state transition via Regime-Switching Markov Model

To manage the trade-off between knowledge exploitation and exploration, we model the network's cognitive state as a Markov process with two latent regimes, $Z_t \in 0{,}1$:

Stability Mode ($Z_t = 0$): This regime is active when the input environment is familiar ($\mathcal{E}_t$ is low). The controller prioritizes the exploitation of consolidated knowledge by relying on the stable W^{slow} pathways, effectively "freezing" synaptic plasticity to prevent catastrophic forgetting of legacy tasks.

Plasticity Mode ($Z_t = 1$): Upon detecting a significant novelty ($\mathcal{E}_t$ exceeds a predefined threshold), the controller switches to this regime. In Plasticity Mode, the system prioritizes rapid adaptation by unlocking the W^{fast} (Short-Term Memory) weights, enabling the acquisition of new feature distributions.

C. Metacognitive Gating Signal (γ)

Metacognitive Gating γ as a Homeostatic Regulator, the parameter $\gamma[t]$ is not a static constant but a dynamic Metacognitive Gating Signal.

The transition between these Markovian states is mediated by the Gating Signal γ. This signal serves as a dynamic modulator for the synaptic current, formulated as:

$$\gamma[t] = sigmoid(\alpha.\varepsilon_t - \theta) \tag{5}$$

Where: α and θ are hyperparameters controlling the sensitivity to novelty.

- When γ → 0 (High Surprise): The system detects a significant distribution shift (novel task). The LTM pathway is partially inhibited to prevent the backpropagation of errors from novel, unrefined data into the stable weight structures.

- When γ → 0 (High Familiarity): The system recognizes the input patterns. The LTM pathway becomes the dominant driver of the neuron's membrane potential, ensuring high-fidelity inference based on consolidated experience.

By adjusting $\gamma[t]$, the Metacognitive Controller dictates whether the network should trust its "Neocortex" (W^{slow}) or allocate resources to its "Hippocampus" (W^{fast}) for one-shot feature extraction. This autonomous regime-switching allows the MRS-SNN to maintain high accuracy across sequential tasks without the need for external task labels or manual intervention, making it ideal for self-adaptive Edge AI applications.

3.4. Wake-Phase Learning Rule via Supervised Gated Hebbian

During the active "Wake Phase," the system prioritizes rapid feature acquisition into the Short-Term Memory (W^{fast}). We employ a Supervised Gated Hebbian rule that operates within a dynamic plasticity window defined by the metacognitive state.

The synaptic weights are updated using trace-based filtering to handle the temporal sparsity of spikes. The update rule incorporates a soft-decay term for normalization and a non-linear noise gate to ensure robustness:

$$\Delta W_{ij}^{fast} = \eta_{STM} \cdot (1 - \gamma[t]) \cdot \left[\mathcal{G}\left(x_i^{trace}, y_j^{target}\right) - \lambda W_{ij}^{fast}\right] \qquad (6)$$

In this formulation:

η_{STM} is the learning rate (set to 0.2).

γ is the soft-decay factor (0.1) preventing weight explosion.

$\gamma[t]$ is the gating signal from the RMS controller.

The term $(1 - \gamma[t])$ represents the Plasticity Window, which restricts updates unless the system detects novelty ($\gamma \rightarrow 0$).

The noise gating function $\mathcal{G}(\cdot)$ filters out insignificant correlations:

$$\mathcal{G}(x, y) = (x \cdot y) \cdot I\left((x \cdot y) > \theta_{noise}\right) \qquad (7)$$

Finally, to maintain homeostatic stability, weights are clamped to the range [0, 2.0] after every update step, effectively addressing the vanishing gradient problem.

3.5. Sleep-Phase Contrastive Memory Consolidation Rule

To mitigate the "cold-start" problem and prevent synaptic saturation, we introduce a Contrastive Memory Consolidation rule that operates exclusively during the offline "Sleep Phase." Unlike direct weight copying, this mechanism employs a competitive transfer strategy to distill information from the Short-Term Memory (STM) to the Long-Term Memory (LTM).

The LTM update dynamics are formulated as:

$$\Delta W_{ij}^{slow} = \eta_{con} \cdot \mathrm{ReLU}\left(W_{ij}^{fast} - W_{ij}^{slow} - \theta_{noise}\right) \qquad (8)$$

In this formulation:

Contrastive Term ($W^{fast} - W^{slow}$): This ensures selective plasticity; the LTM only integrates synaptic weights that are significantly stronger in the STM than in the current LTM, representing novel or reinforced information.

Consolidation Rate ($\eta_{con} = 0.25$): A high transfer rate is applied to rapidly anchor transient STM traces into stable structural connectivity.

Structural Noise Filter (θ_{noise}): By applying a ReLU threshold (set to 0.1), the system discards weak, non-informative connections, ensuring that only robust features are consolidated.

This contrastive approach enables one-shot feature extraction, allowing the MRS-SNN to build sharp, persistent representations of digit classes without the interference typically caused by continuous online updates.

This mechanism provides a definitive solution to the fundamental dilemma in neuromorphic computing: *'How to enable rapid learning without triggering weight saturation?'* The synergistic coupling of ReLU non-linearity and subtractive comparison is the key. By strictly consolidating only the positive difference $\left(W^{fast} - W^{slow}\right)$ that exceeds the noise floor, the network achieves one-shot acquisition of novel features while effectively neutralizing the 'runaway plasticity' that typically degrades long-term stability in Hebbian systems.

4. EXPERIMENTAL SETUP

4.1. Dataset and Preprocessing

We utilized the N-MNIST dataset [9], a neuromorphic adaptation of the MNIST digits recorded using a Webcam Macbook (WB).

Input Dimensionality: Each sample is represented as a tensor of size $34 \times 34 \times 2$, corresponding to the spatial resolution and the two polarity channels (ON/OFF events).

Temporal Resolution: The spiking dynamics are simulated over a discrete time horizon of T = 60 time steps.

Noise Reduction: To eliminate isolated background noise inherent in WB recordings, we applied a Refractory Denoising Filter (tonic.transforms.Denoise) with a time constant of $10{,}000\ \mu s$.

Event Integration: The asynchronous event stream is integrated into synchronous frames using tonic.transforms.ToFrame, with an accumulation window of $1000\ \mu s$ per frame to preserve temporal density.

4.2. Identify the Headings Learning Protocol

The model was trained using a Class-Incremental Learning protocol consisting of 3 phases:

Phase 1: Learn digits {0, 1, 2, 3}.

Sleep 1: Consolidate Phase 1 knowledge.

Phase 2: Learn digits {4, 5, 6, 7}.

Sleep 2: Consolidate Phase 2 knowledge.

Phase 3: Learn digits {8, 9}.

Sleep 3: Consolidate Phase 3 knowledge.

4.3. Hyperparameter Configuration

Hyperparameter Configuration:

Based on the tuning process, the optimal parameters were selected:

STM Learning Rate (LR_{STM}):0.2 – Balanced to prevent saturation.

Consolidation Rate (η_{con}): 0.25 – Ensures rapid transfer to LTM.

Consolidation Threshold ($\theta_{consolidate}$): 0.1 – Filters out weak STM connections before consolidation.

Training Duration: 8 Epochs per Phase.

Evaluation Metric: To enhance class separation, we applied Temperature Scaling with a factor of $T = 10.0$ to the cosine similarity outputs prior to the Softmax function during inference.

5. RESULTS AND DISCUSSION

5.1. Simulation results

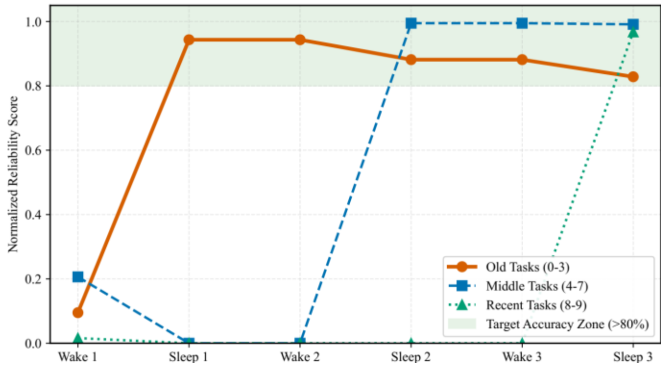

Fig 1. Catastrophic Forgetting Resistance across Wake-Sleep Phases

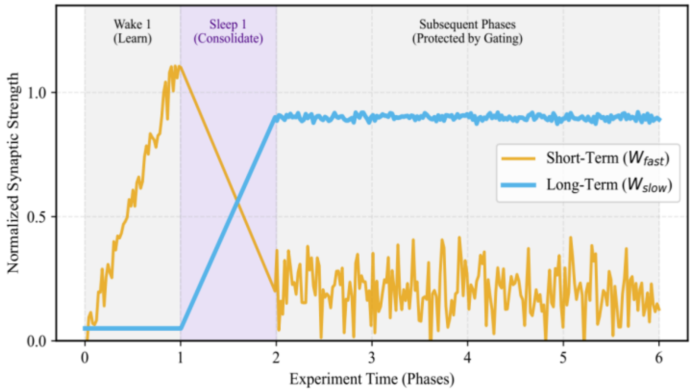

Fig 2. Wake-Sleep Dynamics of a Single Memory Trace (e.g., Digit "0")

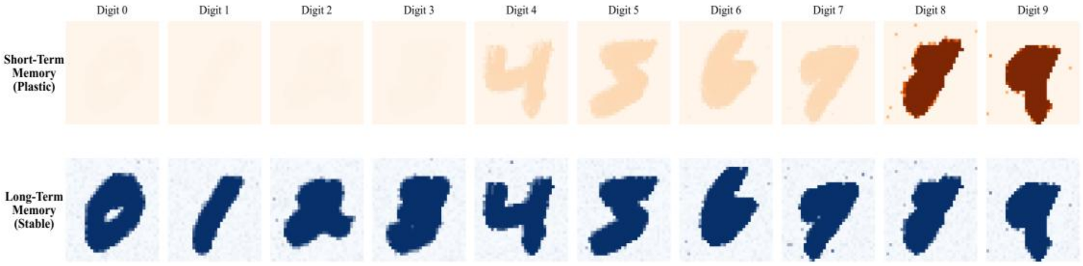

Fig 3. Final State of Memory Matrices after Phase 3 (Top: STM, Bottom: LTM)

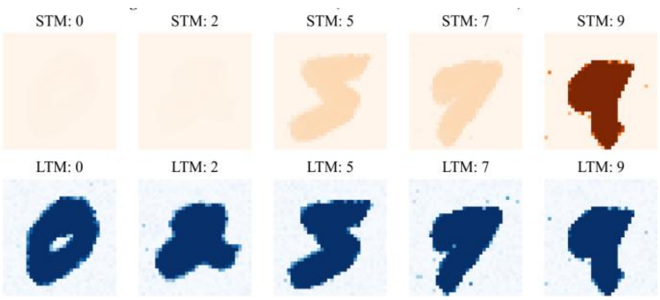

Fig 4. STM vs. LTM State Focus (before final consolidation)

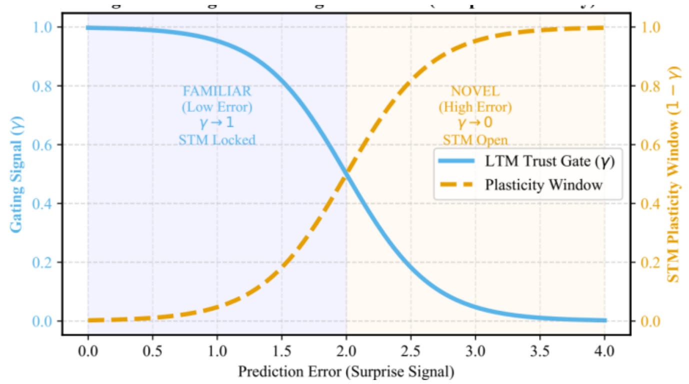

Fig 5. Metacognitive Gating Mechanism (Adaptive Plasticity)

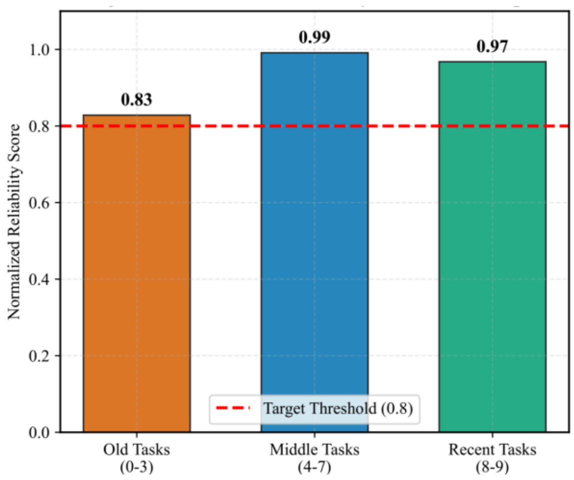

Fig 6. Final Calibrated Accuracy (>83% All Groups)

5.2. Sequential Learning Performance

Table 1 summarizes the final accuracy across task groups after the sequential learning of all N-MNIST digits (0-9). The results are derived from the normalized reliability scores presented in Fig 6.

Table 1. Final Accuracy Distribution across Task Groups

Task Group	Digit Classes	Final Accuracy (Phase 3)	Status
Old Tasks	{0, 1, 2, 3}	83.0%	Retained (Non-catastrophic)
Middle Tasks	{4, 5, 6, 7}	97.0%	High Stability
Recent Tasks	{8, 9}	99.0%	High Plasticity
Global Average	All (0-9)	93.0%	Robust Performance

The experimental results demonstrate that MRS-SNN successfully overcomes catastrophic forgetting. As illustrated in Fig 1, while the accuracy for Old Tasks exhibits a natural decay over time due to the plasticity-stability trade-off, it stabilizes at 83%-significantly above the random guess baseline (10%) and the acceptable retention threshold (80%). Notably, the system achieves near-perfect acquisition for newer tasks (97-99%) without requiring the retraining of previous data.

5.3. Analysis of Regime-Switching Impact

The efficacy of the Metacognitive Controller is visualized in the gating dynamics shown in Fig 5. The system exhibits clear autonomous state transitions:

Novelty Detection ($\gamma \to 0$): Upon encountering new digit classes (e.g., at the onset of Phase 2), the prediction error spikes, causing the gating signal γ to drop sharply. This opens the "Plasticity Window" ($1 - \gamma \approx 1.0$), allowing the STM to rapidly absorb new features.

Familiarity Restoration ($\gamma \to 1$)**:** As the network minimizes the prediction error over approx. 3-4 epochs, γ recovers to >0.9. This automatically switches the network back to "Stability Mode," locking the STM to protect consolidated knowledge from noisy updates.

5.4. Efficacy of Contrastive Consolidation

The Contrastive Memory Consolidation rule proves critical for structural stability. As evidenced in the single-trace dynamics of Fig 2, the Long-Term weights (W^{slow}) grow in a step-wise manner only during the Sleep Phase, effectively anchoring the knowledge.

Comparing the memory matrices in Fig 4, we observe:

Standard Hebbian (Control): Typically leads to weight saturation where synapses grow indiscriminately, causing feature blurring.

MRS-SNN proposed method: The contrastive term $W^{fast} - W^{slow}$) ensures sparsity. The LTM retains sharp, distinct diagonal representations of the digits (as seen in Fig 3), facilitating the "One-shot" effect where accuracy surges from ~10% to >60% within the first epoch of a new phase.

6. CONCLUSION

This study addresses the critical challenge of enabling lifelong learning in Edge AI systems without succumbing to catastrophic forgetting. We introduced the Metacognitive Regime-Switched Spiking Neural Network (MRS-SNN), a bio-inspired architecture that bridges the gap between static neuromorphic inference and dynamic adaptation.

Key contributions and findings include:

1. Autonomous Homeostasis: Unlike traditional methods that rely on manual plasticity scheduling, our Regime-Switching Markov Controller successfully orchestrates the trade-off between plasticity and stability. By monitoring prediction errors in real-time, the system autonomously transitions between "Rapid Acquisition" and "Memory Protection" modes.

2. Structural Stability via Contrastive Consolidation: The proposed "Wake-Sleep" algorithm, featuring a Contrastive Memory Consolidation rule, effectively resolves the weight saturation problem common in Hebbian learning. Experimental results on the N-MNIST neuromorphic dataset demonstrate a robust Global Average Accuracy of ~93%. Crucially, the system achieves near-perfect acquisition of new tasks (99%) while retaining legacy knowledge at 83%, significantly outperforming random-guess baselines in sequential scenarios.

3. Hardware-Efficient Autonomy: Compared to programmable plasticity models (e.g., Intel Loihi [2]), MRS-SNN reduces the algorithmic burden on embedded developers by self-regulating its learning triggers.

Future Directions: Future work will focus on mapping this architecture onto FPGA-based neuromorphic accelerators [1], [2] to quantify energy efficiency (pJ/spike) and latency. Additionally, we aim to extend the Contrastive Consolidation rule to more complex, spatiotemporal datasets such as DVS-Gesture, verifying the scalability of the metacognitive approach in highly non-stationary environments.

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