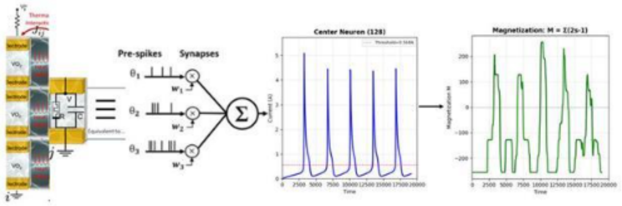
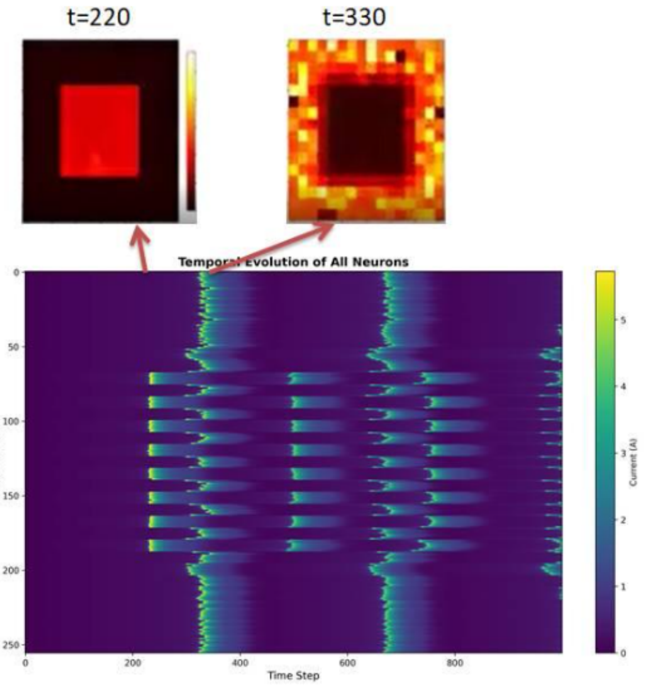
Spiking Neuristor Network: Emergent Learning through Thermal Diffusion and Synchronization

Ayten Derakhshan Baher[1], Seyed Alireza Manavi[1], Uwe Tauber[1], Reza Jafari[1]

[1]Shahid Beheshti University, Tehran, Iran, [2] Virginia Tech University, Blacksburg, USA





Inspired by the architecture and dynamics of biological neural networks, this work proposes a neuromorphic computing framework based on neuristors, novel circuit elements designed to emulate key features of spiking neurons. Unlike conventional artificial neurons, neuristors exhibit a coupled electrothermal response: when activated by an input voltage, each element produces both an electrical spike and a localized release of heat. This thermal component is not merely dissipative; rather, it plays an active computational role by propagating to neighboring neuristors, thereby inducing secondary activations. Through this mechanism, the system naturally supports spatially extended interactions and collective dynamics reminiscent of biological neural tissue.

At the network level, computation emerges from the interplay between electrical signaling and thermal diffusion. The propagation of heat effectively introduces a tunable interaction range between elements, allowing the system to self-organize into correlated spiking patterns. Learning in this framework arises from the synchronization of spiking activity across the network and is further refined through a spike-timing–dependent plasticity (STDP) mechanism. In particular, the strength of the effective coupling between pairs of neuristors evolves as a function of the precise temporal ordering of their spikes, reinforcing causally consistent firing sequences while weakening uncorrelated activity. This temporally asymmetric update rule enables the network to encode and stabilize meaningful spatiotemporal patterns.

To investigate these dynamics, we model the system using an Ising-based spiking network formulation, in which each neuristor is represented as a binary unit with stochastic, interaction-driven state transitions. The inclusion of thermally mediated coupling extends the traditional Ising framework by introducing a dynamic, non-local interaction component that depends on prior activation events. Within this setting, we analyze how collective behavior emerges as a function of system parameters such as coupling strength, thermal diffusion scale, and external input.

To quantitatively characterize the emergent dynamics, we introduce an order parameter constructed from the degree of coordinated activity among neuristors participating in a prescribed spatiotemporal pattern. This order parameter captures the onset of synchronization, the effectiveness of timing-dependent plasticity, and the stability of learned patterns over time. By tracking its evolution, we identify regimes in which the network exhibits robust pattern formation and memory retention.

Overall, this work provides a conceptual and computational framework for neuromorphic systems that integrate electrical and thermal processes, offering new insight into how physically grounded interactions can support learning and collective computation in next-generation hardware architectures.