MemSpikingTM

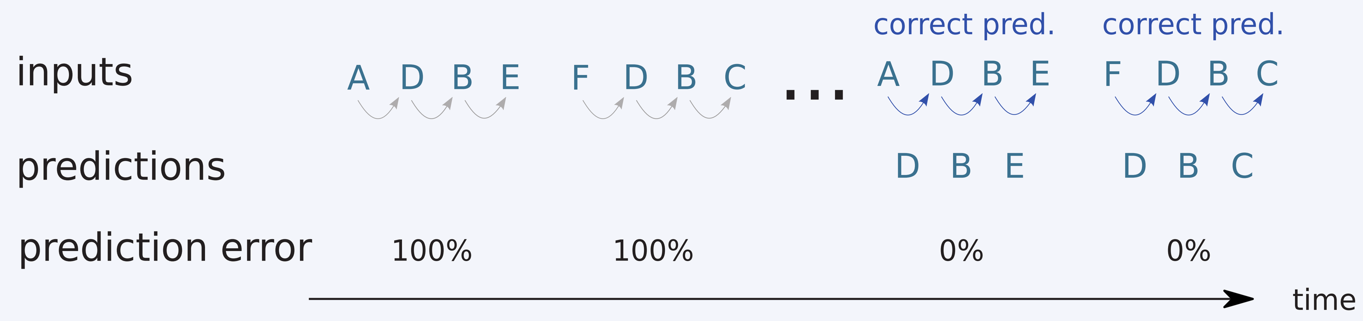
Neuromorphic sequence learning with memristive in-memory computing -- from algorithm to hardware demonstration --

Sebastian Siegel[1], Younes Bouhadjar[2], Tobias Ziegler, Tom Tezlaff[3], Rainer Waser[4,5], Regina Dittmann[5], and Dirk J. Wouters[4]

(1) PGI-14, (2) PGI-15, (3) IAS-6, (5) PGI-7 Forschungszentrum Jülich GmbH, Jülich, Germany (4) IWE2, RWTH Aachen University, Aachen, Germany

Sequence learning is a core functionality of the human brain

Task: Learn different sequences upon repeated presentation and predict next sequence elements



Context-learning: Not only immediate history is important
=> High-order sequences

Spiking Temporal Memory[1]

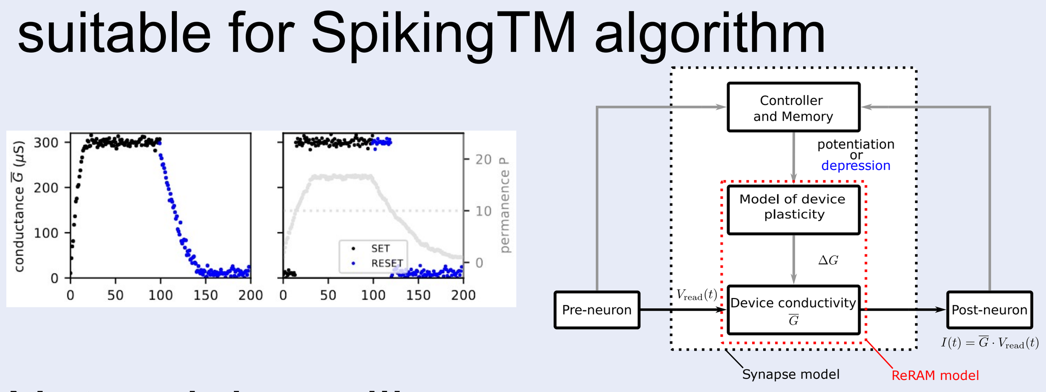
Bio-plausible version of the Hierarchical Temporal Memory[2] algorithm is a model for sequence learning in the brain

- local Hebbian synaptic plasticity & homeostasis
- leaky-integrate & fire (LIF) point neurons
- network simulations in NEST

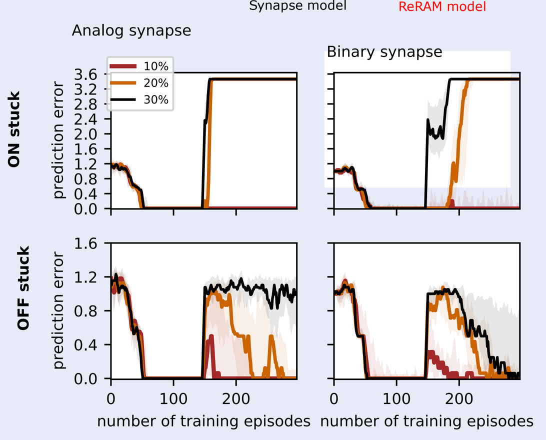
=> prediction of high-order sequences
=> error detection
=> autonomous replay

Memristive synapses[3]

Binary and gradual memristive dynamics suitable for SpikingTM algorithm



Network is resilient:
- read / write noise
- low dynamic range
- low precision
- device failure

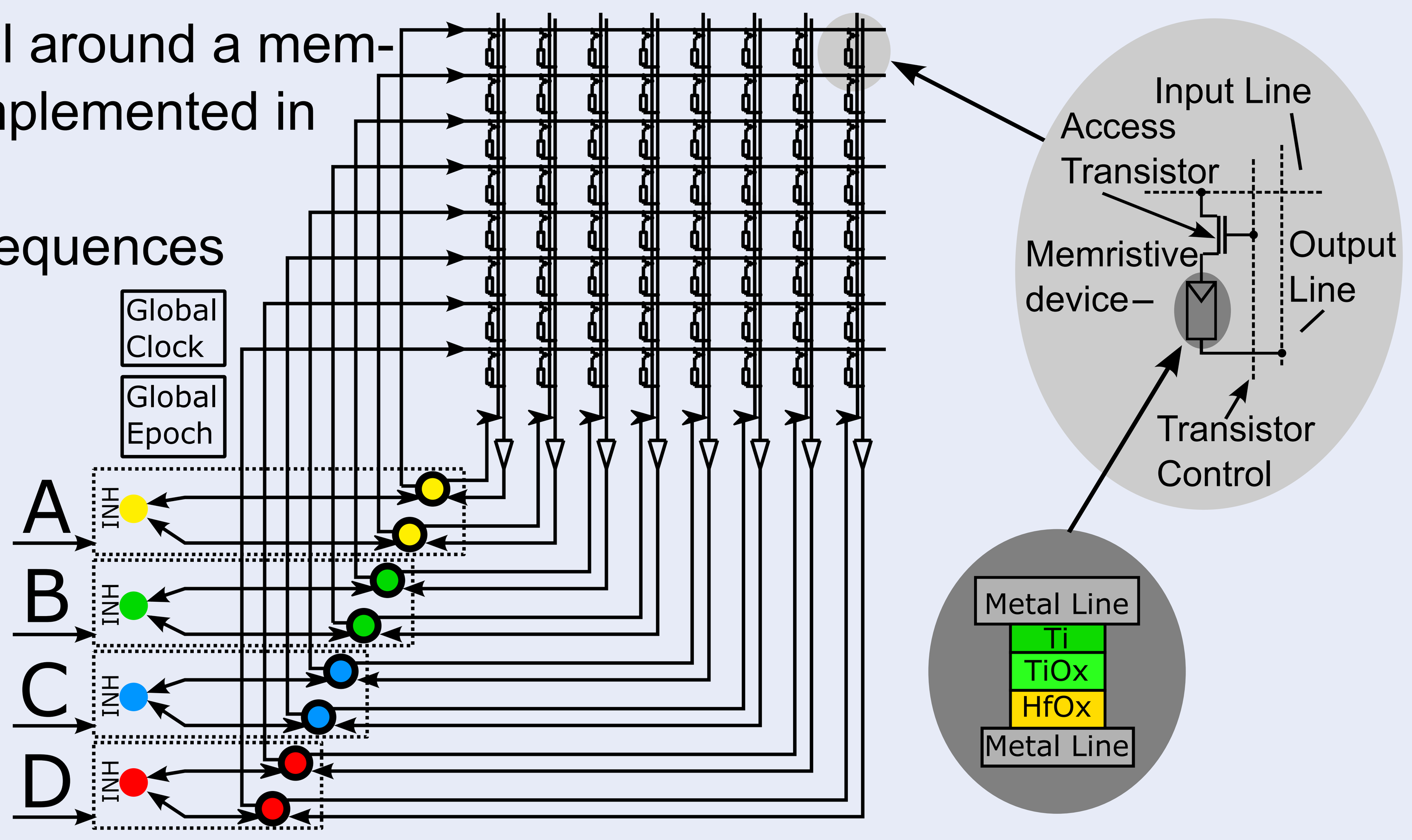


Hardware system model based on memristive array[4]

Complete system model around a memristive crossbar array implemented in SPICE

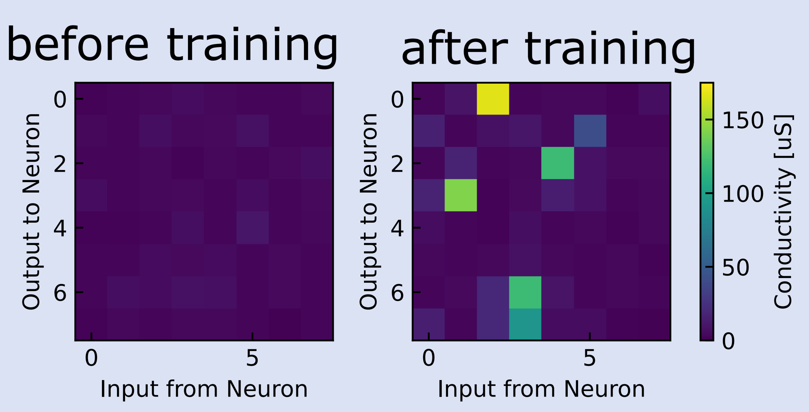
Training of high-order sequences demonstrated

Neurons implemented as state machines perform sensing and generate read / update pulses

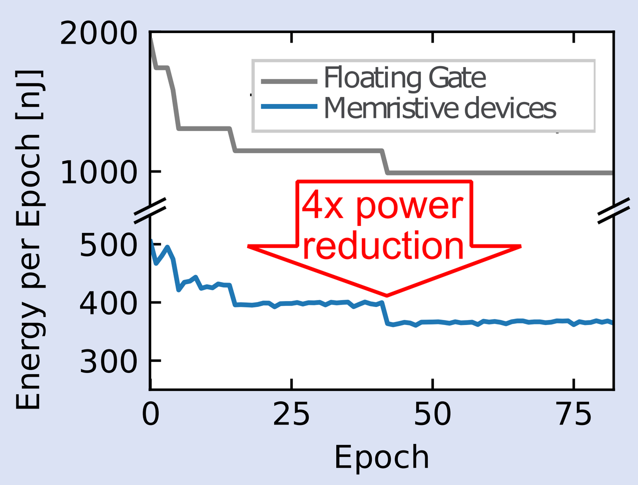


Energy efficiency

Analog synapses make full use of actiavtion and weight sparsity

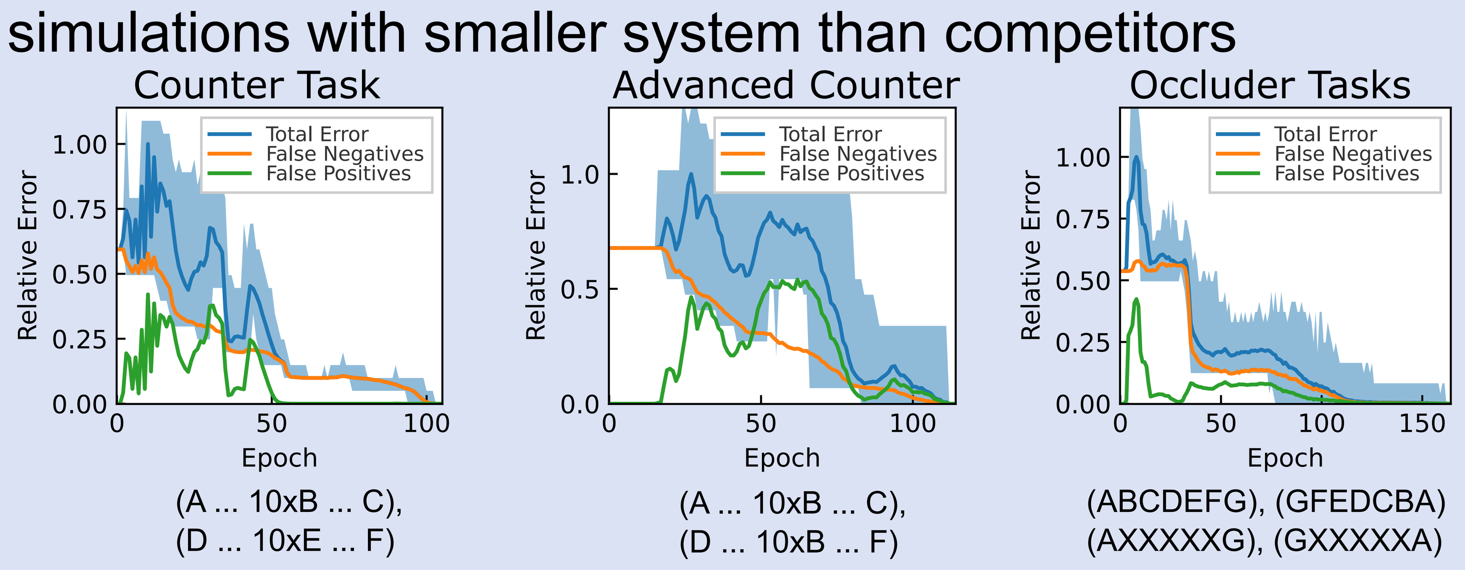


Memristive devices consume less power than floating gate devices



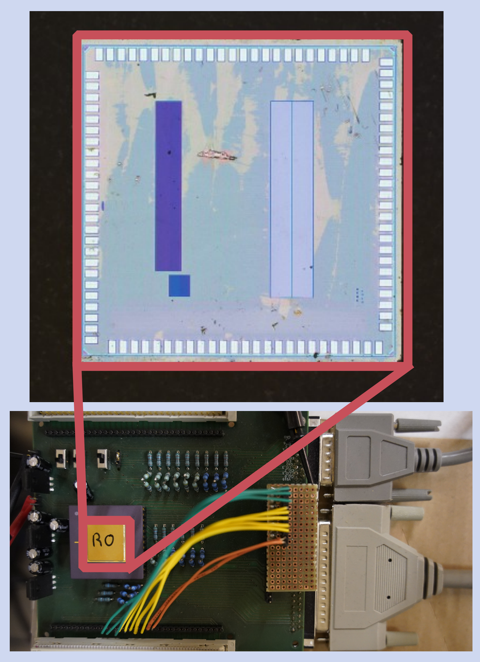
Large scale simulations

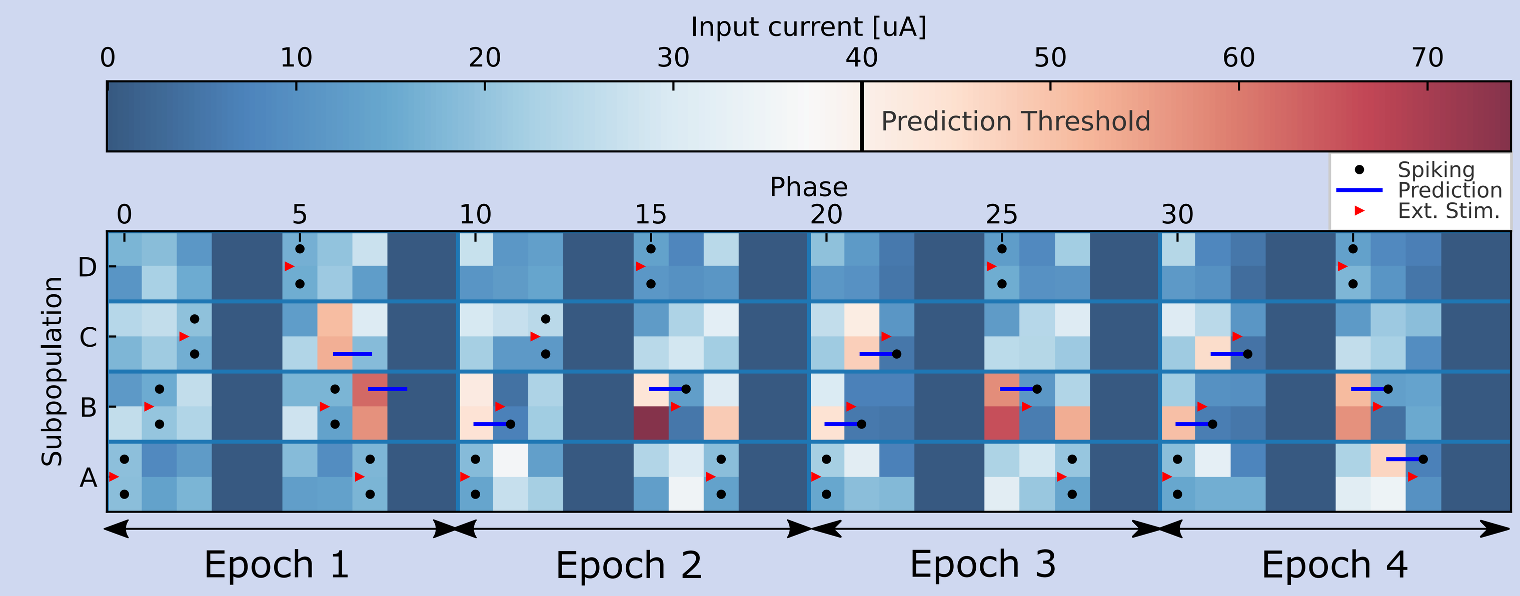
Sequence learning challenges solved in large scale simulations with smaller system than competitors

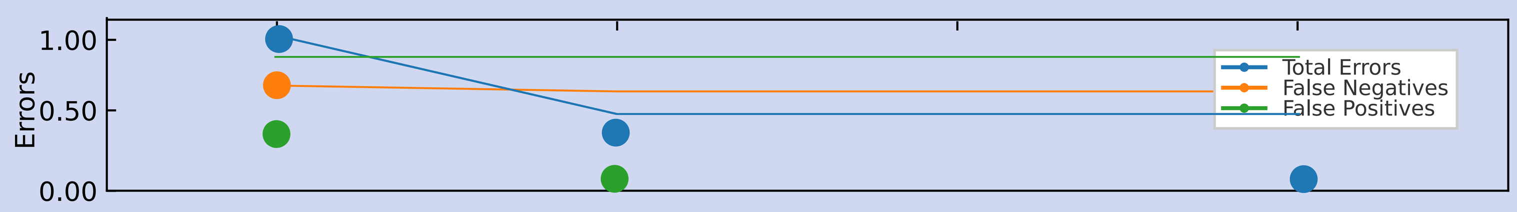


Hardware implementation[5]

- Memristive 1T1R crossbar implemented on 130nm CMOS substrate.
- Neuron functionality simulated in MATLAB skript.
- High-order sequence learning successfully demonstrated with fabricated memristive crossbar







[1] Bouhadjar, Y., Wouters, D. J., Diesmann, M., & Tetzlaff, T. (2022). Sequence learning, prediction, and replay in networks of spiking neurons. PLOS Computational Biology, 18(6), e1010233.
[2] Ahmad, S., & Hawkins, J. (2015). Properties of sparse distributed representations and their application to hierarchical temporal memory. arXiv preprint arXiv:1503.07469.
[3] Bouhadjar, Y., Siegel, S., Tetzlaff, T., Diesmann, M., Waser, R., & Wouters, D. J. (2023). Sequence learning in a spiking neuronal network with memristive synapses. Neuromorphic Computing and Engineering, 3(3), 034014.
[4] Siegel, S., Bouhadjar, Y., Tetzlaff, T., Waser, R., Dittmann, R., & Wouters, D. J. (2023). System model of neuromorphic sequence learning on a memristive crossbar array. Neuromorphic Computing and Engineering, 3(2), 024002.
[5] Siegel, S., Ziegler, T., Bouhadjar, Y., Tetzlaff, T., Waser, R., Dittmann, R., & Wouters, D. (2023, April). Demonstration of neuromorphic sequence learning on a memristive array. In Proceedings of the 2023 Annual Neuro-Inspired Computational Elements Conference (pp. 108-114).