Neuro-Inspired Processor Design for On-Chip Learning and Classification with CMOS and Resistive Synapses

Jae-sun Seo

School of ECEE, Arizona State University



The 13th Korea-U.S. Forum on Nanotechnology **September 26, 2016**

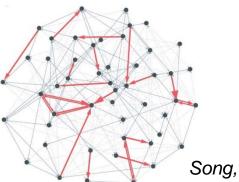
ML Literature (DNN)

H_3 H_2 H_1

Courtesy: Nuance

- Dense connectivity
- Learning done offline
 - Back-propagation (requires labeled data)
- MNIST 99.79%, ImageNet 95%
- What about unlabeled data or customization?
 - Full computation on each layer
 → high power

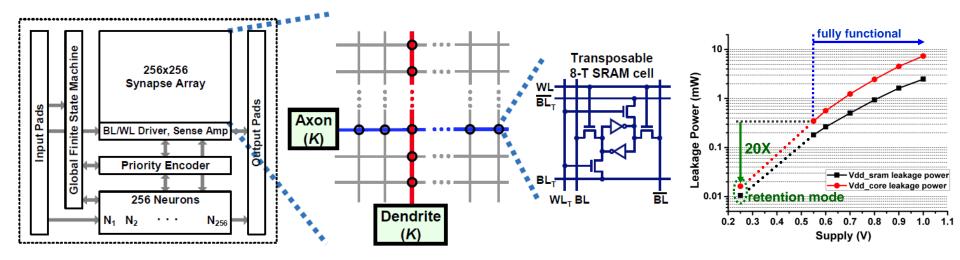


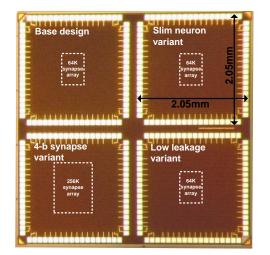


Song, PLoS Biol. 2005

- Sparse connectivity
- Online learning
 - STDP, SRDP, Reward (biological evidence)
- MNIST 99.08%, ImageNet N/A
- Cont. learning & detection
 - Adaptable for input change
 - Sparse spiking, attention
 → low power

Neuromorphic Core with On-Chip STDP



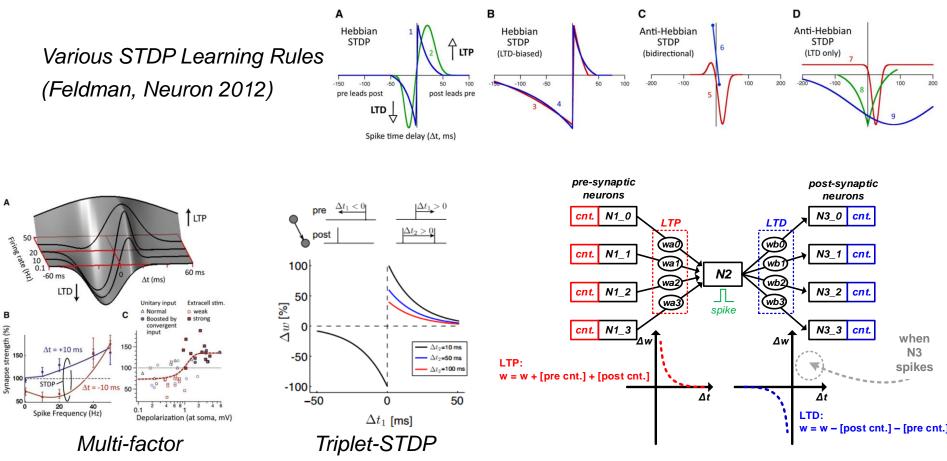


Seo. CICC. 2011

- Under STDP learning, when neuron K spikes, all synapses on row K and column K may update
- Transposable SRAM: single-cycle read & write in both row and col. directions
- Efficient pre- and post-synaptic update
- Near threshold operation
- Pattern recognition

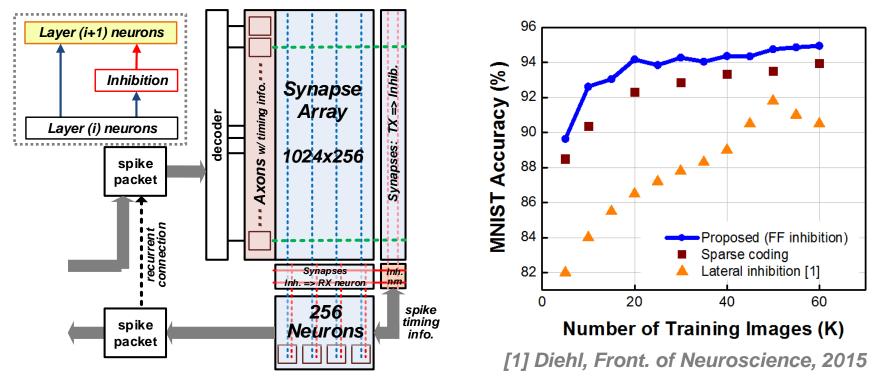
3

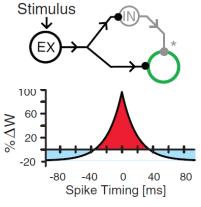
Versatile Learning in Neuromorphic Core



- A versatile neurosynaptic core to support various learning rules, large fan-in/-out, sparse connectivity
- Triplet STDP (*Pfister, J. of Neuroscience, 2006, Gjorgjieva, PNAS 2011*)
 - post-pre-post: post nrn. spike & pre nrn. timing & post nrn. timing
 - pre-post-pre: pre nrn. spike & post nrn. timing & pre nrn. Timing

Feedforward Excitation & Inhibition

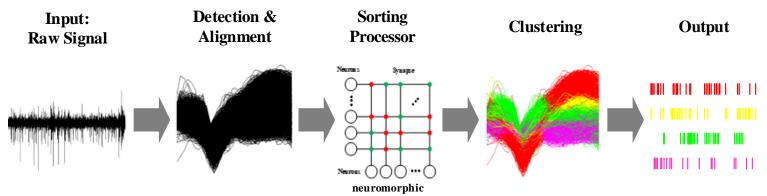




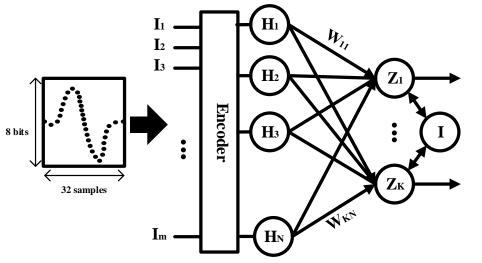
Vogels, Science, 2011

- Joint feed-forward excitation and inhibition
- For a small number of inhibitory neurons, add pre=>inh, inh=>post synapses
 - Balance excitatory & inhibitory synaptic inputs

Neural Spike Sorting Processor (for deep brain sensing & stimulation)

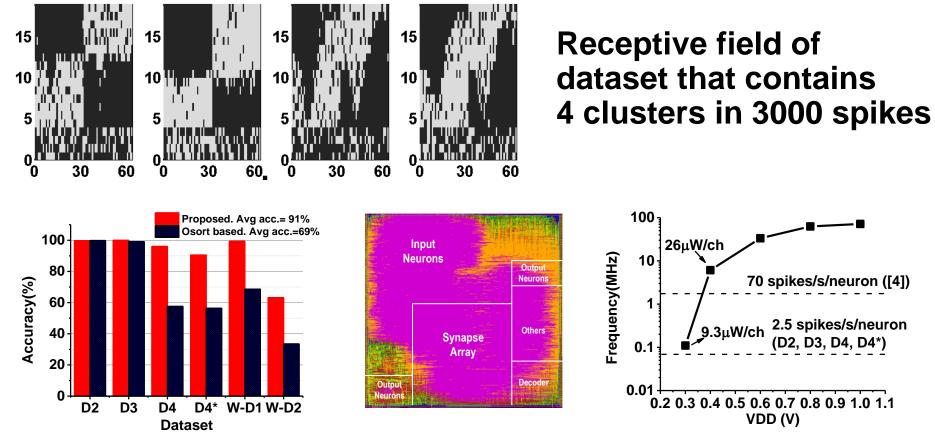


- Signals from invasive electrodes: spikes from multiple neurons
- Online, unsupervised neuromorphic spike-sorting processor Collaboration with Columbia University (ISLPED 2015)



- Weight update through STDP
- Start with K=2, automatically increases # of output neurons if the spike difference is large enough (self-organized map)

Exp. Results: Clustering Accuracy

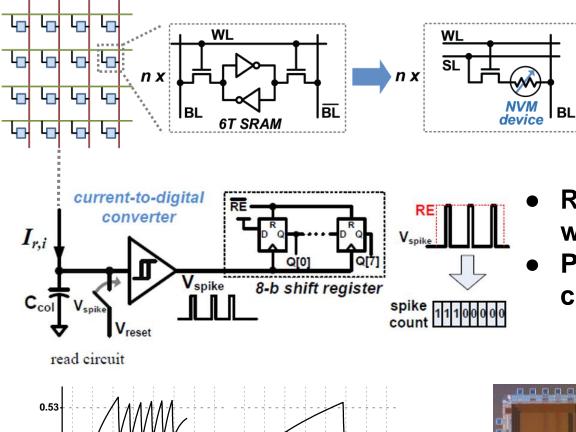


Spike sorting accuracy more reliable than other low-complexity algorithms such as O-sort

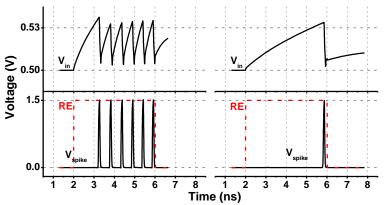
Avg. accuracy: <u>91%</u> vs. 69%

- 65nm GP, high-Vth, 0.5x0.5mm²
- 9.3µW/ch at 0.3V
- Layout of the design is dominated by memory elements, as well as power.

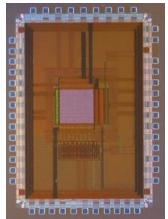
Neuromorphic Computing w/ NVMs



- Emerging NVMs (e.g. RRAM) could alleviate power/area bottleneck of conv. memories
- Read rows in parallel: weighted sum current
- Peripheral CMOS read: current-to-digital converter



Simulation results for 4ns read timing window



130nm RRAM array + CMOS read circuits (under testing)

Summary

- Neuromorphic computing hardware
 - 45nm testchip with on-chip STDP learning
 - Versatile learning neuromorphic core & architecture
 - 65nm spike clustering processor
 - Emerging NVM arrays + peripheral read/write circuits
- Future research with circuit-device-architecture codesign and optimization

Collaborators

- ASU
 - Faculty: Yu Cao, Shimeng Yu, Chaitali Chakrabarti, Sarma Vrudhula, Visar Berisha
 - Students: Minkyu Kim, Deepak Kadetotad, Shihui Yin, Abinash Mohanty, Yufei Ma
- Intel: Gregory Chen, Ram Krishnamurthy
- Columbia University: Mingoo Seok, Qi Wang