

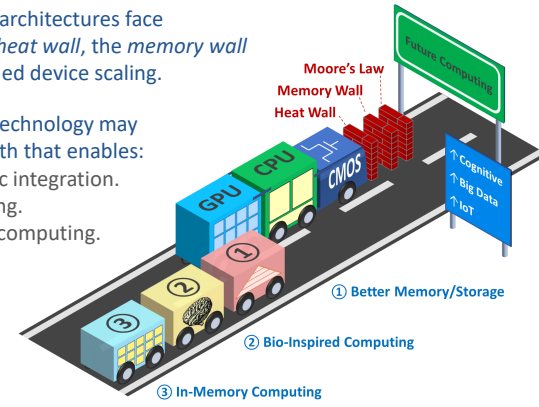


RRAM fabric for neuromorphic and in-memory computing applications

Mohammed Zidan and Wei Lu

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Electrical Engineering and Computer Science

- Conventional computing architectures face challenges including the *heat wall*, the *memory wall* and difficulties in continued device scaling.
- Developments in RRAM technology may provide an alternative path that enables:
 - Hybrid memory–logic integration.
 - Bioinspired computing.
 - Efficient in-memory computing.



M. A. Zidan, J. P. Strachan, and W. D. Lu, *Nature Electronics* 1: 22–29 (2018)

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Two-Terminal Memory Devices and Crossbar Arrays

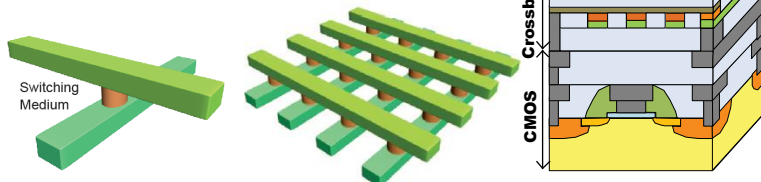


Physically reconfigurable materials and devices: Resistive Memory



Single-cell structure

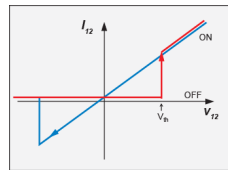
Crossbar Structure



Resistive memory (RRAM), *memory + resistor (memristor)*

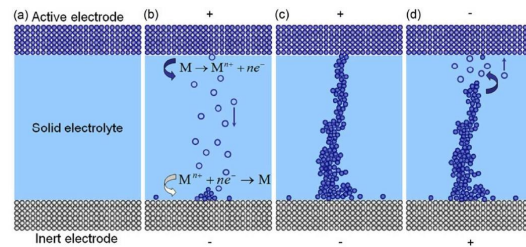
Hysteretic resistive switches and crossbar structures

- Simple structure
 - Formed by two-terminal devices
 - Not limited by transistor scaling
- Ultra-high density
 - NAND-like layout, cell size $4F^2$
 - Terabit potential
- Large connectivity
- Memory, logic/neuromorphic applications



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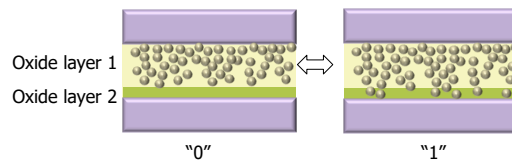
ElectroChemical Metallization Cell (ECM, CBRAM)



• Creating “new” materials on the fly

- Active electrode material + inert dielectric
- “Filament” based on electrode material injection and redox at electrodes
- Switching layer facilitates ionic movement

Valency Change Cell (VCM)

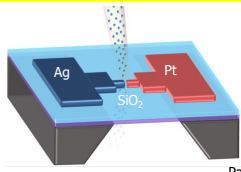


• Modulating existing material properties

- Filament based on oxygen exchange between two oxide layers

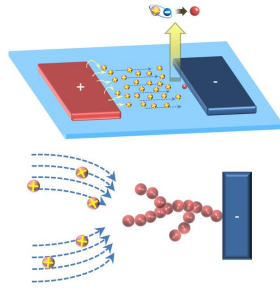
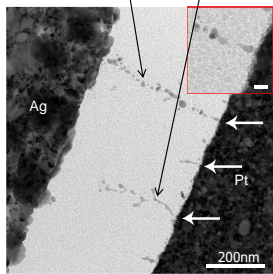
• Electrode plays minor role
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Yuchao Yang and Wei Lu, *Nanoscale*, 5, 10076 (2013)



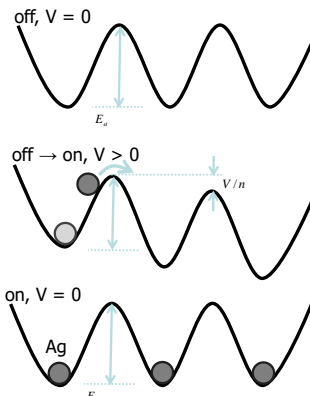
- Ag/SiO₂/Pt structure, sputtered SiO₂ film
- The filament grows from the IE backwards toward the AE
- Branched structures were observed with wider branches pointing to the AE

Completed filament Partially formed filaments



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Y. Yang, Gao, Chang, Gaba, Pan, and W. Lu, *Nature Communications*, 3, 732, 2012.

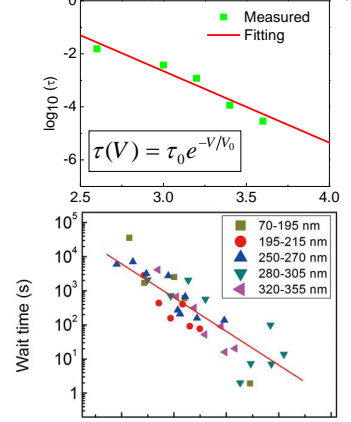


$$\Gamma = 1/\tau = \nu e^{-E_a'(V)/k_B T}$$

$$E_a'(V) = E_a - V/2n$$

Jo, Kim, Lu *Nano Lett.* 9, 496-500 (2009).

$$\nu = 2d\lambda e^{-E_a/k_B T} (e^{qEd/2k_B T} - e^{-qEd/2k_B T})$$

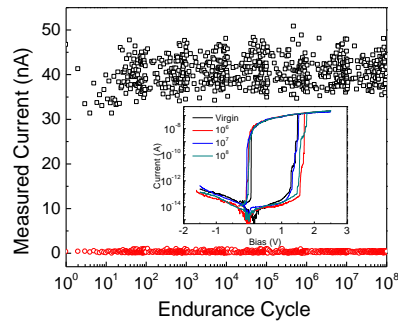
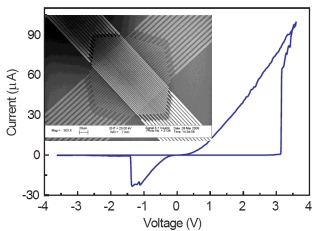


- Filament formation is a thermally activated process.
- Activation energy reduced by applied bias.
- Speed is a ca. exponential function of voltage.

Resistance Switching Characteristics



Integrated RRAM Crossbar/CMOS System

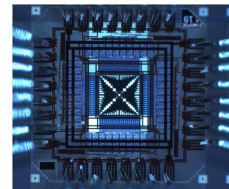
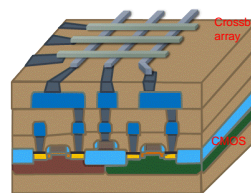


- 1e6 on/off
- 1e8 W/E endurance
- Switching speed ~10ns

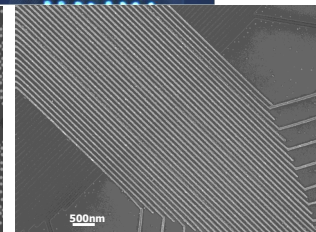
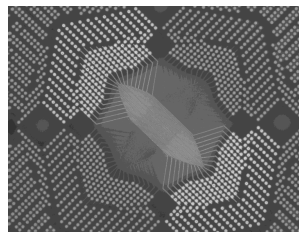
Jo, Kim, W. Lu, *Nano Lett.* 8, 392 (2008)

Kim, Jo, W. Lu, *Appl. Phys. Lett.* 96, 053106 (2010)

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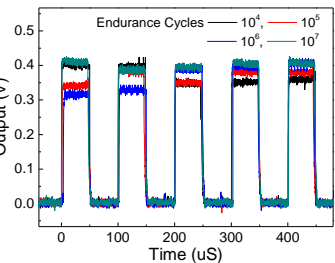


- Low-temperature process, RRAM array fabricated on top of CMOS
- CMOS provides address mux/demux
- RRAM array: 100nm pitch, 50nm linewidth with density of 10Gbits/cm²
- CMOS units – larger but fewer units needed. 2n CMOS cells control n² memory cells



Kim, Gaba, Wheeler, Cruz-Albrecht, Srivinaru, W. Lu *Nano Lett.* 12, 389-395 (2012).

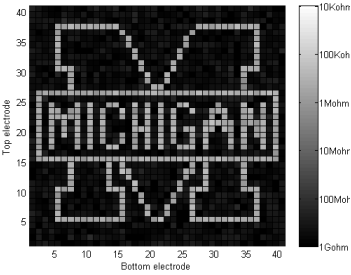
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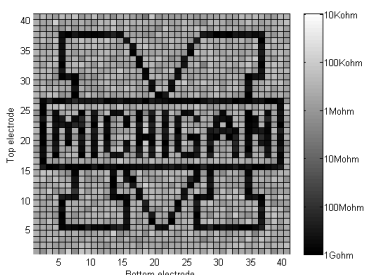


- Crossbar array operation, array written followed by read
- Programming and reading through integrated CMOS address decoders
- Each bit written with a single pulse

Stored/retrieved array 1

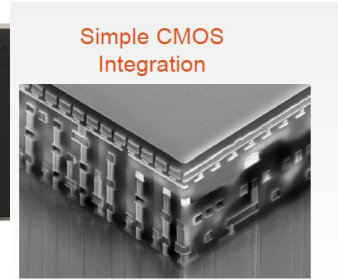
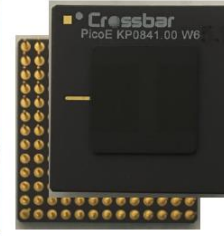
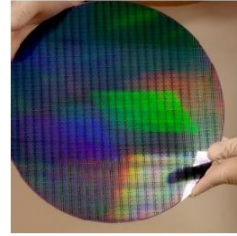


Stored/retrieved array 2



Results from a 40x40 crossbar array integrated on CMOS

- CMOS Compatible
- 3D Stackable, Scalable Architecture – Low thermal budget process
- Architectures proven include multiple Via schemes and Subtractive etching
- Crossbar Inc founded in 2010, \$100M VC funding to date
- Commercial Products offered in 2016 based on 40nm CMOS



Kim, Gaba, Wheeler, Cruz-Albrecht, Srivinara, W. Lu *Nano Lett.*, 12, 389–395 (2012).

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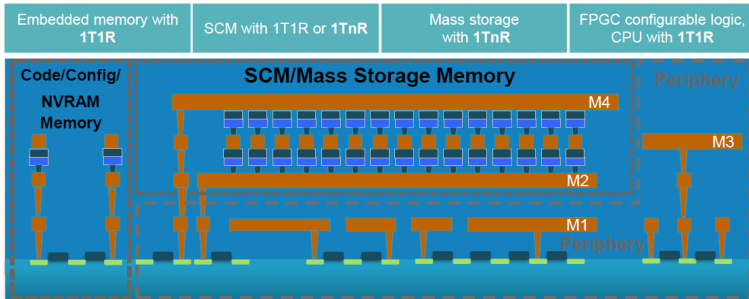


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Hybrid Integration of Memory with Logic 1T1R and 1TnR 3D stackable memory arrays



Improving Computing Efficiency using RRAM Arrays



- Monolithic logic/memory integration
- Different memory components integrated on the same chip
- Flexibility of speed/density/cost

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Different approaches for improving computing efficiency (depending on the application):

- Bring memory as close to logic as possible, still largely based on conventional architecture
- Neuromorphic computing in artificial neural networks
- More bio-inspired, taking advantage of the internal ionic dynamics at different time scales
- Other compute applications based on vector-matrix multiplications

Towards a general in-memory computing fabric based on a common physical substrate

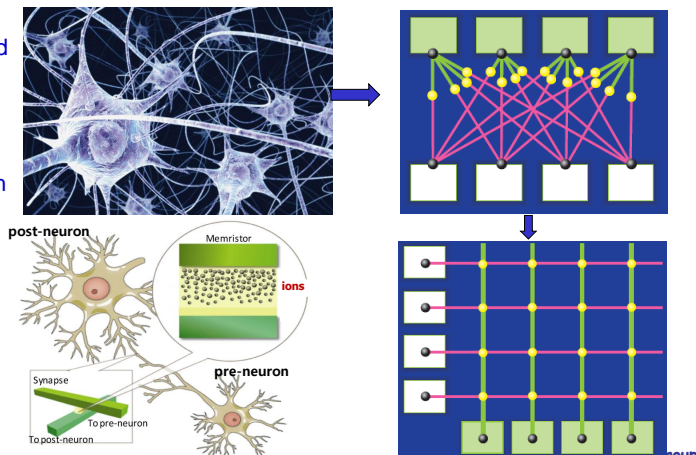
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Synapse – reconfigurable two-terminal resistive switches

Co-located memory-compute

High parallelism



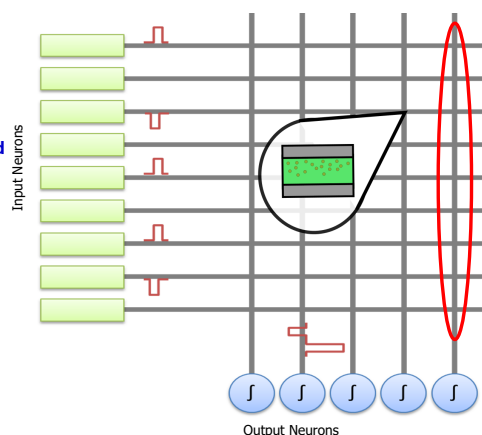
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S. H. Jo, T. Chang, I. Ebong, B. Bhavitavya, P. Mazumder, W. Lu, *Nano Lett.* 10, 1297 (2010).

RRAM perform learning and inference functions

DARPA UPSIDE program

- RRAM weights form dictionary elements (features)
- Image input, Pixel intensity represented by widths of pulses
- Memristor array natively performs matrix operation $\vec{I} = \vec{v} \cdot \vec{\Phi}$
- Integrate and fire neurons
- Learning achieved by backpropagating spikes

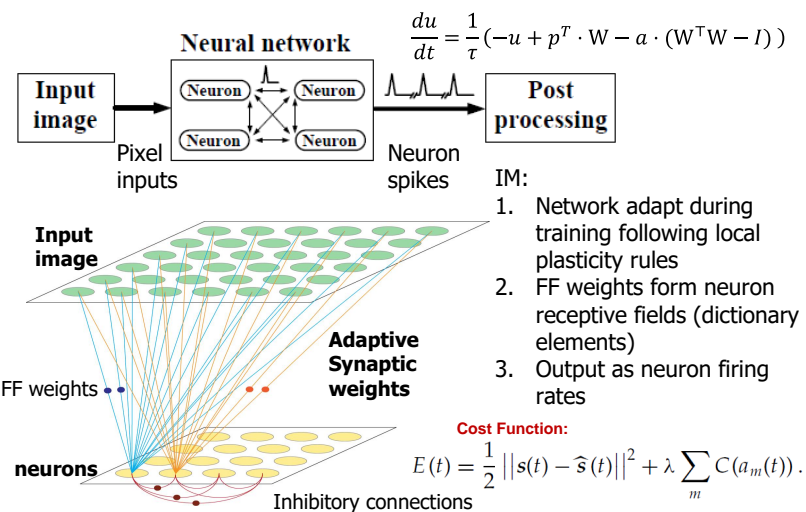


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Neural Network for Image Processing based on Sparse Coding

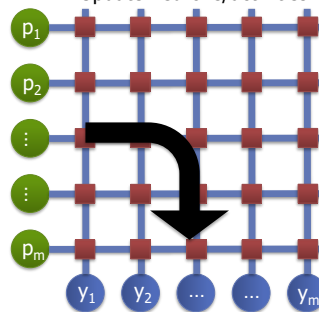


Sparse Coding Implementation in RRAM Array



Forward Pass

Update neurons/activities



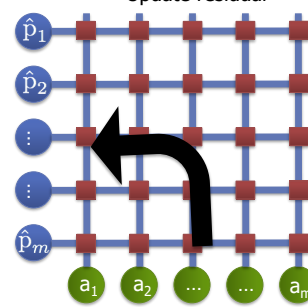
$$y = p^T W$$

$$\frac{du}{dt} = \frac{1}{\tau}(-u + p^T \cdot W - a \cdot (W^T W - I))$$

$$\frac{du}{dt} = \frac{1}{\tau}(-u + (p - \hat{p})^T W + a)$$

Backward pass

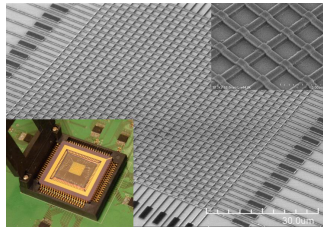
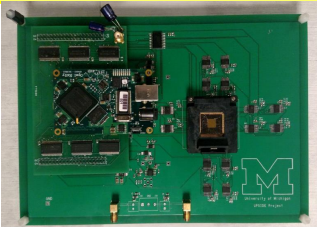
Update residual



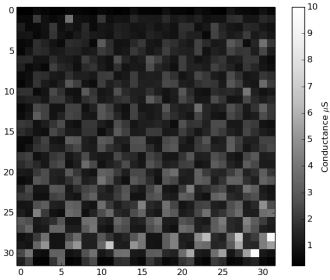
$$\hat{p} = a W^T$$

Neuron membrane potential

Sheridan et al., *Nature Nanotechnology*, 12, 784–789 (2017)

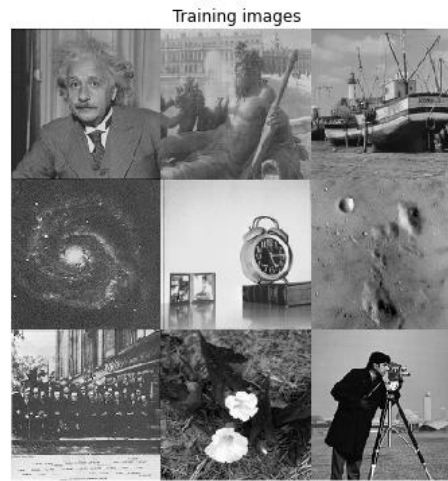


32x32 memristor array



- Checkerboard pattern
- 32 x 32 array
- Direct storage and read out
- No read-verify or re-programming

Sheridan et al., Nature Nanotechnology 12, 784–789 (2017)

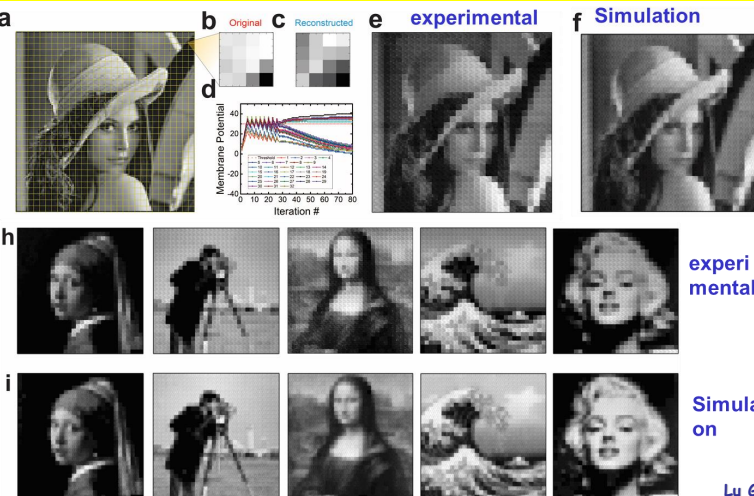


Sheridan et al., Nature Nanotechnology 12, 784–789 (2017)

9 Training Images
128x128px
4x4 patches
Trained in random order

Image Reconstruction with RRAM Crossbar

Improving Computing Efficiency using RRAM Arrays



Sheridan et al., Nature Nanotechnology 12, 784–789 (2017)

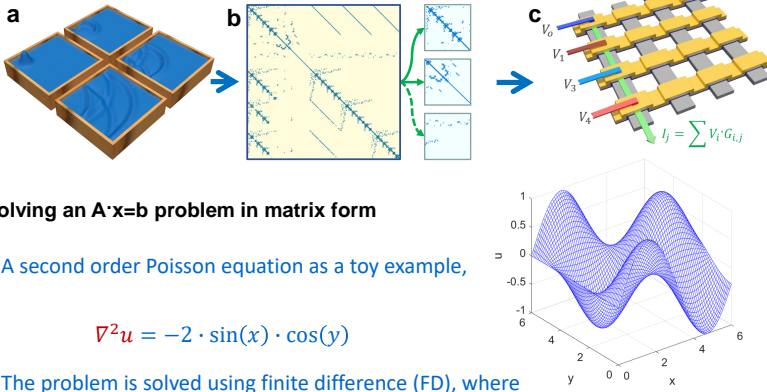
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- **Other compute applications based on vector-matrix multiplications**

Towards a general in-memory computing fabric based on a common physical substrate



Solving partial-differential equations (PDEs)



Solving an $A \cdot x = b$ problem in matrix form

- A second order Poisson equation as a toy example,

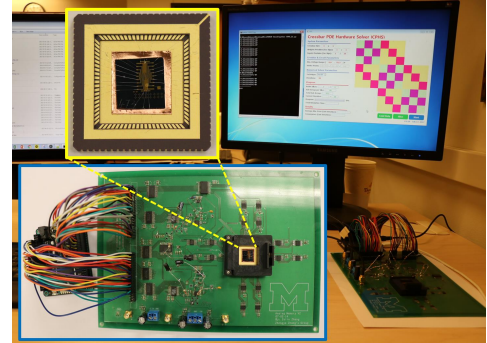
$$\nabla^2 u = -2 \cdot \sin(x) \cdot \cos(y)$$

- The problem is solved using finite difference (FD), where matrix can be sliced into a set of few similar slices.

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» Hardware Test bench

- The test board consists of: (i) RRAM crossbar, (ii) DACs to control the input signals, (iii) sense amplifiers and ADCs to sample the output current, (iv) MUXs to route the signals, and (v) FPGA to enables the software interface and control.



M. A. Zidan, Y.J. Jeong, J. Lee, B. Chen, S. Huang, M. J. Kushner, & W. D. Lu, Nature Electronics, 1, 411–420 (2018)

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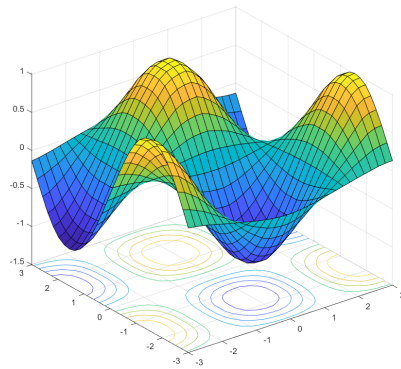
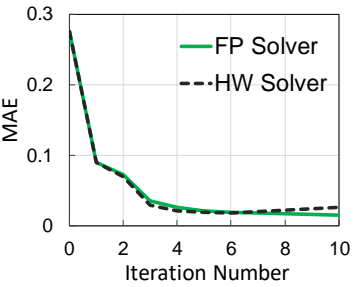
Hardware Prototyping



» Results Reconstructed as a 3D Animation

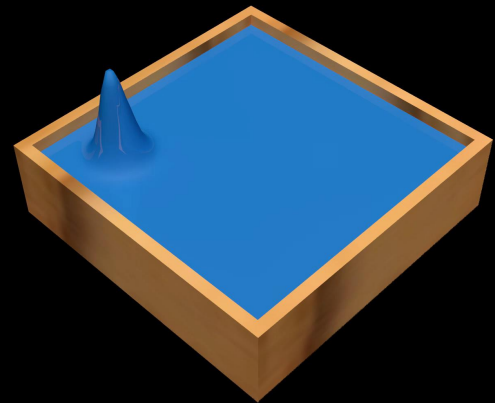
» Solving a toy example

Measured Results for the toy Example

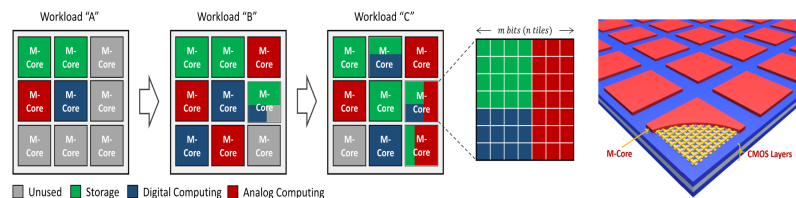


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Memory-Computing Unit (MPU)

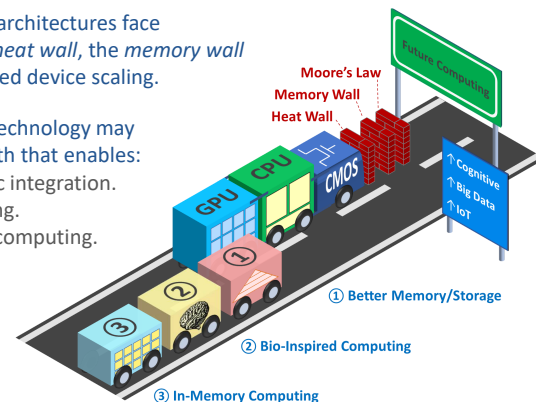
- "General" purpose by design: the same hardware supports different tasks – low precision or high precision. Not just a neuromorphic accelerator
- Dense local connection, sparse global connection
- Run-time, dynamically reconfigurable. Function defined by software.

M. Zidan, Y. Jeong, J. H. Shin, C. Du, Z. Zhang, and W. D. Lu, *IEEE Trans Multi-Scale Comp Sys*, DOI 10.1109/TMCS.2017.2721160 (2017)

M. A. Zidan, J. P. Strachan, and W. D. Lu, *Nature Electronics* 1: 22–29 (2018)

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Summary



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➡ Towards a general in-memory computing fabric based on a common physical substrate

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