Our Research in a Nutshell

“Our goal is to develop disruptive new computing paradigms and machines that will allow for lasting breakthroughs and open new application domains in the next 5-20 years.”

Emerging paradigms

- Algorithms
- Architectures

Emerging devices

- Memristors
- Memcapacitors
- Biomolecules
- ...
Computing with Structured vs Unstructured Substrates

Key challenges:
• precise positioning and
• low-resistance contacts

Polyaniline (PANI) conductive polymer, LANL, Wang et al.

Melosh et al., Science, 2003

Computing with Structured vs Unstructured Substrates

hard to fabricate
top-down engineered

easy to design logic, circuits, and architectures

bottom-up self-assembled
easy to fabricate

how do we compute with this mess?

Melosh et al., Science, 2003

Polyaniline (PANI) conductive polymer, LANL, Wang et al.
Computing with Structured vs Unstructured Substrates

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Embracing Randomness

- Error-resiliency
- Self-Adaptivity
- Concurrency And Flexibility

Fully structured and regular fabrics

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2000 2005 2010 Beyond The far beyond
What’s the next big thing in computing? 
And how do we get there?

As feature-size scaling and "Moore’s Law" in CMOS circuits further slow, attention is shifting to computing by non-von Neumann, non-CMOS, and non-Boolean computing models.

Material Implication

Digital Logic Synthesis for Memristors (1)


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Digital Logic Synthesis for Memristors (2)

There is no general design theory on how to obtain a desired computation from intrinsic dynamics for devices that behave beyond simple Boolean switching.
Reservoir Computing / Liquid State Machines

- Fixed reservoir with “interesting” dynamics. No state needed.
- Only the output layer is trained. → Low learning complexity.
- Variation is good! → Easy to fabricate.

```
input layer
  reservoir
output layer
```

- Quantum dots
  - [Obst et al., 2013]
- Water bucket
  - [Fernando and Sojakka, 2003]
- Atomic switches
  - [Sillin et al., 2013]
- Photonics
  - [Vandoorne et al., 2011]
Reservoir Computing / Liquid State Machines

Issues and Challenges

Hierarchical and modular systems

1. Create digital building blocks, then use traditional design tools?
2. New approach?

Lack of composability
Solve large-scale real-world problems

Lack of scalability
Monolithic systems
Signal attenuation

Training
Hierarchical Networks

Hierarchical Composition of Memristive Networks for Real-Time Computing

Burger et al, Nanoarch, 2015
Hierarchical Composition of Memristive Networks for Real-Time Computing

Hierarchical composition of heterogeneous small networks outperforms monolithic memristive networks by at least 20% on waveform generation tasks.

On the NARMA-10 task, we reduce the error by up to a factor of 2 compared to homogeneous reservoirs with sigmoidal neurons.

Single memristive networks are unable to produce the correct result.

Network Topologies: Initial Steps

- **M**: number of hierarchical levels
- **n**: number of modules grouped together to constitute the modules of the next hierarchical level
Random Boolean Network Reservoir

**NK Networks:**

- \( N \) = number of nodes
- \( K \) = interaction between the nodes, i.e., the number of incoming links per node

![Node LUT](image)

\( N = 8, K = 3 \)

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**X-O Tasks**

![Accuracy Chart](image)

- \( M = 4 \)
- \( M = 3 \)
- \( M = 2 \)
- \( M = 1 \) (monolithic)

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Labyrinth Tasks

Fig. 6.1. 1-turn labyrinth

Fig. 6.2. 1-turn labyrinth

Labyrinth Tasks

Hierarchical levels

Number of modules

Hierarchical levels

M = 4  M = 3  M = 2  M = 1 (monolithic)
Deep LSM network (D-LSM)

![Diagram of Deep LSM network](image)

Fig. 4: The proposed deep LSM network. The image pixels are first converted to spike trains. Each 1st-stage LSM receives 25 spike trains which corresponds a sub-region of the input image selected by a 5×5 sliding window. As the sliding window moves to cover the entire image, each 1st-stage LSM generates 24×24 new spike trains. The pooling/sub-sampling stage is realized by 4-inputs OR gates. After multiple LSM stages and pooling stages, the extracted features enter the last LSM stage which also incorporates the final readout layer.

Wang and Li, D-LSM: Deep Liquid State Machine with Unsupervised Recurrent Reservoir Tuning, 3rd International Conference on Pattern Recognition (ICPR), December 4-8, 2016

Memcapacitive RC

![Graph and diagram of Memcapacitive RC](image)
Memcapacitive RC: MNIST

![Graph showing performance and power consumption for MNIST task.]

Fig. 4: Reservoir performance and power consumption for the MNIST task. $I = 784$, $O = 600$, $N = 2100$. The power measurements represent the average per image.

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- **SRC Education Alliance, Undergraduate Research Opportunities (URO) Program**, Sep 2012 – Sep 2016.
- **Unified English Braille through a Powerful and Responsive eLearning Platform (UEB PREP)**, Rehabilitation Services Administration, Department of Education, Sep 1, 2014 – Aug 31, 2019. $548,483$.
- **DARPA, Sparse Adaptive Local Learning for Sensing and Analytics (SALLSA)**, May 3, 2013 – Aug 2, 2017. The project is in collaboration with the University of Michigan and Los Alamos National Laboratory. $5.69$ million.
- **Inference at the Nanoscale**, National Science Foundation (NSF), Cyber-enabled Discovery and Innovation (CDI), Type II award. NSF grant no: 1028378, Sep 15, 2010 – Aug 31, 2016 (with NCE).