Neuromorphic Computing

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Lecture series contents

- The state of computer hardware today.
- Challenges in hardware driven by societal needs (data science).
- What future solutions could answer current (and near future) data processing needs?
- How are brains like computers?
- How are computers like brains?
- What lessons learnt about human brains can we apply to computers?
- What is neuromorphic computing?
- The three main approaches to neuromorphic computing.
- Examples of the state of the art in neuromorphic computing.

Lecture review of last week

- Shannon capacity theorem lets us know how much data we can move down a noisy channel.
  - All channels are noisy
  - Applies to silicon and biological communications
  - $C = B \log (1 + S/N)$
  - Shows us there is a maximum rate
  - Shows us there is a most efficient rate
  - These are rarely the same!
- Computers operate in a very high precision very high energy manner
- Brains operate in a low precision, efficient energy use manner
- There exists a large unfilled gap between these ‘opposites’

Neuromorphic Computing

Goals

- Scalable architecture designed to run brain like computations
- Replace virtual neurons/synapses with physical, analog devices
- ‘In memory’ devices
- Reduce power consumption
- Enable ‘edge computing’
- Sit in the gap between high accuracy, high energy classical computing and low accuracy, low energy neural computation
- Become standard CPU/hardware extension like SIMD SSE
- Learn more about how the human brain works

The Neuromorphic Computing Roadmap

The main academic approach

1) Implement computation with analog circuits (elements) to consume close to the theoretical minimum energy.

2) Implement communication with asynchronous digital circuits to be robust to transistors that shut off intermittently.

3) Distribute a computation across a pool of (silicon) neurons to be robust to transistors that shut off intermittently or permanently.

4) Communicate spikes from pool to pool at a rate that scales linearly with the number of neurons per pool.

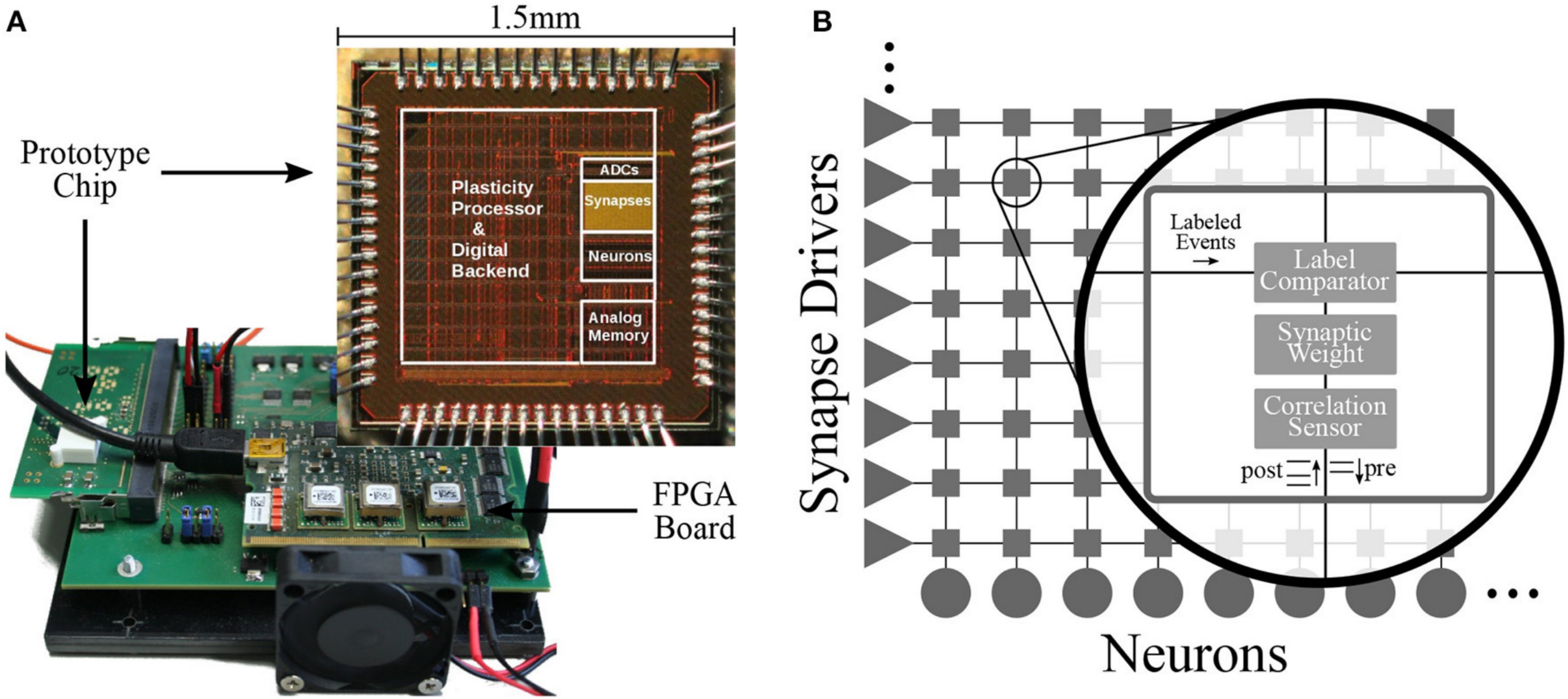
5) Encode continuous signals in these spike trains with precision that scales linearly with the number of neurons per pool.

Kwabena Boahen. A Neuromorph’s Prospectus. IEEE, 2017

Neuromorphic brains vs brains

- Timing matters for the delivery of action potential signals
  - Spikes in the brain are essentially asynchronous but the delivery time matters in many cases
  - As spikes are electrochemically regenerated they generally carry no information on the original size or shape of the spike
  - A close hardware copy should have one wire per axon?
  - Multiplexing and memory are things that computer memory and networks handle very well
  - Varying transmission and delivery times can be handled in hardware/software. Is this brainlike?
- What about other ‘features’ such as inherent errors and biological mess?
  - Seems inefficient to model these electronic in hardware?
  - Do we really want our ‘computers’ to be more brainlike and less efficient or more efficient and less brainlike?

Neuromorphic Computing, Brainscales

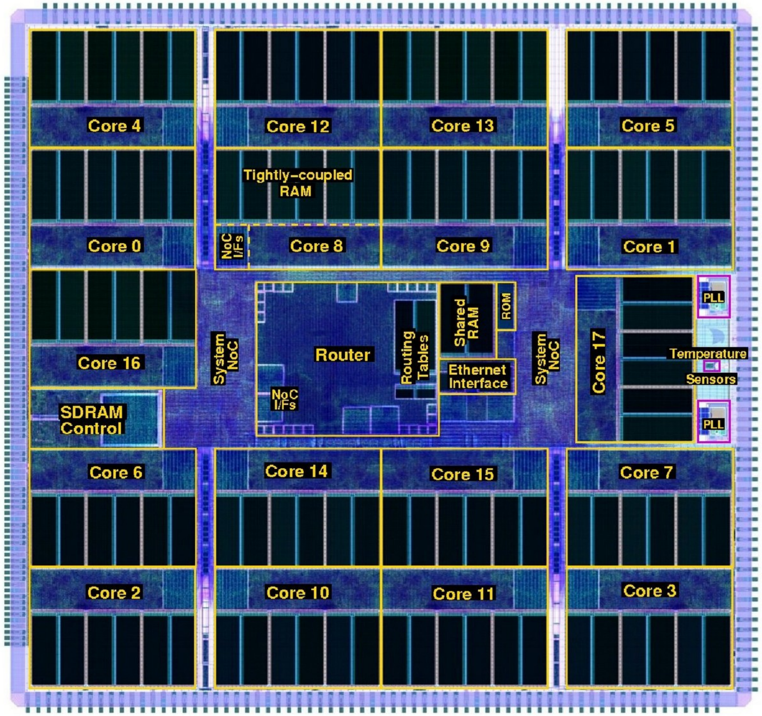


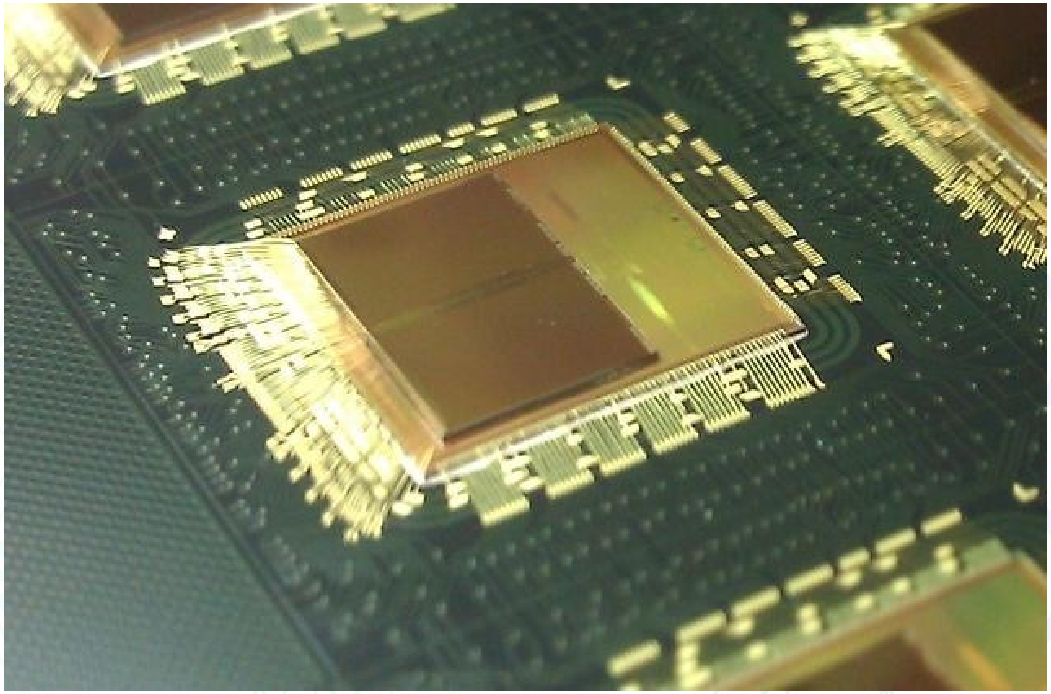
Brainscales-2 chip

- CMOS based analogue neurons, Leaky Integrate-and-Fire (LIF)
- Electronic bus for connections and instructions
- Weights stored in RAM

Wunderlich et al., Frontiers in Neuroscience, 2019

Neuromorphic Computing, Spinnaker





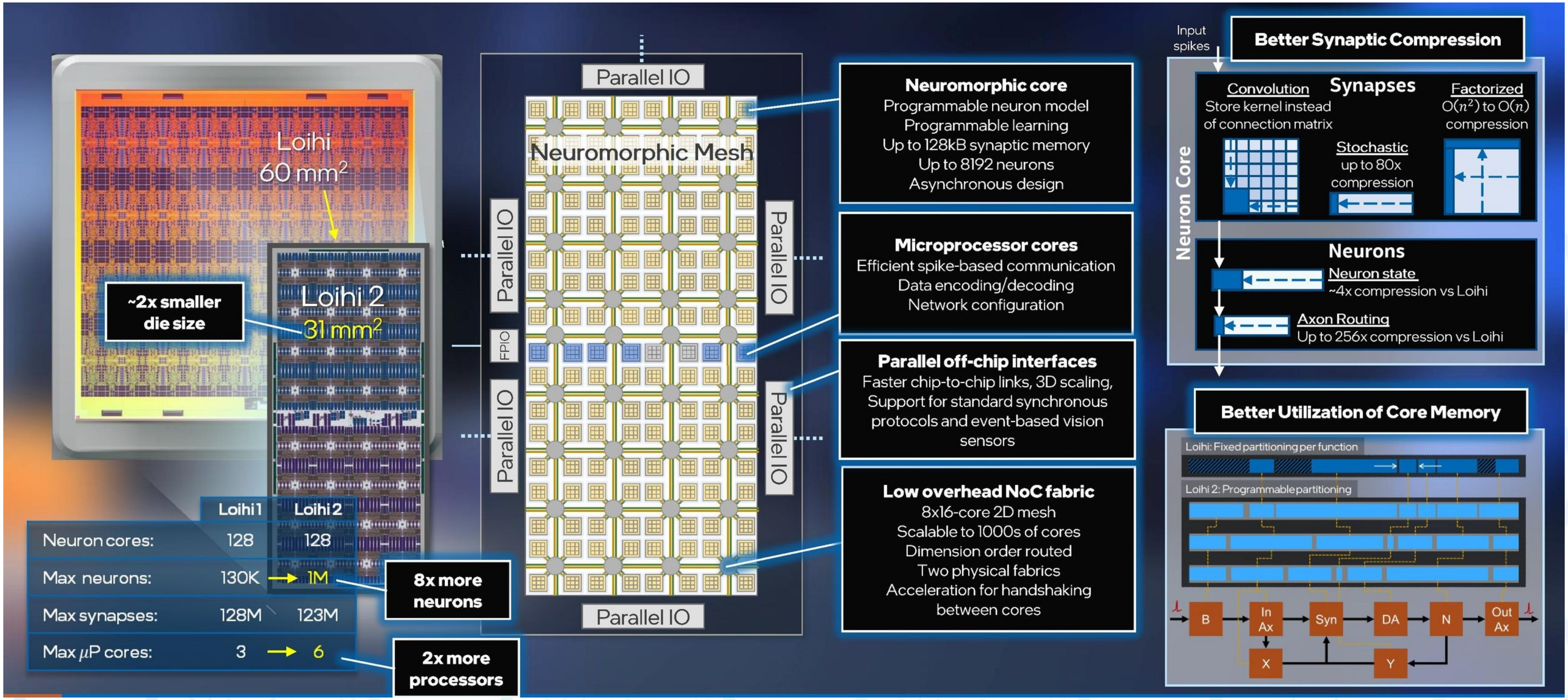
Spinnaker chip design and physical chip (Manchester University)

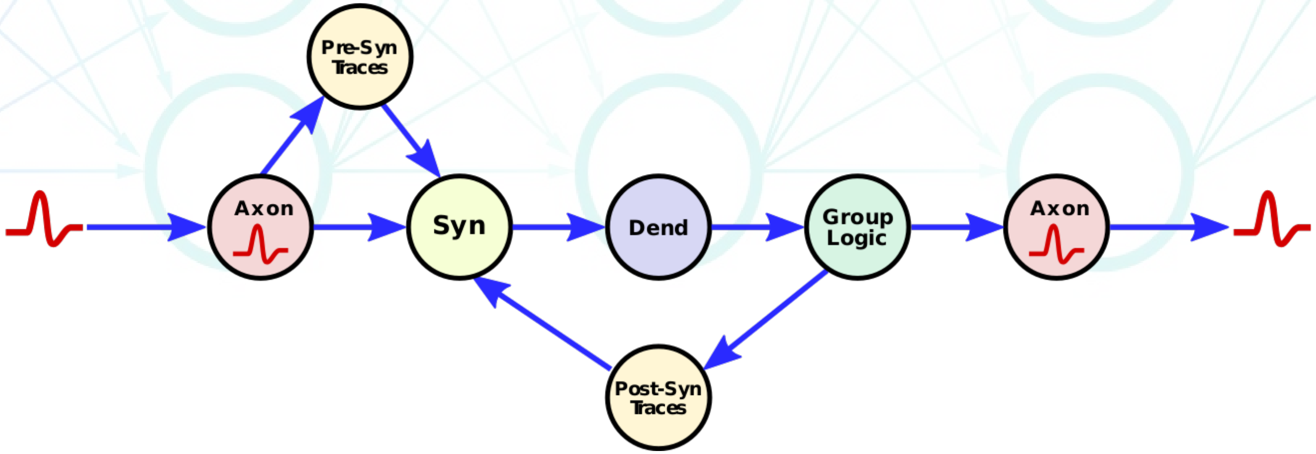
The philosophy here is that it is the abstract neural network that matters:

- An array of (say 256) neurons talking to a similar array will approximately require a 256*256 array of numbers representing the ‘weights’
- This could then be scaled to multiple sets of communicating networks and handled by say 8 bit weights (precision matters!)
- We can manage the scaling of address issues in very large networks as if the entire system was a packet switched network like the internet.

G Haessig et al,. Neuromorphic networks on the SpiNNaker platform, ieee 2019

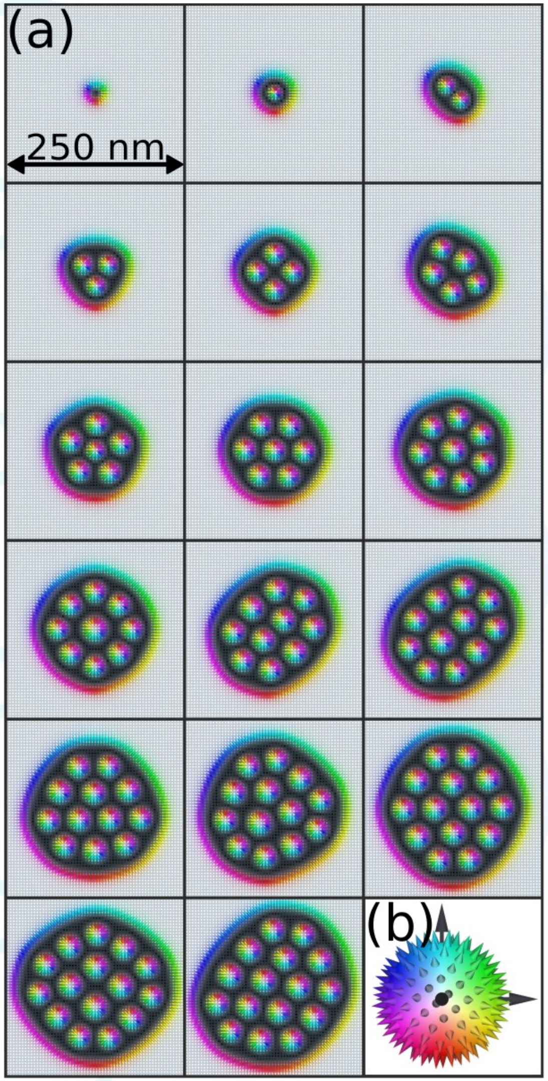
Neuromorphic Computing, Loihi



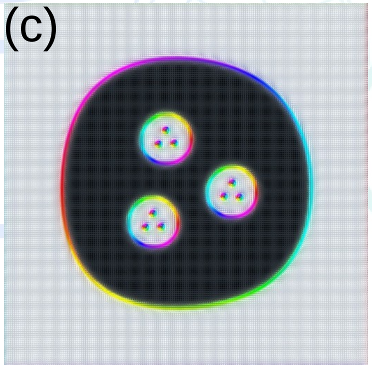


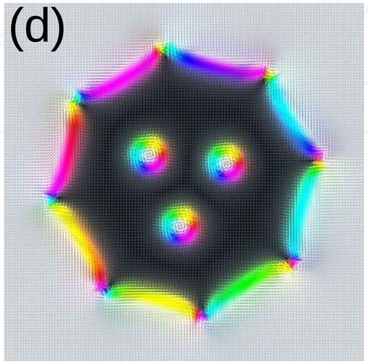
Skyrmions and skyrmion bags

- Skyrmions are particle like objects found in some magnetic fields:
  - Very stable
  - Extremely low power to write/move/delete
- Skyrmion bags are made up of many skyrmions:
  - Similar basic properties to skyrmions
  - Emergent properties from their composite nature
- Designing neurons and synapses using skyrmion bags:
  - Exploit emergent skyrmion bag properties
  - New direction for neuromorphic computing



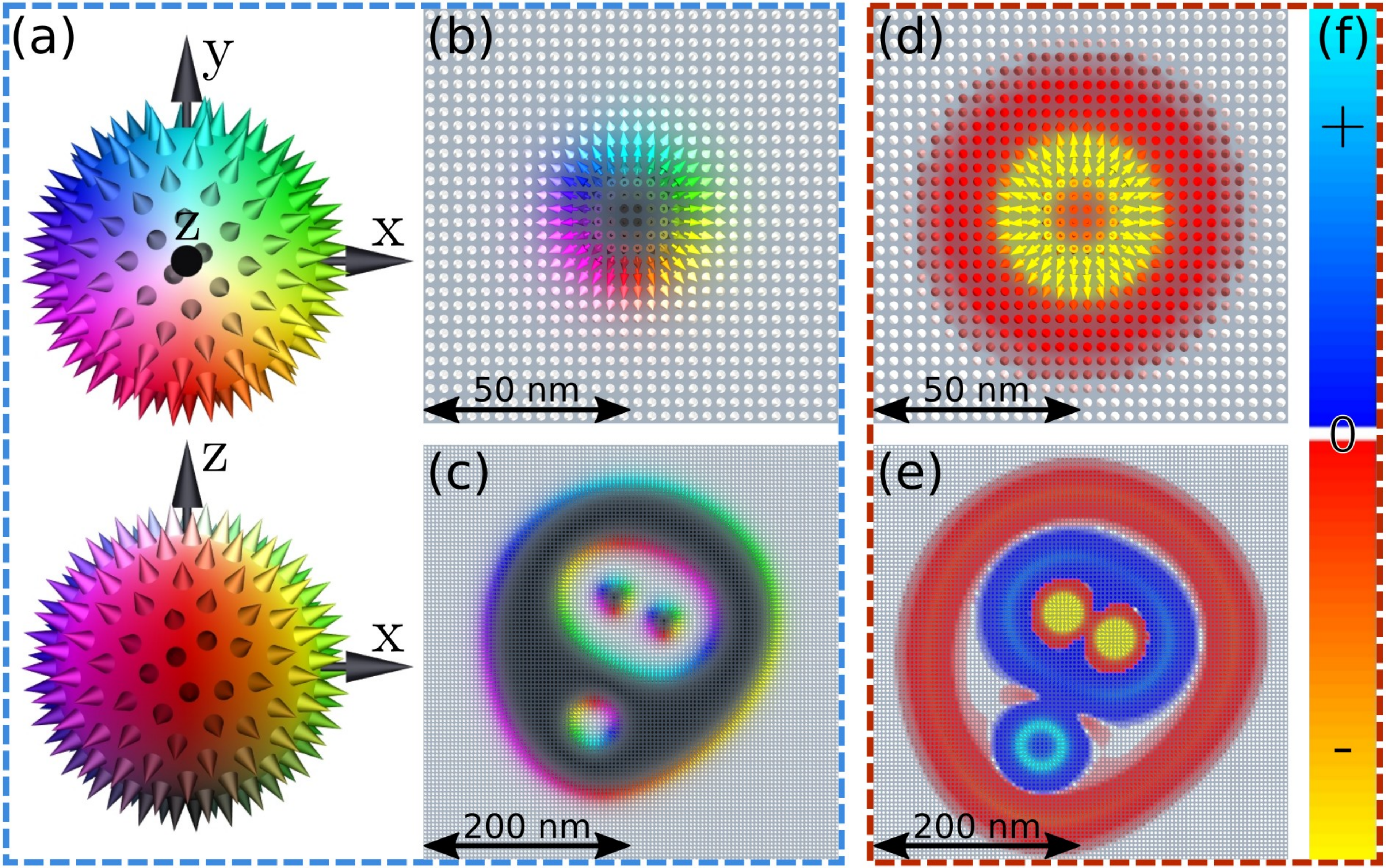
(a) A simulated skyrmion (top left) and skyrmion bags increasing in size. (b) A mapping of a single skyrmion to the sphere. C. Kind, D. Foster, Physics Review B, 2021





(c) A nested skyrmion bag. (d) A skyrmion bag with skyrmions embedded in the boundary.

Neuromorphic Computing, skyrmionics



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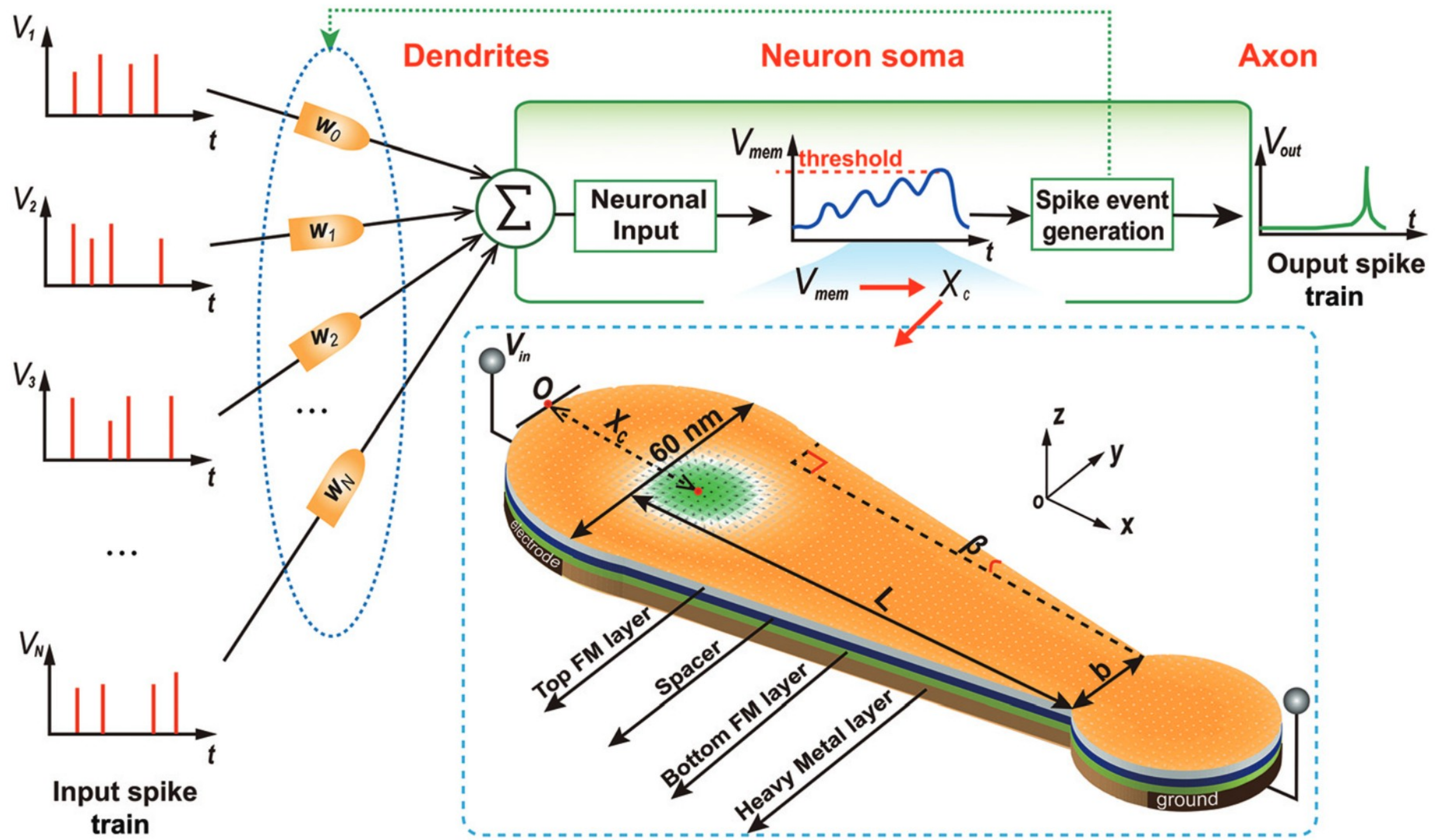
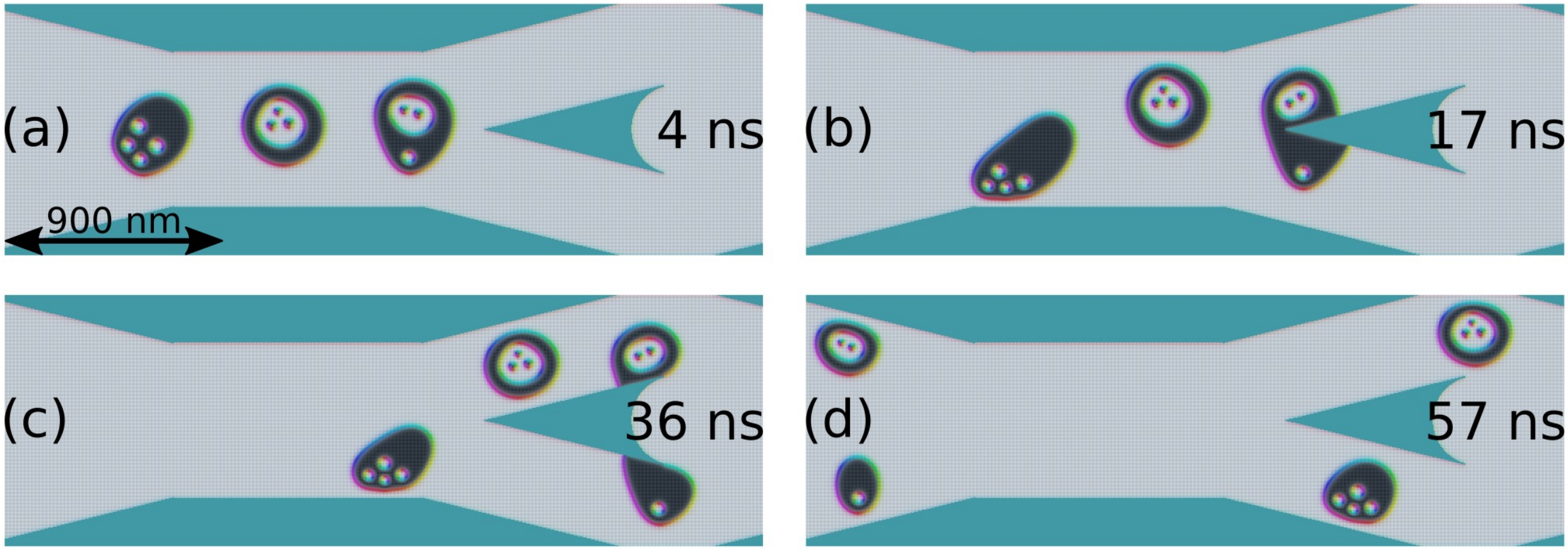
Neuromorphic Computing, new directions

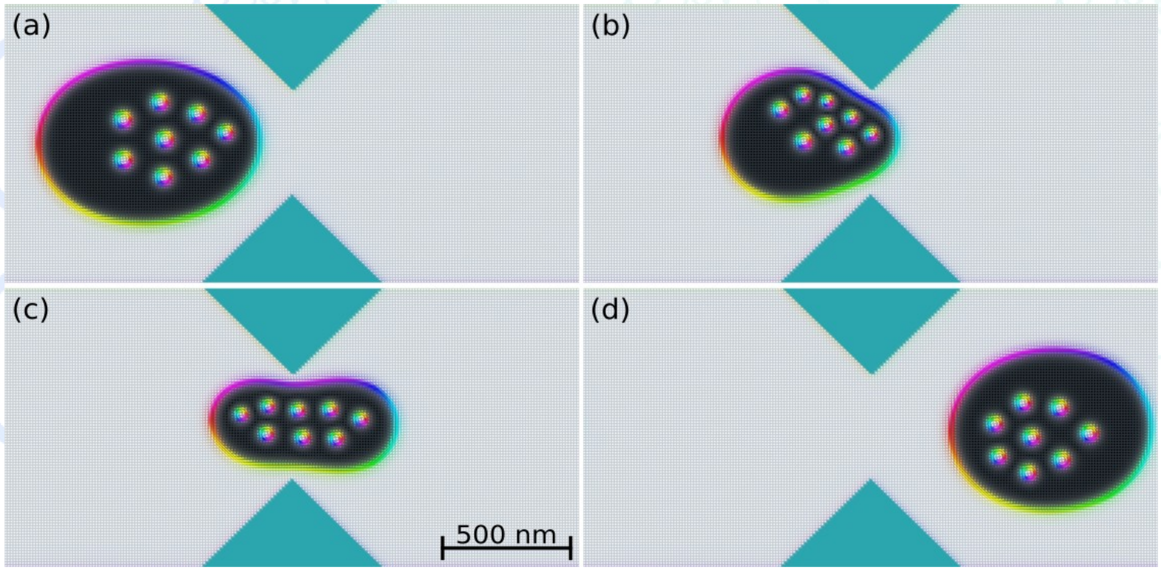
A proposed skyrmion based neuron

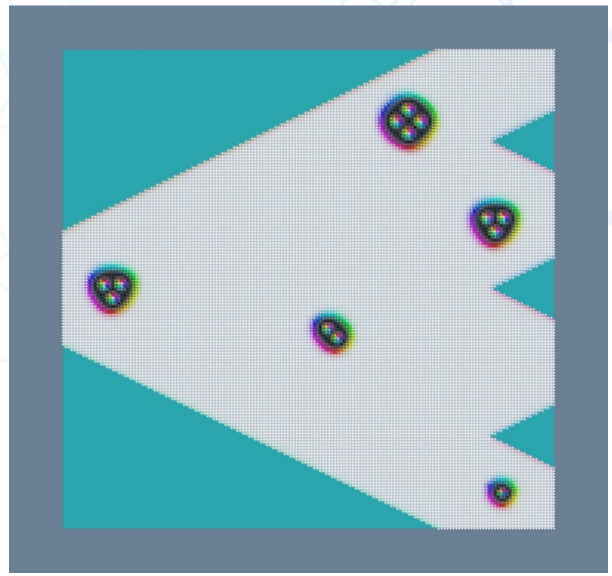


Chen et al., Nanoscale, 2017

Bio-inspired computing







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Thank you :)