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Benchmarking Spike-Based Visual Recognition:

a Dataset, Evaluation and Algorithms

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Aims and Motivations

- Unified spiking data
- Comparisons
- Evaluation methodology
- Promote future research

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A Dataset: NE15-MNIST

- AER format
- jAER support code
- 4 subsets
  - Poisson: unified data generation
  - FoCal: Rank-Order-Coding
  - Flash: fast recognition
  - Moving: invariant recognition

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Evaluation

- SNN models
  - biological training time
  - biological testing time
  - response latency
- H/W platforms
  - feasibility due to H/W limits
  - simulation time
  - energy use

	Preprocessing	Network	Training	Recognition
Brader et al. (2007)	None	Two layer, LIF neurons	Semi-supervised, STDP, calcium LTP/LTD	96.5%
Beyeler et al. (2013)	None	V1 (edge), V4 (orientation), and competitive decision, Izhikevich neurons	Semi-supervised, STDP, calcium LTP/LTD	91.6% 300 ms per test
Neftci et al. (2013)	Thresholding	Two layer RBM, LIF neurons	Event-driven contrastive divergence, supervised	91.9% 1 s per test
Diehl and Cook (2015)	None	Two layers, LIF neurons, inhibitory feedback	Unsupervised, exp. STDP, 3,000,000 s of training 200,000 s per iteration	95%
Diehl et al. (2015)	None	ConvNet or Fully connected, LIF neurons	Off-line trained with ReLU, weight normalization	99.1% (ConvNet), 98.6% (Fully connected); 0.5 s per test
Zhao et al. (2015)	Thresholding or DVS	Simple (Gabor), Complex (MAX) and Tempotron	Tempotron, supervised	Thresholding 91.3%, 11 s per test DVS 88.1%, 2 s per test

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	System	Neuron Model	Synaptic Plasticity	Precision	Simulation Time	Energy/Power Usage
SpiNNaker (Stromatias et al., 2013)	Digital, Scalable	Programmable Neuron/Synapse, Axonal delay	Programmable learning rule	11- to 14-bit synapses	Real-time Flexible time resolution	8 nJ/SE 54.27 MSops/W
TrueNorth (Merolla et al., 2014)	Digital, Scalable	Fixed models, Config params, Axonal delay	No plasticity	122 bits params & states, 4-bit synapse [a]	Real-time	46 GSops/W
Neurogrid (Benjamin et al., 2014)	Mixed-mode, Scalable	Fixed models, Config params	Fixed rule	13-bit shared synapses	Real-time	941 pJ/SE
HI-CANN (Schemmel et al., 2010)	Mixed-mode, Scalable	Fixed models, Config params	Fixed rule	4-bit synapses	Faster than real-time [b]	198 pJ/SE 13.5 MSops/W (network only)
HiAER-IFAT (Yu et al., 2012)	Mixed-mode, Scalable	Fixed models, Config params	No plasticity	Analogue neuron/synapse	Real-time	22-pJ/SE (Park et al., 2014) 20GSops/W

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Algorithms

- state-of-the-art
  - 2-Layer STDP learned
  - Spiking ConvNet (off-line training)
  - Spiking DBN (off-line training)
- Case studies
  - STDP online training on SpiNNaker
  - Spiking DBN on SpiNNaker (Evangelos Stromatias)

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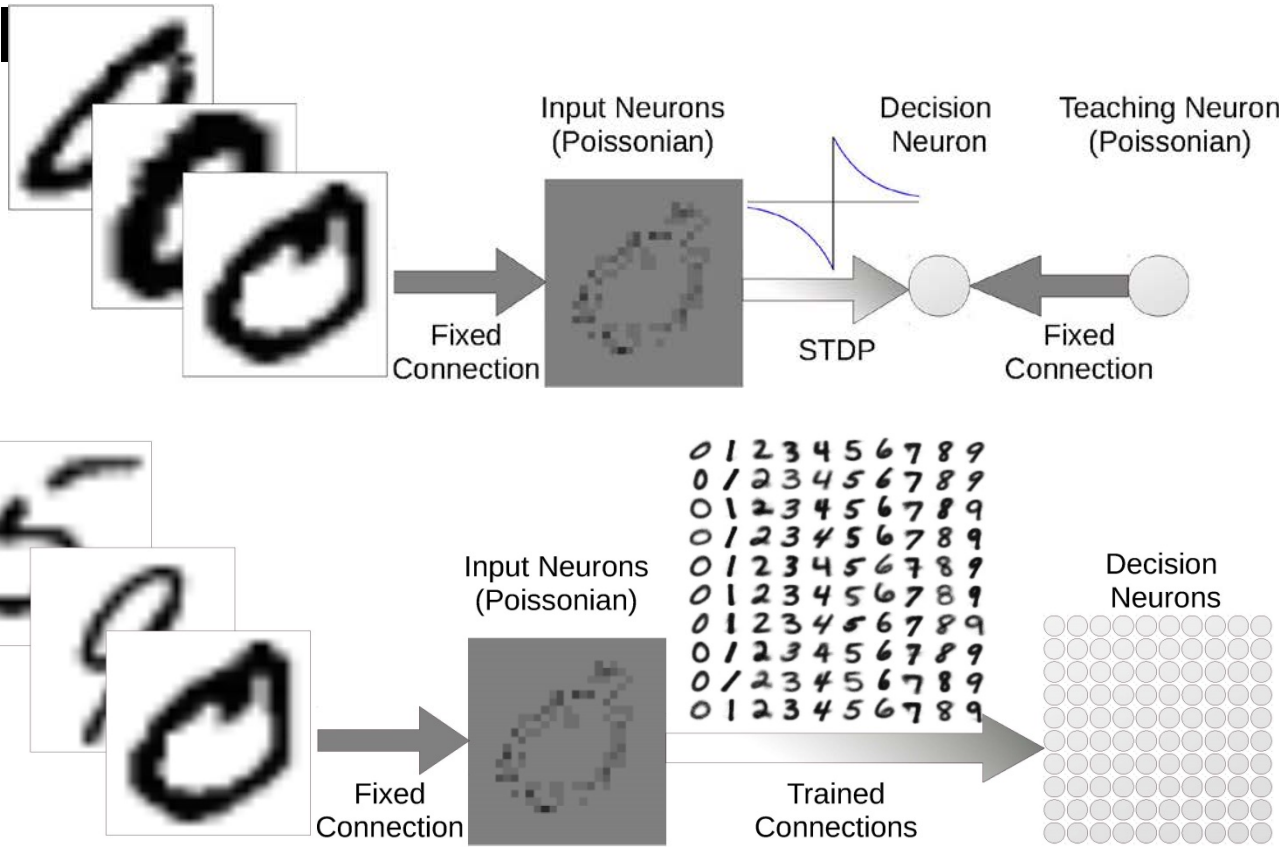
Case Study I: 2-layer STDP

- a simple model
- fast training
- short latency



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Case Study I: 2-layer STDP

Subclasses per digit	Accuracy (%)		Simulation (s)		Power Use (W)	
	N	S	N	S	N	S
1	79.62	79.50	554.77		~20	0.38
10	91.29	91.43	621.74		~20	0.38
50	92.98	92.92	1,125.12	12,000	~20	0.41
100	87.27	86.83	1,406.01		~19	0.44
1000	89.65	89.74	30,316.88		~17	1.50

The network with 500 decision neurons achieved a CA of 92.98% and average latency of 10.70 ms, and the simulation costs SpiNNaker 0.41 W on power use and 4,920J on energy use.

The work is submitted to the Frontiers in Neuromorphic Engineering under review process.

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Future Work:
Towards the Robust Object Recognition

- state-of-the-art
  - 2-Layer STDP learned – 1 case study
  - Spiking ConvNet (off-line training) – future case study
  - Spiking DBN (off-line training) – online formalised training
- My exploration on Spiking DBN
  - Restricted Boltzmann Machine (RBM)
  - Deep Belief Net
  - Future work: spiking RBM & DBN

Current work has been written down in a study report.

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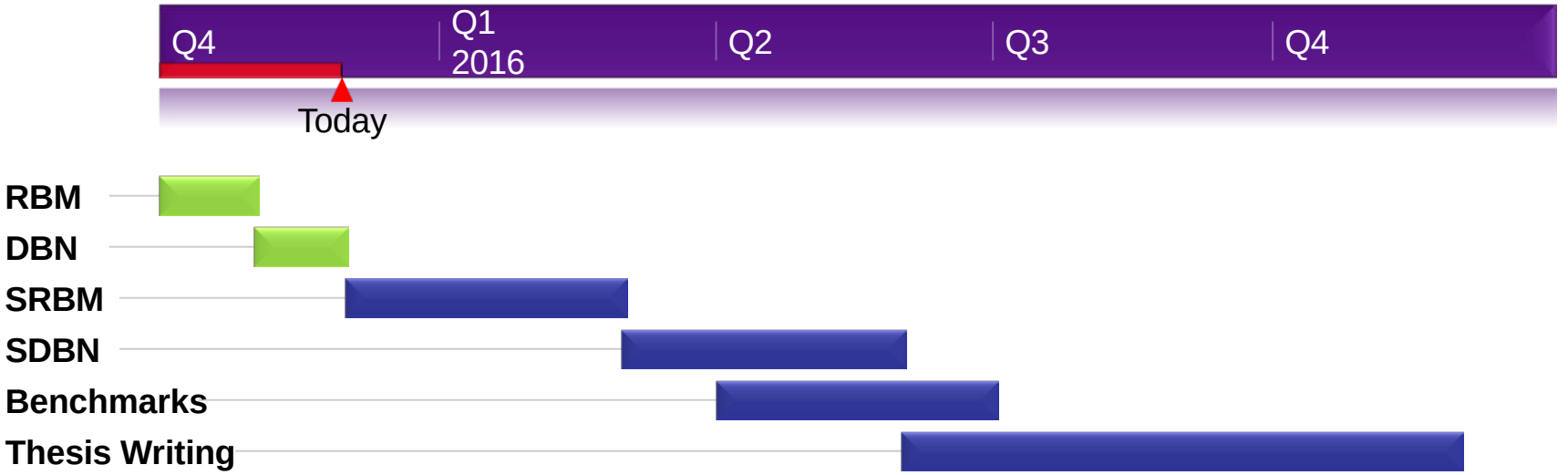
Potential Research Tasks

- Contrastive Divergence
  - RBM Validation
    - Maths of DBN
      - Practical Training Methods

Future Tasks

- Mean-Field Theory
  - SRBM Structure
    - STDP Learning for CD
      - Layered STDP Learning



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Questions?