Flow cytometry with event-based vision and spiking neuromorphic hardware

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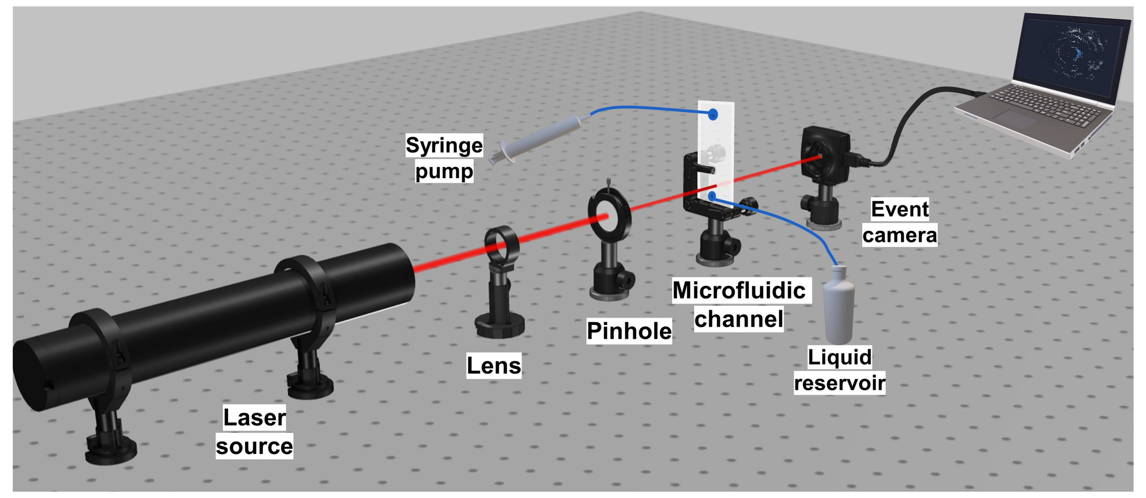
Introduction

- **Flow cytometry** identifies & analyzes different types of cells
  - Uses physical and chemical properties like shape or fluorescence
  - Label-free = not using biomarkers -> more robust and versatile
- **Goals**: high accuracy and low latency
- **Rationale**: event-based camera replaces high-speed camera ($$)
  - Less data (sparse, only differences), lower latency
  - Neuromorphic hardware (Loihi 2) for SNN classification model

Free-space optical setup

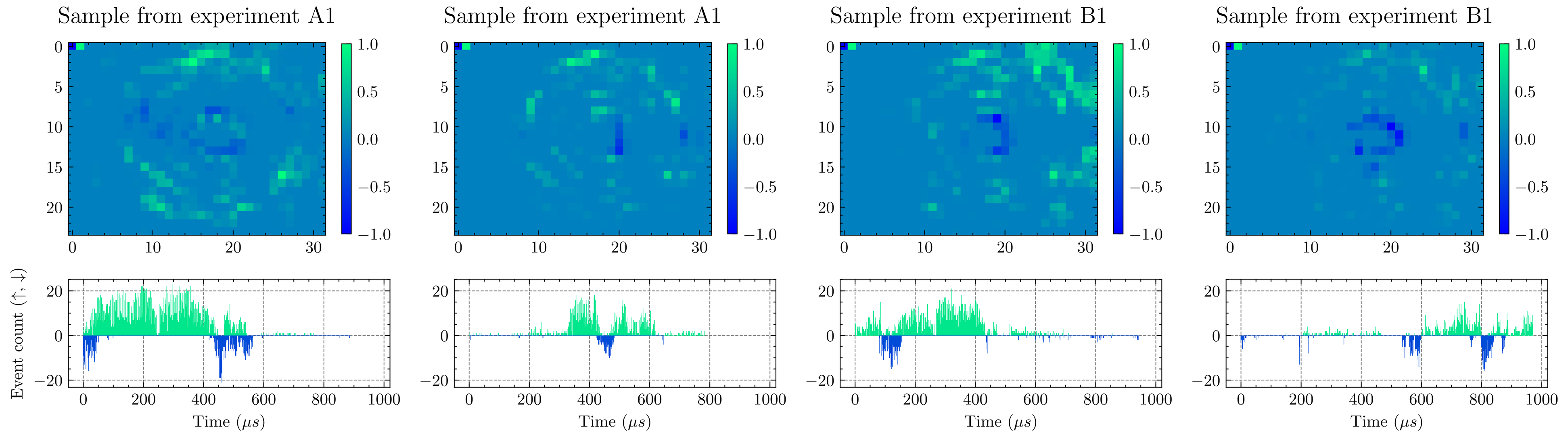
- **Coherent laser**: leverage light-matter interactions as nonlinear high-dimensional feature map. Allows simpler classification model.



633nm He-Ne laser focused on polymethyl methacrylate microfluidic channel of width 200μm.

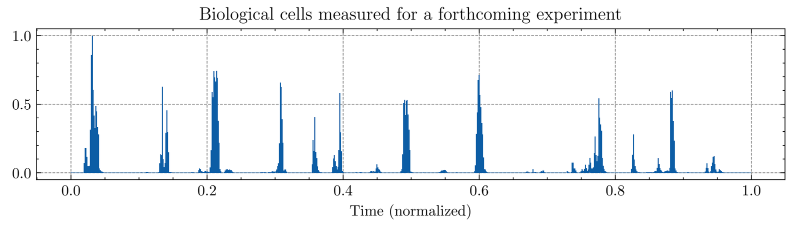
Data

- 2 classes of spherical microparticles (diameter 16μm and 20μm)
- 10x data compression compared to frame-based camera



4 experiment trials à $T_{exp} = 60s$, accumulation time for particle $T_{acc} = 1ms$, event-camera sensor of size 640x480

Automated pump gives more constant flow rate:



Data processing

- Time binning ($T_{acc} = 1ms$), remove bins with low activity (<1k events)
- 20x downsampling, yielding 32x24 resolution with 2 channels
- Preprocess using LIF neuron with $T_{refractory} = 2$ and $v_{rest} = 0$:

$$v_{xyp}(t) = \sigma v(t-1) + w n_{xyp}^{in}(t) \qquad \sigma = 0.9$$
$$s_{xyp}(t) = v_{xyp}(t) > v_{thr} \qquad w = 1.0, \; v_{thr} = 3.0$$

with $n_{xyp}^{in}(t)$ being number of input spikes at pixel xyp at time t (in μs).

Training setup

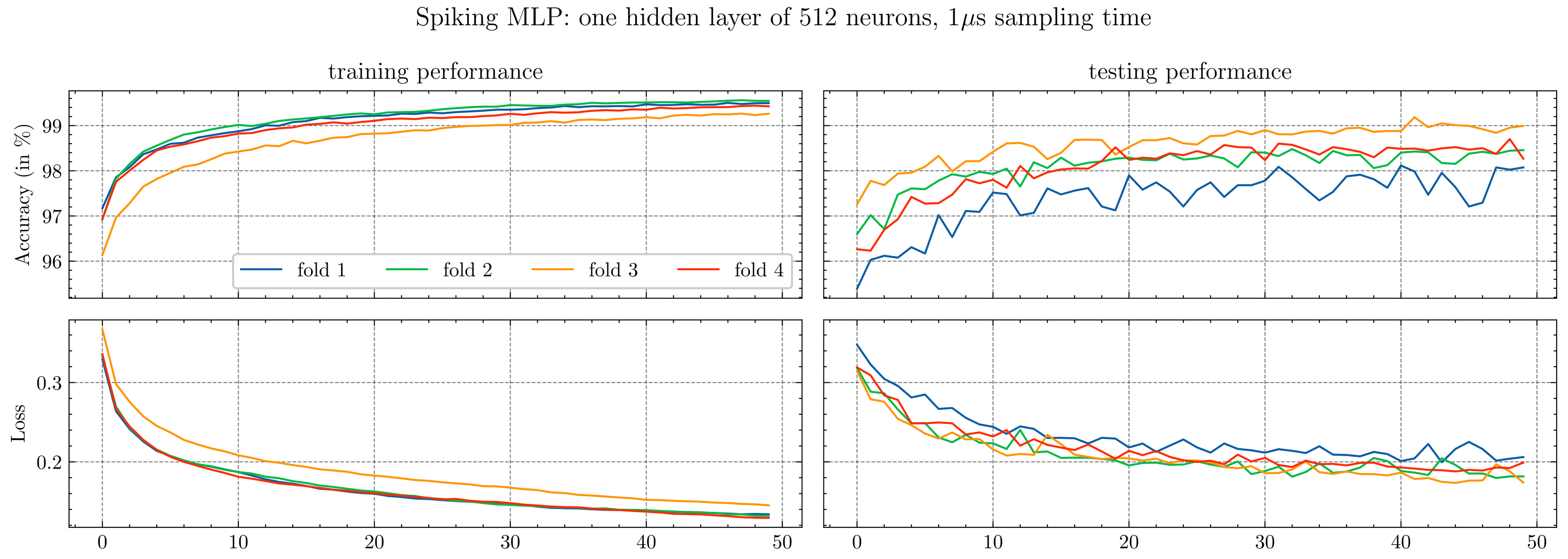
- Training: three trials, testing: one trial *(validation: last 12s of training trials)*
- Trained on GPU with Torch, then transferred to Loihi 2 for inference.

Spiking neural network

- Spiking MLP, using CUBA LIF neurons compatible with Loihi 2:

$$u_n = (1-\tau_u)u_{n-1} + a_{in} \qquad s_n^{out} = v_n^* > v_{thr}$$
$$v_n^* = (1-\tau_v)v_{n-1} + u_n + b \qquad v_n = v_n^*(1 - s_n^{out})$$

- Using SLAYER [1] for training, using rate coding for the output neurons with $r_{true} = 0.3$ and $r_{false} = 0.02$



Experiments

- Linear classifier on frames (accumulated over $T_{acc} = 1ms$)
- Neural networks on frames: MLP (512 or 512-512) and CNN
  - MLP: 512 or 512-512
  - CNN: 32 filters, 64 filters (3x3 kernel, 2x2 pool size), then 512 neuron MLP
- Spiking MLP on event data: with/without trainable delays, 512 or 512-512, different sampling times (1μs, 10μs, 100μs)

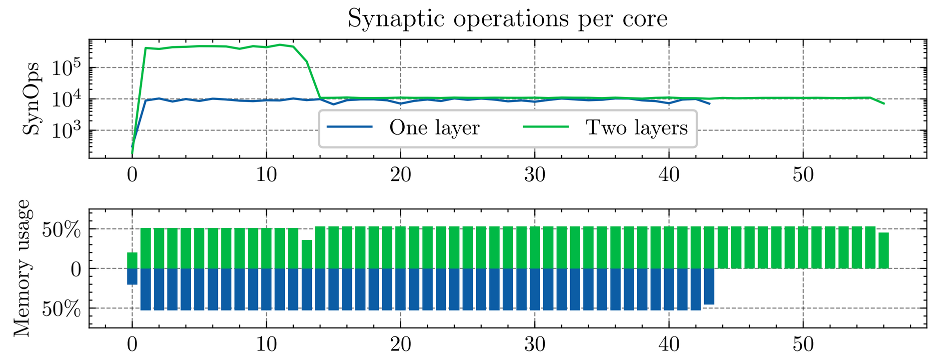
Results

- Event-based setup outperforms frame-based setup

Frame-based data	
Linear	98.86% ± 0.21% 96.05% ± 0.80%
1 layer	99.46% ± 0.20% 97.32% ± 0.55%
2 layers	99.52% ± 0.23% **97.51% ± 0.35%**
CNN	99.67% ± 0.05% 97.09% ± 0.70%

Event-based data				
Model		1 μs	10 μs	100 μs
Linear		98.11% ± 0.30% 96.81% ± 0.96%	97.72% ± 0.21% 95.53% ± 2.13%	86.73% ± 0.67% 83.08% ± 2.12%
1 layer	No delay	99.46% ± 0.10% 98.26% ± 0.42%	99.35% ± 0.07% 98.09% ± 0.47%	87.47% ± 0.61% 84.20% ± 4.42%
1 layer	Trained delay	99.43% ± 0.11% **98.45% ± 0.34%**	99.37% ± 0.11% **98.13% ± 0.29%**	91.51% ± 0.76% **88.99% ± 1.56%**
2 layers	No delay	99.60% ± 0.17% 98.12% ± 0.38%	99.18% ± 0.12% 97.25% ± 0.67%	51.97% ± 3.42% 50.72% ± 15.29%
2 layers	Trained delay	99.74% ± 0.12% 98.29% ± 0.41%	99.47% ± 0.03% 97.44% ± 0.58%	68.00% ± 11.34% 68.98% ± 2.43%

- Verified results on Loihi 2



Summary/Conclusion

- Sampling time of 100μs too long, 10μs still okay
- Delay improves classification accuracy
- For real-time classification at 1000 samples/second, need neuromorphic hardware with input-to-SNN-output latency of <= 10μs.

References

1) S. Shrestha & G. Orchard. *SLAYER: Spike Layer Error Reassignment in Time*. In: Advances in Neural Information Processing Systems, Volume 31, 2018.
2) Howard M. Shapiro. *Practical Flow Cytometry, 4th edition*. Wiley, 2003.

Acknowledgements

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