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Institute of Neuroinformatics

# Temporally-Variable Stimulations for Cortical Visual Neuroprosthetics using Spiking Neural Networks

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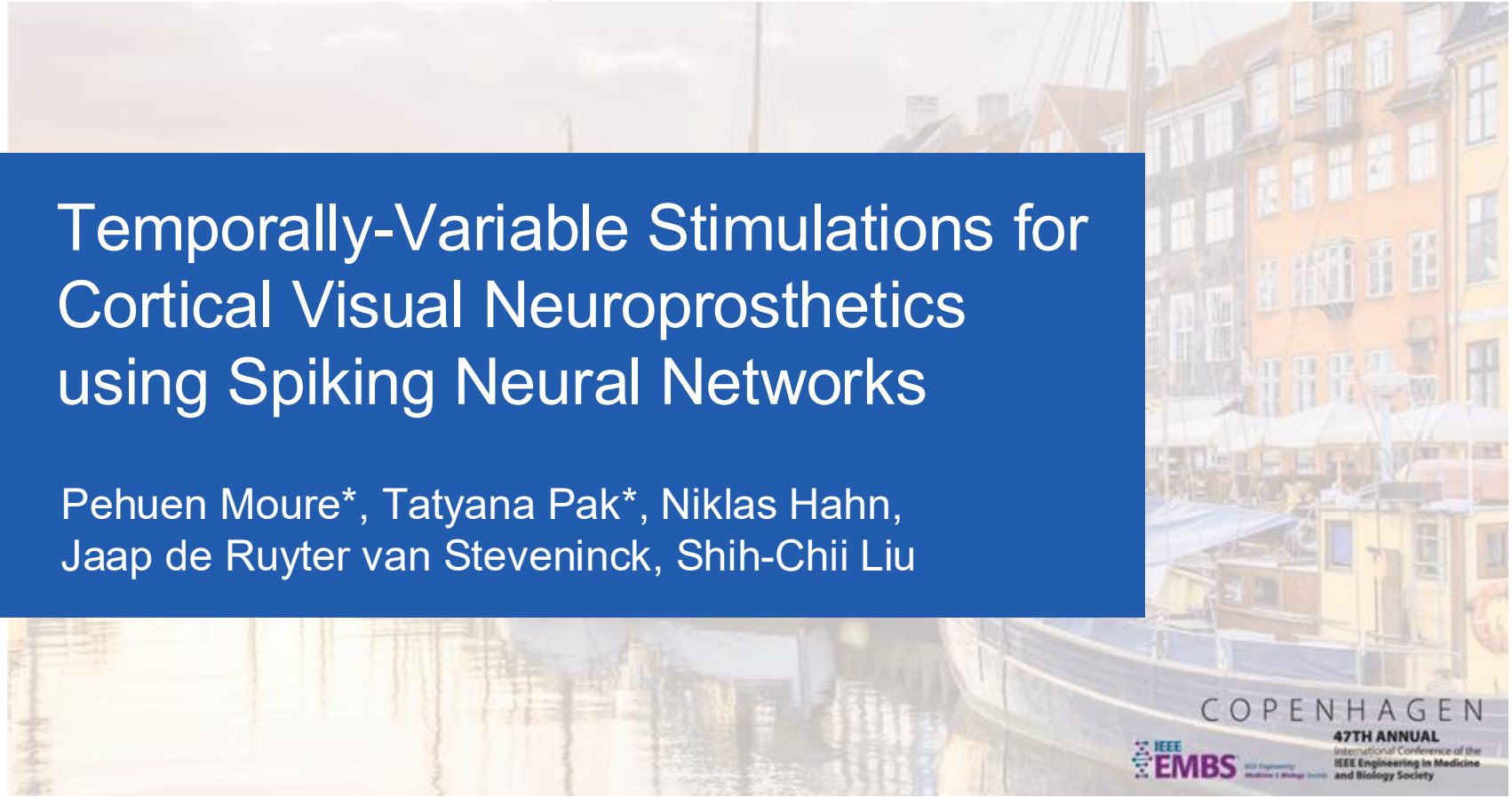
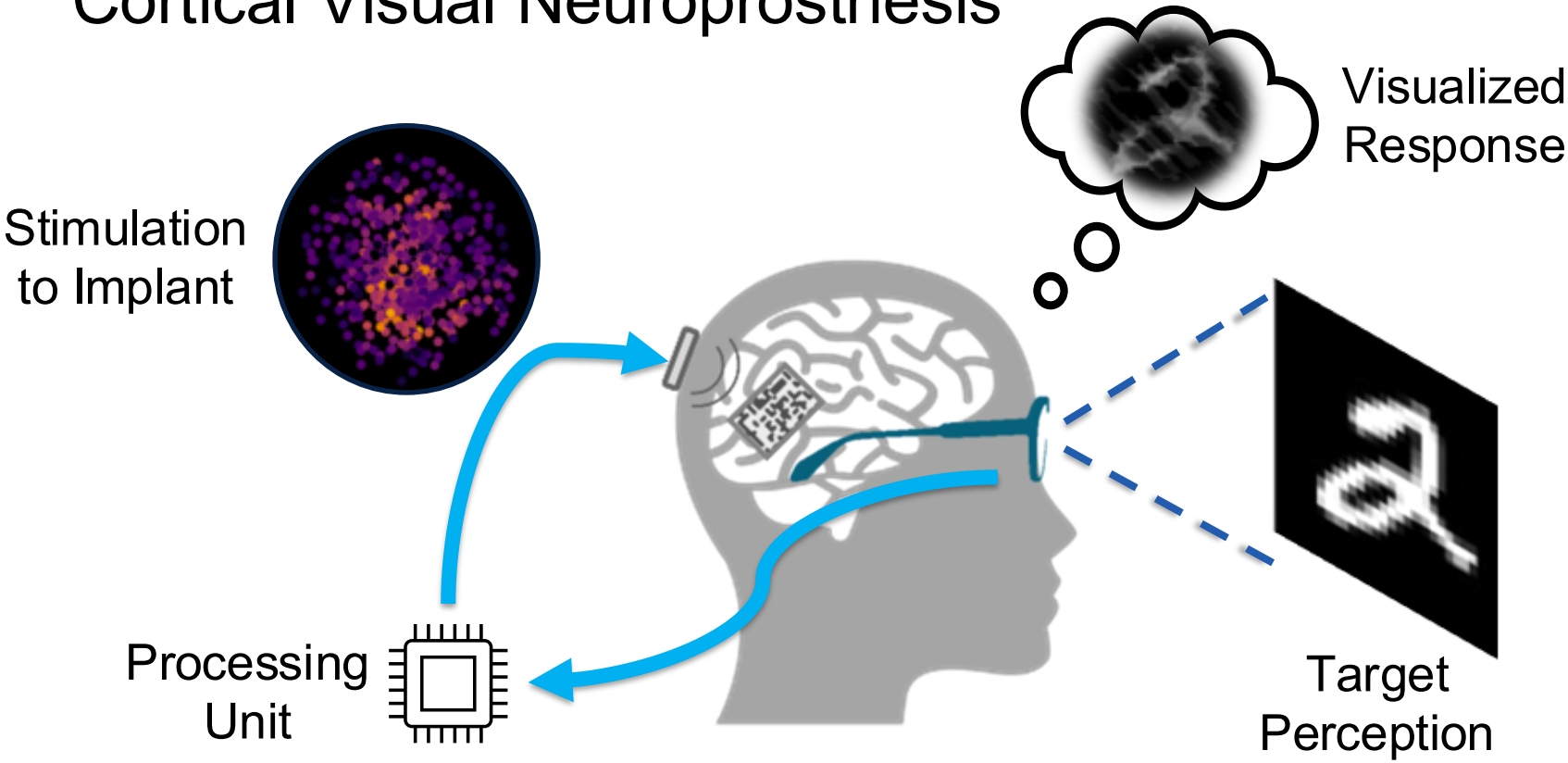
Jaap de Ruyter van Steveninck, Shih-Chii Liu



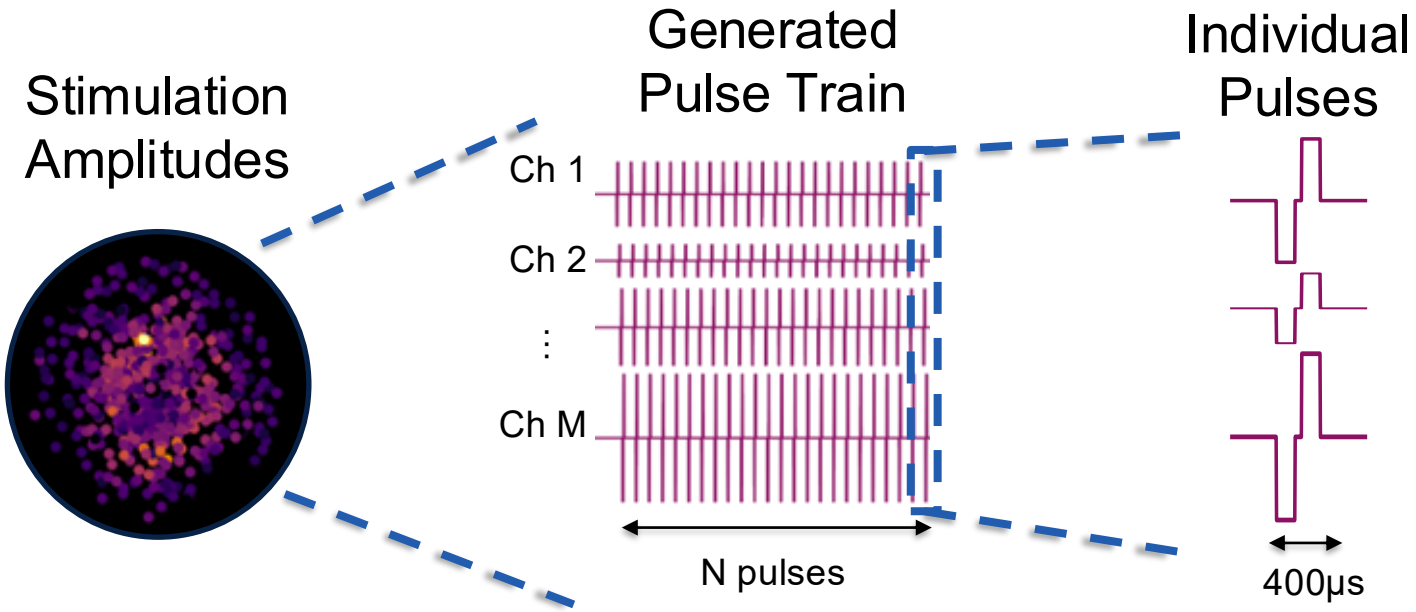
# Cortical Visual Neuroprosthesis



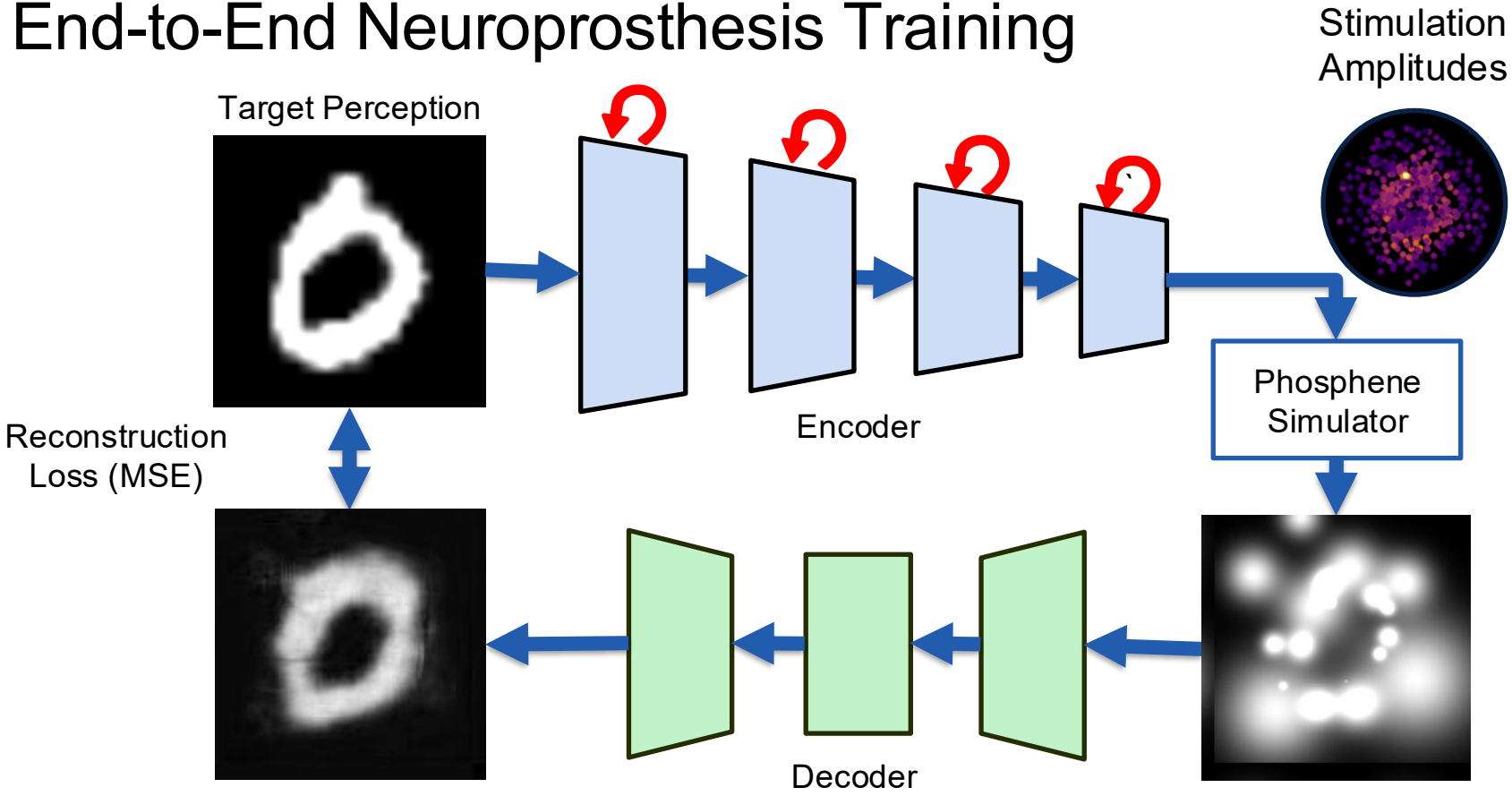
# Simulated Phosphene Vision

van der Grinten, et.al “Towards biologically plausible phosphene simulation for the differentiable optimization of visual cortical prostheses”

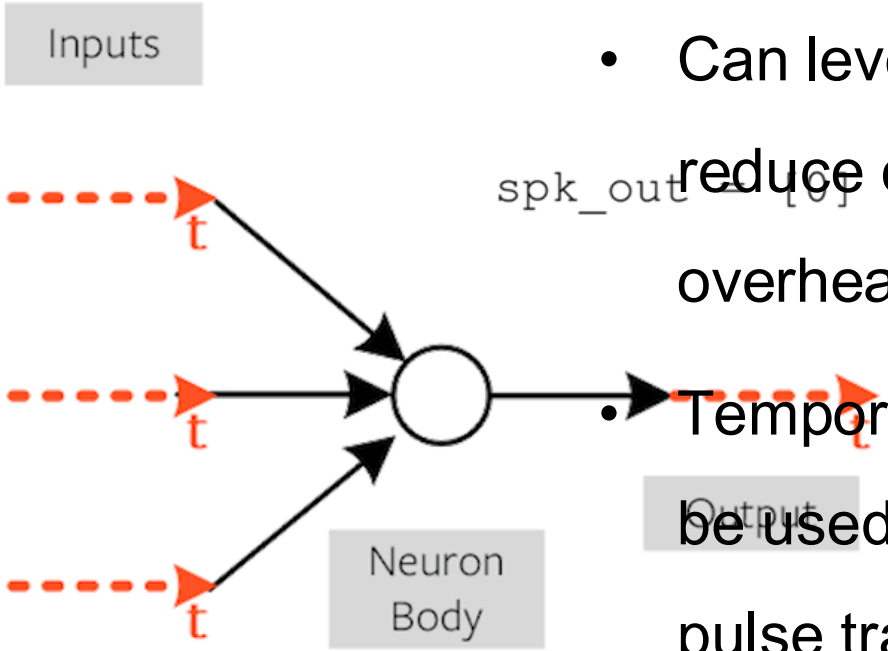
# Multi-Pulse to Single Pulse Stimulation



# End-to-End Neuroprosthesis Training



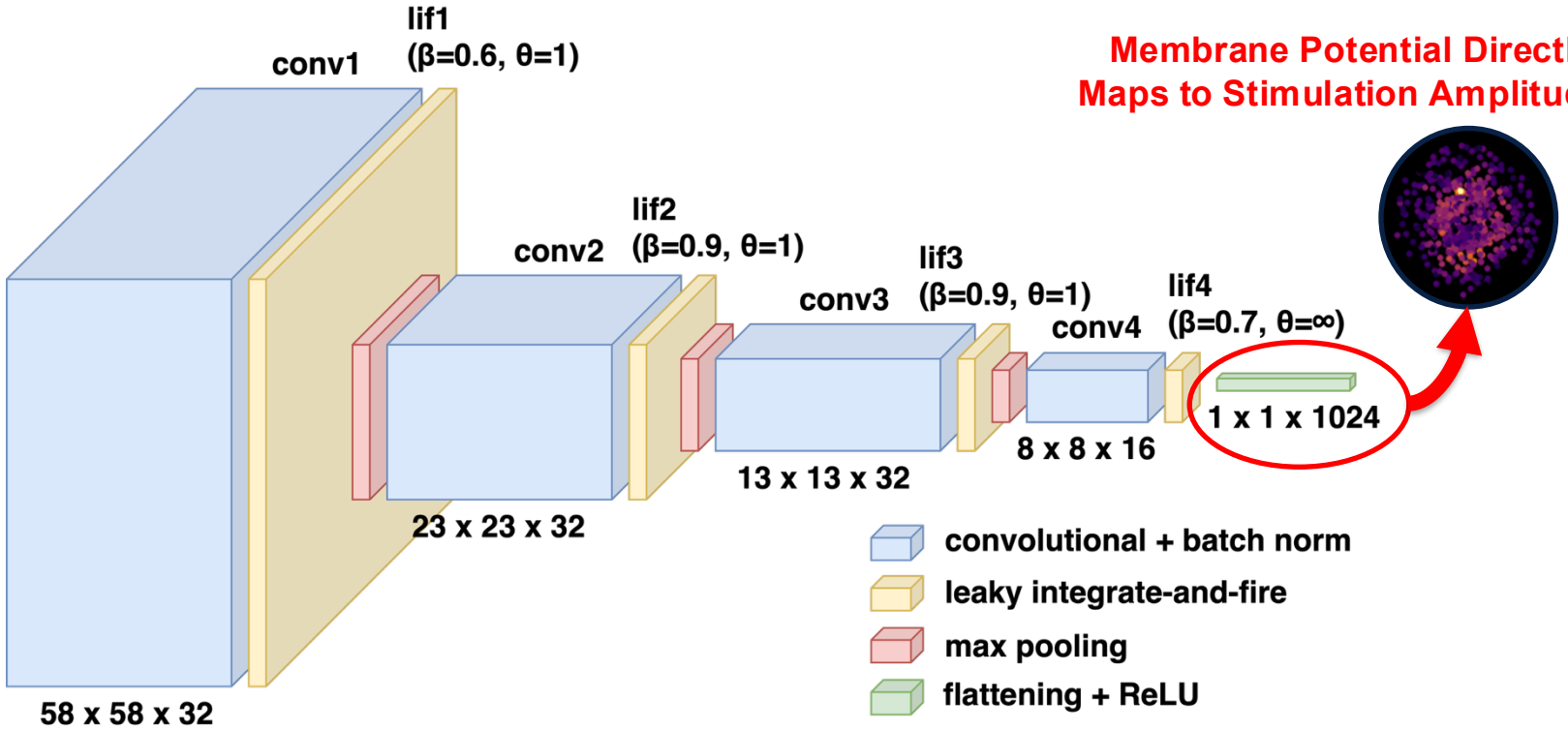
# Why use a Spiking Neural Network (SNN)?



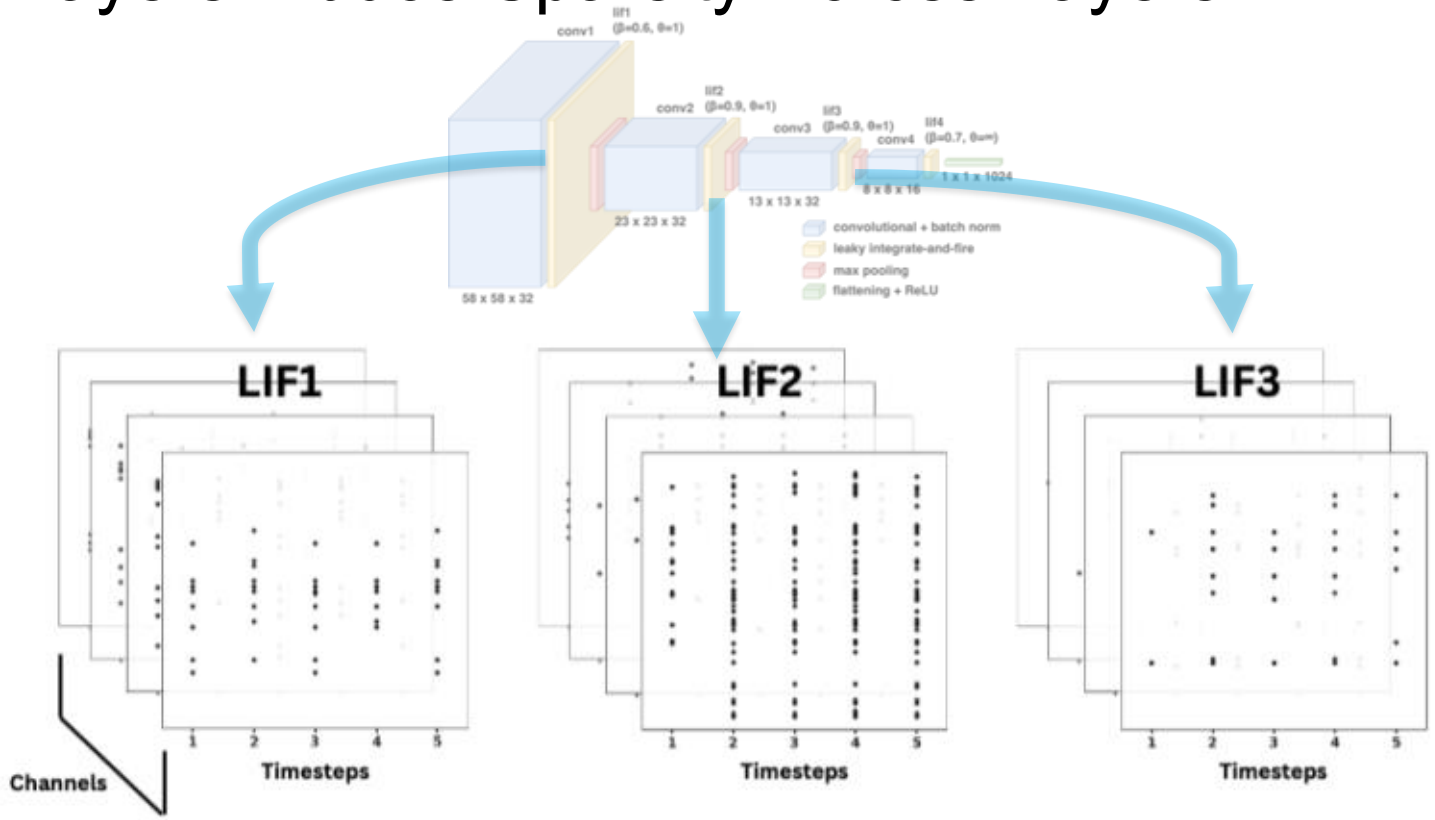

- Can leverage sparsity to reduce computational overhead
- Temporal dynamics can be used to generate pulse train

J. K. Eshraghian et al., "Training Spiking Neural Networks Using Lessons From Deep Learning".

# Spiking Neural Network for Encoder Network



# LIF Layers Induce Sparsity Across Layers

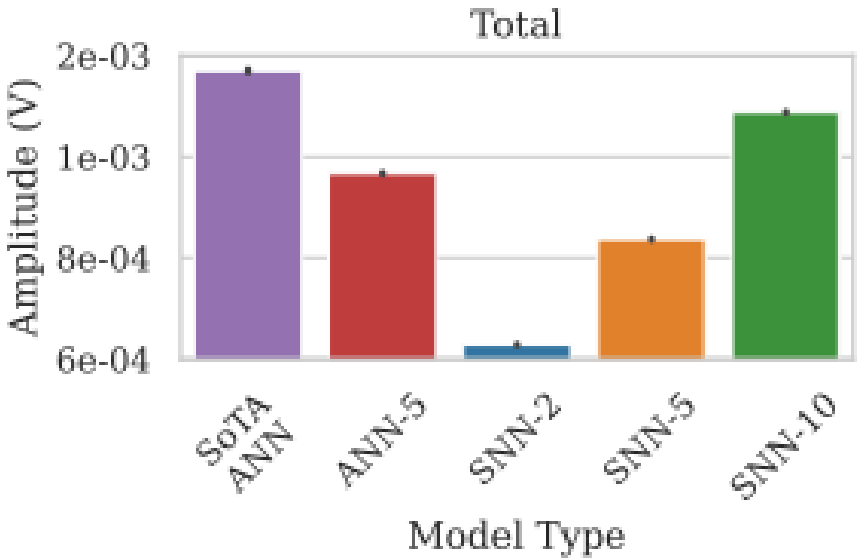


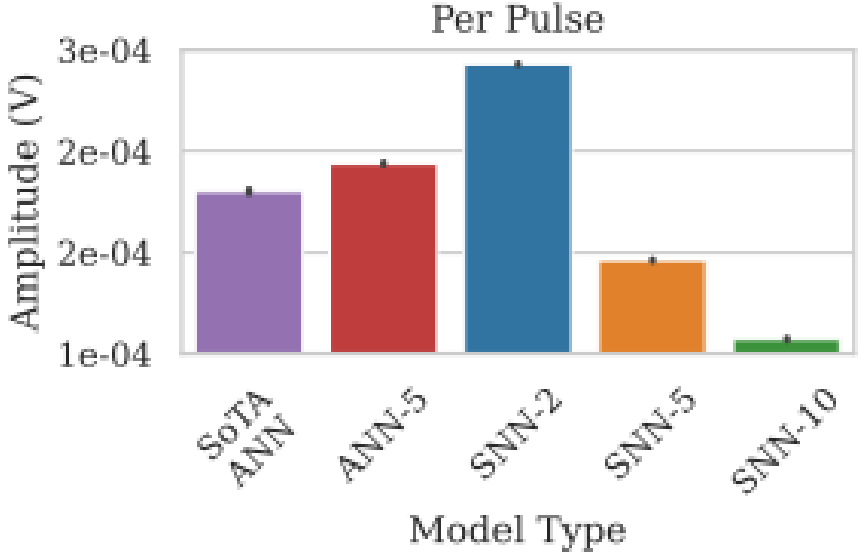
# SNN Improves Efficiency while Maintaining Performance

| Model | Recognizability Score (%) | # of Params | GFLOPS |
|---|---|---|---|
| SoTA ANN [1] | 63.3 | 1,110,225 | 2.44 |
| ANN-5 | 47.6 | 127,344 | 1.68 |
| SNN-5 | 62.1 | 127,351 | 0.58 |

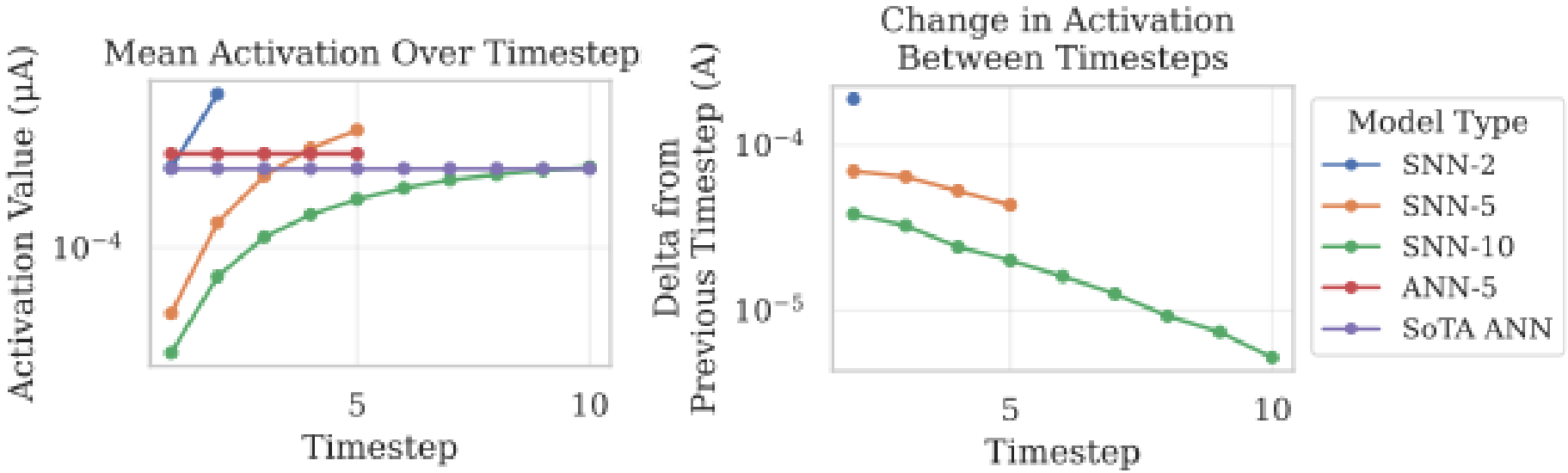
[1] van Steveninck, Jaap de Ruyter, et al. "End-to-end optimization of prosthetic vision." Journal of Vision

# Total Stimulation Charge is Smaller for SNN than ANN



# SNN Accumulates Charge Slowly Across Timesteps



# Conclusions

- SNNs can reduce computational overhead substantially
- SNN temporal dynamics can be leveraged to generate time-varying stimulation patterns
  - Also produce stimulations with a lower average total charge
- Limitations:
  - Realizing these benefits requires custom hardware

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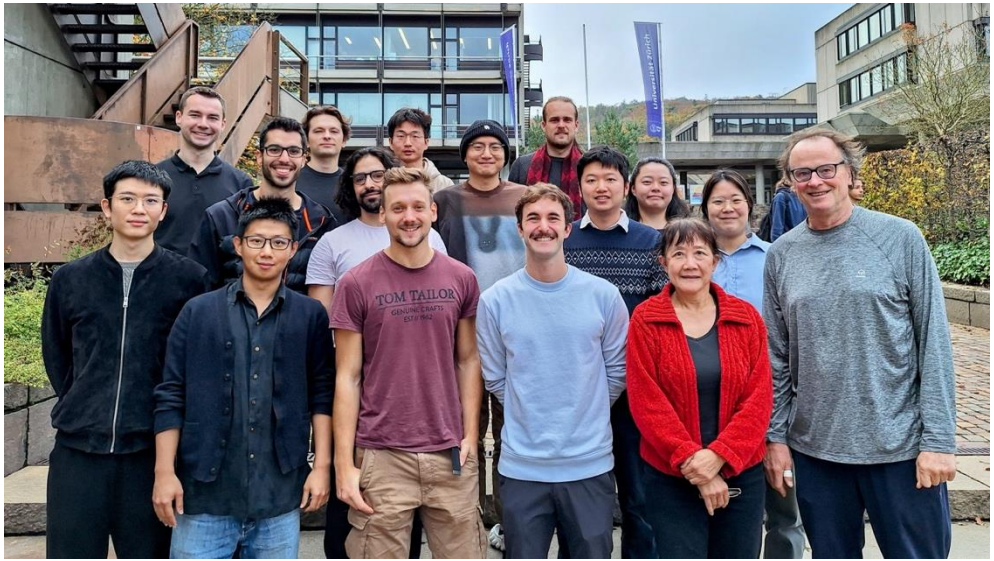
# Thank you for your attention!



Swiss National Science Foundation

Partially funded by SNSF: CA-DNN Edge