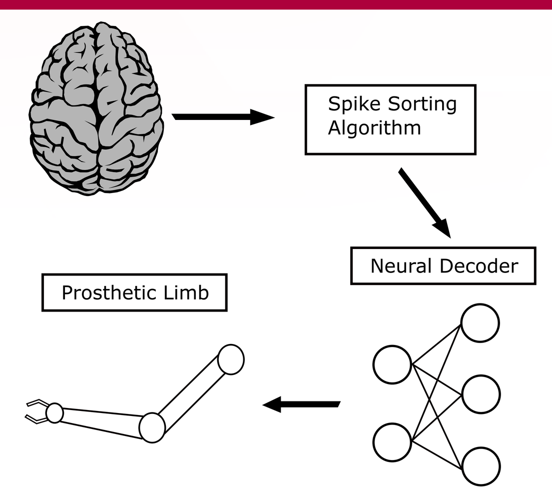
Spike Timing Dependent Plasticity for Unsupervised Adaptive Brain Machine Interface

Elijah Taeckens and Sahil Shah

Electrical and Computer Engineering
University of Maryland, College Park

Motivation

- There are over 18,000 new cases of spinal cord injuries each year in the U.S.
- BMI can help restore motor function
- Current problems with BMI: long-term stability
- Performance degrades due to **shifting electrodes** and **loss of neurons** [1]
- Goal: System that can **adapt to changes** in neural input with **minimal disruption**

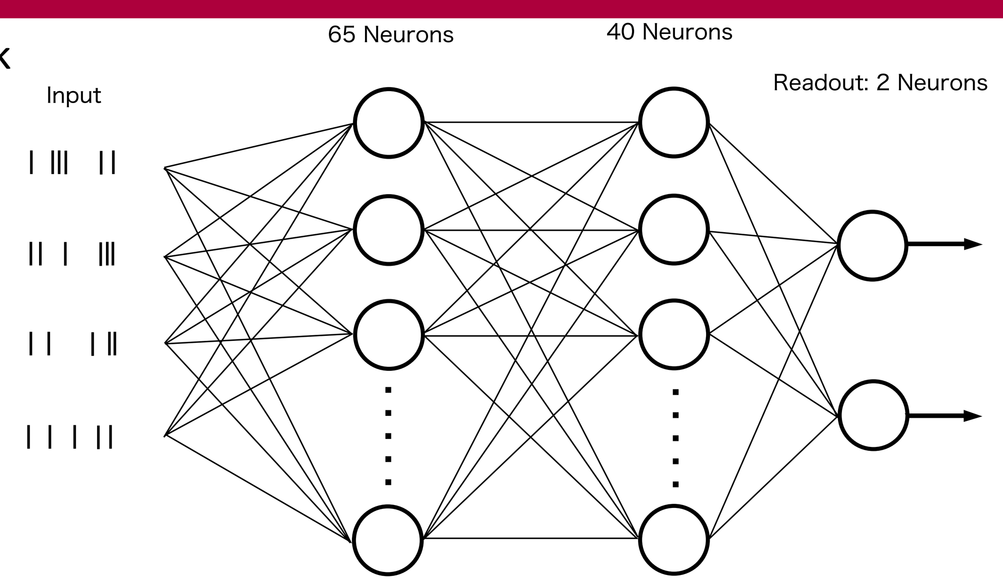


Spiking Neural Network

- Category of neural network that closely imitates biological neurons
- Information is transmitted by sequences of events called **spike trains**:

$$S(t) = \sum_{k \epsilon C} \delta(t - t^{(k)})$$

- Spike trains are typically **sparse** (mean << 1)



Architecture of SNN. The number of input neurons varied for different data sessions. Two hidden layers with a fixed number of neurons were used.

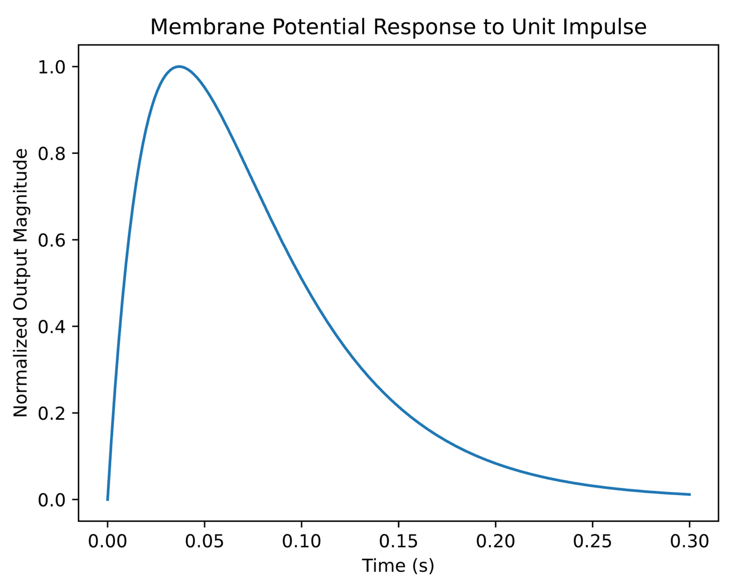
Neuron Models

- Computational model simulates **action potentials** in biological neurons
- We use **Leaky Integrate-and-Fire** model, governed by:

$$\frac{dI_i}{dt} = \frac{-I_i(t)}{\tau_{syn}} + \sum_j W_{ij} S_j^{(l-1)}(t) + \sum_j V_{ij} S_j^{(l)}(t) \qquad S_i^{(l)}(t) = \Theta(U_i^{(l)}(t) - \nu)$$

$$\frac{dU_i^{(l)}}{dt} = \frac{-1}{\tau_{mem}} (U_i^{(l)}(t) - U_0 + I_i^{(l)}(t))$$

- LIF model maintains 2 values, U(t) and I(t), which simulate the membrane potential and synapse current of a biological neuron [2]
- A spike is emitted when U(t) crosses a threshold
- Allows for efficient encoding of temporal information

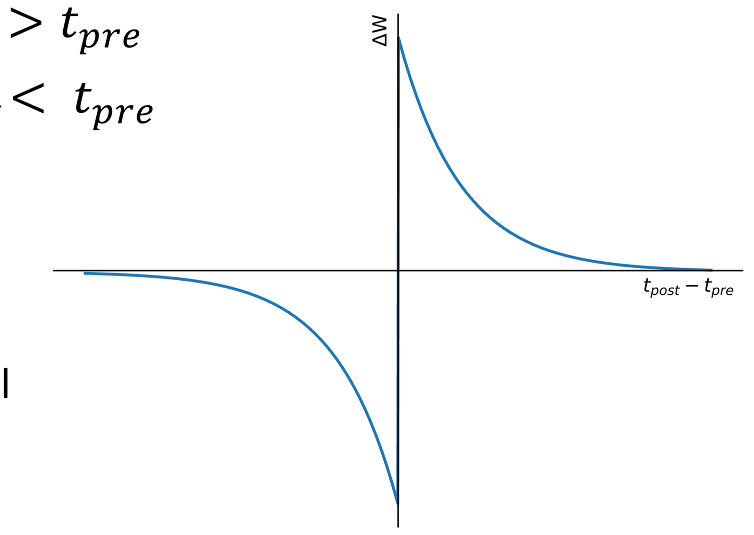


Relative impact of a spike from a hidden layer neuron on the membrane potential.

Spike Timing Dependent Plasticity

- **Unsupervised** weight update mechanism for SNNs
- Neurons that "wire together fire together" [3]
- Strengthens connection when post-synaptic neuron fires after pre-synaptic

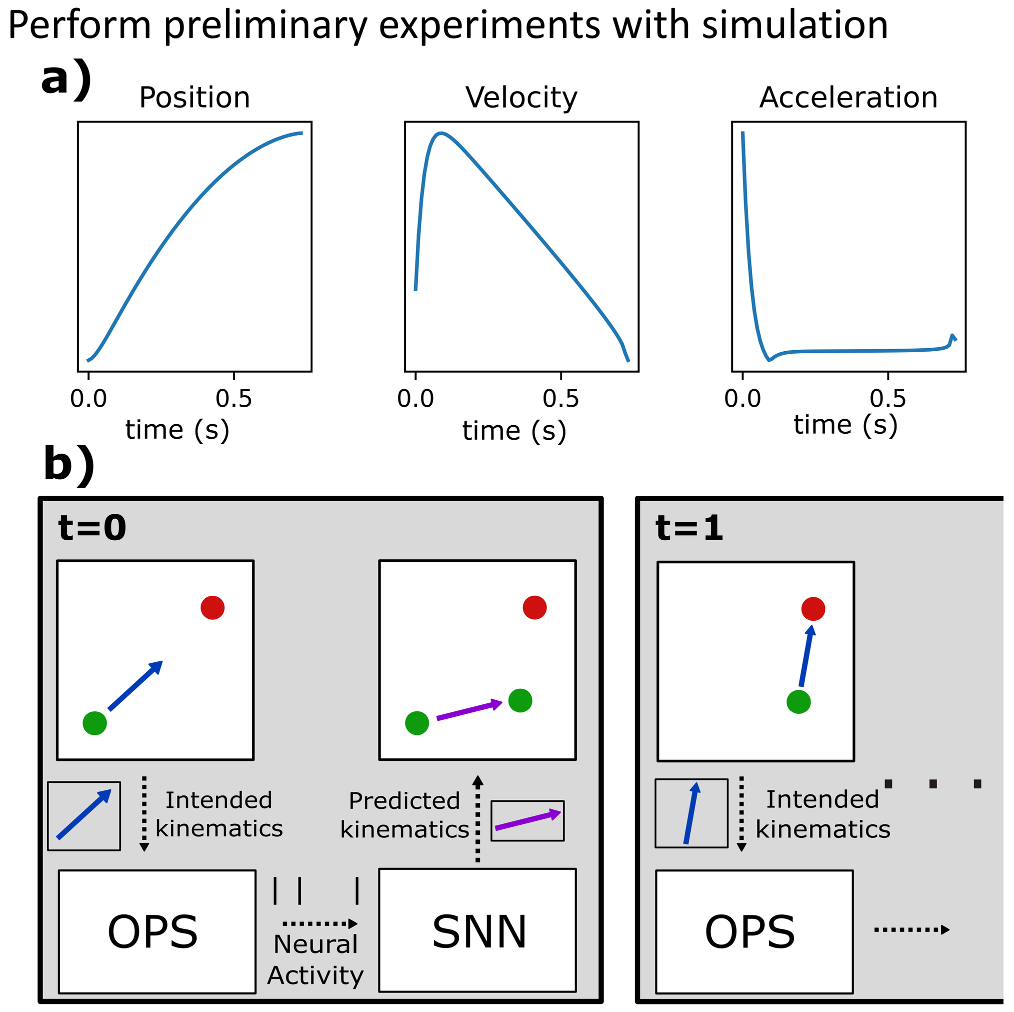
$$\Delta W = \begin{cases} \eta e^{t_{post} - t_{pre}}, & t_{post} > t_{pre} \\ -\eta e^{t_{pre} - t_{post}}, & t_{post} < t_{pre} \end{cases}$$



- Not ideal for training regression model from scratch
- Good for **correcting errors** when some of the original neurons are still accessible

Online Prosthetic Simulator

- Adaptation to neural disruption is difficult to test with offline data sets
- Clinical trials require some evidence that the proposed method is feasible
- Solution: Perform preliminary experiments with simulation



- OPS: Simulator based on research that shows neural firing rate correlates with direction [4]

$$\lambda_t = (\lambda_{max} - \lambda_{min}) c_k * x_t + \lambda_{min}$$

- Experiment: Simulated reaching task; move cursor to one of 8 targets

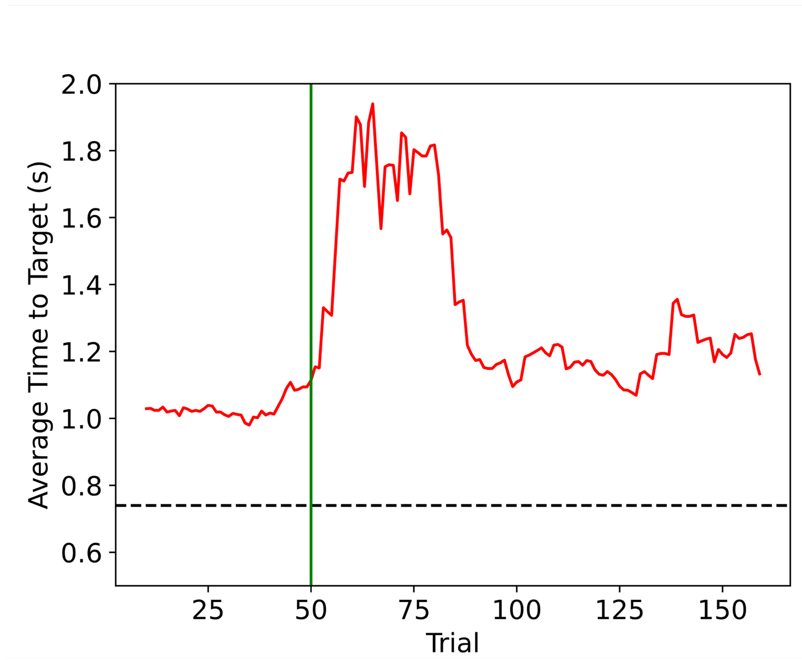
1) Intended kinematics are used to determine neural firing rate via OPS
2) Neural activity is decoded by SNN to produce predicted movement
3) Predicted movement is used to update cursor position

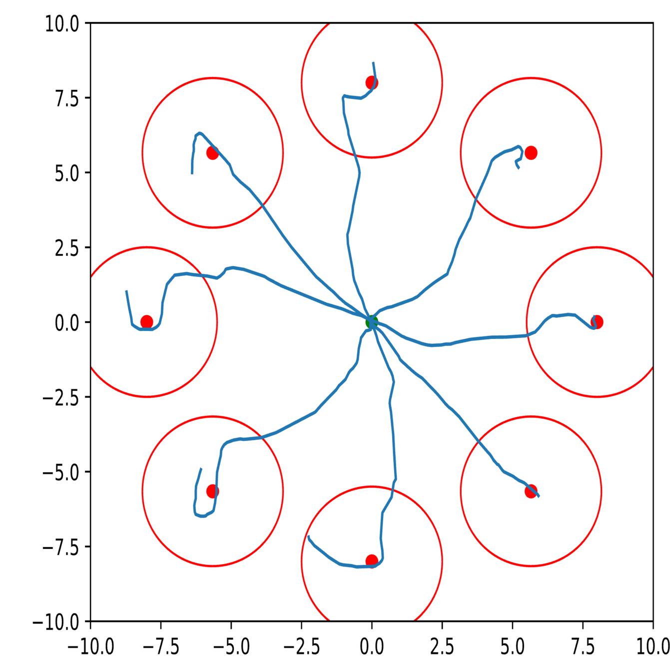
Previous Work

- SNNs can achieve comparable accuracy to existing decoding methods on real offline neural datasets [5]
- These SNNs were trained using gradient descent

Preliminary Results

- SNN trained using gradient descent on 250 OPS reaching tasks
- After 50 control reaching tasks, 65% of neurons removed (green line)
- Performance measured using average time-to-target
- STDP enabled return of high performance **without supervision**





Future Research

- Test a larger variety of neural disruptions to determine limitations of STDP
  - Neural dropout, electrode shift, changing firing rates
  - Under which conditions does STDP consistently find a solution?
- Test STDP adaptation in a real online BMI experiment with human or animal subjects

Acknowledgements & References

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Selected References

[1] Wallace et. al. Error detection and correction in intracortical brain-machine interfaces controlling two finger groups. *J. Neural Eng*, 20, 2023. doi: 10.1088/1741-2552/acef95

[2] Neftci et. al. Surrogate Gradient Learning in Spiking Neural Networks, *arXiv:1901.09948 [cs, q-bio]*, May 2019,

[3] Jiang et. al. A Spiking Neural Network with Spike-Timing Dependent Plasticity for Surface Roughness Analysis. *IEEE Sens. J.*, 22(1), 2022. doi: 10.1109/JSEN.2021.3120845

[4] Cunningham et. al.. A closed-loop human simulator for investigating the role of feedback control in brain-machine interfaces. *Journal of Neurophysiology*, 105, 2011.

[5] Taeckens et. al. A Spiking Neural Network with Continuous Local Learning for Robust Online Brain Machine Interface. *Bioarxiv.*, 2023. doi: 10.1101/2023.08.16.553602 .