A Biologically Plausible Spiking Neural Network for Decoding Kinematics in the Hippocampus and Premotor Cortex

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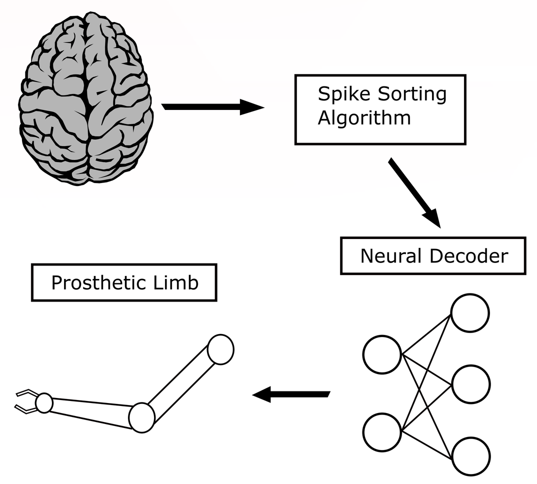
Motivation

- There are over 18,000 new cases of spinal cord injuries each year in the U.S.
- BMI can help restore motor function
- Key metrics for neural decoding algorithms:
  - Power efficiency
  - Accuracy
  - Latency
  - Biological Plausibility

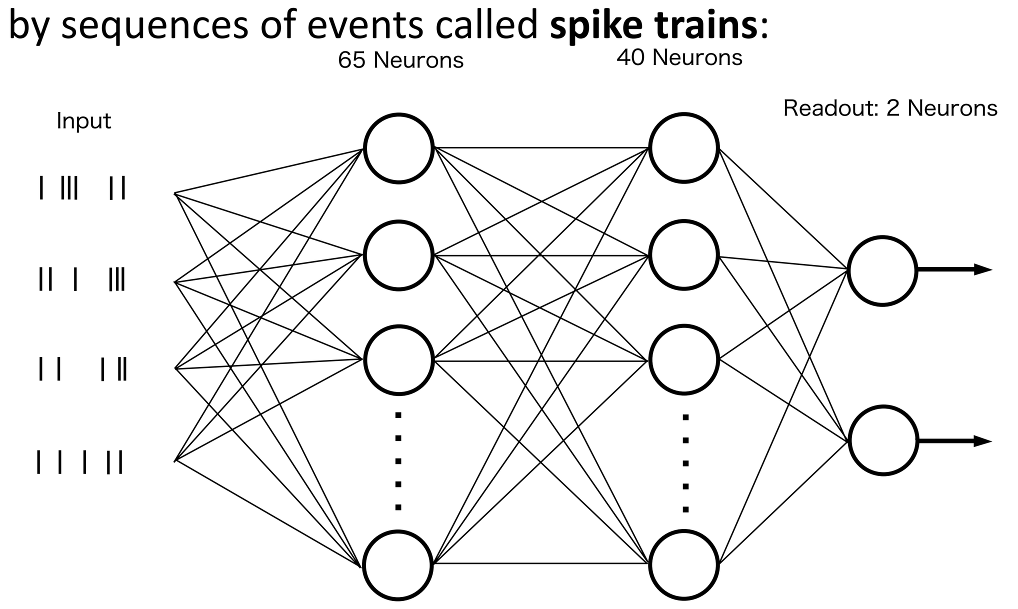


Spiking Neural Network

- 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)
- Sparse representation allows for **minimal power consumption**
  - Consume as little as **4 µW / neuron**



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

Data Recording and Preprocessing

Data Sets

- 2 public datasets from CRCNS initiative
- Premotor cortex recordings from monkeys performing reaching tasks [1]
  - Neural and kinematic data sampled at same rate
- Hippocampus recordings from rats navigating a platform [2]
  - Neural and kinematic data sampled at different rates

Preprocessing Methods

- Spikes were extracted using threshold crossing and subsequently spike sorted to obtain neural units
- Three recording sessions from each dataset
- Hippocampus data split into 10 second training segments

Biologically Plausible Local Learning

- Backpropagation learning is not biologically plausible- requires information about activity of other neurons to update a given neuron
- Local learning: Assign readout to each hidden layer in network [4]
  - Allows local update of weights with no backpropagation
  - Much lower memory overhead
- Surrogate gradients: Spiking nonlinearity $\Theta(U_i(t))$ replaced with differentiable approximation $\sigma(U_i(t))$ to calculate gradients [3]

Neuron Models

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

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

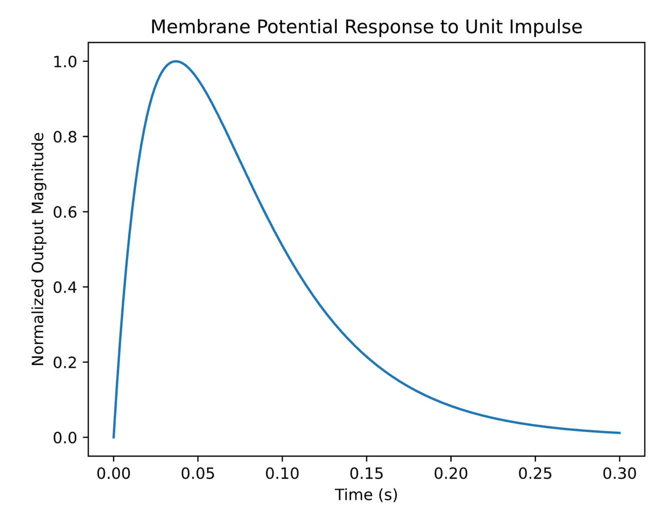
$$\frac{dU_i^{(l)}}{dt} = \frac{-1}{\tau_{mem}} (U_i^{(l)}(t) - U_0 + I_i^{(l)}(t))$$

- LIF model maintains 2 values, U(t) and I(t), which simulate the membrane potential and synapse current of a biological neuron [3]
- A spike is emitted when U(t) crosses a threshold
- Allows for efficient encoding of temporal information

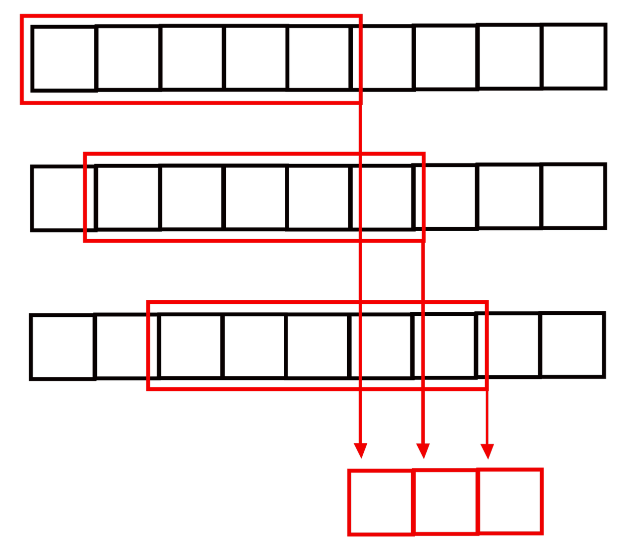
Regression Learning Methods

- Output function to model kinematic data should mimic
- Desired properties:
  - Continuous and differentiable (in time)
  - Output time step matches kinematic time step
- 2 proposed methods:
- **Membrane Potential:** Output neurons modeled as non-spiking LIF neurons, U(t) is the output
- **Spike Counting**: Output is weighted sum of T previous spikes, given by:

$$Y_k(t) = \sum_i G_{ki} \sum_{t'=t-T}^{t} S_i(t')$$



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

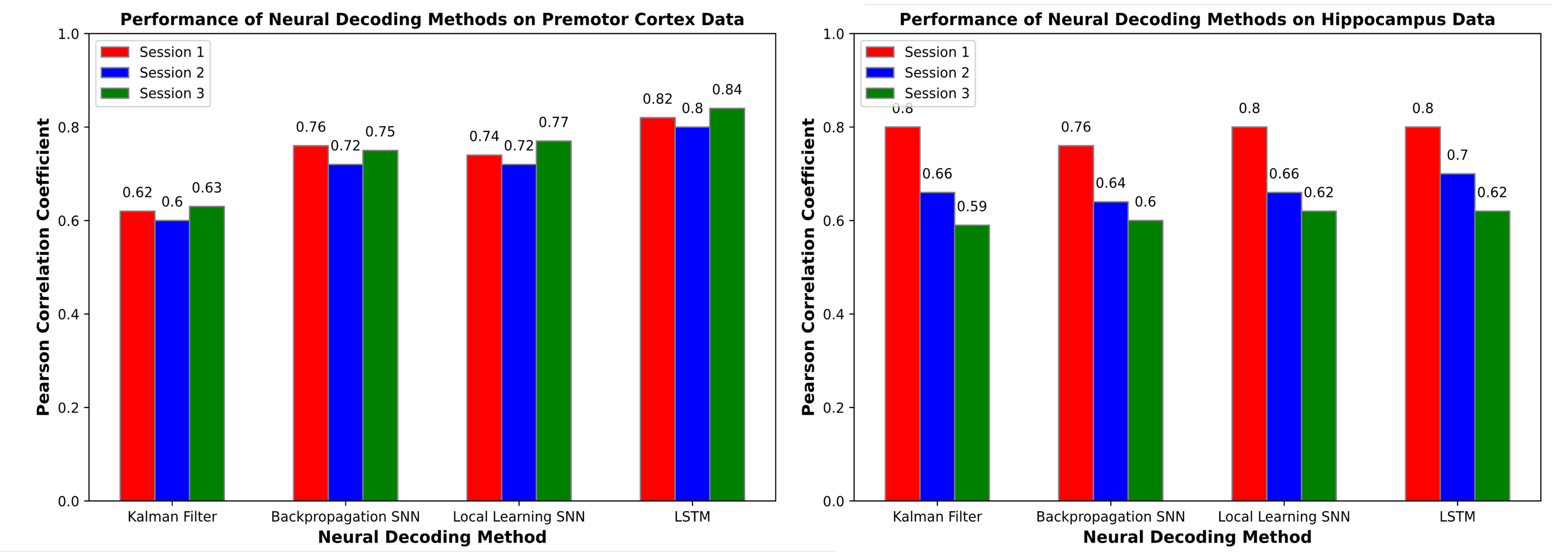


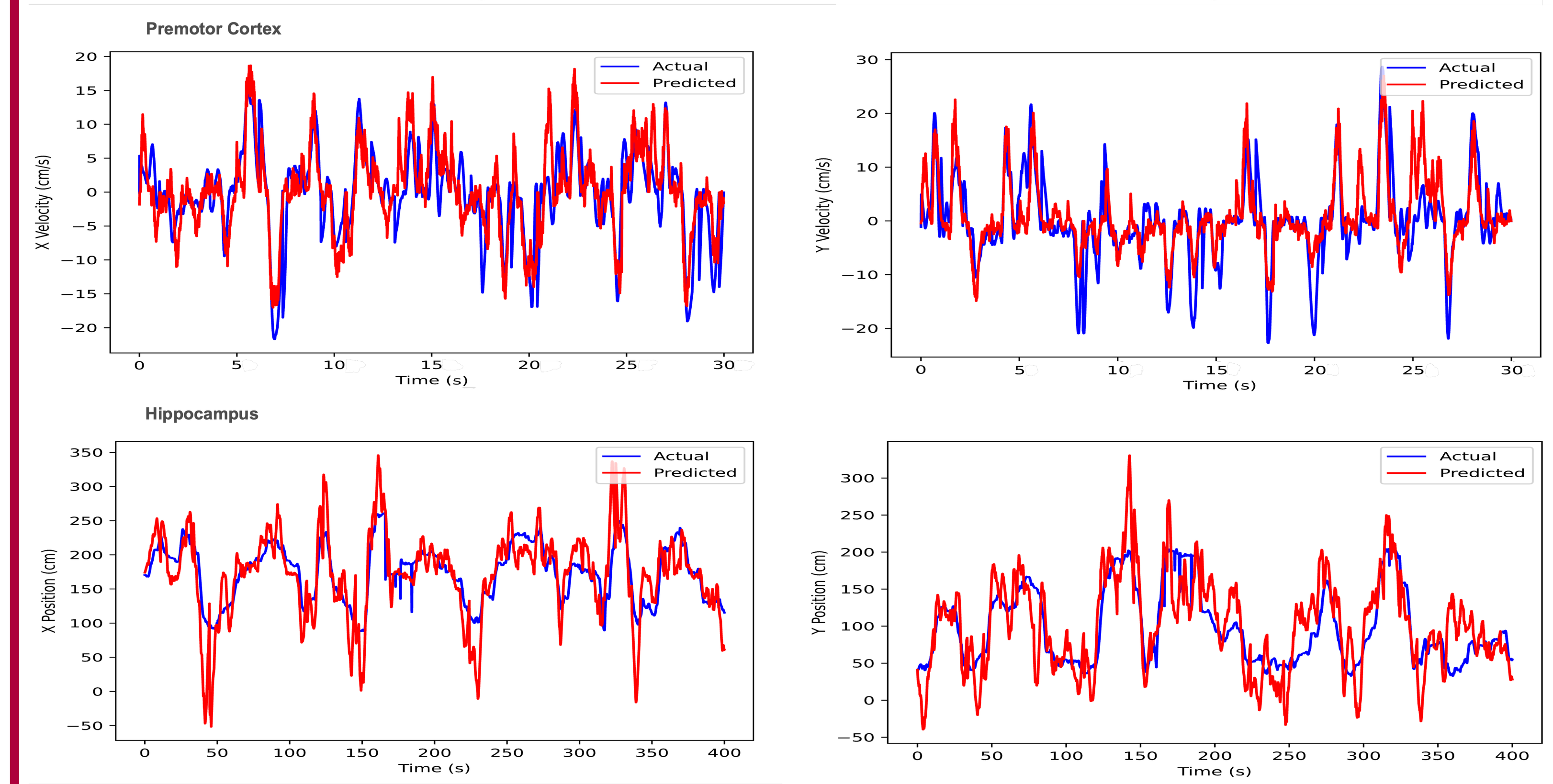
Graphical depiction of spike counting regression method.

Membrane Potential	Spike Counting
• Continuous and differentiable in time • Output time step same as spiking input time step • Always initialized at 0 • Used for premotor cortex data set (Distinct reaching tasks, same neural and kinematic time steps)	• Not continuous or differentiable (sudden jumps common) • Output timestep can be adjusted • Easier to implement on hardware • Can take any initial value • Requires overlap of training samples • Used for hippocampus data set (Different neural and kinematic timesteps, one continuous recording allows overlap)

Results

- Achieved peak correlations of **ρ = 0.77** and **ρ = 0.80** for premotor cortex and hippocampus data, respectively
- SNN with local learning shows comparable accuracy to Kalman filter, LSTM, and SNN with backpropagation when tested on same data sets.





Comparison of ground-truth kinematic data and prediction from SNN. Top graph represents 30 second sample from premotor cortex data using membrane potential regression, bottom is 400 second sample from hippocampus data using spike counting regression.

Future Research

- Hardware implementation of SNN needed to evaluate power efficiency
  - Currently designing FPGA model with on-chip learning
- Adaptive systems: Algorithm should not have to be re-calibrated each day
  - Should be able to adapt to neurons being added and dropped

Acknowledgements & References

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Selected References

[1] M. G. Perich *et al.*, "Extracellular neural recordings from macaque primary and dorsal premotor motor cortex during a sequential reaching task," 2018.
[2] K. Mizuseki *et al.*, "Multi-unit recordings from the rat hippocampus made during open field foraging," 2009.
[3] E. O. Neftci *et al.*, "Surrogate Gradient Learning in Spiking Neural Networks," *arXiv:1901.09948 [cs, q-bio]*, May 2019,
[4] J. Kaiser *et al.*, "Synaptic Plasticity Dynamics for Deep Continuous Local Learning (DECOLLE)," *Frontiers in Neuroscience*, vol. 14, p. 424, May 2020