
🧠 1. Introduction & Motivation

- We consider a **two-layer spiking network**:
  - **Layer 1**: 10 input neurons, each firing at ~2 Hz following Poisson statistics.
  - **Layer 2**: A single target neuron receiving multiple delayed inputs from each Layer 1 neuron, plus background noise.
- **Key interest**: Investigate how **spike-time-dependent plasticity (STDP)**, combined with **variable transmission delays**, can temporally align synaptic inputs that carry a repeating temporal pattern—thereby enhancing pattern detection.

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2. Network Architecture

- **Connections**: Each of the 10 inputs projects via **multiple synapses** to the target neuron, on average 5 per neuron.
- **Delays**: These synapses have random delays (uniformly between 1–10 ms). The synapses from an specific neuron to the target neuron can not have the same delay.
- **Noise baseline**: Calibrated so that **without Layer 1 input**, Layer 2 fires at ~1 Hz and in ~2 Hz with the input from the first layer.

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3. Input Spike Trains

- **Poisson firing** (2 Hz) for all 10 neurons in the first layer.
- **Superimposed repeating temporal pattern** on 5 of them:
  - Pattern spans **~20 ms**, with intervals ~5 ± 0.5 ms between spikes.
  - One full sequence occurs every ~2 seconds.

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5. Learning Rule & Hypothesis

- **STDP (spike-time–independent plasticity)** modulates synaptic weights based on the timing of presynaptic vs postsynaptic spikes.

- Hypothesis: The synapses carrying the structured pattern will **selectively strengthen**. Through learning, the system will compensate **for their relative time offsets** (due to delays), aligning their post-synaptic effects *coincidentally* at the somatic target.

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6. Experimental Procedure

1. **Initialization**: Assign random delays (1–10 ms) and baseline noise/weights to yield Layer 2 ~2 Hz with input.
2. **Pattern injection**: Repeated every 2 s on 5 inputs.
3. **Learning phase**: Apply STDP plasticity while running the network for multiple minutes.
4. **Measurement**: Track changes in:
    - Synaptic weights of pattern-bearing vs non-pattern synapses.
    - Effective delays.
    - Coincidence or synchrony of EPSPs upon pattern replay.

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7. Expected Results & Analysis

- **Selective potentiation**: Pattern synapses should amplify relative to background Poisson inputs.
- **Delay compensation**: Synaptic weights should fine-tune to offset temporal dispersal—effectively compressing pattern within membrane integration window. It means that ultimately the inputs from the pattern neurons arrive simultaneously on the target neurons.
- **Improved downstream detection**: Even with noise, replay of the 20-ms pattern should trigger **more reliable, time-locked spiking** in Layer 2.

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8. Significance & Applications

- Demonstrates how **delay diversity + STDP** enables neurons to learn and temporally align input sequences.

- Supports theories of **temporal coding**, **polychronization**, and **sequence detection** in spiking neural networks.
- Insights transferable to **neuromorphic systems** and learning algorithms that rely on precise spike timing.

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10. Conclusion

In summary, this proposal sets out to demonstrate how a simple two-layer spiking network with **random delays + spike-time–independent plasticity** can adapt synaptic delays/strengths such that a recurring temporal pattern becomes aligned and reliably detected at the postsynaptic neuron—even under noisy Poisson input. If confirmed, it would reveal a self-organizing mechanism by which neurons discover and encode *temporal structure* in their inputs.
