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HetSyn: Versatile Timescale Integration in Spiking Neural Networks via Heterogeneous Synapses

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Motivations & Contributions

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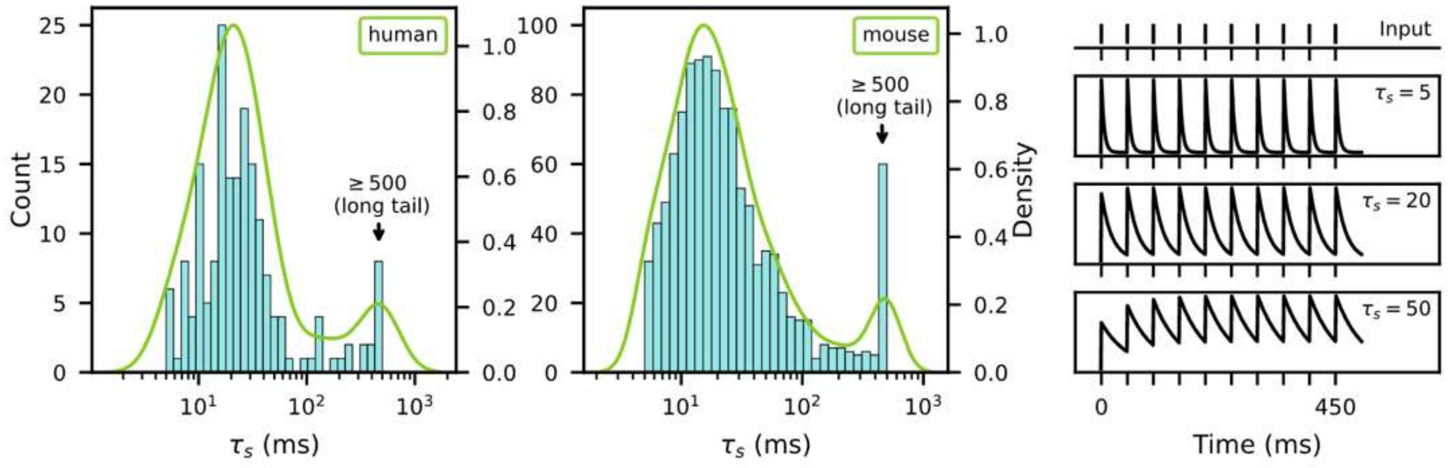
Motivations

1. Spiking Neural Networks (SNNs) offer a biologically plausible and energy-efficient computing paradigm characterized by sparse, event-driven signaling and intrinsic temporal processing capabilities.
2. Synaptic heterogeneity, which is widely observed across brain regions and cell types, has been largely overlooked in the design of SNNs, and its computational potential remains underexplored.

Synaptic Time Constants Distributions



Contributions

1. We propose HetSyn, the first modeling framework to explicitly explore synaptic heterogeneity in SNNs.
2. We demonstrate that HetSyn serves as a unified and extensible framework, capable of representing a wide range of existing spiking neuron models.
3. We instantiate HetSyn as HetSynLIF and demonstrate its effectiveness across multiple temporal tasks.

Methods

Neural Dynamics

Vanilla LIF

$$\frac{dV}{dt} = -\frac{V - V_{\text{rest}}}{\tau_{\text{m}}} + \sum_{i,j} w_i \cdot \delta\left(t - t_i^j\right) - \vartheta \cdot \sum_j \delta\left(t - t_{\text{s}}^j\right)$$

$$V^t = \rho \cdot V^{t-1} + \sum_i w_i \cdot z_i^t - \vartheta \cdot z^{t-1} \qquad z^t = \text{H}(V^t - \vartheta)$$

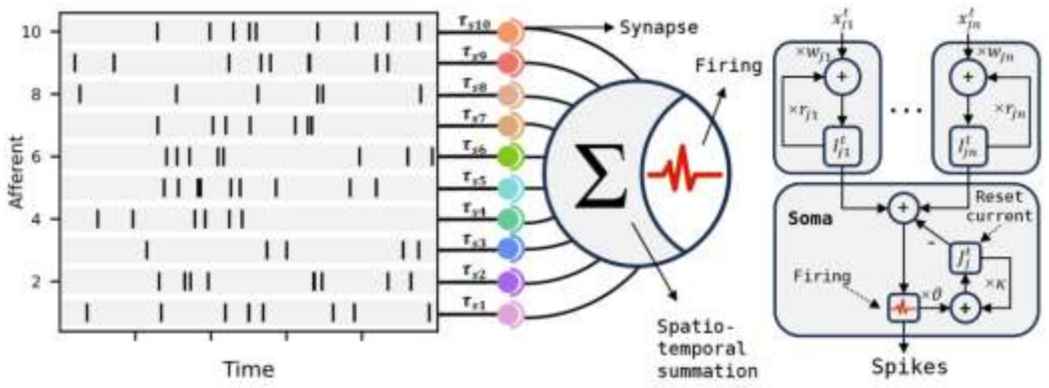
Equipped with HetSyn

HetSynLIF

$$\frac{dI_i^t}{dt} = -\frac{I_i^t}{\tau_{\text{s},i}} + \sum_j w_i \cdot \delta\left(t - t_i^j\right) \qquad \frac{dJ^t}{dt} = -\frac{J^t}{\tau_J} + \sum_j \vartheta \cdot \delta\left(t - t_{\text{s}}^j\right)$$

$$V^t = \sum_i I_i^t - J^t \qquad I_i^t = r_i \cdot I_i^{t-1} + w_i \cdot z_i^t \qquad J^t = \kappa \cdot J^{t-1} + \vartheta \cdot z^{t-1}$$

Model Structure



Generalization

$$r_{ji} = \kappa_j = \rho \rightarrow \text{HomNeuLIF}$$

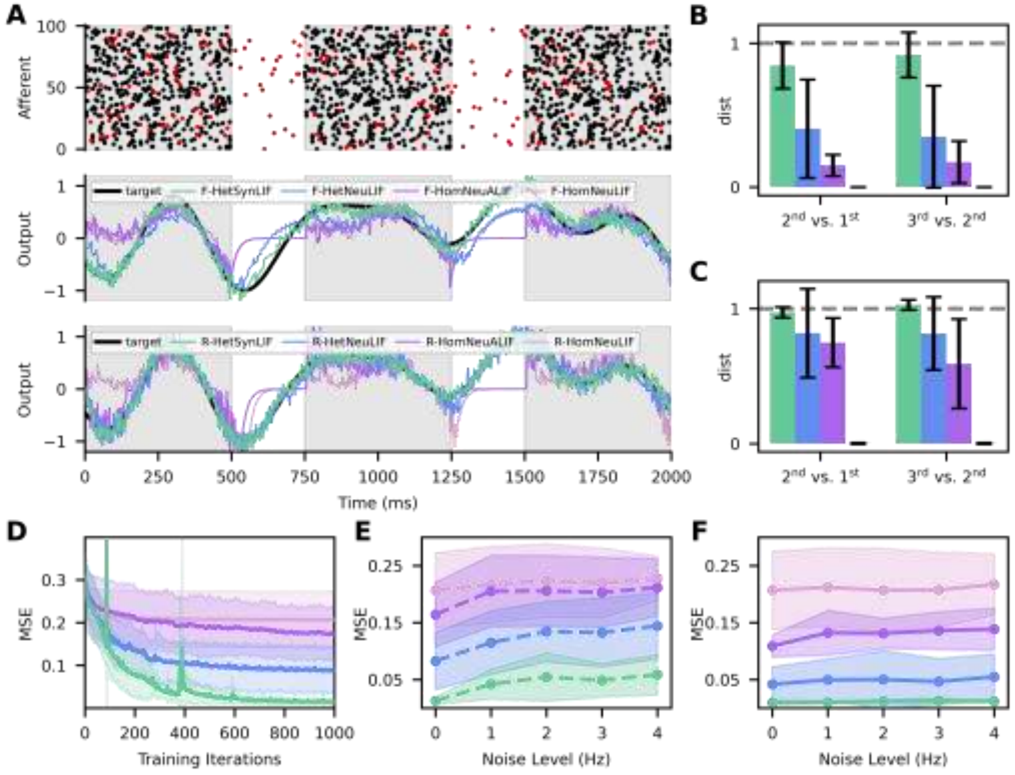
$$r_{ji} = \kappa_j = \rho \;\&\; V_j^t = \sum_i I_{ji}^t - J_\vartheta^t - J_\alpha^t \rightarrow \text{HomNeuALIF}$$

$$r_{ji} = \kappa_j = \rho_j \rightarrow \text{HetNeuLIF}$$

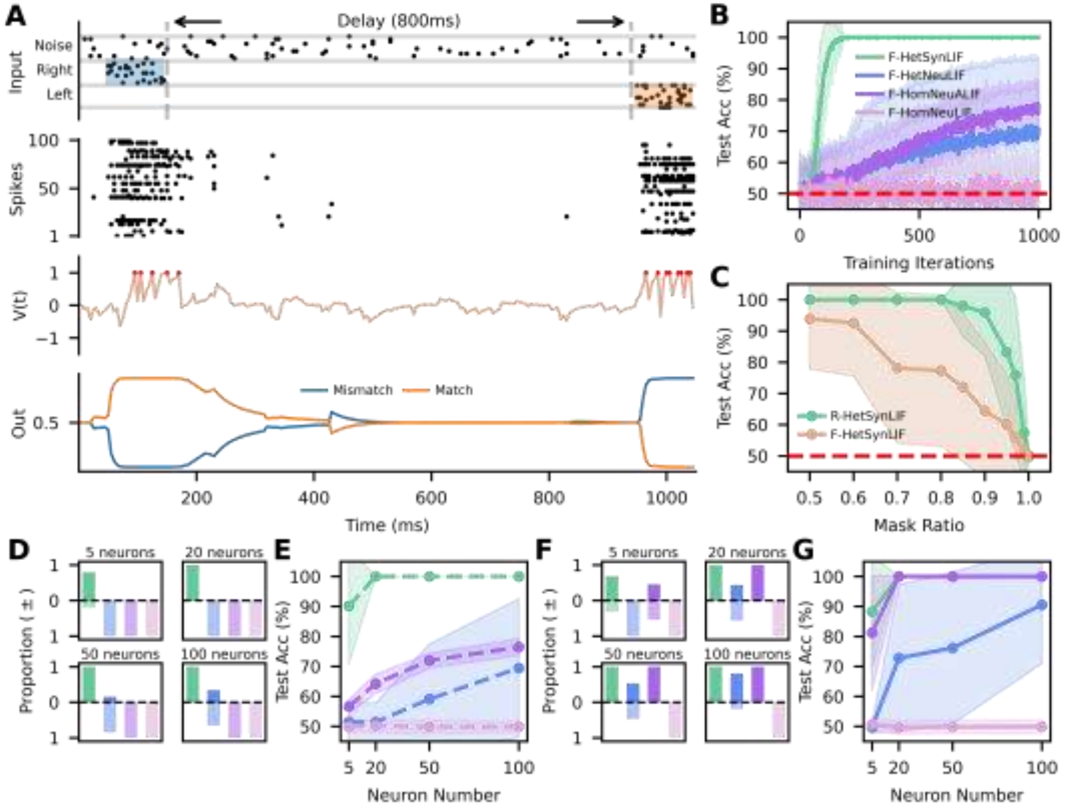
Experiments

We demonstrate that HetSynLIF not only improves the performance of SNNs across a variety of tasks, but also exhibits strong robustness to noise, enhanced working memory performance, and efficiency under limited neuron resources.

Performance on Pattern Generation Task

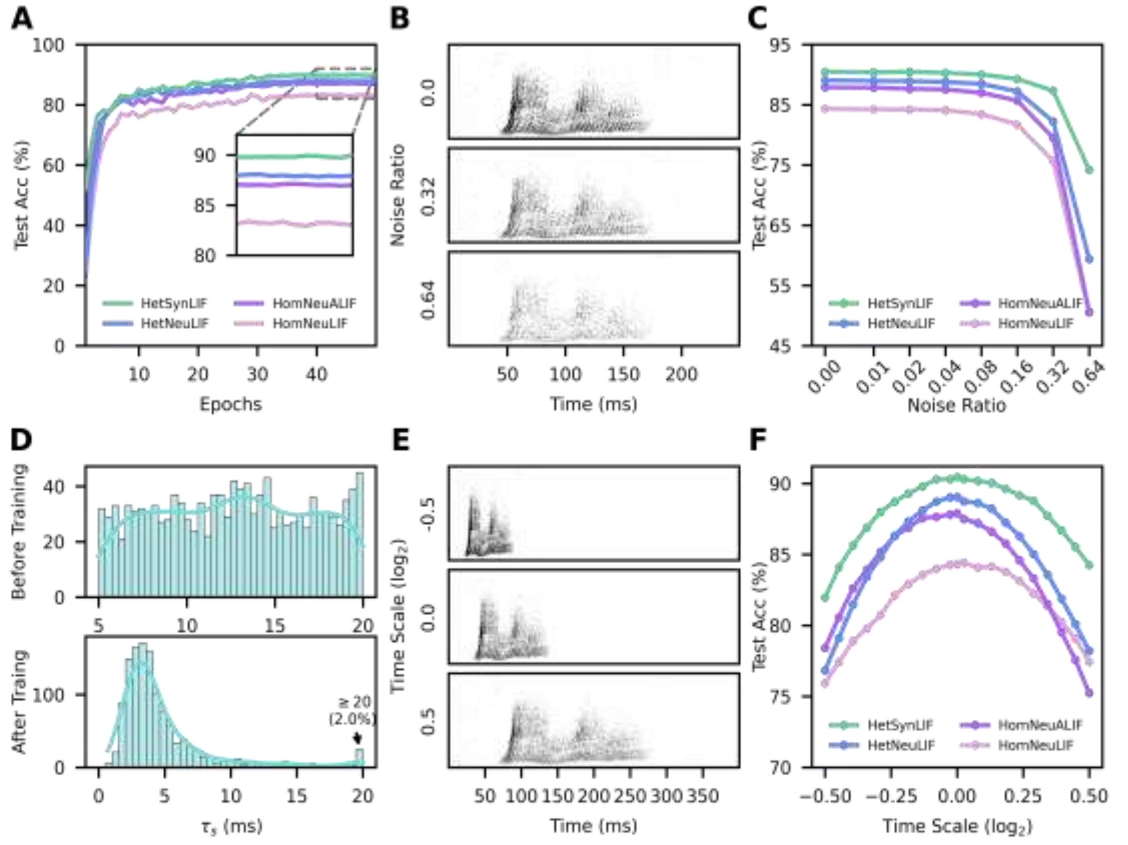


Performance on Delayed Match-to-Sample Task



Experiments & Conclusion

Performance on Speech Recognition



Accuracy Comparison on Four Datasets

Dataset	Method	Acc	Dataset	Method	Acc
SHD	DH-SFNN[Nat.Commun24] [23]	92.1	TiDigits	BPT-SNN [50]	98.1
	DH-SRNN[Nat.Commun24] [23]	91.34		M-STIP[TNNLS22] [51]	98.1
	SRNN[ICLR25] [52]	91.19		MPD-AL[AAAI19] [53]	97.5
	SRNN[NMI21] [54]	90.4		BAE-MPDAL [55]	97.4
	NeuHet-SRNN[NatCom21] [22]	82.7		TDP-DL [56]	97.16
	SRNN[PNAS22] [57]	81.6		PBSNLR-DW [58]	96.5
	HetSynLIF (Ours)	**92.36**		**HetSynLIF (Ours)**	**98.99**
S-MNIST	DH-SRNN[Nat.Commun24] [23]	98.87	Ti46	RSNN [59]	96.44
	SRNN[NMI21] [54]	98.7		SeSr-SNNs [60]	95.9
	LSTM[ICML16] [61]	98.2		RSNN[NeurIPS19] [62]	93.5
	LSNN[NeurIPS18] [12]	96.4		LSM [63]	92.3
	AHP-SNN[NMI22] [41]	96.0		S-MLP[NeurIPS18] [64]	90.98
	HetSynLIF (Ours)	**98.93**		**HetSynLIF (Ours)**	**96.53**

Conclusion

We propose a SNN modeling framework that incorporates synaptic heterogeneity, an essential property largely overlooked in previous studies, and demonstrate its computational advantages and generalizability.

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