TIDE: Asymmetric Neural Circuits for Stabilized Temporal Inhibitory-Excitatory Dynamics

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TIDE: Dale-constrained Wilson-Cowan E-I dynamics architecture with lateral inhibition, persistent memory, and receptive field

80:20	+1.65 to +6.42 pp	+2.83 pp
E:I neuron split	Performance under perturbation	Avg. performance across all datasets

I. Background & Motivation

Motivation: Continuous Thought Machines (CTM) [1] uses unconstrained MLP recurrence, whereas cortical excitatory and inhibitory (E-I) neurons use Dale's principle.

Research question: What effect does Wilson-Cowan [2] E-I recurrent dynamic has on Robustness?

Contributions:

E-I recurrent core: Wilson-Cowan dynamics with non-negative weights, E-I NLMs, and lateral inhibition with persistent memory.

HRF backbone: Learnable center-surround filters, with end-to-end training.

II. E-I Dynamics & Theory

$$r_E^{(t)} = (1-\alpha_E)\, r_E^{(t-1)} + \alpha_E\, \varphi\big(h_E^{(t)}\big), \qquad h_E^{(t)} = W_{EE}\, r_E^{(t-1)} - W_{EI}\, r_I^{(t-1)} + W_E^{\text{in}}\, a^{(t)},$$

$$r_I^{(t)} = (1-\alpha_I)\, r_I^{(t-1)} + \alpha_I\, \varphi\big(h_I^{(t)}\big), \qquad h_I^{(t)} = W_{IE}\, r_E^{(t-1)} - W_{II}\, r_I^{(t-1)} + W_I^{\text{in}}\, a^{(t)},$$

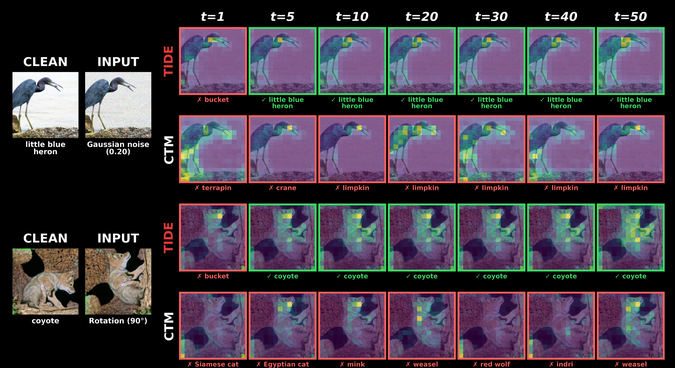
$$\alpha_\bullet = \Delta t/\tau_\bullet, \quad \tau_E = 20\,\text{ms}, \ \tau_I = 5\,\text{ms}, \quad W_{XY} \leftarrow \max\big(W_{XY}, 0\big) \ \text{ after every optimizer step.}$$

Forward-Euler Wilson-Cowan update of the E-I rates. In TIDE, *h* is normalized by RMSNorm.

Dale's driven training: Projected gradient descent, where W ≥ 0.

Game-theoretic loss: A fixed-point residual minimization of per-neuron energies [3].

Stability: Lyapunov diagonal stability via Perron sum-ratio surrogate caps ρ(W_{EE}) and ρ(W_{II}).



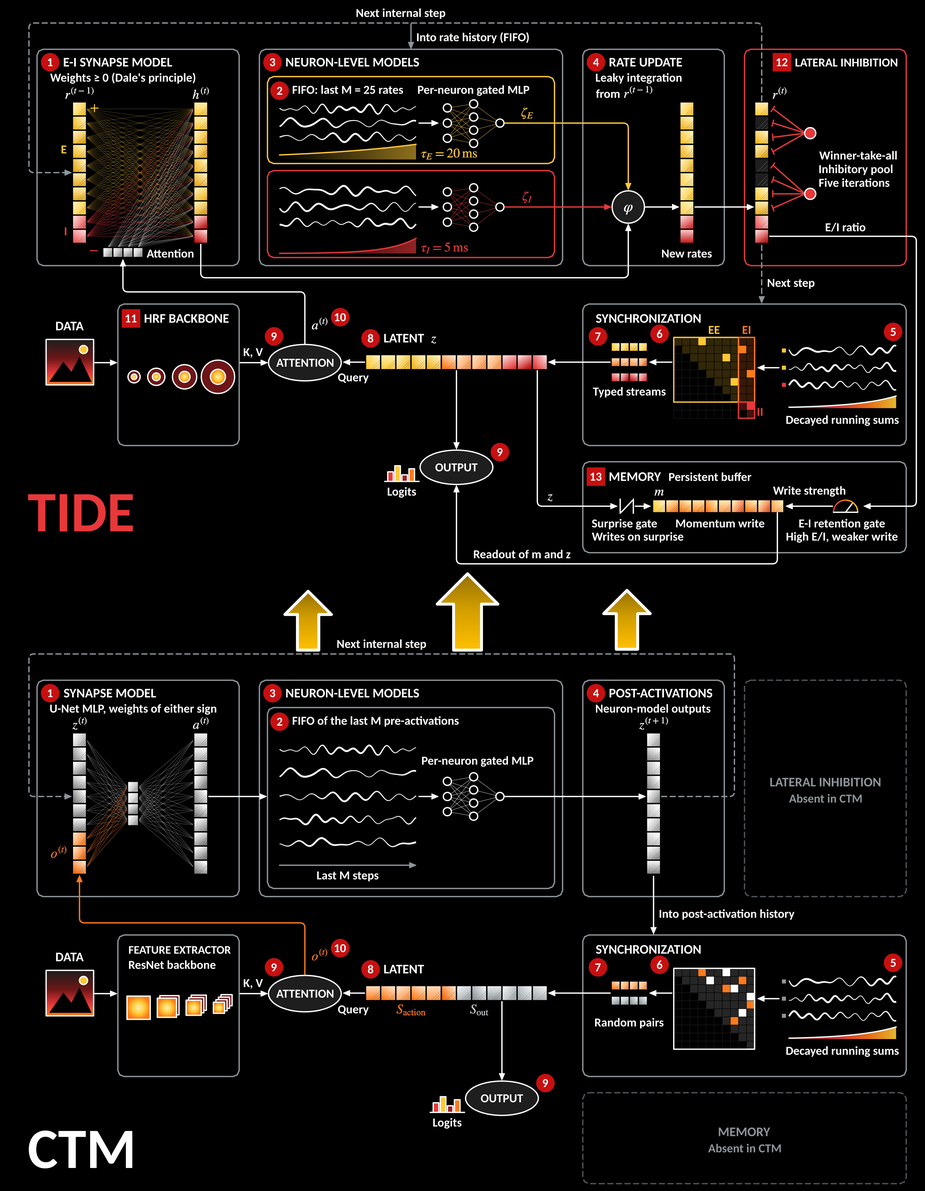
Attention of TIDE and CTM over internal steps on perturbed ImageNet images (green: correct, red: wrong).

Limitations & Outlook:

Theory scope: Stability analysis covers an idealized, un-normalized Wilson-Cowan surrogate.

Outlook: Augmented-Lagrangian E-I balance, stricter biophysical constraints, SNN-based.

III. TIDE Architecture



One internal step of TIDE (top) and of CTM (bottom).

IV. Main Benchmark & Ablation

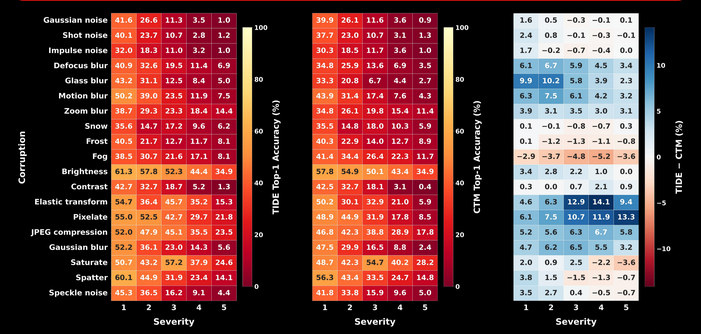
Dataset	Steps (TIDE / CTM)	TIDE best seed	TIDE mean ± std	CTM
MNIST	200K / 200K	99.67	99.60 ± 0.05	99.59
Fashion-MNIST	200K / 200K	94.42	94.12 ± 0.19	92.80
CIFAR-10	600K / 600K	90.68	90.62 ± 0.06	86.16
CIFAR-100	600K / 600K	65.79	62.68 ± 0.18	64.75
ImageNet-1K	200K / 200K	69.55	68.40 ± 1.91	64.06
ImageNet-1K	500K / 500K	69.90	—	71.78‡

Best test top-1 accuracy (%). TIDE: best seed and mean ± sample std.

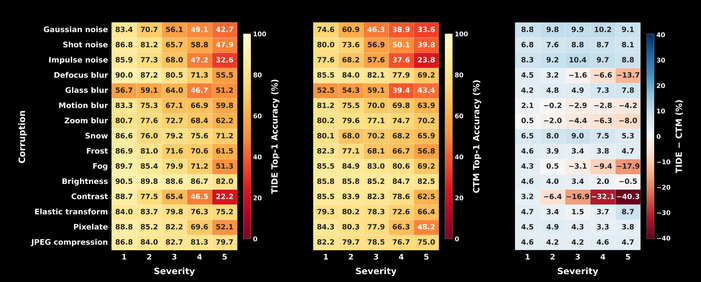
Configuration		MNIST	Fashion-MNIST	CIFAR-10	CIFAR-100
Reference					
CTM		99.54 ± 0.03	92.51 ± 0.11	86.23 ± 0.34	65.19 ± 0.48
TIDE (full, λ_{spec} = 0.0)		**99.64 ± 0.02**	94.21 ± 0.21	**90.62 ± 0.06**	**65.68 ± 0.18**
Component removed					
− Wilson-Cowan update	4	99.61 ± 0.02	93.70 ± 0.12	90.18 ± 0.26	64.52 ± 0.67
− Dale's law constraint	1	99.59 ± 0.03	93.55 ± 0.18	89.01 ± 1.74	65.39 ± 0.39
− Lateral inhibition (WTA)	12	99.61 ± 0.02	93.80 ± 0.17	89.13 ± 1.20	64.94 ± 0.30
− Surprise-gated memory	13	99.59 ± 0.01	92.95 ± 0.16	88.97 ± 1.41	64.32 ± 0.30
− ResNet-18 inst. of HRF backbone	11	99.60 ± 0.03	93.03 ± 0.12	83.02 ± 2.02	54.49 ± 0.76
Component added					
+ Spectral regularizer (λ_{spec} = 0.1)	1	**99.64 ± 0.03**	**94.31 ± 0.06**	89.02 ± 2.93	65.38 ± 0.35

Multi-seeded leave-one-out ablation: best top-1 accuracy (%) during training, mean ± std. Bold: highest per dataset.

V. Robustness to Corruptions



ImageNet-C [4] top-1 accuracy (%) of TIDE, CTM and TIDE − CTM (blue: TIDE better).



CIFAR-10-C [4] top-1 accuracy (%) of TIDE, CTM and TIDE − CTM (blue: TIDE better).

[1] L. Darlow, C. Regan, S. Risi, J. Seely, and L. Jones, "Continuous thought machines," in *NeurIPS*, 2025.

[2] H. R. Wilson and J. D. Cowan, "Excitatory and inhibitory interactions in localized populations of model neurons," *Biophysical Journal*, vol. 12, no. 1, pp. 1–24, 1972.

[3] S. Betteti, W. Retnaraj, A. Davydov, J. Cortés, and F. Bullo, "Competition, stability, and functionality in excitatory-inhibitory neural circuits," arXiv:2512.05252v1, 2025.

[4] D. Hendrycks and T. Dietterich, "Benchmarking neural network robustness to common corruptions and perturbations," in *ICLR*, 2019.