A Second-Order SpikingSSM for Wearables

Kartikay Agrawal[1], Abhijeet Vikram[2], Vedant Sharma[2], Vaishnavi Nagabhushana[1], Ayon Borthakur[1]

{a.kartikay,n.vaishnavi, ayon.borthakur}@iitg.ac.in

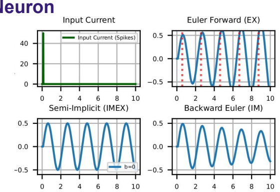
Motivation

- ***Wearables*** produce ***huge, continuous physiological time series***.
- Requires **models** that handle ***long-range temporal dependencies***.
- ***Spiking SSMs*** offer ***low power + high throughput solutions → perfect for on-device health analytics***
- ***Second-order oscillatory neuronal states can capture long range dynamics and enable efficient parallel scans for SSMs.***

Methods

- **Harmonic-Resonate & Fire Neuron**

$$u'(t) = -\Omega v(t) + Bx(t)$$
$$v'(t) = u(t) \qquad (1)$$
$$z(t) = \Theta(v(t) - \theta_C)$$



- **Discretisation**

❖ Implicit Euler (IM)

$$u_n = u_{n-1} + \Delta t(-\Omega v_{n-1} + Bx_n),$$
$$v_n = v_{n-1} + \Delta t\, u_n,$$
$$s_n = Ms_{n-1} + F_n,$$

❖ Implicit Explicit (IMEX)

$$u_n = u_{n-1} + \Delta t(-\Omega v_n + Bx_n),$$
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$$s_n = Ms_{n-1} + F_n,$$

- **SHaRe-SSM**: A second-order **S**piking **Ha**rmonic-**Re**sonate & Fire **S**tate-**S**pace **M**odel
  - *Encoder*: data-driven spike encoding via linear layer + no-reset IF neuron (no manual rate coding).
  - *SHaRe-SSM Block:* HRF-based oscillatory dynamics, no resets, and parallel scan computation.
  - *Decoder:* linear classifier or **learnable kernel regressor** (convolutional filter) for regression outputs.

Algorithm

Algorithm 1 SHaRe-SSM Algorithm

Require: Input sequence x
Ensure: N-blocks, spike function Θ , output sequence o
  $x^0 \leftarrow Encoder(x)$ {Encode input sequence into spikes}
  for $n = 1, \ldots, N$ **do**
    $z^n \leftarrow$ solution of HRF in (1) with input x^{n-1} via parallel scan aggregated
    $y^n \leftarrow Cz^n + Dx^{n-1}$ {Weighted spike mixing in (1)}
    $y^n \leftarrow \Theta(y^n - \theta^n_D)$
    $y^n \leftarrow Linear(y^n)$
    $y^n \leftarrow \Theta(y^n - \theta^n)$
    $x^n \leftarrow y^n + x^{n-1}$ {Spike mixing}
  end for
  $o \leftarrow Decoder(x^N)$ {Decode spikes}

Very-Long Range Interactions

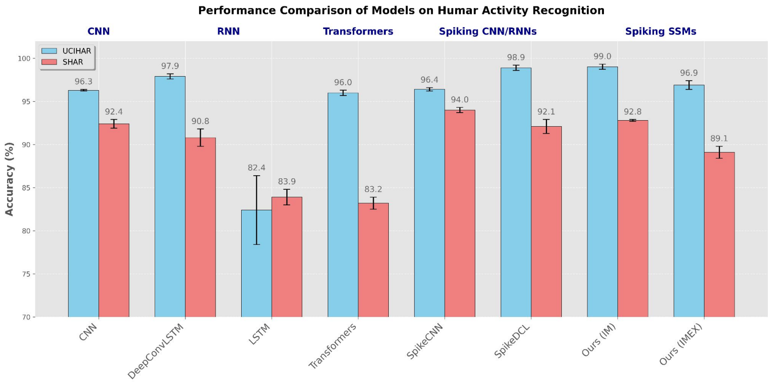
Highlights the potential of *spiking models* for *scalable*, *real-world health monitoring*.

Method	Integrator	SNN	PPG (MSE ↓)	EW (ACC ↑)	
NRDE		No	9.9 ± 1.0	83.9 ± 7.3	
NCDE		No	13.5 ± 0.7	75.0 ± 3.9	
Log-NCDE		No	9.6 ± 0.6	85.6 ± 5.1	
LRU		No	12.2 ± 0.5	87.8 ± 2.8	
S5		No	12.6 ± 1.3	81.1 ± 3.7	
S6		No	12.9 ± 2.1	85.0 ± 16.1	
Mamba		No	10.7 ± 2.2	70.9 ± 15.8	
LinOSS	IM	No	7.5 ± 0.5	95.0 ± 4.4	25.4× less Energy
Ours	IM	Yes	11.8 ± 0.9	92.8 ± 3.3	
RHEL-Lin	IMEX	No	9.5 ± 1.0	75.0 ± 9.9	
RHEL-Nonlin	IMEX	No	8.4 ± 0.5	50.1 ± 6.7	
LinOSS	IMEX	No	6.4 ± 0.2	80.0 ± 4.4	52.1× less Energy
Ours	IMEX	Yes	9.1 ± 0.2	90.0 ± 5.7	

- **EigenWorms**: *18k extremely long 18k sequences of very long C. elegans motion traces*.
- **PPG-DaLiA**; *50k heart-rate sequences* (128 Hz, long 150-min sessions × 15 participants).

Human Activity Recognition

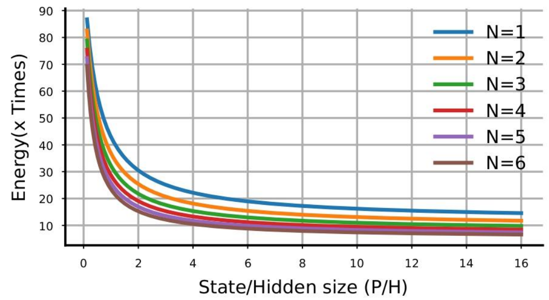
Short-window wearable-sensor to demonstrate *real-world*, *low-power human activity recognition*.



- **UCI-HAR:** 10.3k samples • 30 subjects • 6 activities • Acc+Gyro @ 50 Hz
- **UniMB-SHAR:** 11.7k samples • 17 activities • Acc only ≤ 50 Hz

Energy Estimate

- **IMEX: ~52.1× and IM: ~25.4×** more energy-efficient than LinOSS on EigenWorms.
- **IMEX improves accuracy by ~10%**, while **IM trades a slight drop (92.8% vs. 95%) for massive energy savings**.



Conclusion and Future Work

➔ **SHaRe-SSM:** A second-order **spiking state-space model** using harmonic resonate-and-fire neurons.
➔ **Fully spike-based:** No GeLU/GLU → **lower energy**, **neuromorphic-optimal**.
➔ **Learns end-to-end:** Includes **trainable encoder, decoder**, and **parallel scan** for long sequences.
➔ **Optimized for long-range modeling:** Handles **18k–50k length** sequences efficiently.
➔ **Energy-efficient:** Outperforms prior SSMs with **significantly lower compute cost**.
Wearable-ready: Ideal for **healthcare edge devices** due to low power + long-sequence capability.
➔ **Future direction:** Deployment on **real-time edge AI**.

References

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*AV, VS are BS interns from IISER Pune, KA, VN are PhD students, AB is the PI.
* For more details about our team, scan the QR code given here.
* Paper Link: https://openreview.net/forum?id=hv52KEOshb