Hybrid ST-GCN/HMM Tremor Detector for a Wearable MR-Fluid Exoskeleton

Toufic Jrab[1]

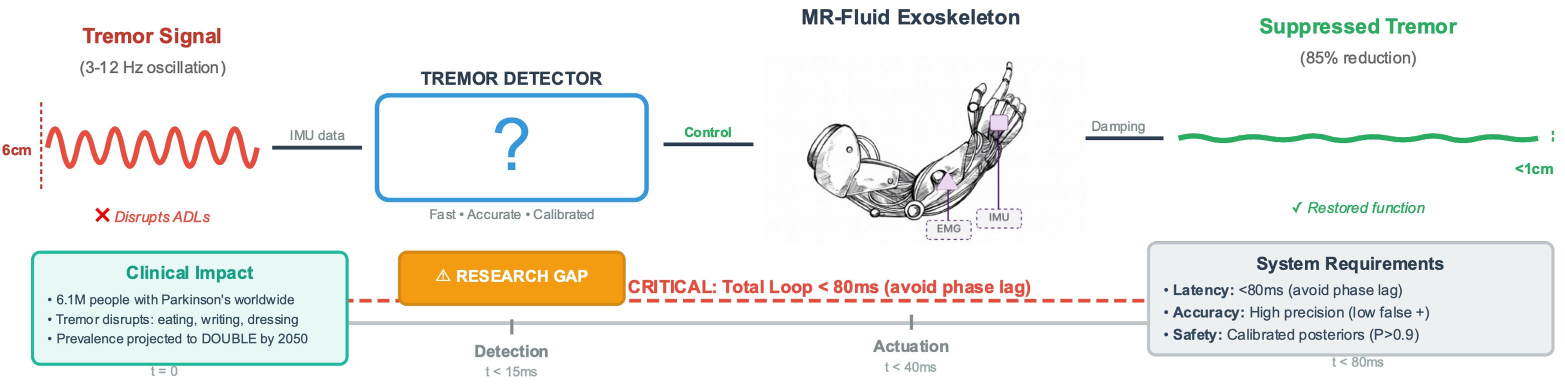
[1]Department of Bioengineering, McGill University, QC Canada

toufic.jrab@mail.mcgill.ca

23rd ANNUAL IEEE-EMBS International Conference on Body Sensor Networks

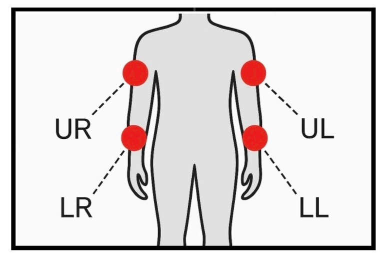
Motivation

- 6.1M with Parkinson's → DOUBLES by 2050 [1]
- Tremor: 3-12 Hz, 6cm amplitude disrupts ADLs [2]
- Current detectors: >100ms latency, overconfident P(tremor) [3]
- Need: Real-time + calibrated uncertainty for 15Nm damper



Problem Statement

- **Input Window:** $X_t \in \mathbb{R}^{256\times 6}$, $[a_x, a_y, a_z, g_x, g_y, g_z]$
- **Objective:** $f_\theta(X_t) = \Pr(T_t = 1 \mid X_t)$
- **Constraints:** $t_{\text{sense}} + t_{\text{infer}} + t_{\text{act}} < 80\,\text{ms}$
- **Trigger:** $u_t = \mathbb{I}[\Pr(T_t{=}1 \mid X_t) > 0.9]$



IMU placement (MetaMotion R)

Subjects:	34 (15 PD, 19 Ctrl, 21 M / 13 F)
Tasks:	Toast, Cardigan, Door (3× each)
Sampling:	200 Hz, 0.5–20 Hz band-pass
Window:	256 samples (1.28 s), 50 % overlap
Split:	Train 4 887 / Val 1 125 / Test 1 552
Labels:	Clinician video scoring (± 200 ms)

Methodology

IMU → ST-GCN $\xrightarrow{p_t}$ BN $\xrightarrow{\ell_t}$ HMM $\xrightarrow{u_t}$ Damper

Graph Construction $\quad G = (V, E), \quad |V| = 6,$

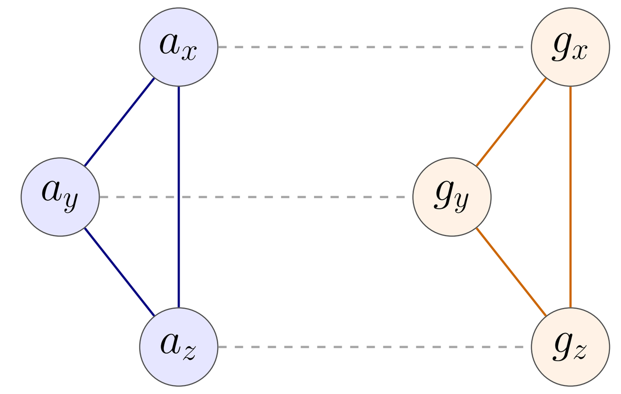
Model 6 IMU axes as a spatial graph: $V = \{a_x, a_y, a_z, g_x, g_y, g_z\}.$

Edges.

- Intra-modal: complete graphs within $\{a_x, a_y, a_z\}$ and $\{g_x, g_y, g_z\}$
- Cross-modal: $a_u \leftrightarrow g_u,\ \forall u \in \{x, y, z\}$

Adjacency. $\quad A \in \{0,1\}^{6\times 6}, \quad A_{ij} = 1$ if $(v_i, v_j) \in E$, row-normalized.

Temporal kernel: $k = 3$ (short-range dynamics)



Intra-modal (solid) and cross-modal (dashed) edges.

Methodology

2. ST-GCN Encoder

- **Input:** $X_t \in \mathbb{R}^{256\times 6}$ (window length 256 at 200 Hz)
- **Three spatio-temporal blocks:** Block$_i$: $X^{(i)} \leftarrow \mathrm{BN}\Big(\mathrm{ReLU}\big(\mathrm{Conv1D}_{k=3}(\mathrm{GCN}(A, X^{(i-1)}))\big)\Big)$
- **Channel expansion:** $6 \to 16 \to 32$
- **Global pooling:** $$\boldsymbol{h}_t = \frac{1}{|V|\,T}\sum_{v=1}^{|V|}\sum_{\tau=1}^{T} X^{(3)}_{v,\tau} \qquad (|V| = 6,\ T = 256)$$
- **Output (probability):** $$\hat{\boldsymbol{p}}_t = \mathrm{softmax}(W\,\boldsymbol{h}_t + \boldsymbol{b}), \qquad \hat{p}_t \equiv \Pr(\mathrm{Tremor} = 1 \mid X_t, \theta)$$
- **Complexity:** $|\theta| \approx 22\text{k}$ (INT8-ready) **Inference:** $\sim 15\,\text{ms}$ on Jetson Nano

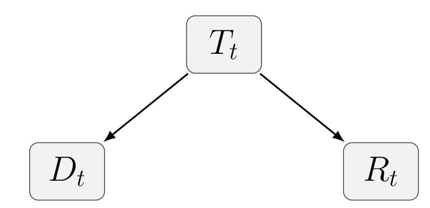
3. Bayesian Network

- **Handcrafted features from** X_t: D_t (dominant frequency, FFT peak), R_t (RMS amplitude)
- **Discretization:** Scott's rule → 3 bins each.
- **Structure:** $D_t \leftarrow T_t \to R_t$
- **Posterior:**

$$o_t = \Pr(T_t{=}1 \mid D_t, R_t) = \frac{\Pr(T{=}1)\,\Pr(D_t \mid T{=}1)\,\Pr(R_t \mid T{=}1)}{\Pr(D_t, R_t)}.$$

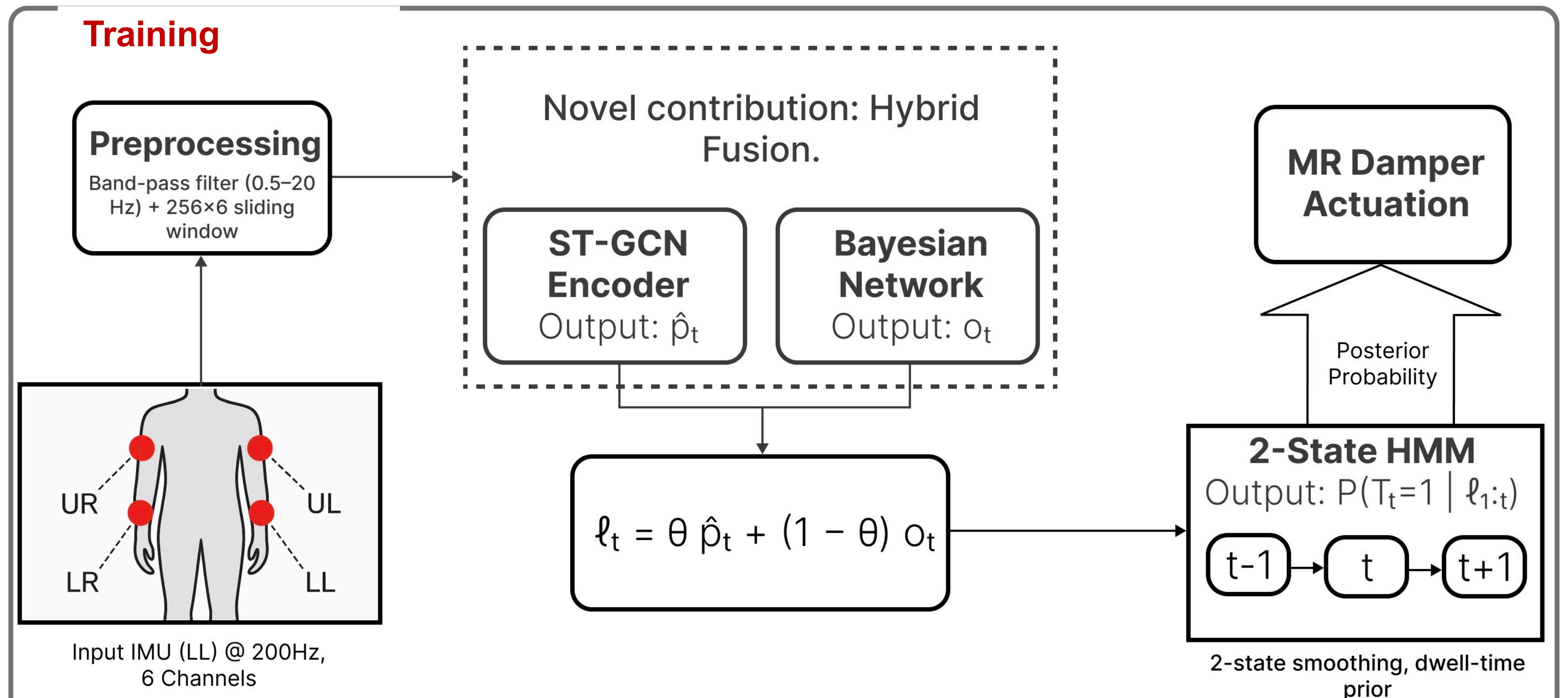
Closed-form (multinomial–Dirichlet conjugate)

Compute: $O(1)$, $< 0.05\,\text{ms}$



Conditional independence: $D_t \perp R_t \mid T_t$

Training



Methodology

4. HMM Fusion & Temporal Smoothing

- **Fusion:**

$$\ell_t = \theta\,\hat{p}_t + (1-\theta)\,o_t, \quad \theta = 0.6$$

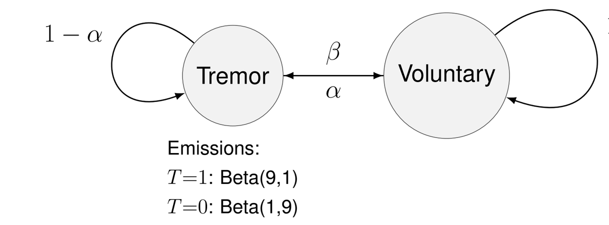
Combines ST-GCN output $\hat{p}_t$ and BN prior o_t.

- **2-State HMM:**

$$A = \begin{bmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{bmatrix}, \quad \alpha = 0.01,\ \beta = 0.10$$

Enforces ∼100 ms dwell for stable state transitions.

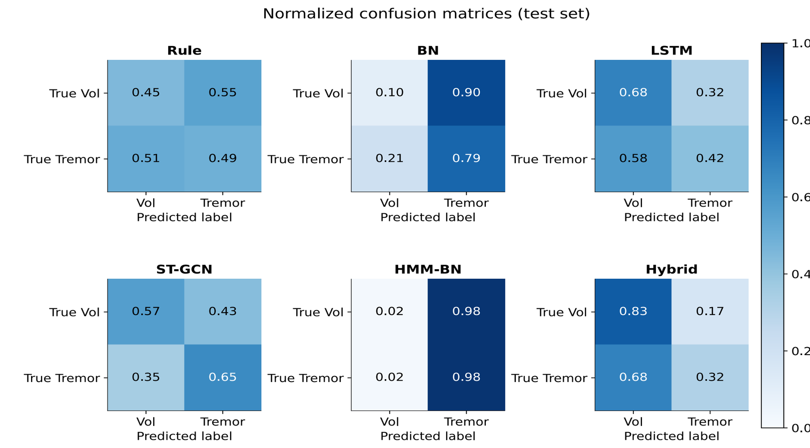
- **Emissions:** Tremor ⇒ $\mathrm{Beta}(9,1)$, Voluntary ⇒ $\mathrm{Beta}(1,9)$
- **Output:** Posterior $P(T_t{=}1 \mid \ell_{1:t})$, 0.05 ms/step → smooth, spike-free detection.

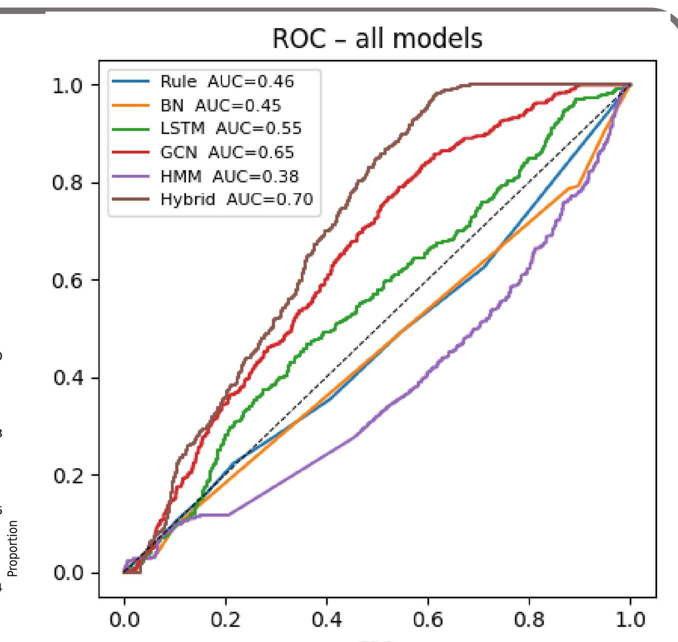


Fusion $\ell_t = \theta\hat{p}_t + (1-\theta)o_t$; HMM filtering yields calibrated, temporally stable $P(T_t{=}1)$.

Results & Conclusion

Model	Prec	Rec	F1	AUC	NLL	Lat (ms)
Rule	.26	.49	.34	.55	.89	0.02
BN	.25	.79	.38	.62	.76	0.03
LSTM	.33	.42	.37	.64	.72	21.6
ST-GCN	.37	.65	.47	.68	.66	16.6
HMM-BN	.28	.98	.43	.38	.98	0.05
HYBRID*	**.41**	.32	.36	**.70**	**.61**	**15.2**





Performance summary (test set):

- **AUC:** 0.70 ± 0.01 (+4 pp vs. ST-GCN)
- **Precision:** 0.41 (+11% fewer false triggers)
- **NLL:** 0.61 (−8% better calibration)
- **Latency:** 15.2 ms (30% faster than LSTM, <80 ms safe)

Observations:

- HMM fusion smooths predictions and suppresses transient spikes.
- Posterior probabilities remain stable during voluntary motion.
- Hybrid model achieves best AUC–latency trade-off among all baselines.

Conclusion:

- First integration of ST-GCN with Bayesian and HMM layers for real-time tremor detection.
- Meets power (<10 mJ), latency (<80 ms), and calibration requirements for safe actuation.

References

[1] V. L. Feigin, A. A. Abajobir, K. H. Abate, F. Abd-Allah, A. M. Abdulle, S. F. Abera, G. Y. Abyu, M. B. Ahmed, A. N. Aichour, I. Aichour et al., "Global, regional, and national burden of neurological disorders during 1990–2015: a systematic analysis for the global burden of disease study 2015," The Lancet Neurology, vol. 16, no. 11, pp. 877–897, 2017.

[2] W. A. Rocca, "The burden of parkinson's disease: a worldwide perspective," The Lancet Neurology, vol. 17, no. 11, pp. 928–929, 2018.

[3] H. S. Nguyen and T. P. Luu, "Tremor-suppression orthoses for the upper limb: Current developments and future challenges," Frontiers in Human Neuroscience, vol. 15, p. 622535, 2021

Acknowledgements

McGill Biomechanics design group, Human-Machine Interface led by Prof. Jeremy Cooperstock, and the course taught by Dr. Siamak Ravanbakhsh

Paper #154

IEEE BSN 2025 · LOS ANGELES, CA