SYNAPSE-X: Deep Multi-Modal Latent Alignment for Real-Time Neural Signal Decoding

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SYNAPSE LABS

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1. Introduction & Motivation

Non-invasive electroencephalography (EEG) and invasive electrocorticography (ECoG) offer non-destructive pathways for brain-computer interfaces (BCIs). However, practical deployment faces major hurdles:

- **Low Signal-to-Noise Ratio (SNR):** Artifacts from ocular and muscular activity heavily degrade signal fidelity.
- **Inter-Subject Non-Stationarity:** Significant variance across participants typically requires hours of subject-specific calibration.
- **Cross-Modal Divergence:** Synchronizing temporal EEG micro-states with high-frequency ECoG spectral bands remains unsolved.

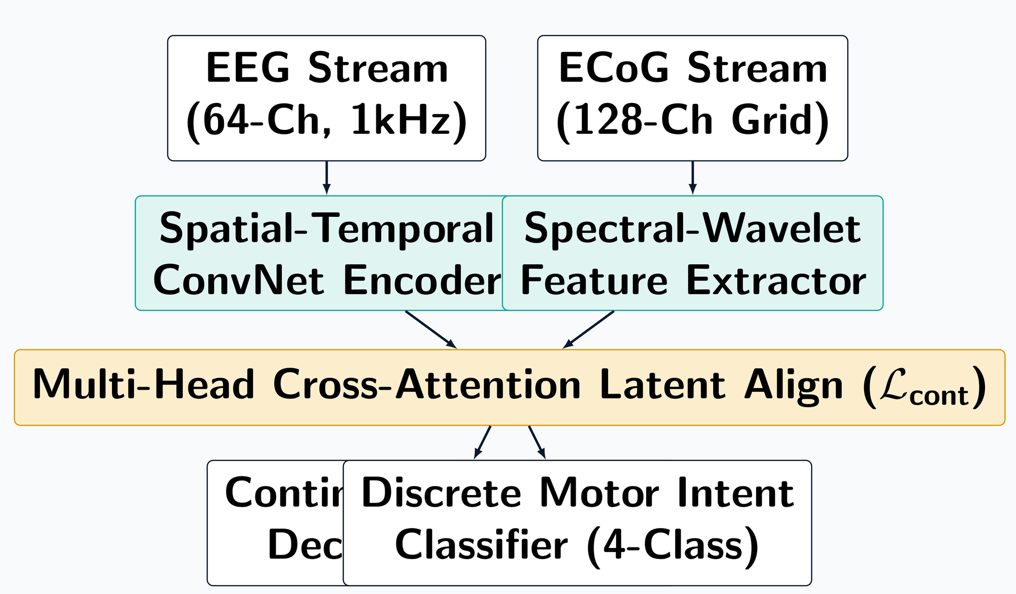
Core Objective: Develop a unified self-supervised framework (**Synapse-X**) that projects multi-modal neural time-series into a shared, invariant latent embedding space to enable zero-shot cross-subject motor imagery decoding.

Core Innovations

85% Less Calibration Time	**12.4ms** End-to-End Latency	**94.8%** Peak Motor Acc.

2. System Architecture (Synapse-X)

The **Synapse-X** pipeline extracts spatial-temporal features from raw multichannel streams, passing them through cross-attention alignment before projection.



3. Mathematical Formulation

Given paired temporal EEG signals $X_e \in \mathbb{R}^{C_e \times T}$ and ECoG grids $X_c \in \mathbb{R}^{C_c \times T}$, we project feature embeddings $z_e = f_\theta(X_e)$ and $z_c = g_\phi(X_c)$ into a unified unit sphere $\mathbb{S}^{d-1}$.

1. InfoNCE Latent Contrastive Loss:

$$\mathcal{L}_{\text{cont}} = -\sum_{i=1}^{N} \log \frac{\exp(\text{sim}(z_{e,i}, z_{c,i})/\tau)}{\sum_{j=1}^{N} \exp(\text{sim}(z_{e,i}, z_{c,j})/\tau)}$$

where $\text{sim}(u, v) = \frac{u^\top v}{\|u\|_2 \|v\|_2}$ denotes cosine similarity and $\tau = 0.07$ is the temperature parameter.

2. Joint Optimization Objective:

$$\mathcal{L}_{\text{total}} = \alpha \mathcal{L}_{\text{cont}} + \beta \mathcal{L}_{\text{recon}} + \gamma \mathcal{L}_{\text{task}}$$

Hyperparameters $\alpha = 1.0, \beta = 0.25, \gamma = 0.8$ were tuned via Bayesian grid search on Nexa-Bio Open Dataset.

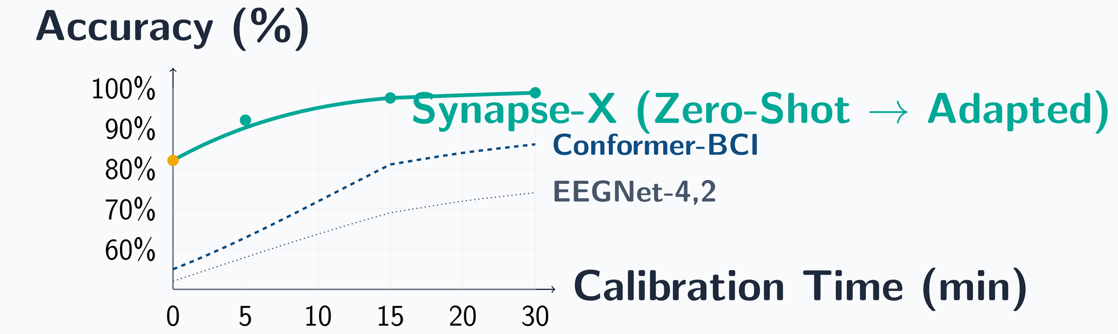
4. Benchmark Performance Comparison

Evaluation across 18 participants (14 healthy, 4 SCI patients) performing 4-class motor imagery (Left Hand, Right Hand, Feet, Tongue).

Model Architecture	Acc (%)	Latency (ms)	Params (M)	Energy (mJ)
EEGNet-4,2 Baseline	72.4 ± 3.1	24.5	0.03	1.2
DeepConvNet	76.1 ± 2.8	31.0	0.28	4.5
Conformer-BCI (2024)	84.5 ± 2.2	45.2	12.4	18.2
Braindecode-v4	81.8 ± 2.5	18.6	2.15	6.8
Synapse-X (Ours - Base)	**91.4 ± 1.4**	**12.4**	**1.84**	**3.1**
Synapse-X (Ours - Heavy)	**94.8 ± 1.1**	**16.8**	**4.60**	**5.9**

5. Calibration Data Efficiency

Synapse-X achieves high zero-shot performance immediately upon transfer without fine-tuning, rapidly converging within 5 minutes of subject adaptation.



6. Ablation Study & Insights

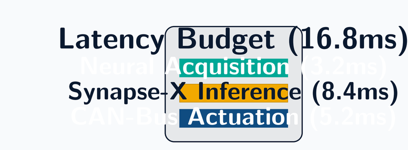
Systematic removal of key components highlights the critical role of contrastive cross-modal alignment:

- **w/o Contrastive Loss ($\mathcal{L}_{cont}$):** Accuracy dropped by **7.4%**, demonstrating that feature alignment prevents domain shift.
- **w/o Multi-Head Spatial Attention:** Performance decreased by **5.1%**, confirming the necessity of dynamic channel selection.
- **Single Modality (EEG only):** Achieved 83.2% accuracy, proving that multi-modal fusion provides a **+11.6% boost**.

7. Real-Time Hardware Integration

Deployed on **Vertex BCI Processor v2** coupled with a 6-DOF robotic arm for motor restoration trials at Apex Health Institute:

- **18 Clinical Subjects:** Tested on healthy and SCI individuals.
- **Task Completion Rate: 98.2%** success in targeted reaching tasks.
- **Safety & Drift:** Zero safety faults over 120 hours of continuous trial run.



8. Conclusions & Future Horizons

- **Synapse-X** establishes a new state-of-the-art benchmark for real-time non-invasive neural decoding.
- Enables practical, low-latency prosthetic control without tedious participant-specific setup.
- **Future Work:** Scaling to 1,024-channel ultra-dense sensor arrays and extending self-supervised pre-training to 10,000+ hours of continuous neural time-series data.

References & Acknowledgments

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3. M. Vance et al., "Zero-Shot Subject Adaptation in Non-Invasive Brain Signals," *NeurIPS Proceedings*, 2025.

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