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# nASR: An End-to-End Trainable Neural Layer for Ch-Level EEG Artifact Subspace Reconstruction in Real-Time BCI

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Building Reliable Advances and BRAIN Innovations in Neurotechnology



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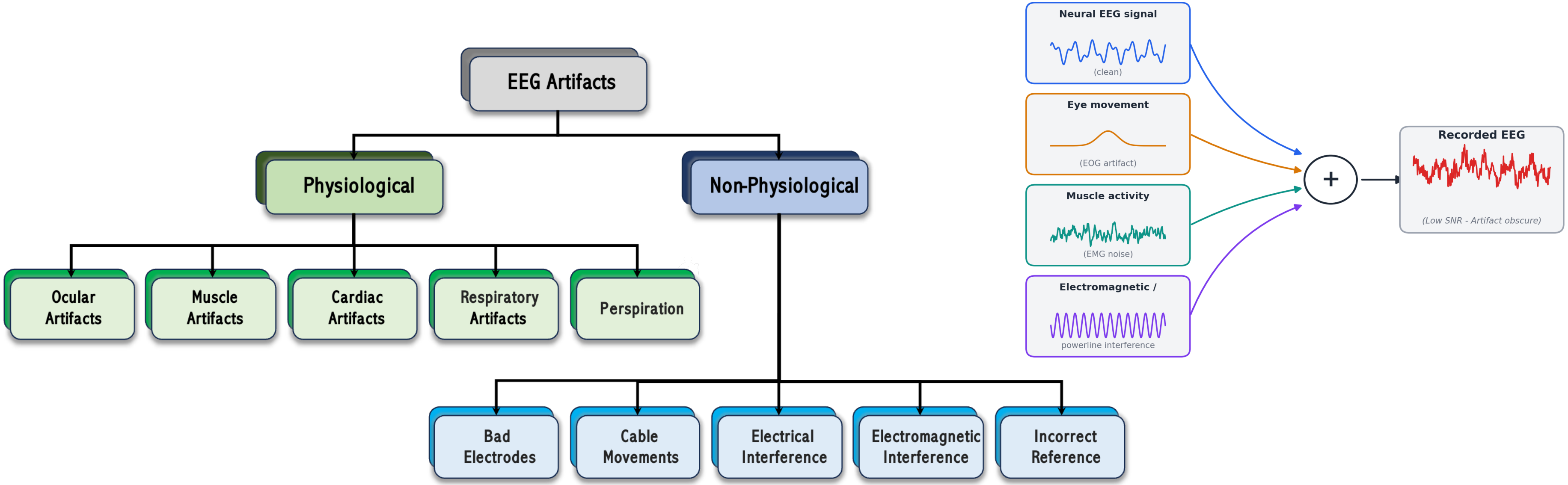
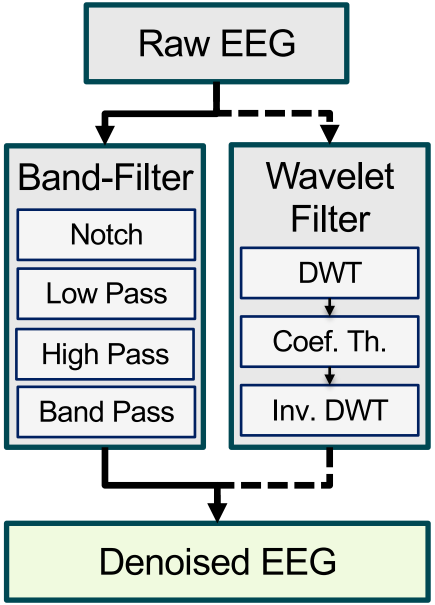
# Motivation

- EEG is noisy (Physiological + Non-Physiological interference). Low SNR hurts feature decoding.
- Denoising remains challenging when artifact frequencies overlap with meaningful EEG activity.
- Existing methods treat artifact rejection separately, rather than jointly optimizing with the BCI decoder.



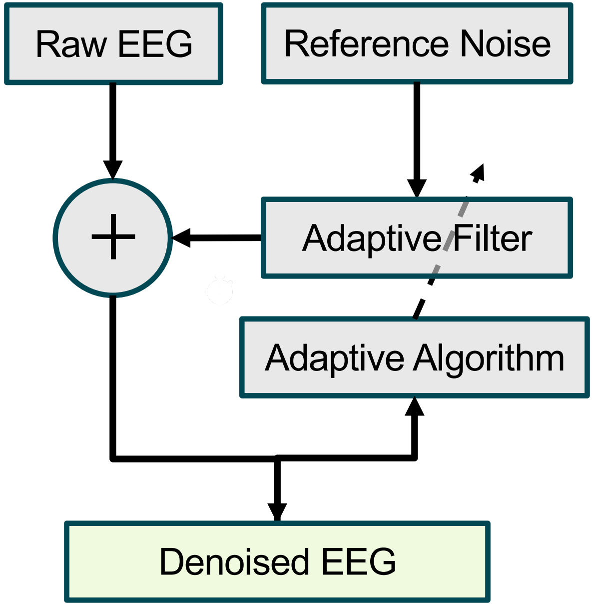
# Real-Time Artifact Removal Techniques

## Frequency-Domain




⚠ *Targets fixed Frequency-band*

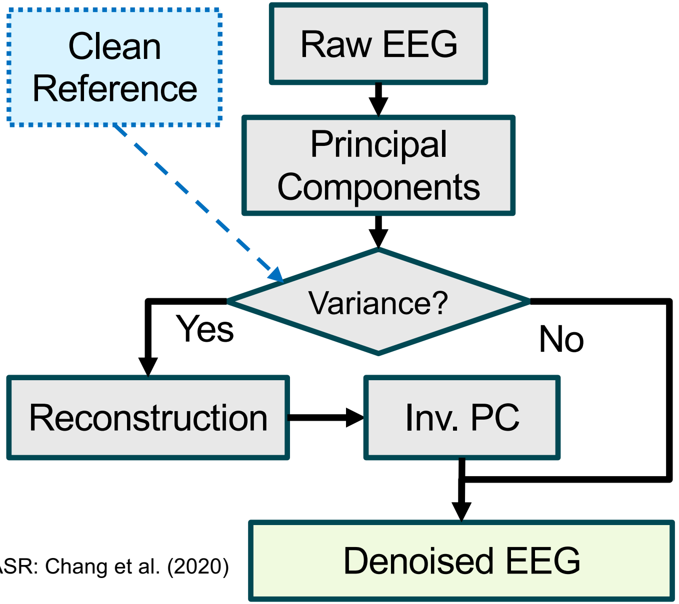
## Adaptive Filter




H-Infinity: Kilicarslan et al. (2016)

⚠ *Requires reference noise.*

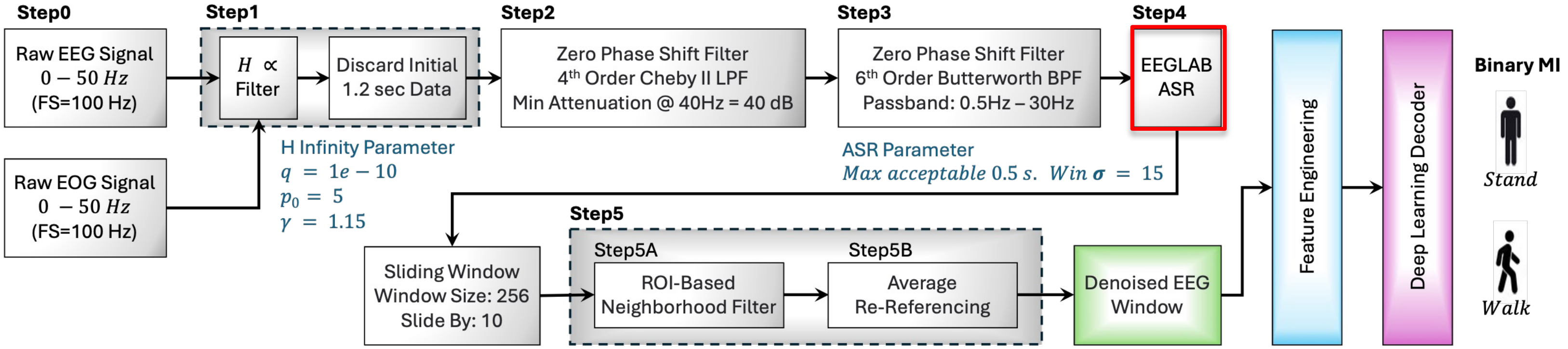
## ASR (Subspace-PC)



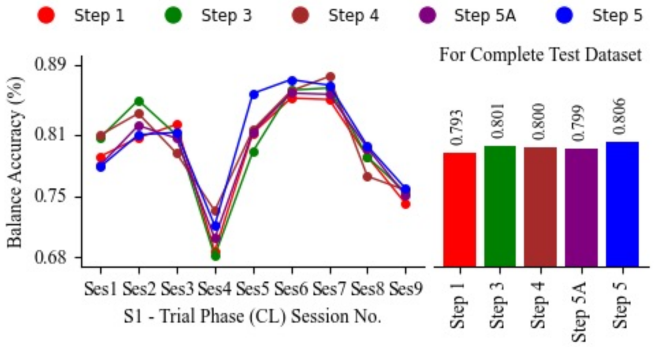

ASR: Chang et al. (2020)

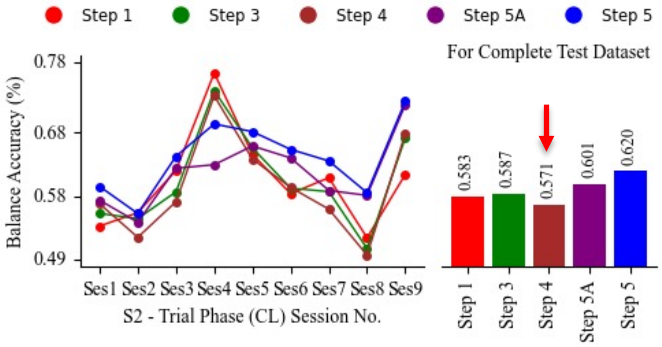
⚠ *Requires a predefined threshold.*
*Reconstructing the PC space alters all channels.*

# EEG Pre-Processing Steps — Ablation Study



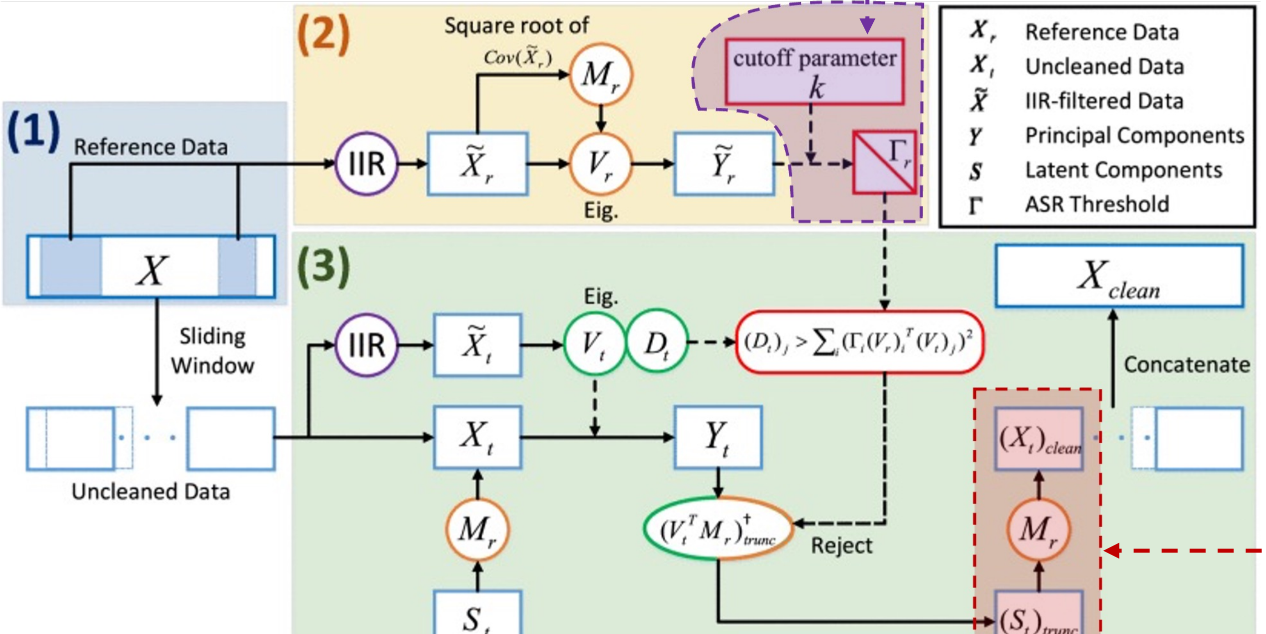

Dataset: Sarkar et al. (2026)



# Artifact Subspace Reconstruction (ASR)

**Flowchart for ASR**




Chang et al. (2020)

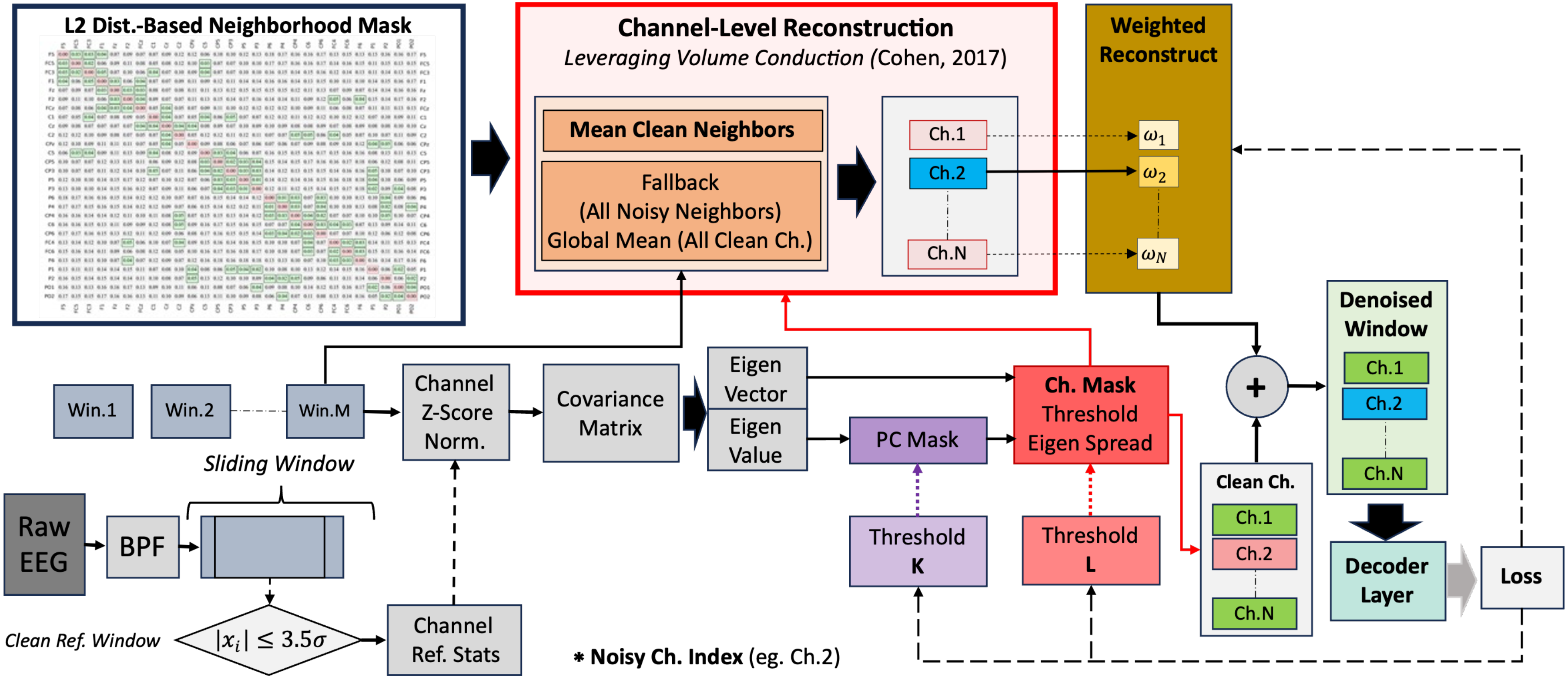
## Hard Thresholding

***Determining the optimal ASR threshold is crucial****. Incorrect settings can remove valuable EEG features along with artifacts, negatively impacting signal quality and analyses.*

## Reconstruction In PC Space

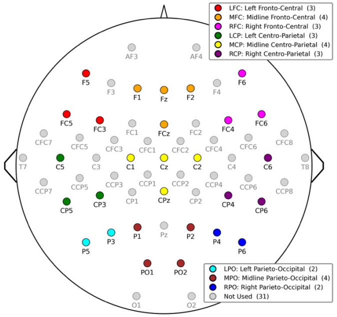
Principal Components are linear combinations of all original channels. ***Reconstructing the PC space can alter the overall data structure and potentially lose*** *valuable features.*

# nASR – Neural Artifact Subspace Detection/Ch. Reconstruction



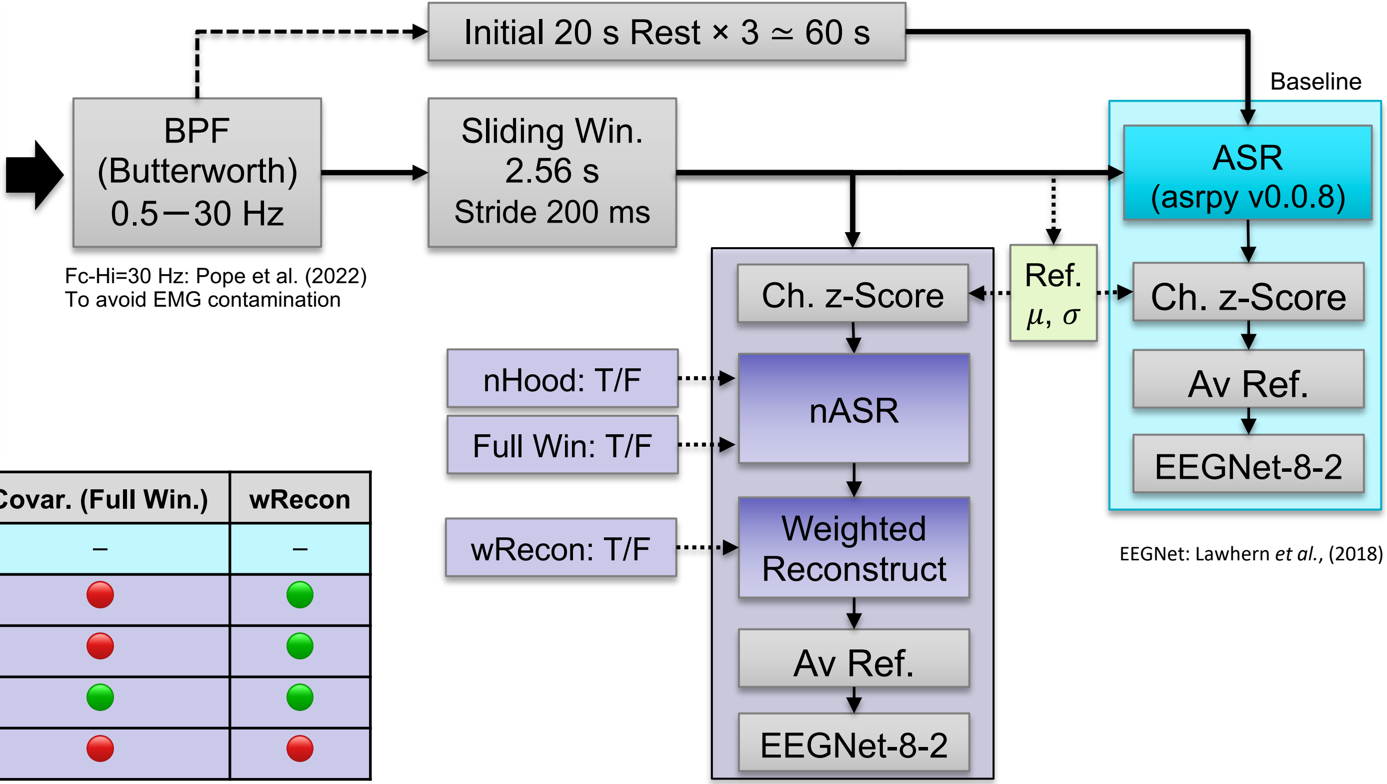
# Ablation Study Design

BCI Competition IV-Dataset-1
(Blankertz et al., 2007)




Used 28 Channels | Subject: a, b, g, f

| Model | ASR / nASR | nHood | Covar. (Full Win.) | wRecon |
|---|---|---|---|---|
| m01 | ASR | – | – | – |
| m02 | nASR | 🔴 | 🔴 | 🟢 |
| m03 | nASR | 🟢 | 🔴 | 🟢 |
| m04 | nASR | 🟢 | 🟢 | 🟢 |
| m05 | nASR | 🟢 | 🔴 | 🔴 |




Fc-Hi=30 Hz: Pope et al. (2022)
To avoid EMG contamination

EEGNet: Lawhern *et al.*, (2018)

# Performance Results

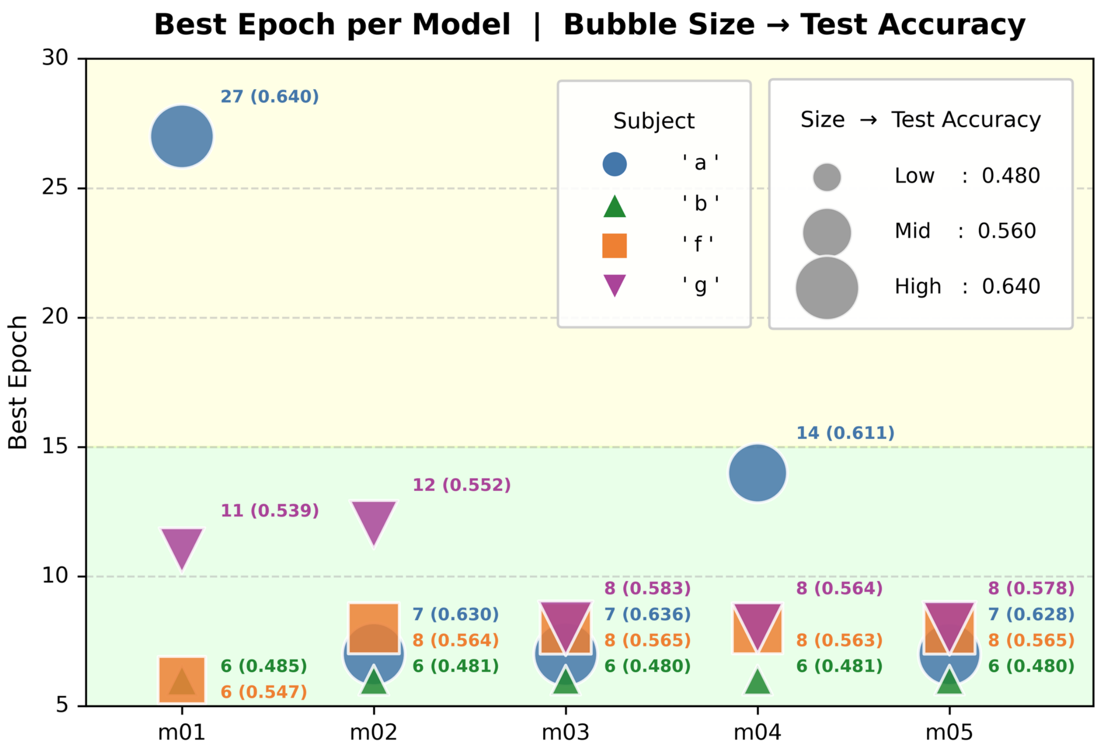
**nASR Ablation Study | Validation vs Test | Rank per Metric**

Rank 1 (Best) | Rank 2 | Rank 3 | Rank 4 | Rank 5 (Worst)

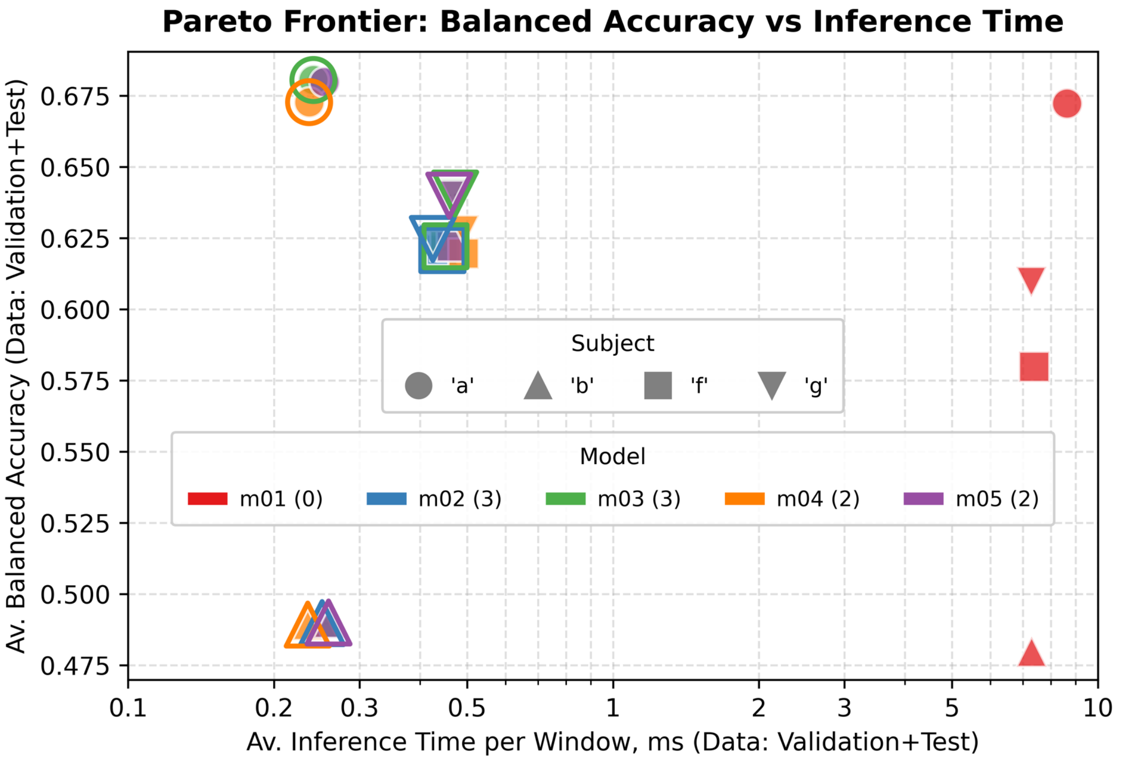
| Model | Subject: 'a' Valid Bal Acc | Subject: 'a' Valid F1 | Subject: 'a' Test Bal Acc | Subject: 'a' Test F1 | Subject: 'b' Valid Bal Acc | Subject: 'b' Valid F1 | Subject: 'b' Test Bal Acc | Subject: 'b' Test F1 |
|---|---|---|---|---|---|---|---|---|
| m01 (Traditional ASR [Th: 20]) Mean Rank: 3.56 (1.00) | 0.700 | 0.722 | 0.645 | 0.568 | 0.464 | 0.548 | 0.495 | 0.536 |
| m02 (nASR w/o Neighbourhood) Mean Rank: 1.69 (1.16) | 0.717 | 0.738 | 0.642 | 0.570 | 0.477 | 0.626 | 0.502 | 0.586 |
| m03 (nASR Including All) Mean Rank: 1.19 (1.18) | 0.717 | 0.730 | 0.644 | 0.569 | 0.479 | 0.627 | 0.501 | 0.585 |
| m04 (nASR Full Window Cov) Mean Rank: 2.31 (1.21) | 0.727 | 0.754 | 0.619 | 0.543 | 0.478 | 0.626 | 0.501 | 0.583 |
| m05 (nASR w/o Recon Weights) Mean Rank: 1.25 (0.97) | 0.716 | 0.739 | 0.644 | 0.573 | 0.479 | 0.627 | 0.501 | 0.585 |

| Model | Subject: 'f' Valid Bal Acc | Subject: 'f' Valid F1 | Subject: 'f' Test Bal Acc | Subject: 'f' Test F1 | Subject: 'g' Valid Bal Acc | Subject: 'g' Valid F1 | Subject: 'g' Test Bal Acc | Subject: 'g' Test F1 |
|---|---|---|---|---|---|---|---|---|
| m01 (Traditional ASR [Th: 20]) Mean Rank: 3.56 (1.00) | 0.618 | 0.555 | 0.541 | 0.489 | 0.680 | 0.706 | 0.540 | 0.554 |
| m02 (nASR w/o Neighbourhood) Mean Rank: 1.69 (1.16) | 0.671 | 0.640 | 0.570 | 0.559 | 0.697 | 0.712 | 0.552 | 0.538 |
| m03 (nASR Including All) Mean Rank: 1.19 (1.18) | 0.671 | 0.640 | 0.573 | 0.565 | 0.699 | 0.706 | 0.583 | 0.554 |
| m04 (nASR Full Window Cov) Mean Rank: 2.31 (1.21) | 0.671 | 0.638 | 0.568 | 0.554 | 0.691 | 0.711 | 0.564 | 0.561 |
| m05 (nASR w/o Recon Weights) Mean Rank: 1.25 (0.97) | 0.671 | 0.639 | 0.573 | 0.565 | 0.702 | 0.721 | 0.577 | 0.567 |

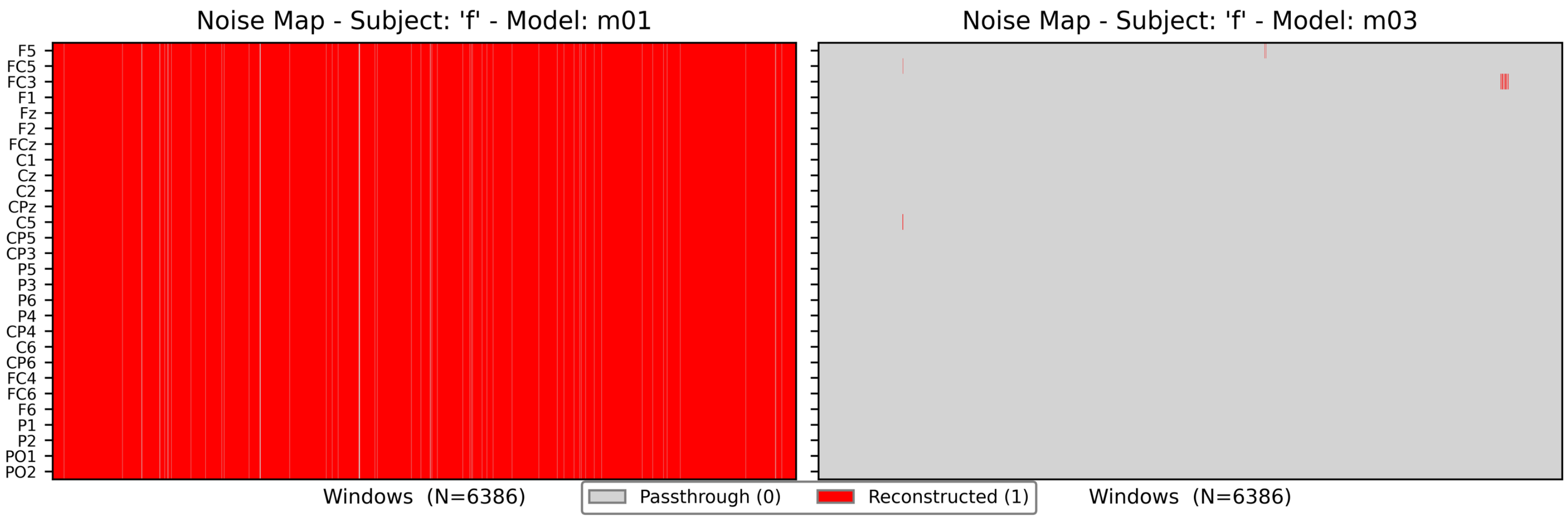
# Training Convergence vs. Accuracy



# Balanced Accuracy Vs Inference Time



# Is It Reconstructing Only Noisy Ch?



# Conclusion

| | |
|---|---|
| nASR | • End-to-end trainable layer with dual learnable thresholds (K, L) for Ch-level EEG artifact reconstruction. |
| Optimization | • Jointly optimize artifact rejection with downstream decoder - No separate hand-tuned stage needed. |
| Accuracy | • Outperforms traditional ASR on classification accuracy across all ablation variants. |
| Inference | • > 20x reduction in inference time – Strong fit for real-time BCI (~0.2–0.5 ms). |

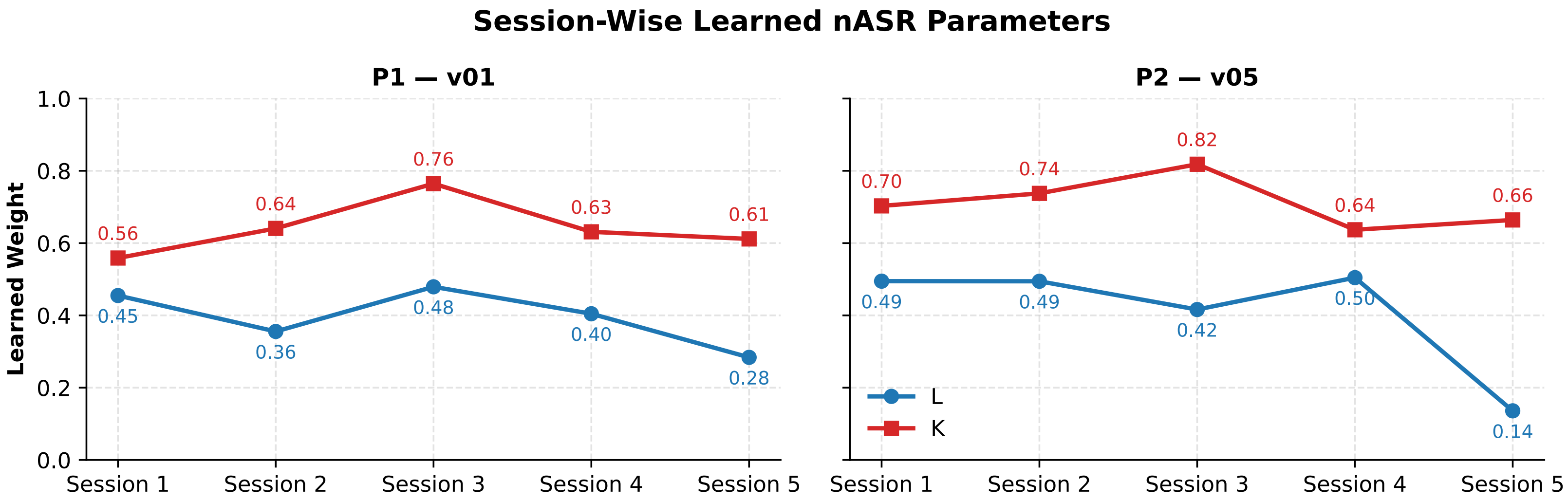
## Future Goals:

| | |
|---|---|
| 1 | • Benchmark against ASR across varied thresholds, not just the default (20). |
| 2 | • Validate on a larger cohort, multiple datasets, and diverse BCI paradigms. |
| 3 | • Extend to real-time closed-loop exoskeleton control. |
| 4 | • Replace simple clean channel averaging with Generative Reconstruction (EEGReXferNet) |
| 5 | • Replace clean channel averaging with reconstructed channel via reconstruction @ PC. – **True nASR** |

Reconstruct PC Subspace → Reconstruct Channels → Ch. Mask → Consider Only – Noisy Ch.

# Annexure − Learned nASR Thresholds

S. Sarkar et al., “A 2-Block Architecture for Real-Time EEG Gait Decoding: A Pilot Study,” arXiv:2608.02083, 2026.(IEEE MLSP 2026)



# Thank You – Q & A

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Noninvasive Brain-Machine Interface Systems

**Source Code:** github.com/ShanSarkar75/nASR.

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