Undergraduate Project

EEG BASED SOURCE LOCALIZATION USING PML

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Acknowledgement

We want to convey our heartfelt appreciation and gratitude to Professor Tushar Sandhan for providing us with the chance to work on this project.

We would also like to thank our Mentor Swathi Pratapa for the project and giving us a chance to take up UGP and for her wonderful guidance throughout the project.

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EEG Cognitive Dataset Overview

Experiment Structure

The COG-BCI database comprises four different tasks independently assessed over three sessions (spaced exactly one week apart). Furthermore, a resting state (one minute of eyes open and one minute of eyes closed) was collected at the beginning and the end of each session.

Overview :

- **Participants** : 29
- **Sessions** : 3 (spaced one week apart)
- **Task** : Flanker Task, PVT

Data Collection:

EEG : system with 64 active Ag-AgCl electrodes

- Sampling rate: 500 Hz
- Electrode placement: Standard 10-20 system
- Note : Electrode Cz missing for participants 1-9
- Electrode 10 (ECG) records electrocardiographic activity

ECG : Electrode 10 placed on the left fifth intercostal records electrocardiographic activity

EEG Cognitive Dataset Overview

Psychomotor Vigilance Task (PVT):

Purpose: Measures vigilance and sustained attention. Participants press the spacebar as soon as a timer appears on the screen

Trial Structure:

- Interstimulus Interval (ISI): 2-10 seconds
- Stimulus: Timer appears on the screen
- Response: Press the spacebar
- Output Display: 500ms
- Feedback: Reaction time displayed for 500 ms

Trials: 90 per session
Duration: 10 minutes
Applications: Used to assess cognitive fatigue and vigilance decrement, commonly in sleep and fatigue studies.

Flanker Task :

Stimuli:

- 5 arrows displayed in a row
- Central Arrow: The target for response
- Flanker Arrows: Can be congruent (same direction) or incongruent (opposite direction) with the central arrow

Objective:

- Focus on the central arrow and respond while ignoring the distracting flanker arrows on the sides

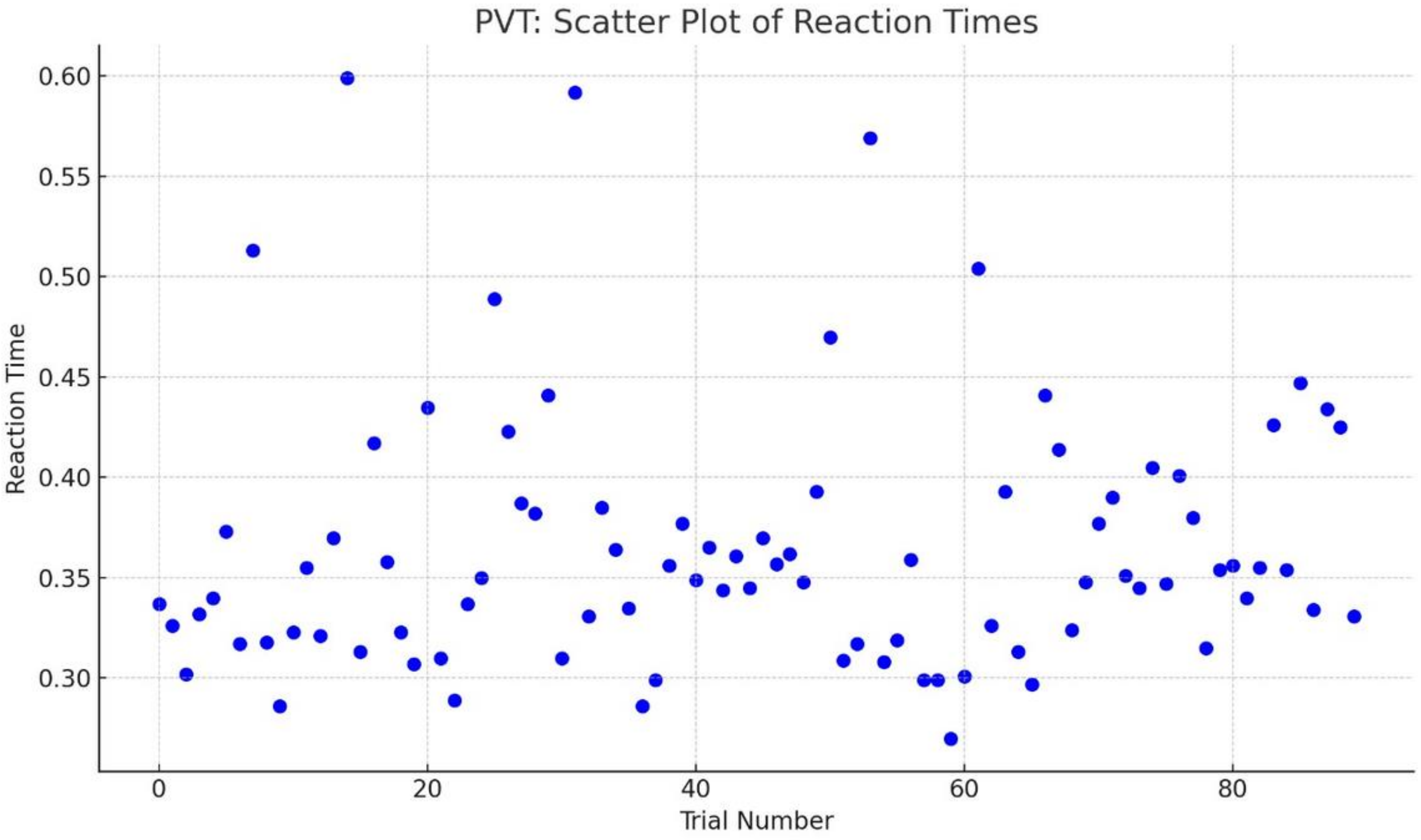
Trial Structure:

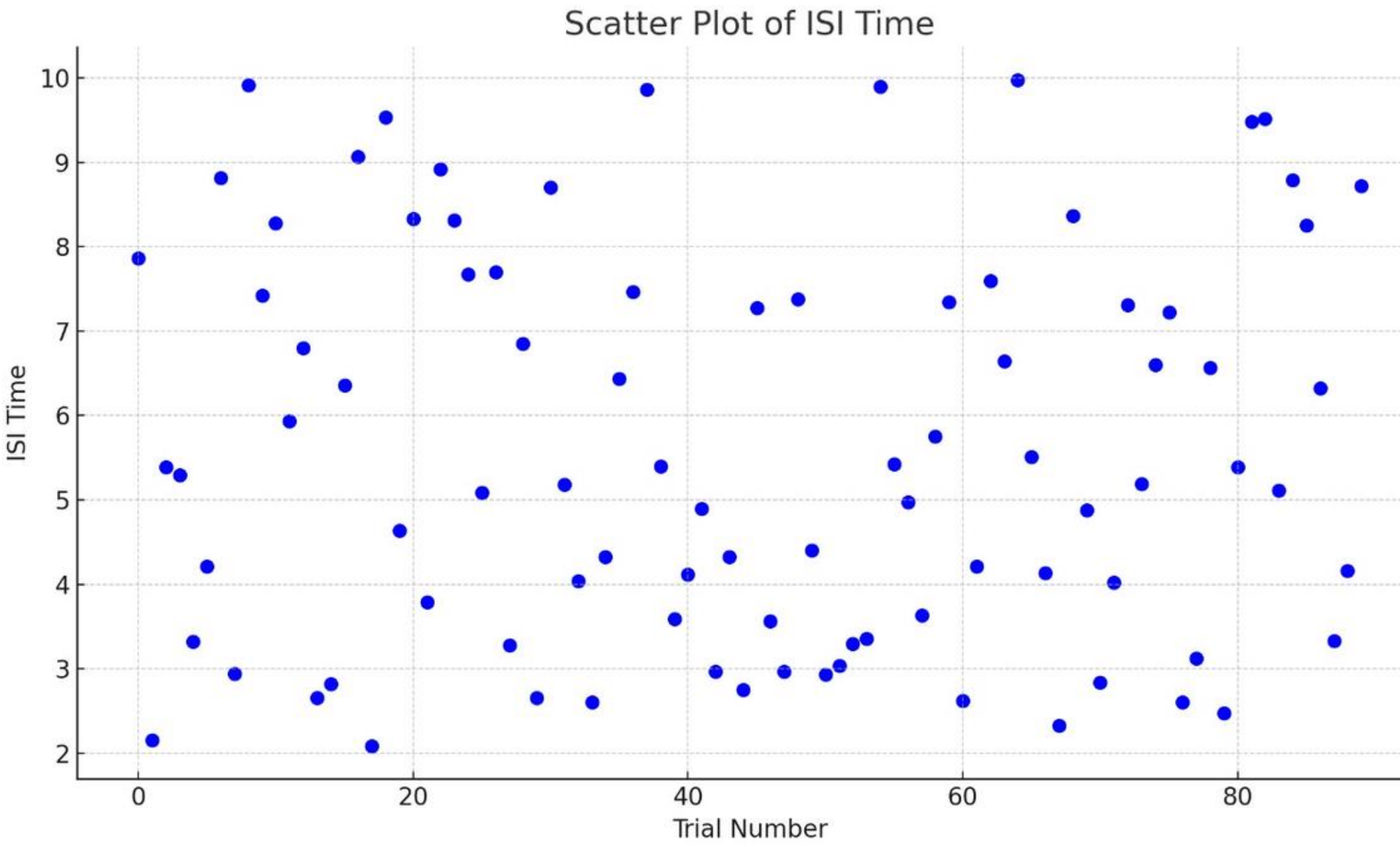
- Trials per Session: 120
- Interstimulus Interval (ISI): 2000 ms
- Stimulus Duration: 16 ms
- Response Window: 2250-2750 ms
- Feedback Display: 500 ms (feedback on performance after each trial)

Purpose: Assesses attention, response inhibition, and conflict resolution by challenging participants to focus on relevant stimuli while ignoring distracting ones

EEG Cognitive Dataset Analysis

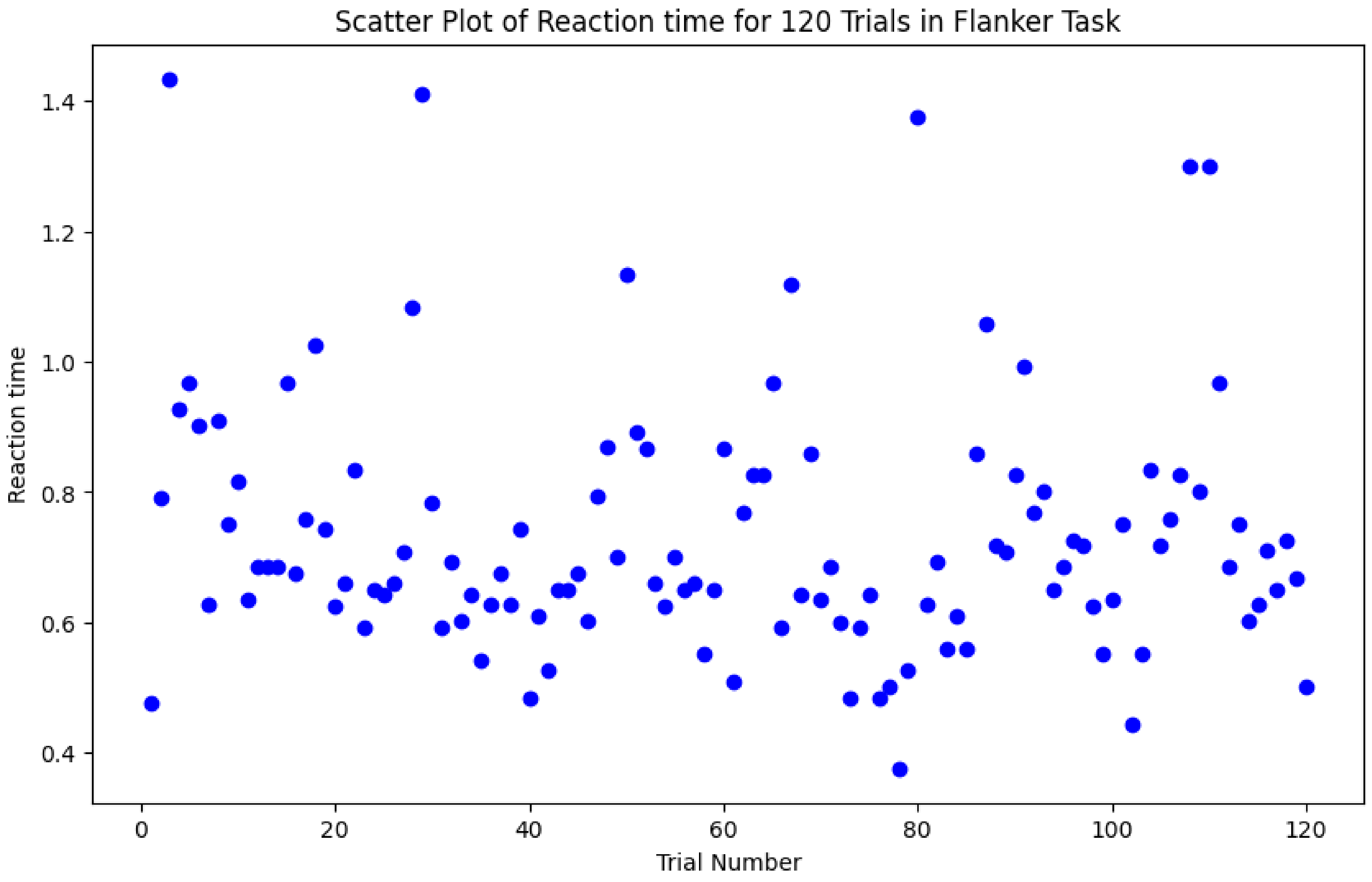
Psychomotor Vigilance Task

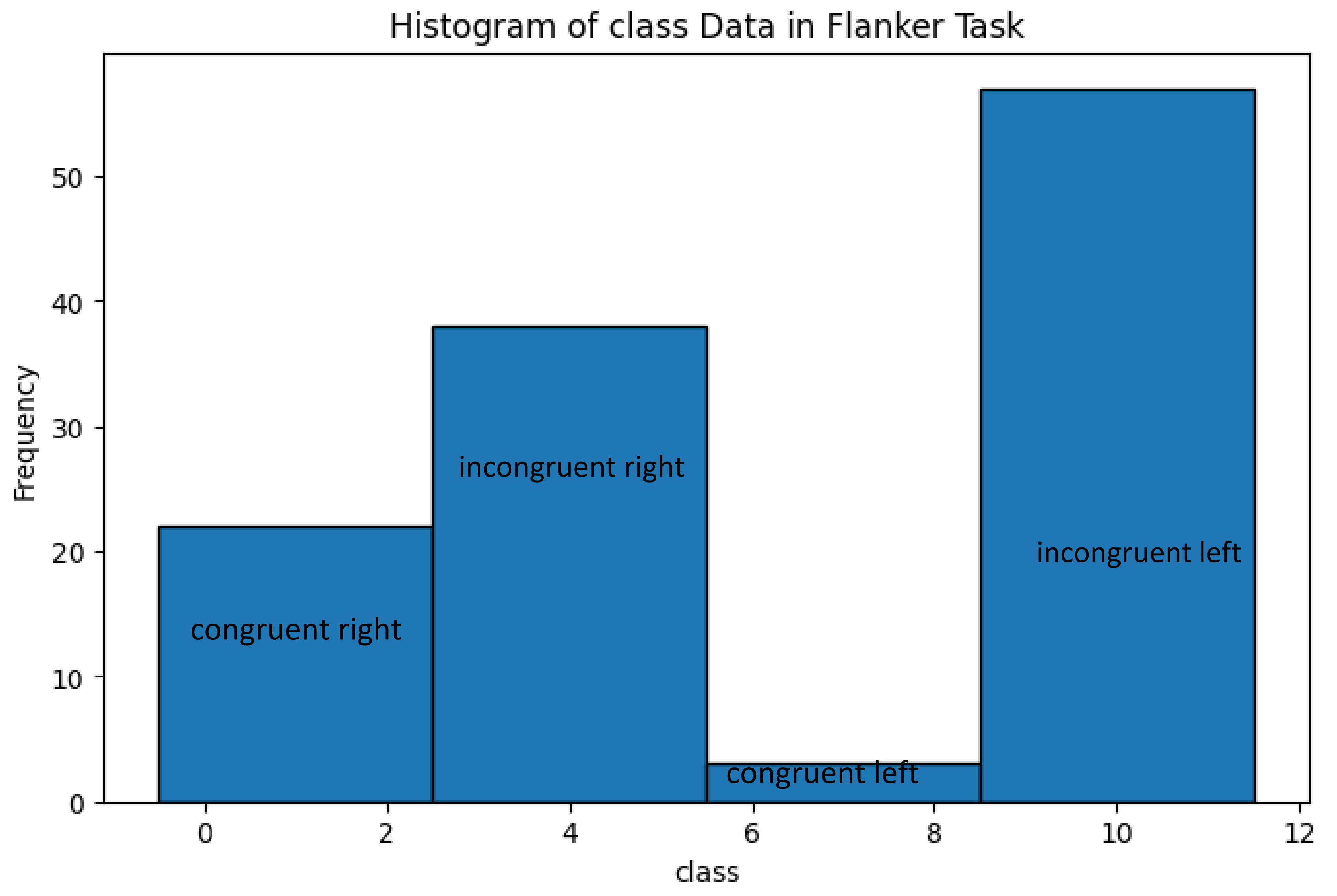




EEG Cognitive Dataset Analysis

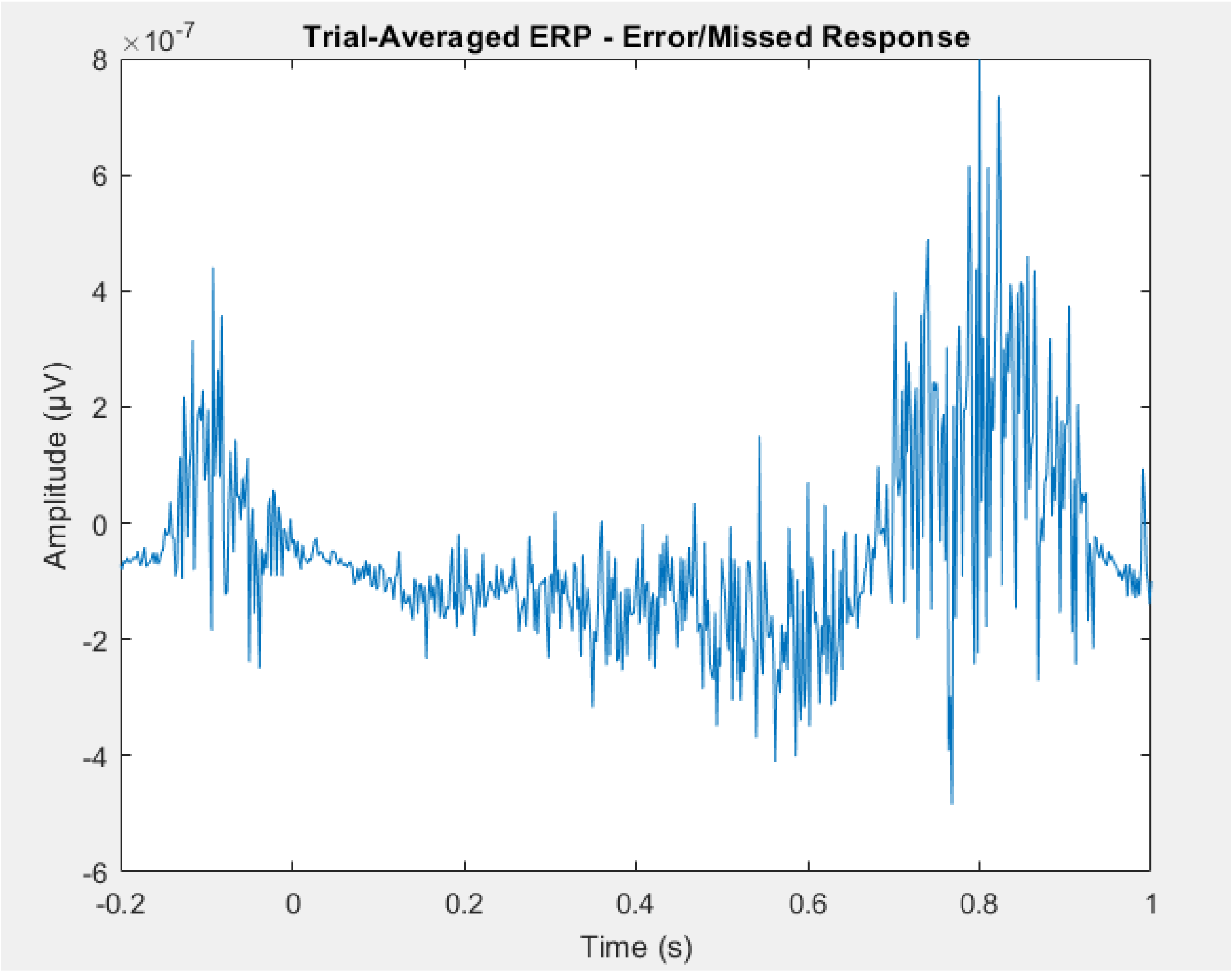
Flanker Task

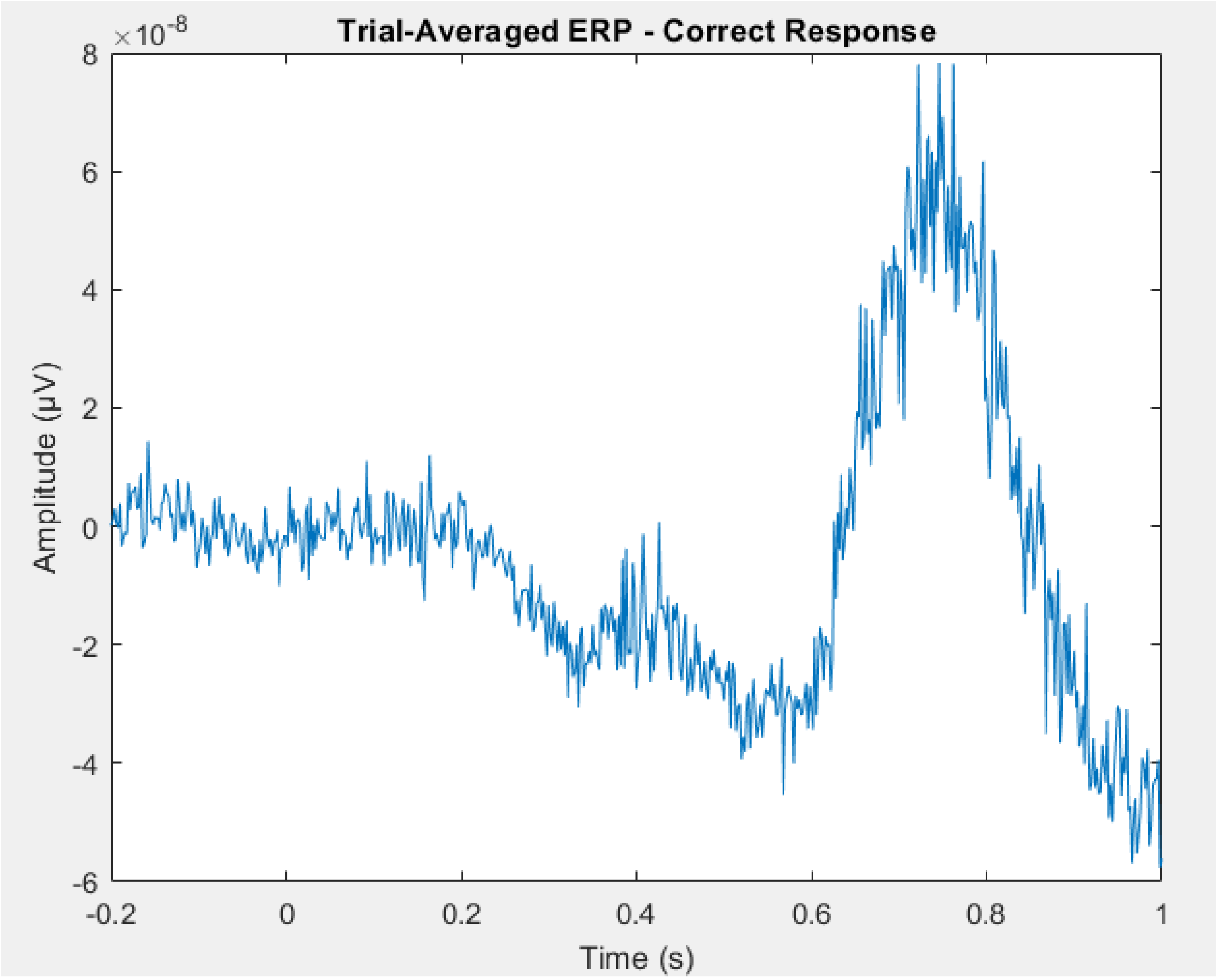




EEG PREPROCESSING

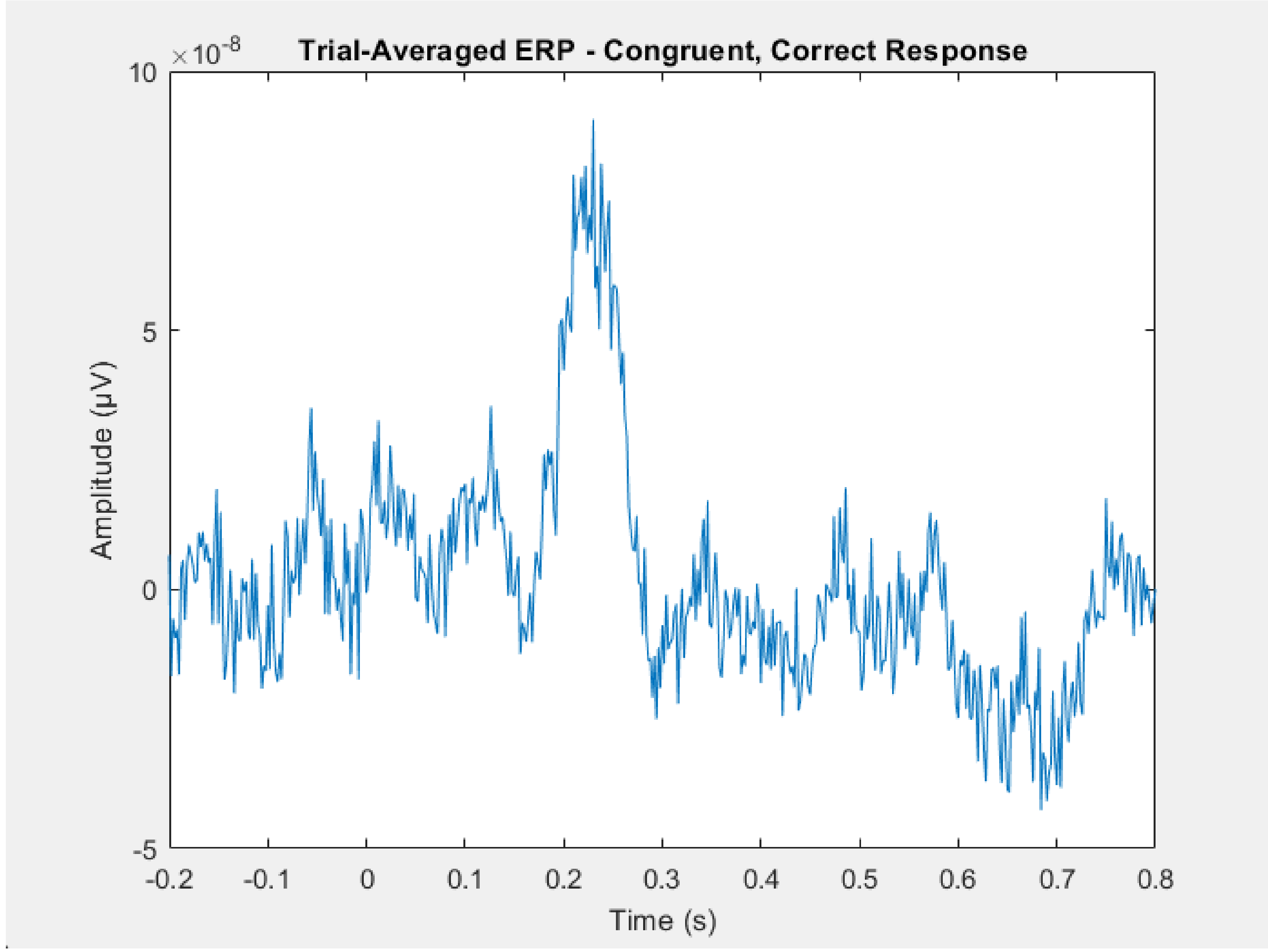
ERP Plots of PVT

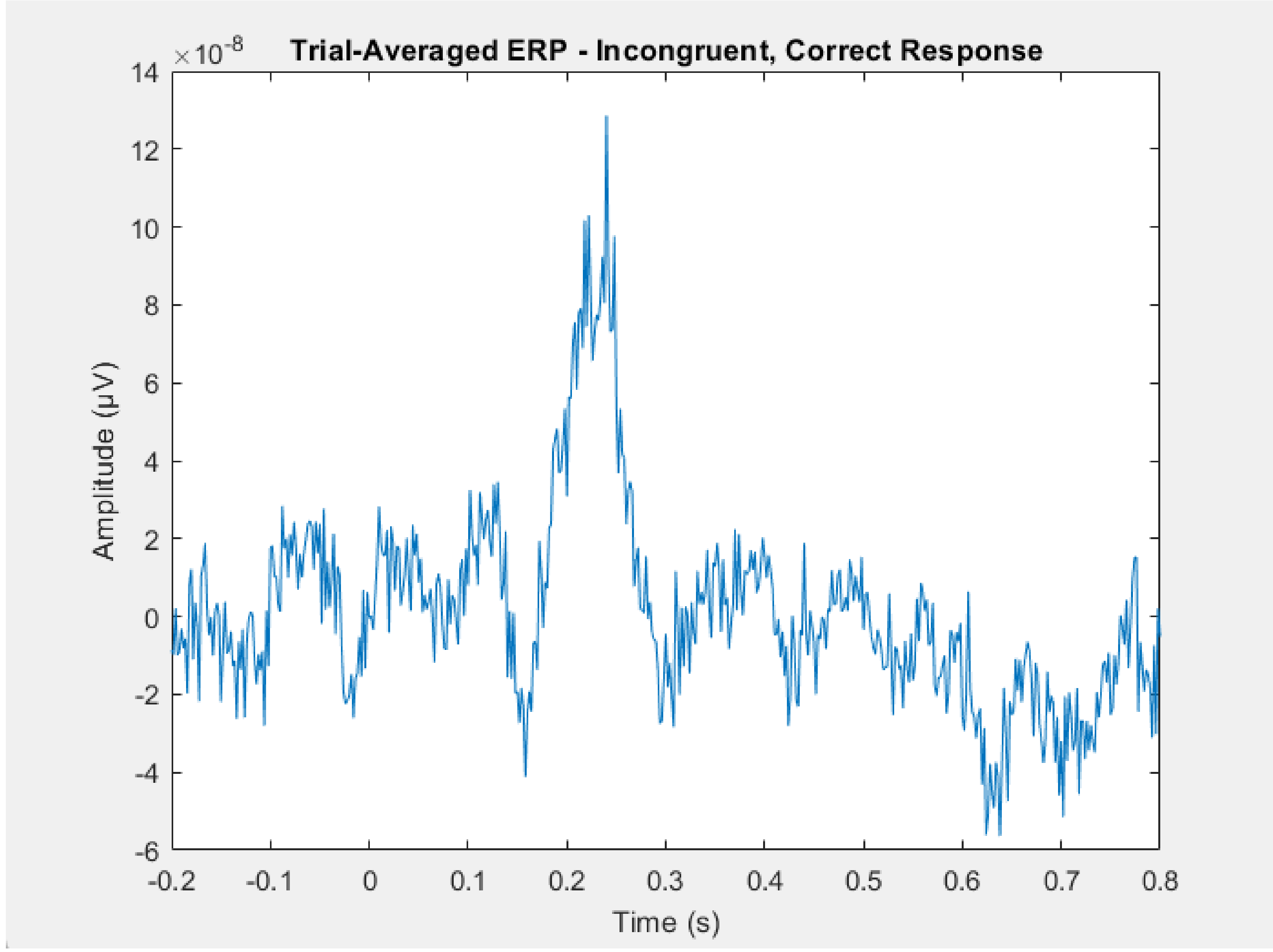




EEG PREPROCESSING

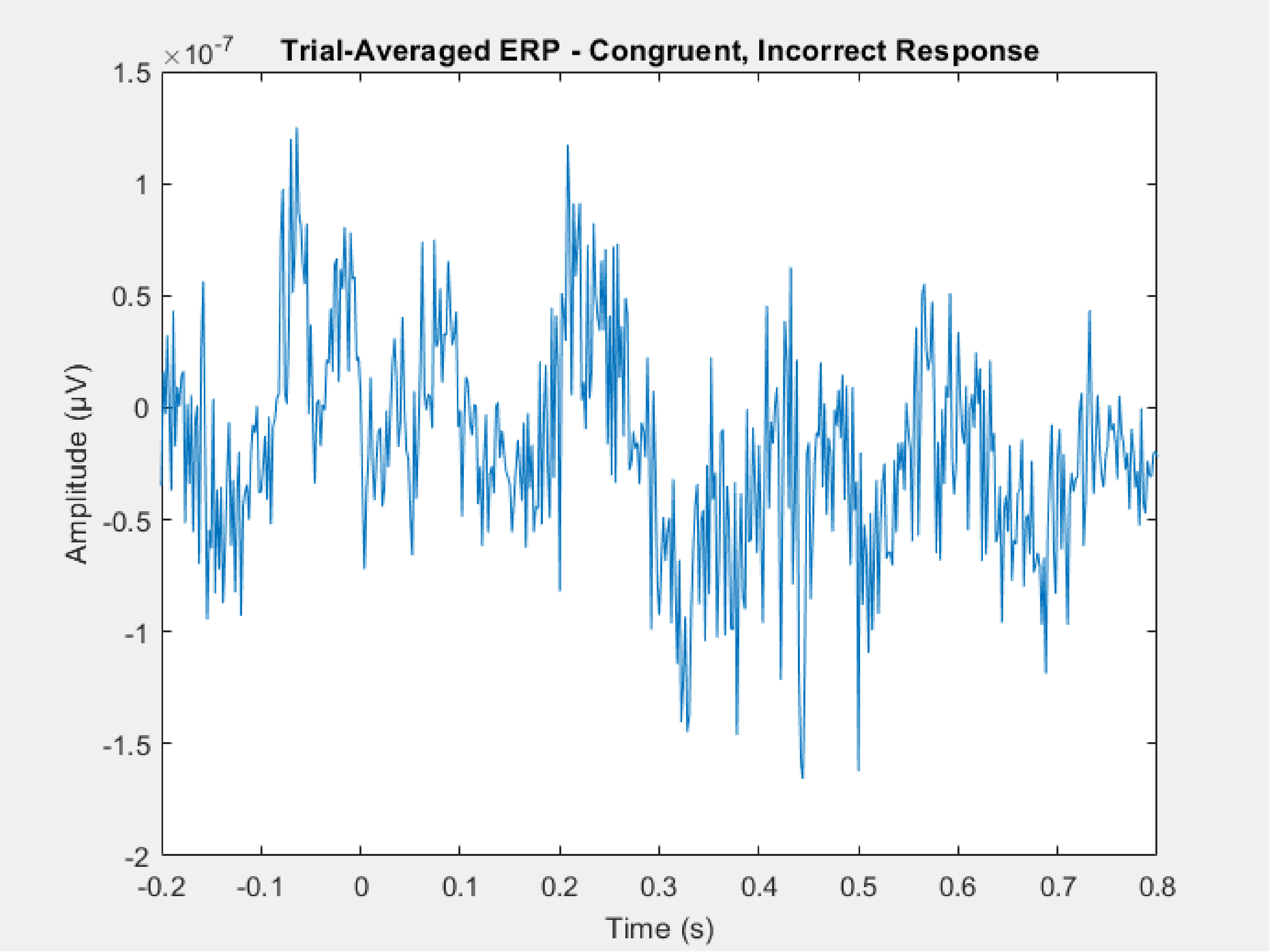
ERP Plots of Flanker Task

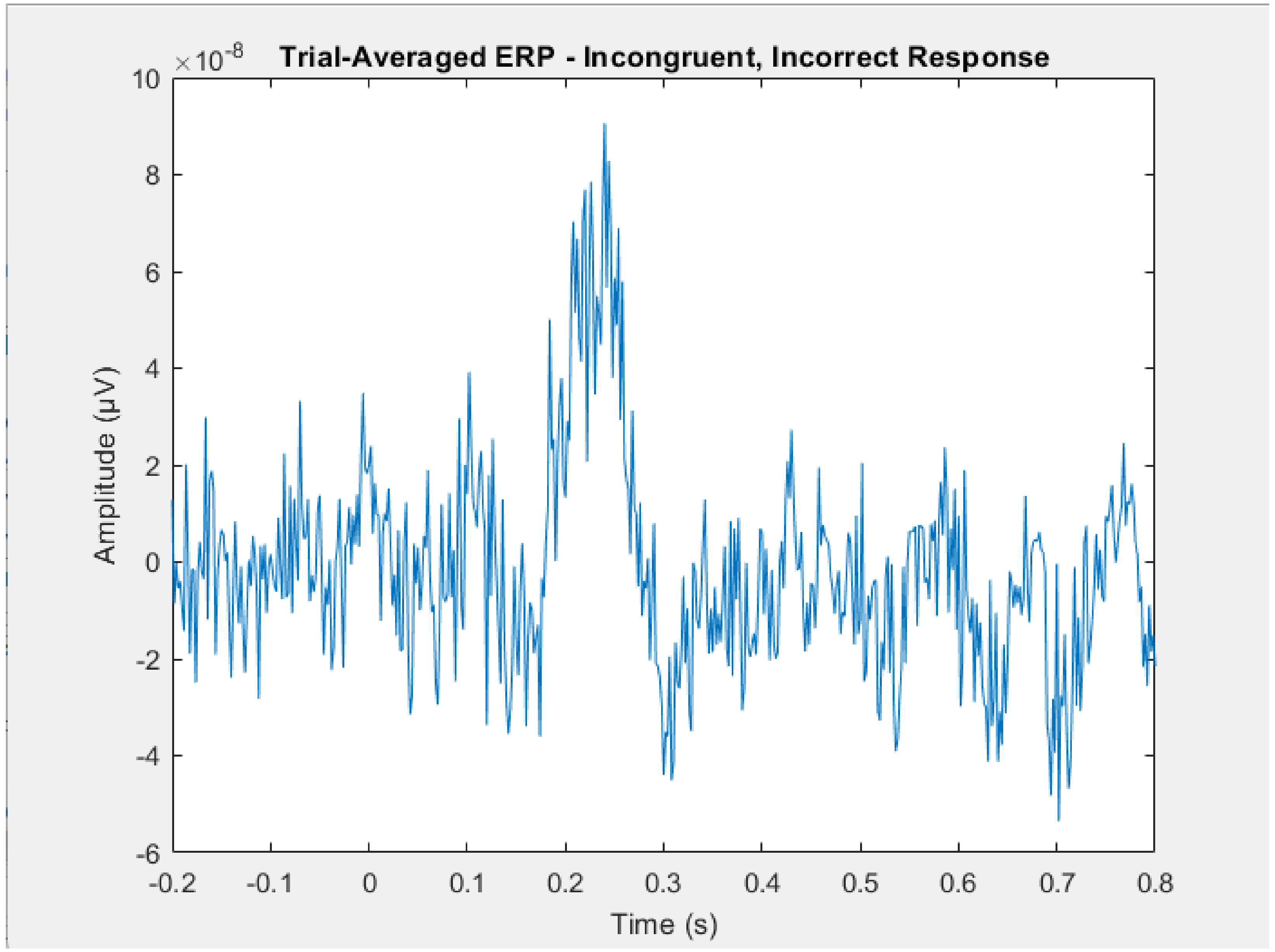




EEG PREPROCESSING

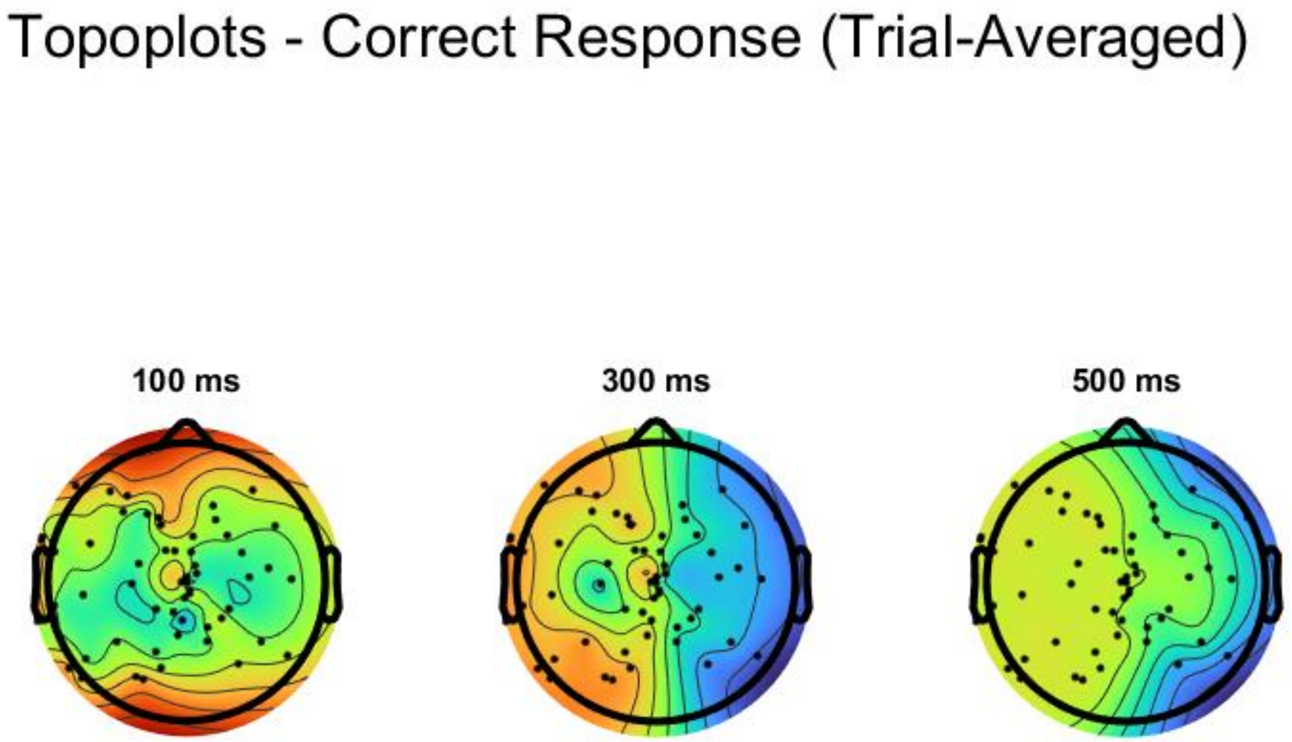
ERP Plots of Flanker Test

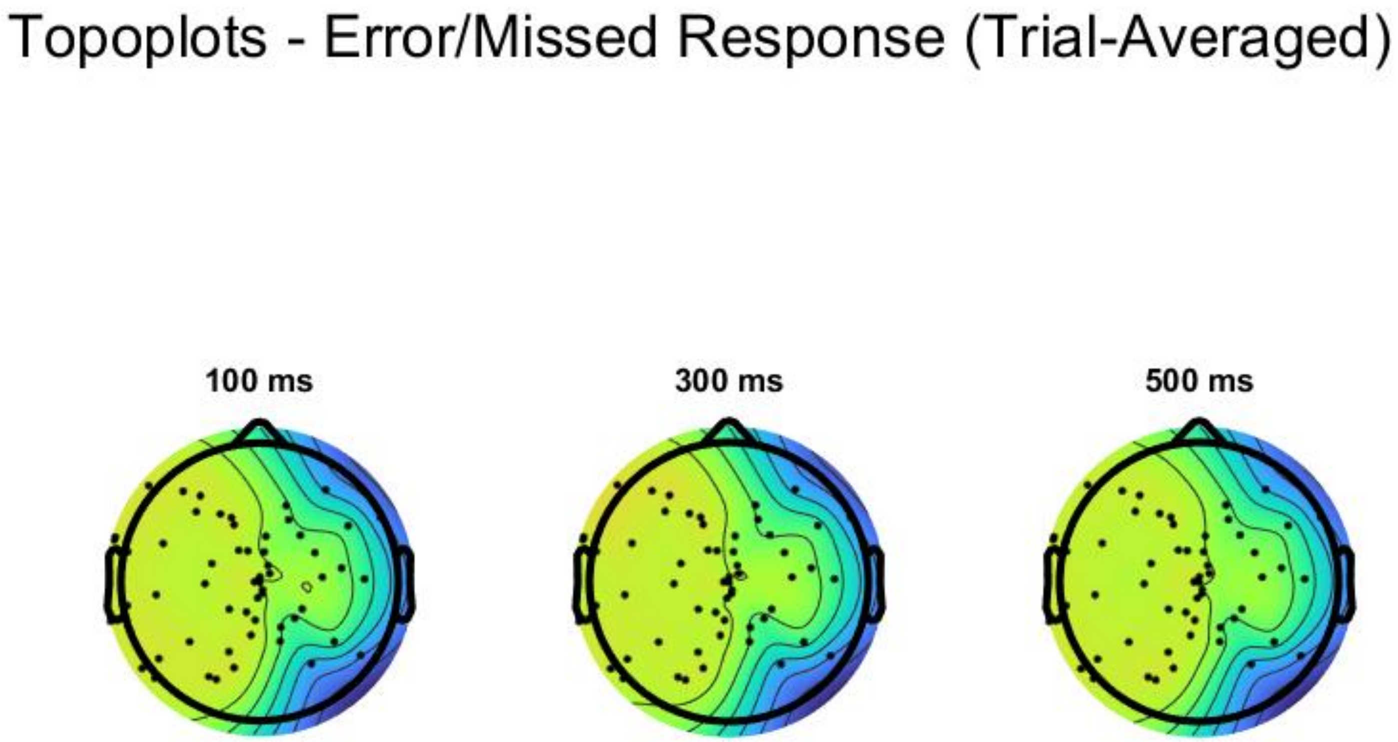




EEG PREPROCESSING

Topoplots of PVT

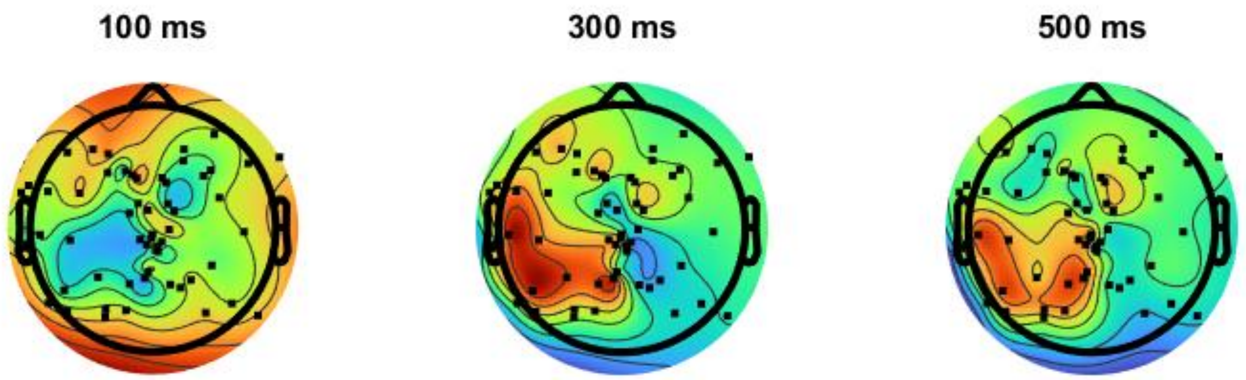




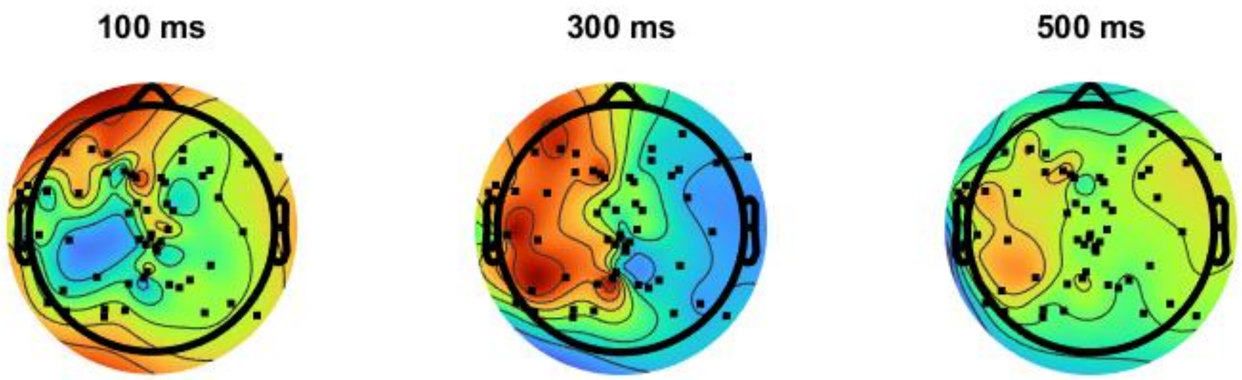
EEG PREPROCESSING

Topoplots of Flanker Test

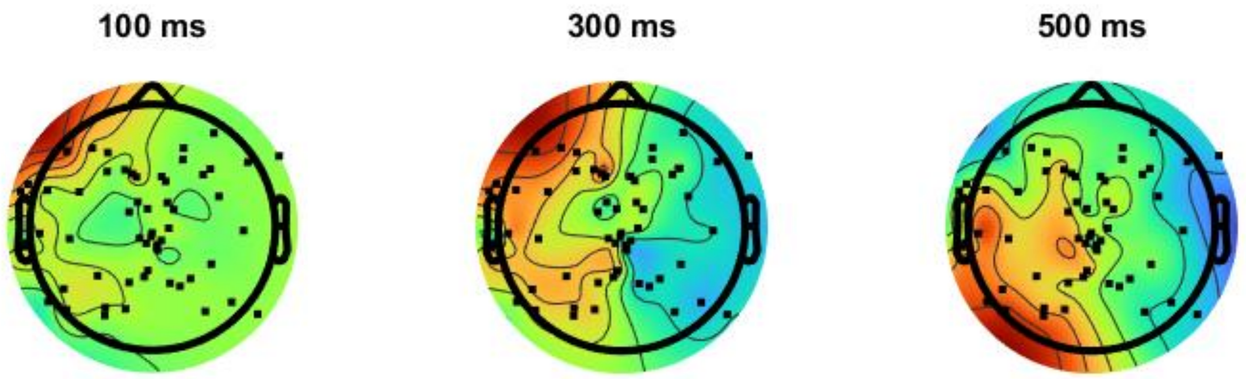
Topoplots - Congruent, Correct Response (Trial-Averaged)



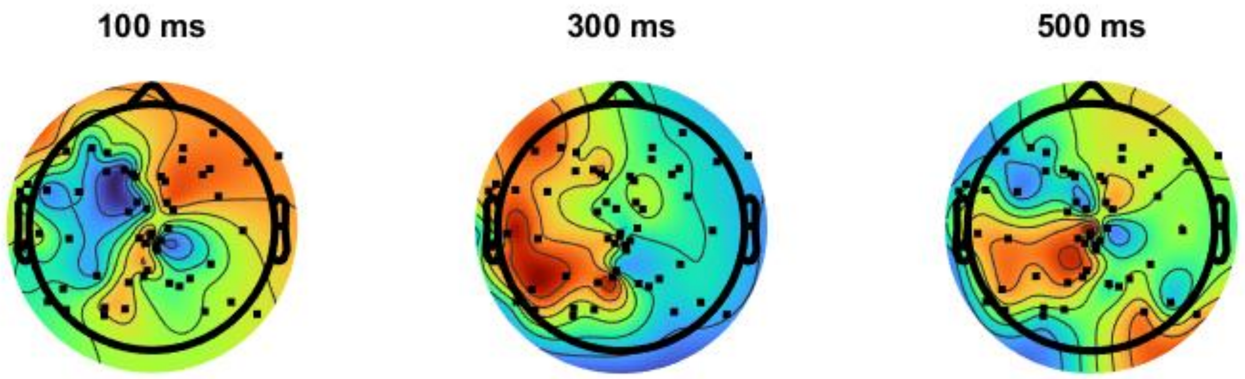
Topoplots - Incongruent, Correct Response (Trial-Averaged)



Topoplots - Congruent, Incorrect Response (Trial-Averaged)



Topoplots - Incongruent, Incorrect Response (Trial-Averaged)



Various Methods for EEG Brain Source Localization

EEG Source Localization: Localizing brain sources from scalp EEG recordings is crucial for understanding neural dynamics, clinical diagnostics, and brain-computer interface (BCI).

Challenges:

Ill-posed inverse problem due to fewer sensors than source locations.

Noise and artifacts contamination.

Correlated source activities and sparse distributions.

Objective:

Develop a robust method to accurately estimate block-sparse EEG sources, even under noise and limited data conditions.

Compare performance across various methods

1) LCMV
2) sLORETA
3) Smooth Champagne
4) BSBL-2S
5) NNBSBL.

Various Methods for EEG Brain Source Localization

NOTATIONS USED

$\mathbf{Y}$: EEG measurement matrix ($M \times T$)

M: Number of electrodes or sensors

T: Number of time samples

$\mathbf{K}$: Lead field matrix ($M \times N$)

N: Number of candidate source locations or voxels

$\mathbf{X}$: Source activity matrix ($N \times T$)

$\mathbf{R}$: Sample covariance matrix of EEG data

$\mathbf{\Sigma}_y$: Covariance matrix of EEG measurements

$\mathbf{\Sigma}_x(\gamma)$: Covariance matrix of sources parameterized by γ

γ: Variance parameter vector for source amplitudes across regions

$\mathbf{C}$: Smoothing kernel matrix for intra-block correlation

α: Regularization parameter

N_s: Number of samples in $\mathbf{Y}$

N_g: Number of brain regions or groups

λ: Noise variance scalar

s^2: Variance of the spatial distribution of sources

$\mathbf{H}_i$: Submatrix of $\mathbf{K}$ corresponding to the i-th brain region

$\mathbf{C}_i$: Smoothing kernel matrix for the i-th brain region

$\mathbf{\Sigma}_x^i$: Covariance matrix of the i-th brain region

T: Transformation matrix in sLORETA

$\mathbf{P}_{\text{cov}}$: Inverse of the covariance matrix of EEG measurements

$\mathbf{A}_{\text{temp}}$: Temporary vector corresponding to a single voxel in $\mathbf{K}$

Γ_{nois}: Noise covariance matrix

$\mathbf{\Lambda}$: Diagonal noise covariance matrix

$\mathbf{\Gamma}$: Source covariance matrix diagonalized over all brain regions

$\text{trace}(\cdot)$: Trace of a matrix

$\|\cdot\|_F$: Frobenius norm of a matrix

$\|\cdot\|_2$: ℓ_2-norm (Euclidean norm) of a vector

$\mathbb{E}[\cdot]$: Expectation operator

$\mathcal{N}^+(\cdot)$: Nonnegative Gaussian distribution

X_{sL}: Standardized source activity (sLORETA)

$\hat{\mathbf{r}}_k$: Estimated center of the k-th localized region

$\mathbf{r}_k$: Ground truth center of the k-th region

R_x: Regional covariance matrix of sources

n: Index for voxels or candidate source locations

i: Index for brain regions

t: Index for time steps

Various Methods for EEG Brain Source Localization

1. sLORETA (Standardized Low-Resolution Electromagnetic Tomography):

sLORETA is a widely used algorithm that assumes the source distribution is smooth and continuous. It regularizes the solution to prevent overfitting by enforcing an $\ell 2$-norm constraint.

It computes the smoothest possible solution for EEG source localization by minimizing the power of source activities while fitting the EEG measurements.

Provides smooth source localization using $\ell 2$-norm regularization

Transformation Matrix:

$$T = K^T(KK^T + \alpha I)^{-1}$$

Source Activity Estimation:

$$J = TY$$

Standardized Source Activity:

$$X_{sL}(n, :) = \frac{J(n, :)}{\sqrt{S_j(n, n)}}$$

where $S_j = TK$.

Regional Variance:

$$\gamma(i) = \frac{\|R_x\|_F}{\|C\|_F}$$

2. LCMV (Linearly Constrained Minimum Variance) Beamforming:

LCMV uses spatial filters to isolate the activity of a specific source location while minimizing contributions from other sources or noise.

It computes source activities by forming a filter that allows only the desired source's contribution while suppressing all other signals.

Covariance Matrix Inversion:

$$\mathbf{P}_{\text{cov}} = (YY^T/N + \alpha I)^{-1}$$

Source Activity Estimation:

$$X_{sL}(n, :) = \frac{A_{\text{temp}}^T \mathbf{P}_{\text{cov}} Y}{A_{\text{temp}}^T \mathbf{P}_{\text{cov}} A_{\text{temp}}}$$

X_{sL}: Standardized source activity

$\mathbf{P}_{\text{cov}}$: Inverse of the covariance matrix of EEG measurements

Various Methods for EEG Brain Source Localization

3. Smooth Champagne Algorithm

Champagne integrates sparsity and smoothness priors in a Bayesian framework, making it well-suited for correlated source activities and noisy data.

It iteratively estimates the variance of source activities and noise while promoting a smooth source distribution across brain regions.

Uses a hierarchical Bayesian model with smooth and sparse priors for source estimation.

Noise Variance Update:

$$\Gamma_{\text{nois}}(k) = \frac{1}{N}\sum_{n=1}^{N}\left[(Y(k,n) - Hg(k,:)X(:,n))^2 + Hg(k,:)\Sigma_x Hg(k,:)^T\right]$$

Source Variance Update:

$$\gamma(i) = \frac{\gamma_{\text{old}}(i)}{\sqrt{N}} \frac{\|H(i)^T \Sigma_y^{-1} Y\|_F}{\sqrt{\text{trace}(H(i)^T \Sigma_y^{-1} H(i))}}$$

4. BSBL-2S (Block Sparse Bayesian Learning - Two-Stage)

BSBL-2S leverages the block-sparsity property of brain sources, which assumes that only certain regions of the brain are active.

It prunes inactive brain regions while iteratively updating source and noise variances.

Leverages block sparsity in source localization with iterative pruning.

Signal Variance Update:

$$\phi = \gamma_F s^2 + \lambda 1$$

Pruning Stage Variance Update:

$$\gamma(i) = \frac{\gamma(i)}{\sqrt{N}} \frac{\|H(i)^T \Sigma_y^{-1} Y\|_F}{\sqrt{\text{trace}(H(i)^T \Sigma_y^{-1} H(i))}}$$

Various Methods for EEG Brain Source Localization

5. NNBSBL (Nonnegative Block-Sparse Bayesian Learning)

NNBSBL incorporates nonnegative Gaussian priors into the block-sparsity framework, enforcing a physically realistic constraint on the source activities.

It circumvents noise covariance estimation by using the sample covariance matrix and updates nonnegative variance parameters iteratively for accurate source localization.

Improves localization using block-sparse priors and nonnegative Gaussian distributions.

Variance Parameter Prior:

$$p(\gamma;\alpha) = \mathcal{N}^{+}(\gamma|0, \operatorname{diag}(\alpha))$$

Posterior Variance Update:

$$\gamma(n) = \mathbb{E}[\gamma|Z;\alpha]$$

Expectation-Maximization:

$$Q(\alpha) = \mathbb{E}[\log p(Z, \gamma; \alpha)]$$

Performance Metrics

Area Under FROC Curve (AUC):

- Measures success in source detection.
- **Formula**:

$$A' = \frac{\text{Hit Rate} - \text{False Rate}}{2} + 0.5$$

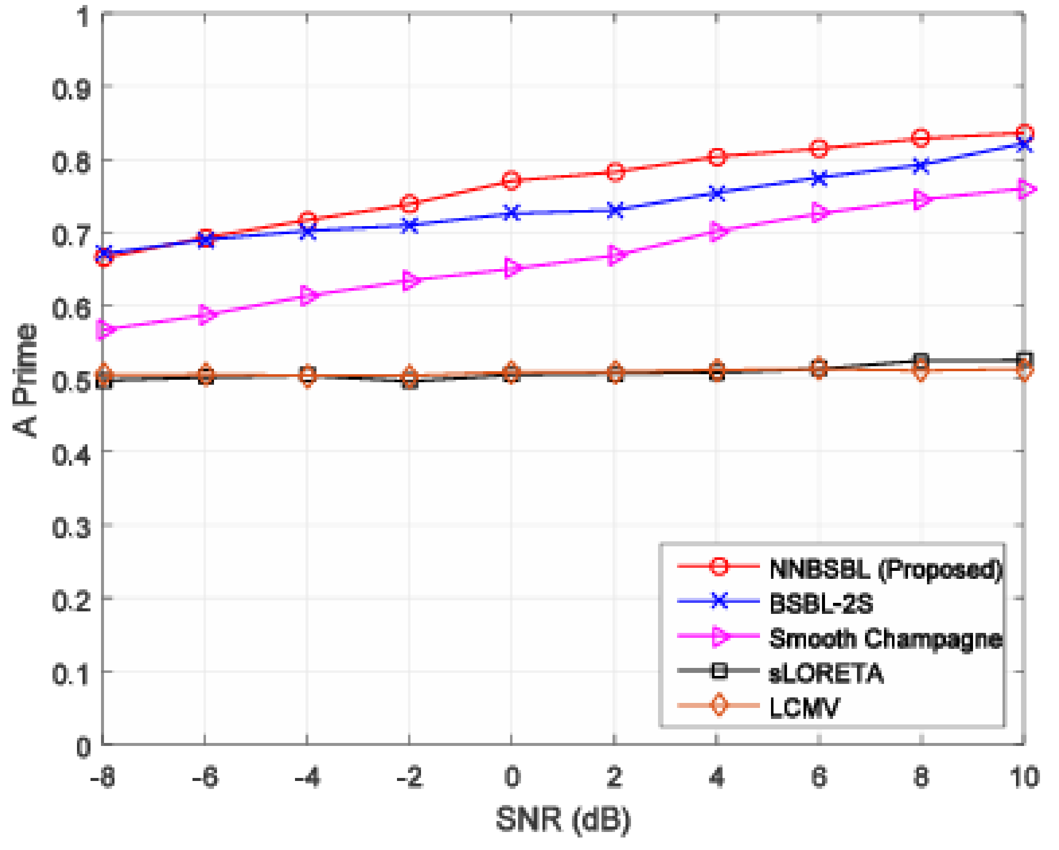
Root Mean Square Error (RMSE):

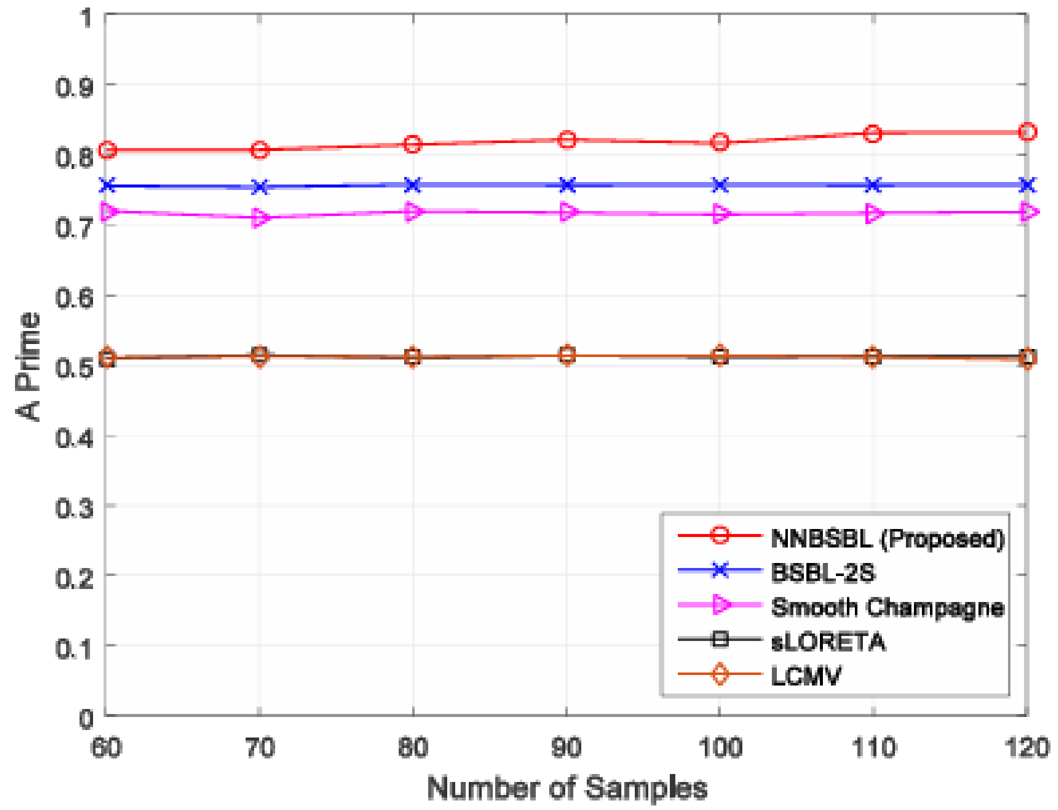
- Measures localization accuracy.
- **Formula**:

$$\text{RMSE} = \sqrt{\frac{1}{K N_{\text{MC}}} \sum_{n=1}^{N_{\text{MC}}} \sum_{k=1}^{K} \|\hat{\mathbf{r}}_{k,n} - \mathbf{r}_k\|_2^2}$$

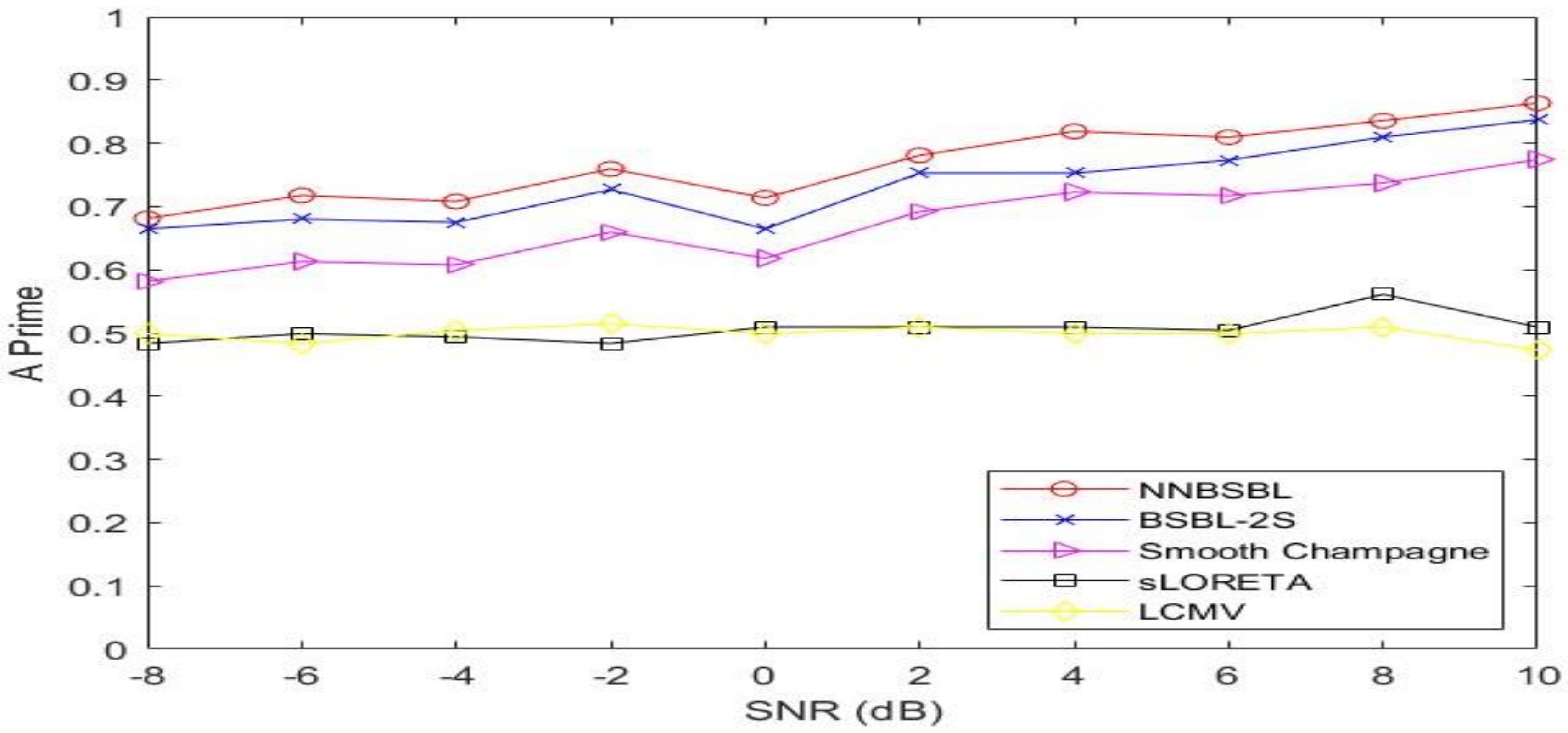
Results

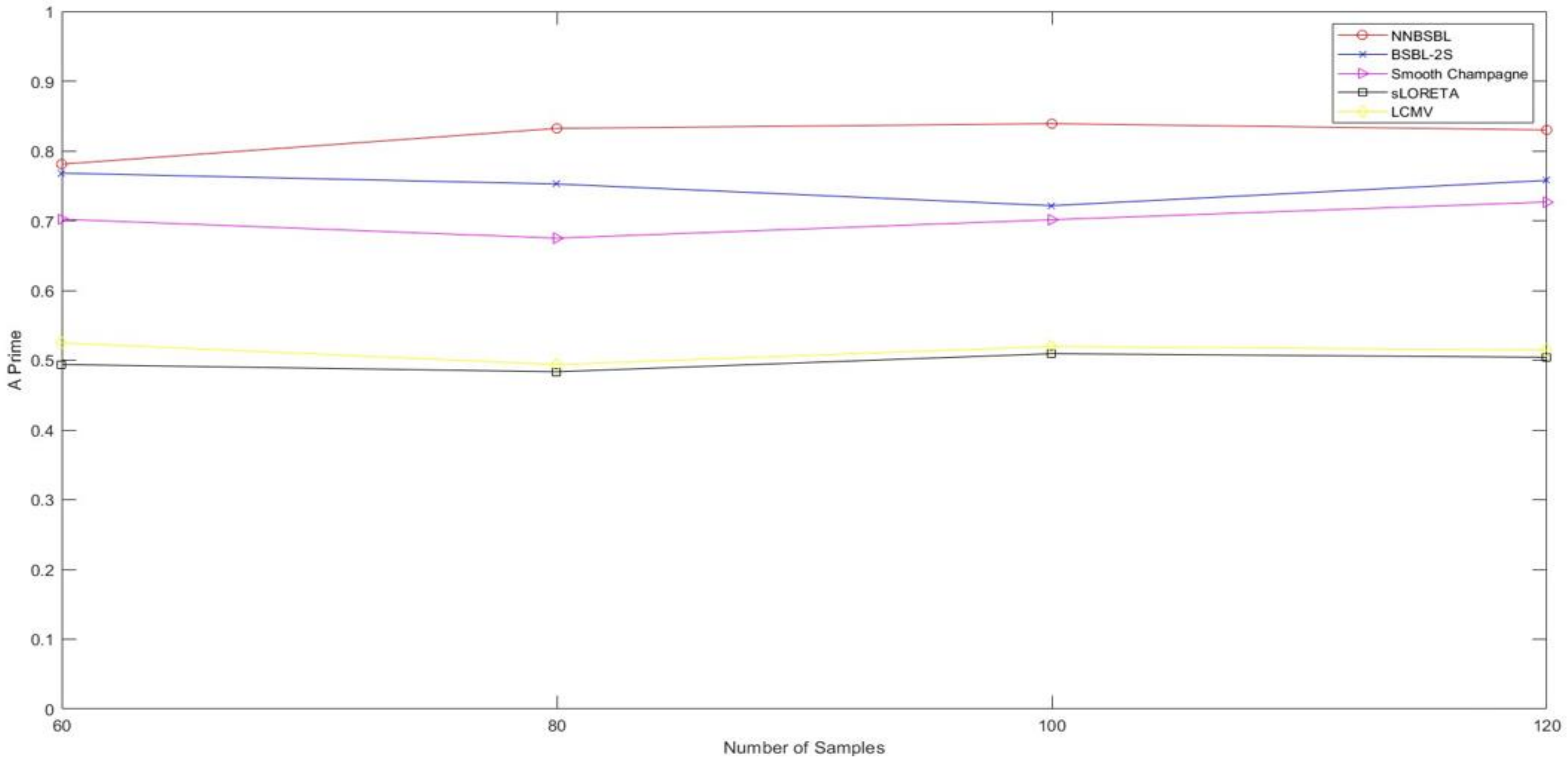
Proposed Results :





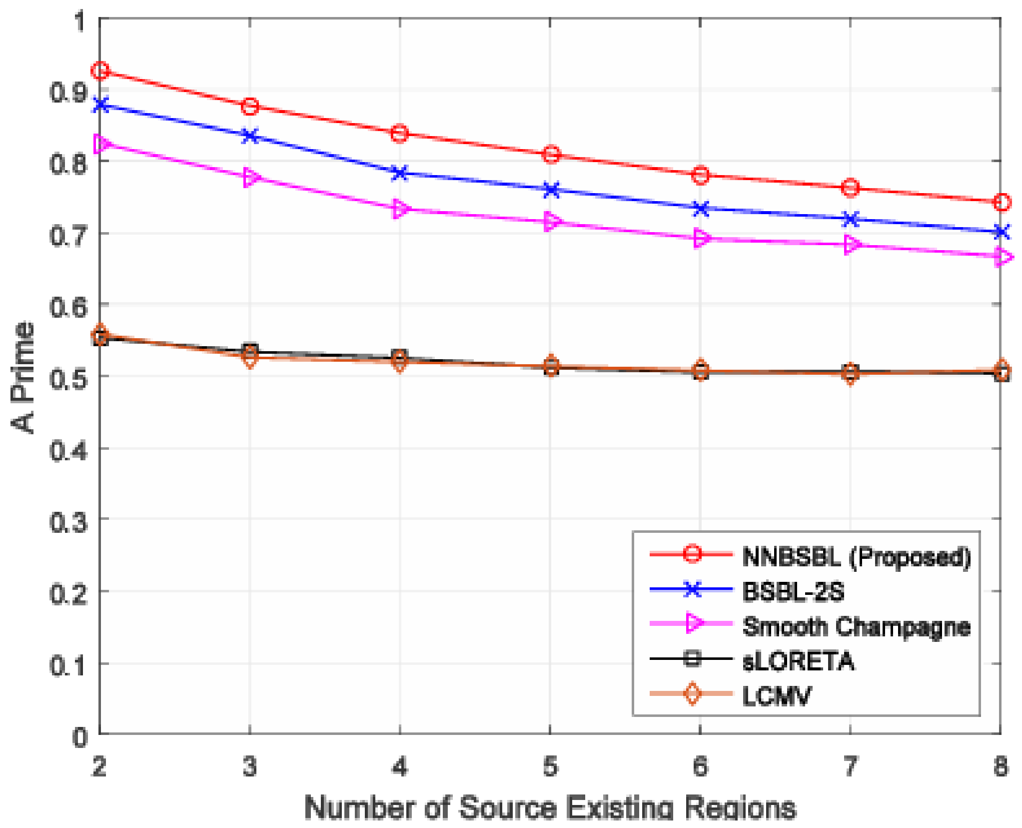
Results :

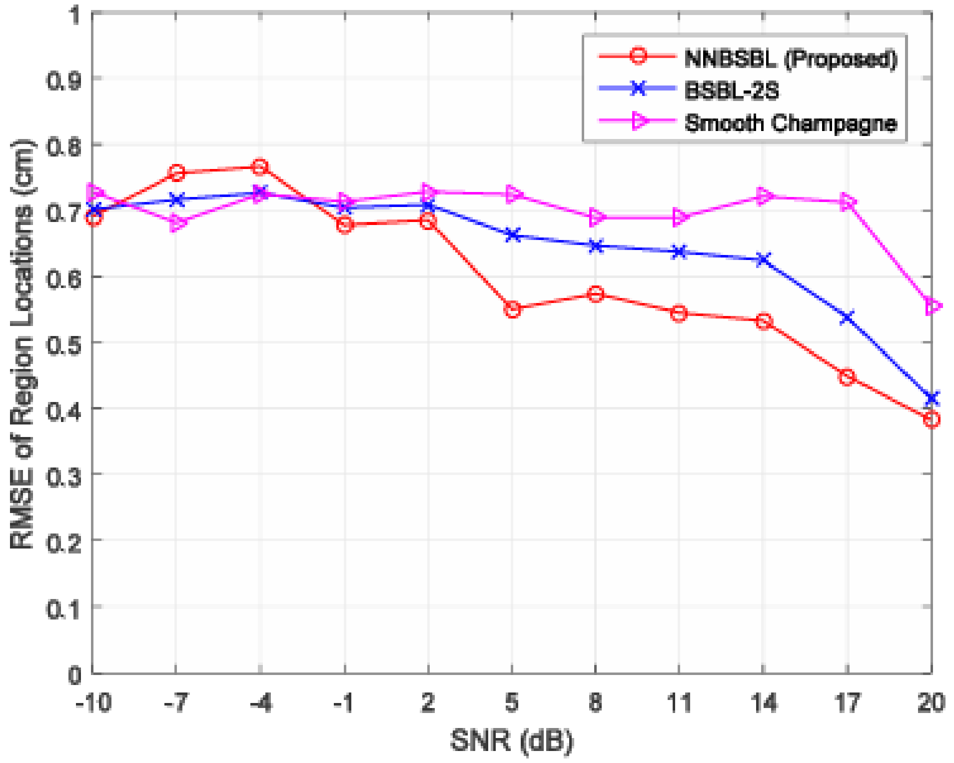




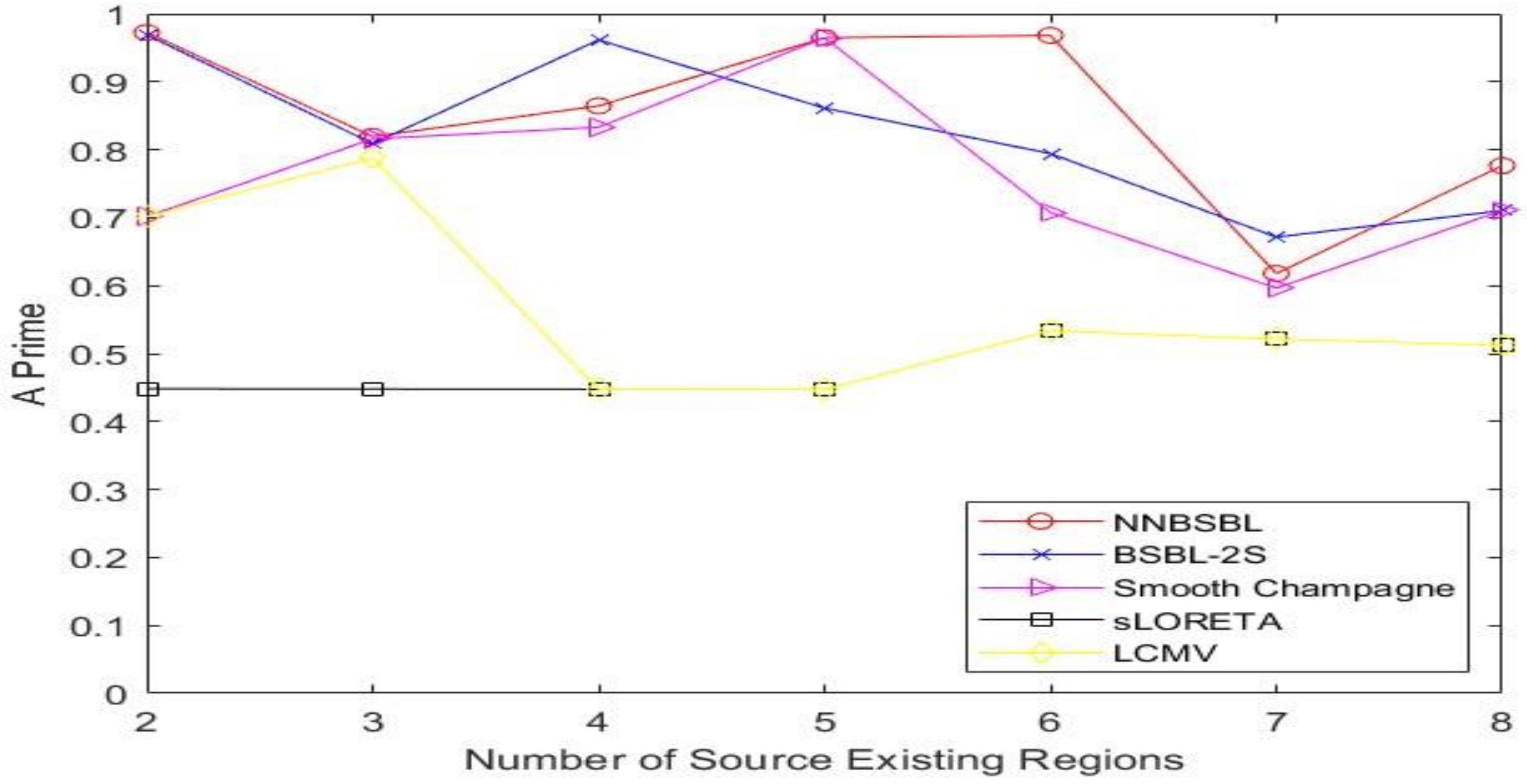
Results

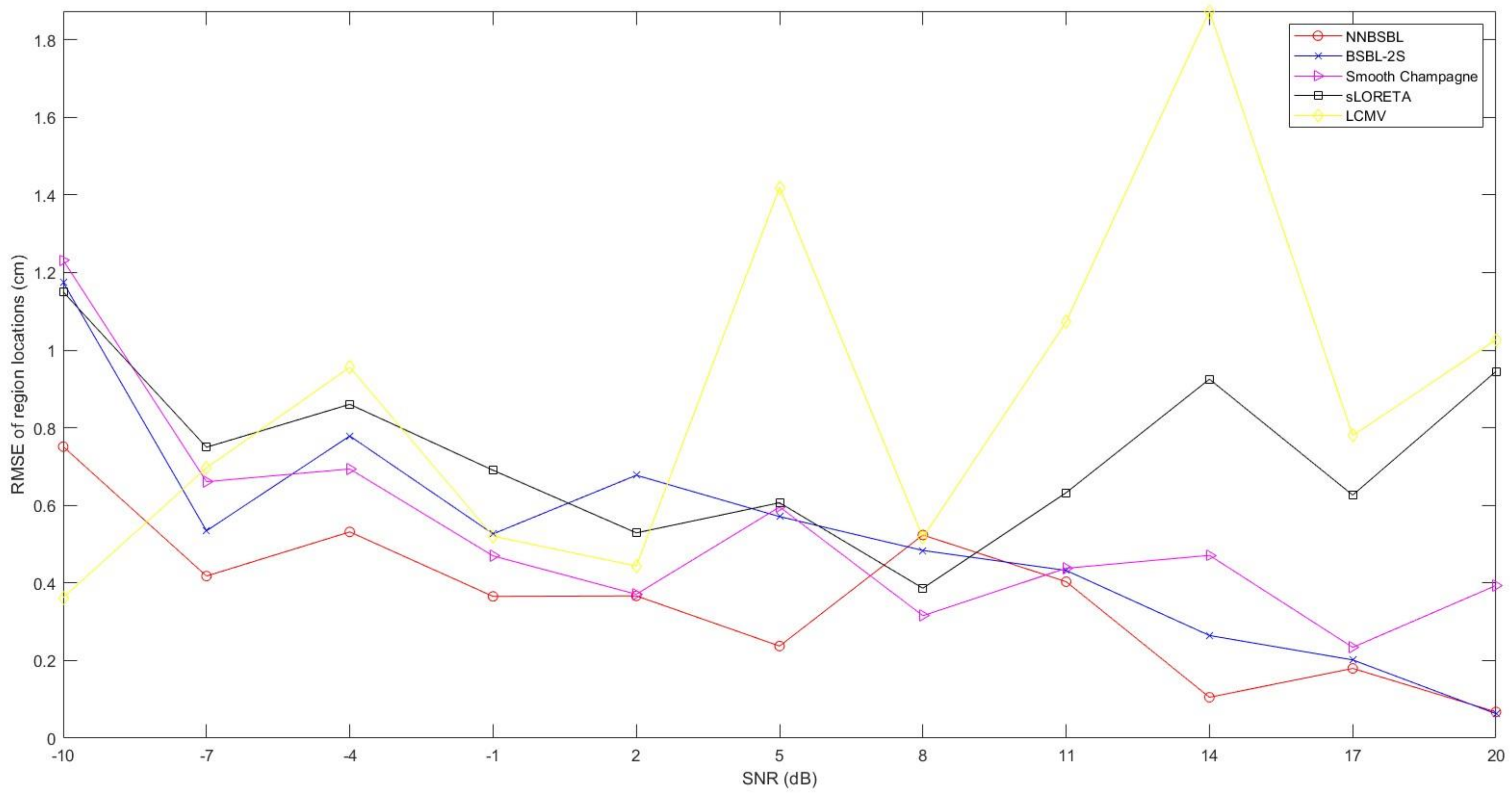
Proposed :





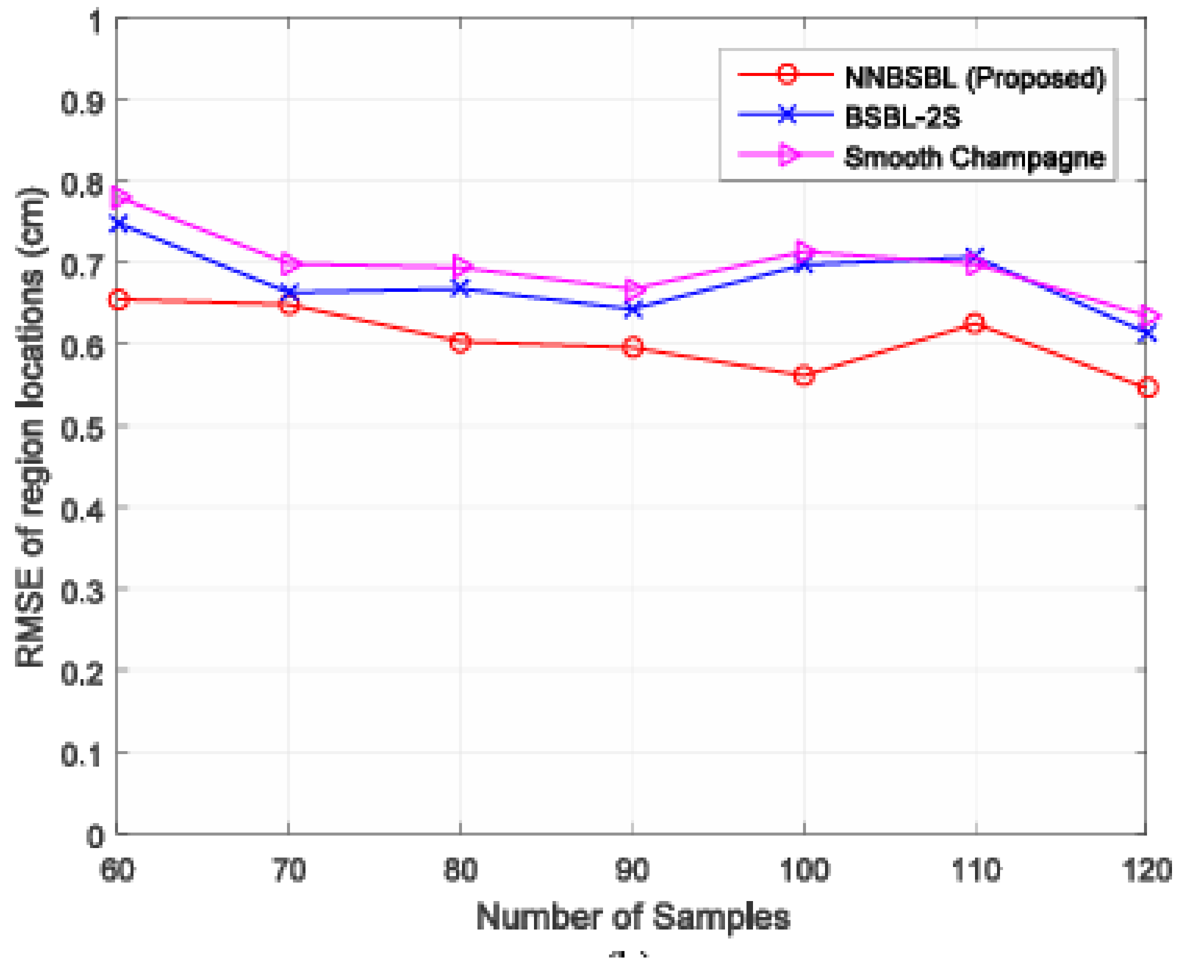
Actual :



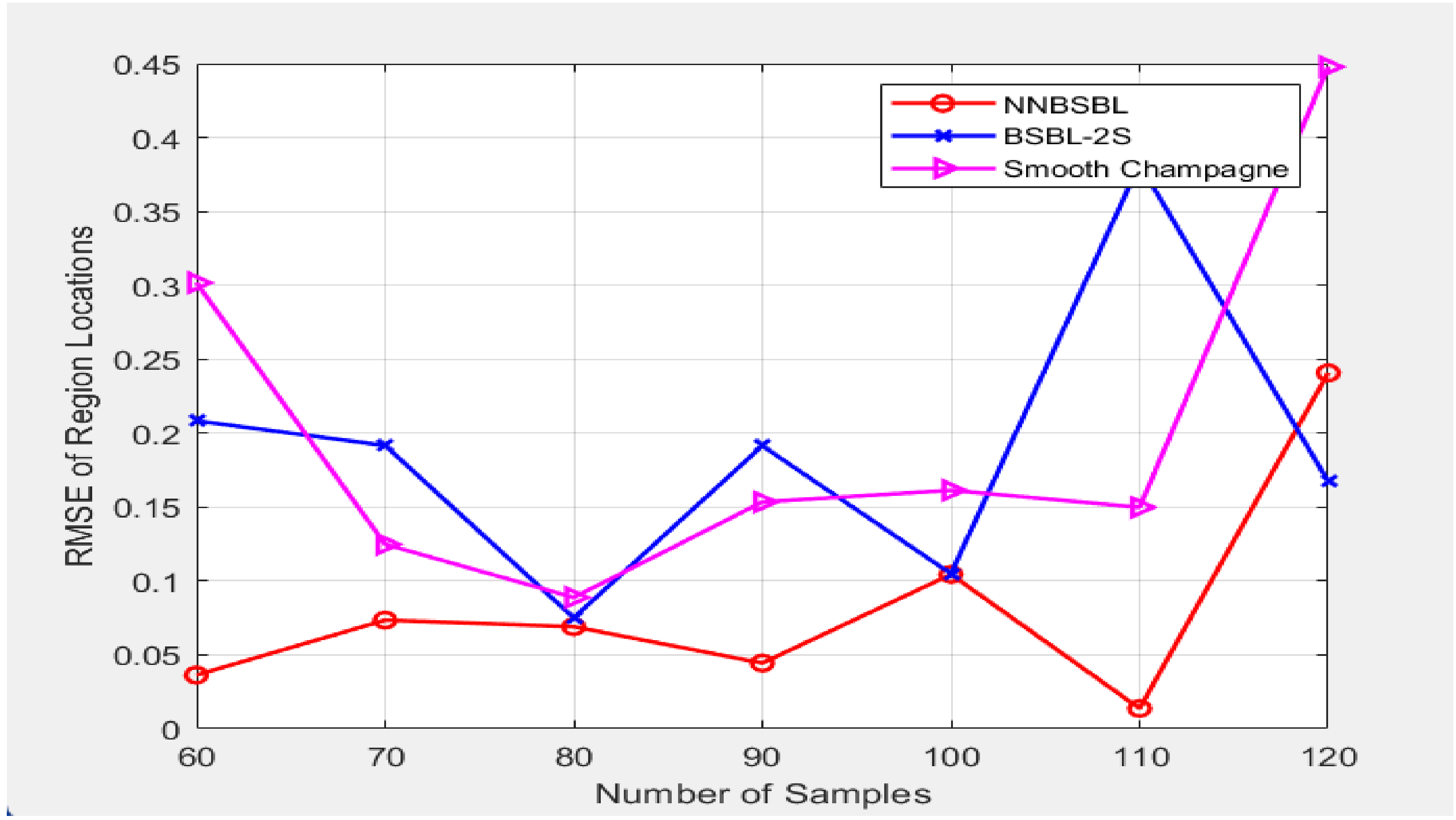


Results

Proposed :



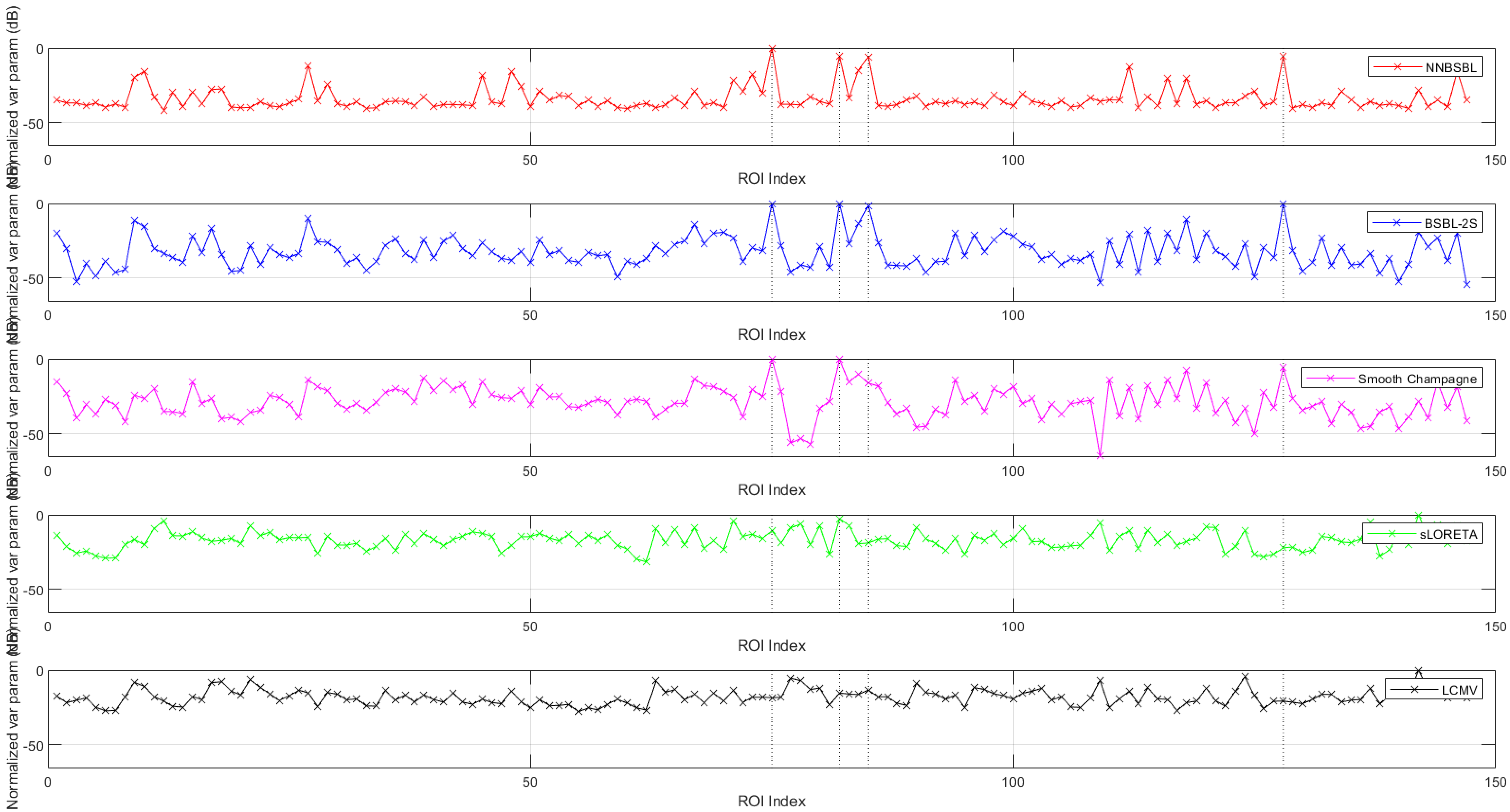
Actual :



NNBSBL is the best-performing algorithm due to:

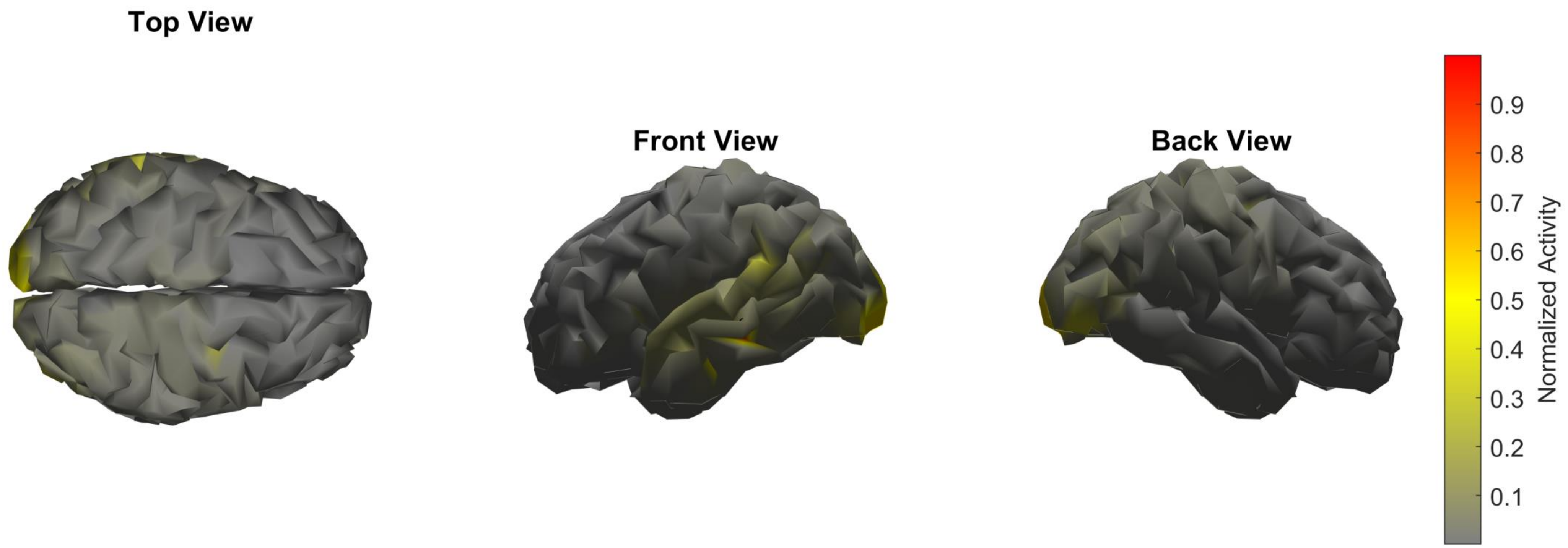
- High Ap
- Low RMSE
- Nonnegative Gaussian priors.
- Avoiding noise covariance estimation.
- High accuracy and robustness under noise.

Results

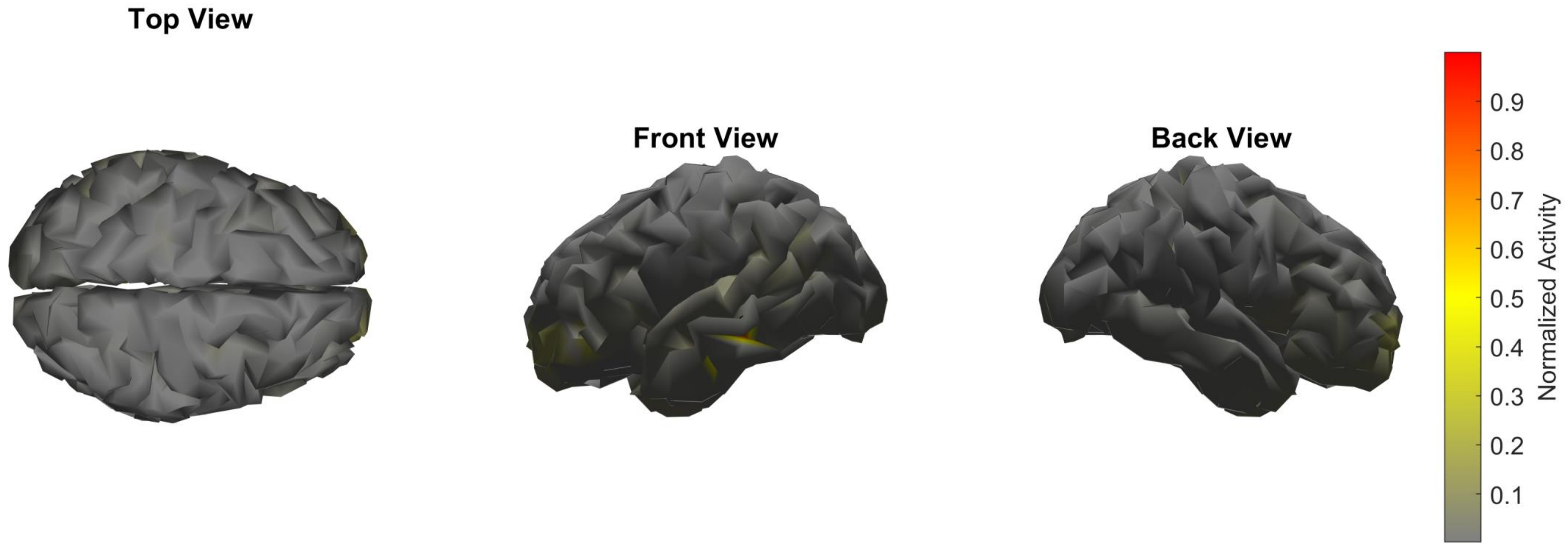

NNBSBL
BSBL-2S
Smooth Champagne
sLORETA
LCMV
Normalized var param (dB)
ROI Index
0
-50
0
50
100
150

Results

sLORETA

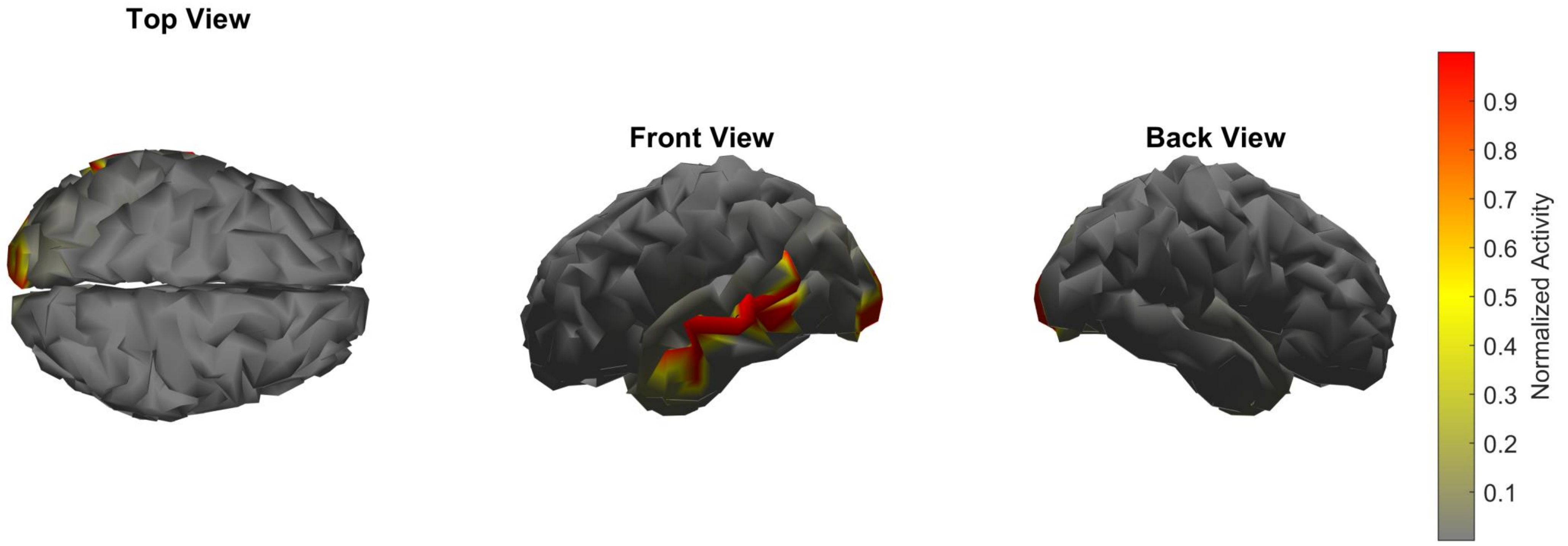


LCMV

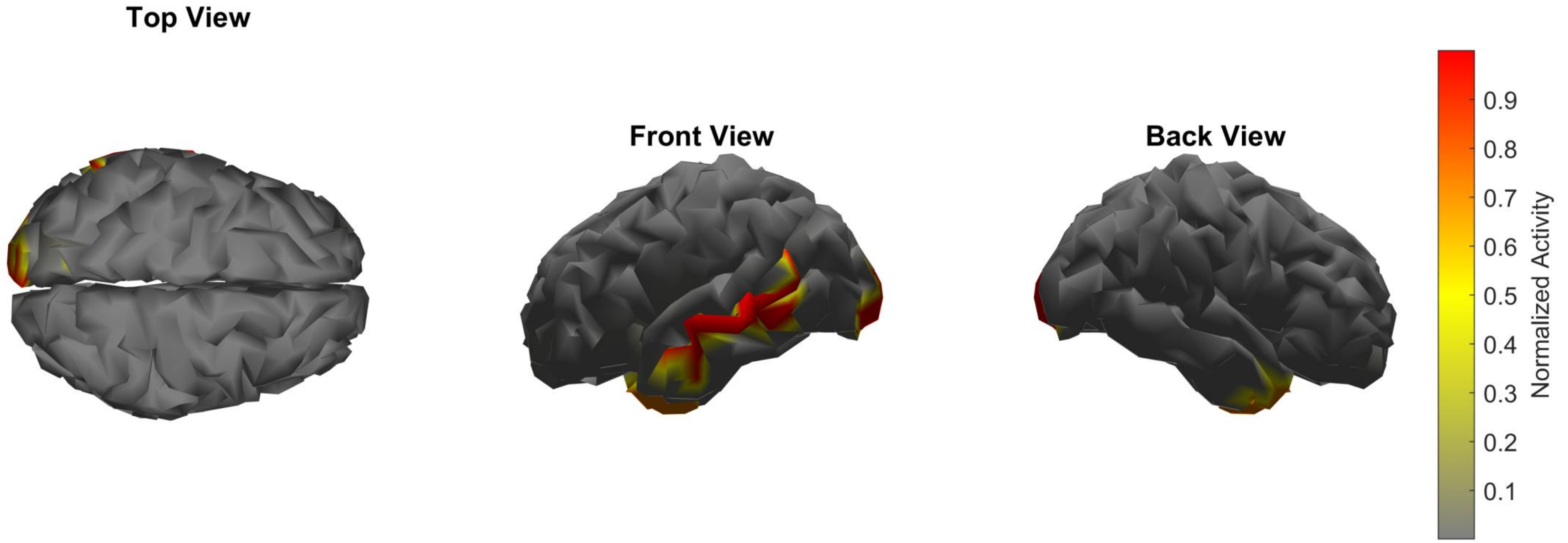


Results

ChampagneEM

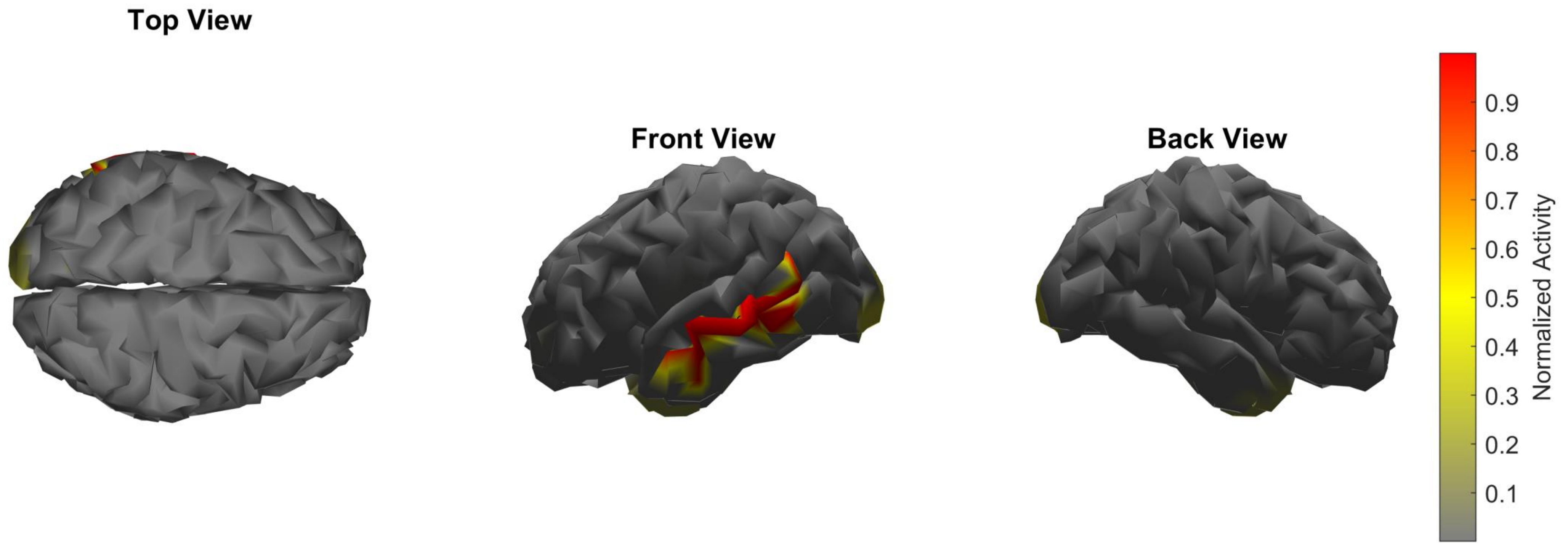


BSBL2S



Results

NNBSBL



Conclusion

The NNBSBL (Nonnegative Block-Sparse Bayesian Learning) algorithm outperforms LCMV, sLORETA, Smooth Champagne and BSBL-2S in EEG source localization. Its use of nonnegative Gaussian priors and sample covariance modeling ensures precise and robust localization, even in noisy conditions. Visualizations confirm NNBSBL's accuracy in identifying brain activity in temporal-parietal and frontal regions, consistent with P300 neural origins. Its ability to avoid spurious activations and handle real-world scenarios makes it the most reliable method for EEG source localization

References :

[1] Hinss, M. F., Jahanpour, E. S., Somon, B., Pluchon, L., Dehais, F., & Roy, R. N. (2022). COG-BCI database: A multi-session and multi-task EEG cognitive dataset for passive brain-computer interfaces . Version 4

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Thank you!