*Journal of Analytical Neuroscience*

METHODS

# A Memory-Efficient SEEG Data Processing Pipeline for Large Datasets

Zarrar Nashman[1,2] and Abdallah Belhadj[1,2]

[1]Nashman Labs, Philadelphia, Pennsylvania, USA
[2]Drexel University College of Medicine, Department of Neurosurgery, Philadelphia, Pennsylvania, USA
**Author for correspondence:** Zarrar Nashman, Email: nashman@nashman.org.
**Accepted:** 17th May 2025
janeuro.org

**Abstract**

Stereoencephalography (SEEG) is a powerful technique for intracranial recording of brain activity, crucial for localizing epileptic foci and studying neural dynamics. However, interpreting SEEG data is computationally demanding due to the high spatial and temporal resolution of recordings, significant data volume, electrode placement variability, intrinsic noise, and complex, non-stationary signals. This paper proposes a memory-efficient SEEG data processing pipeline designed to manage large datasets effectively while preserving critical signal information. The preprocessing pipeline includes loading and inspecting raw data, applying zero-phase FIR band-pass filters (1-50 Hz) to eliminate noise without distorting phase relationships, and segmenting data for frequency-specific analysis. Frequency domain analysis is conducted using Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), Morlet wavelet transforms, and Welch's method for Power Spectral Density (PSD) estimation. These methods enable robust exploration of frequency dynamics, capturing both transient and stable oscillatory brain activity. The presented pipeline maintains computational efficiency through optimized windowing parameters and filtering strategies, ensuring high-quality data interpretation without extensive resource demands. While primarily linear and limited by fixed parameters and potential redundancy in time-frequency overlaps, the approach successfully addresses common challenges in SEEG interpretation, including artifact reduction, spectral clarity, and reproducibility. This work offers a practical framework for large-scale SEEG analysis, facilitating clinical decision-making and advanced neurophysiological research.

**Keywords:** SEEG, stereoencephalography, EEG, signal processing, frequency analysis, large datasets, memory efficiency, epilepsy

## 1. Introduction

Stereoencephalography (SEEG) is an advanced technique used for recording intracranial brain activity in patients with epilepsy, particularly those who are candidates for epilepsy surgery. Unlike traditional scalp electroencephalography (EEG), which captures brain activity from the surface of the skull, SEEG involves the insertion of multiple electrodes directly into the brain, allowing for precise, localized measurements of electrical activity in specific regions of the brain. (Youngerman et al. 2019) This technique provides high spatial resolution and enables the study of deep brain structures that are otherwise difficult to access using non-invasive methods. (Pati and Gonzalez-Martinez 2024)

The primary clinical application of SEEG is in the presurgical mapping of epileptic brain regions. (George and Gonzalez-Martinez 2020) By identifying areas of the brain responsible for seizure activity, clinicians can make informed decisions about whether and where to perform surgical interventions, such as resecting the epileptic focus. Beyond epilepsy, SEEG is also used to study a variety of neurological and neurophysiological phenomena, such as brain connectivity, cognitive function, and network dynamics in healthy individuals and those with neurological disorders. (Bernabei et al. 2021)

Given the high sensitivity that SEEG has and the ability to record deep structures of the brain, it is also a useful tool in the study of the brain at different mental stages as seen during sleep and meditation. (Moroni et al. 2007; Bauer, Fomina, and Vugt 2022) At the same time, given the higher sensitivity of SEEG compared to traditional EEG recordings, their interpretations require higher processing capacity for computers. (Herff et al. 2020) As such, this paper outlines a method of processing SEEG data and further analysis in a data-efficient way. Other common methodologies used in SEEG processing are also explored.

## 2. Interpreting SEEG Data

Interpreting SEEG data involves analyzing the electrical signals recorded from the brain to understand neuronal activity from a population of neurons. These signals are often time-varying, with different oscillatory patterns associated with various cognitive states or pathologies, including seizure onset, spread, and termination. The most commonly studied brain rhythms in EEG are included in Table 1.

For the interpretation of SEEG data, researchers and clinicians often focus on the frequency, amplitude, and phase of these oscillations, particularly in relation to functional connectivity between brain regions and network dynamics. Advanced techniques, such as time-frequency analysis (using methods like FFT, wavelet transforms, and coherence analysis), are employed to investigate how brain activity changes over time and how different regions of the brain interact.(Frauscher et al. 2017)

**Table 1.** Commonly Studied Brain Rhythms and their Function

| Wave | Frequency (Hz) | Physiological Function |
|---|---|---|
| Delta waves | 1–4 Hz | Typically associated with deep sleep or brain inactivity. |
| Theta waves | 4–8 Hz | Often linked to drowsiness, emotional processing, or working memory tasks. |
| Alpha waves | 8–13 Hz | Associated with relaxed alertness, especially when the individual is awake and at rest. |
| Beta waves | 13–30 Hz | Often related to motor activity, movement, and active thinking. |
| Gamma waves | 30–50 Hz | Linked to cognitive processes like attention, memory, and sensory processing. |

## 2.1 Challenges in SEEG data interpretation

However, the complexities of SEEG data present several interpretative challenges:

### 2.1.1 Data Complexity and Noise

Intrinsic Noise and Artifacts: SEEG recordings are subject to noise from a variety of sources, including electrical interference, muscle artifacts, and eye movements. Unlike scalp EEG, where artifacts from muscle contractions (e.g., facial muscles) are common, SEEG electrodes are more prone to noise generated by the surrounding tissues, including brain movement or electrical activity from non-neuronal sources. (Muthukumaraswamy 2013) Effective artifact rejection and noise reduction techniques are essential for preserving the integrity of the data. This is computationally achieved by using band-pass and notch filtering.

Electrode Placement Variability: The placement of SEEG electrodes is highly specific to each patient's anatomy. (Granados et al. 2021) Variability in electrode positioning, even with advanced imaging techniques (e.g., MRI and CT scans), is inevitable and can complicate the interpretation of the data. For instance, a signal recorded from an electrode may be influenced by neighboring regions or structures, leading to challenges in accurately localizing the source of the activity. Various different references exist in order to minimize this variability.

### 2.1.2 High Dimensionality and Volume of Data

Large-scale Data: SEEG involves the simultaneous recording of data from multiple electrodes across different brain regions, generating large volumes of data that are both spatially and temporally rich.(Youngerman et al. 2019) A typical SEEG study may record from dozens or even hundreds of electrodes, each providing continuous data over many hours. The sheer amount of data makes it challenging to manually interpret and analyze, even after implementing montages for simplifying the displayed data. (Frauscher et al. 2017)

High Temporal Resolution: The high sampling rate (often 1-2 kHz) and continuous nature of SEEG recordings provide high temporal resolution, which is necessary for detecting fast neural dynamics, such as seizure propagation. However, the high resolution also results in massive datasets, complicating the computational analysis and storage of data. (Frauscher et al. 2017) Efficient processing algorithms are needed to handle the large amount of information in real time. This compounded with the presence of multiple participants along with multiple electrodes per participant makes this activity even more computationally taxing.

### 2.1.3 Spatiotemporal Dynamics of Brain Activity

Complex Brain Networks: SEEG provides detailed spatial information about brain activity, but the interpretation of these signals requires understanding the complex, dynamic interactions between brain regions. Localized activity may not fully represent the broader network dynamics that are occurring across multiple regions of the brain. (Lagarde et al. 2022) Identifying functional connectivity—the interaction between different brain regions—requires sophisticated mathematical models that can account for the temporal and spatial complexity of the data.

Dynamic Temporal Patterns: SEEG signals are dynamic and can vary across time scales, from the rapid fluctuations of gamma activity to the slower oscillations of delta and theta waves. These different rhythms often coexist and may overlap in time, making it difficult to dissect the individual contributions of different brain regions to observed phenomena (e.g., seizures or cognitive tasks). (Ye et al. 2022) Analyzing these patterns requires methods that can simultaneously capture both short-term dynamics and longer-term trends.

### 2.1.4 Interpretation of Non-Stationary Signals

Non-stationarity: Unlike some simpler signals, SEEG data is non-stationary, meaning that its statistical properties (e.g., mean and variance) change over time. (Dikanev et al. 2005) This is particularly evident during events like seizures, where there is a sudden shift in brain activity. Standard signal processing techniques like the Fast Fourier Transform (FFT) assume stationarity, which can limit their ability to capture the full range of temporal dynamics in non-stationary data. In order to bypass this issue, time segments can be divided and FFT applied independently to each time segment. (Wang and Veluvolu 2017) But this requires the knowledge of cut-off points prior and therefore would be most useful for controlled trials or data that is correlated with clinical observations (as would be observed during seizures).

Need for Advanced Time-Frequency Analysis: To deal with non-stationary signals, techniques like Wavelet Transform, Short-Time Fourier Transform (STFT), or Hilbert-Huang Transform (HHT) are more suitable, as they provide both time and frequency resolution. (Wacker and Witte 2013) However, these methods require significant computational power, particularly when analyzing large-scale, multi-electrode recordings. However, if the electrode contacts are properly identified, it is reasonable to compare single electrode recordings across subjects.

## 3. Role of Computing Power in SEEG Analysis

The evolution of computing power has significantly impacted the way SEEG data are analyzed, allowing for more sophisticated methods and more efficient processing. Some key ways in which increased computing power addresses the challenges of SEEG interpretation include:

### *3.1 Real-Time Analysis and Processing*

With more powerful computational tools, it is now possible to process and analyze SEEG data in real-time. This is especially important for clinical applications, such as guiding neurosurgical procedures during awake surgery. (Nagahama et al. 2023) Real-time signal processing allows for immediate feedback on brain activity, helping clinicians make informed decisions about the location of epileptic foci or optimal surgical targets.

### *3.2 Handling Large Datasets*

Advances in computing have made it feasible to handle the large volumes of SEEG data generated from multi-electrode arrays. High-performance computing clusters or cloud-based infrastructure enable efficient storage, processing, and analysis of these datasets, which would have been computationally prohibitive just a few years ago. (Cai et al. 2022) This has opened the door to more in-depth analyses of brain activity over extended periods, from several hours to days.

### *3.3 Advanced Machine Learning and AI*

Machine learning (ML) and artificial intelligence (AI) algorithms have benefited from the increasing availability of computing power, allowing for automated feature extraction, pattern recognition, and predictive modeling of SEEG data. These techniques can identify complex patterns in the data that might be difficult for human researchers to detect. For example, ML algorithms can be trained to predict seizure onset based on historical SEEG data, potentially improving the accuracy of surgical planning. (Bernabei et al. 2023) Deep learning methods, such as neural networks, are increasingly used to classify brain states, detect seizure activity, or predict the outcome of neurosurgical interventions. (Johnson et al. 2022) These methods are particularly powerful in identifying subtle temporal or spatial features in SEEG data that may not be immediately apparent through traditional analytical techniques.

### *3.4 Improved Signal Decomposition and Source Localization*

Source localization techniques, which attempt to pinpoint the origin of brain activity recorded by SEEG electrodes, have also benefited from improved computational methods. Using techniques like beamforming, inverse modeling, or dynamic causal modeling (DCM), researchers can better estimate the sources of brain activity and understand how these sources interact within complex neural networks. (Cooray et al. 2016) Additionally, advancements in signal decomposition methods (such as Independent Component Analysis (ICA)) have made it easier to separate different sources of activity, including the removal of artifacts like eye movements or muscle contractions. (Medina Villalon et al. 2024)

### *3.5 Multi-Scale Analysis and Modeling*

The increased computing capacity enables multi-scale analysis, which allows researchers to simultaneously study brain activity at different levels of analysis—ranging from individual electrodes to entire brain networks. This is essential for understanding how localized activity in a single brain region contributes to broader network dynamics. Advanced simulation models also benefit from more powerful computers. Researchers can now create detailed, realistic brain network models that simulate the dynamics of brain activity at a larger scale, helping to link SEEG data with computational neuroscience.

## 4. Proposed Processing Pipeline

The proposed pipeline aims to process SEEG data efficiently, particularly concerning memory usage for large datasets. Figure 1 provides a schematic overview.

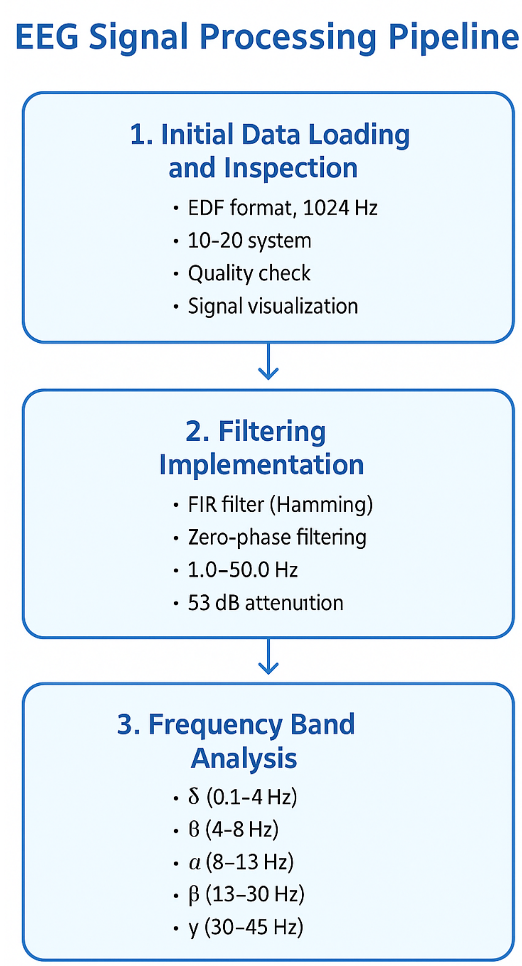


**Figure 1.** Schematic of Signal Processing Pipeline. Illustrates the flow from raw data loading, through filtering and frequency analysis stages.

### 4.1 Preprocessing

The preprocessing pipeline is crucial for preparing the raw signal data for further analysis. In this implementation, we begin by loading and inspecting the data, followed by filtering to remove noise and ensure that the signal components of interest are preserved.

#### 4.1.1 Initial Data Loading and Inspection

The raw data used in this study are stored in the European Data Format (EDF), which is commonly used for storing physiological signals, including EEG data. Each dataset typically contains continuous recordings from multiple channels, and the signals are sampled at a rate of 1024 Hz. This sampling rate provides adequate resolution to capture the fast dynamics of brain activity. The channel configuration adheres to the standard 10-20 system, which is a widely used electrode arrangement for EEG studies, ensuring consistency across datasets and comparability of results. After loading the data, an initial inspection is performed to check for any obvious issues such as missing or corrupted data. This inspection also involves visualizing the signals across different channels to ensure that the data quality is sufficient for further processing.

#### 4.1.2 Filtering Implementation

Once the raw data is inspected, we apply a series of filtering steps to remove unwanted noise and emphasize the frequency bands of interest. A Finite Impulse Response (FIR) filter is employed due to its precise frequency characteristics and lack of phase distortion. The filter is designed using the Hamming window method, which provides a good balance between the filter's transition width and its ability to minimize ripple in the passband. The filter order is set to 3381 points, which provides a high level of frequency selectivity.

The filtering process involves zero-phase forward and reverse filtering, ensuring that no phase distortion is introduced into the signal. This step is essential, particularly for EEG signals, where maintaining the phase relationships between frequencies is critical for accurate analysis. The transition bandwidth specifications are carefully chosen to maintain a sharp cutoff while avoiding significant signal distortion. The lower transition is set at 1.00 Hz, while the upper transition is set at 12.50 Hz (example range, adjusted per band), which allows us to preserve the essential low-frequency components of the signal while removing high-frequency noise. The stopband attenuation is set to 53 dB, which ensures that any unwanted frequencies outside the passband are effectively attenuated. The passband ripple is kept to a minimal 0.0194, ensuring a smooth frequency response within the desired frequency range.

#### 4.1.3 Filter Response Characteristics

The primary frequency range of interest for our analysis spans from 1 to 50 Hz. This range encompasses several key neural oscillations, including delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz) bands, which are associated with different cognitive and physiological processes. To capture these frequencies, we implement individual band-pass filters for each of the neural oscillation bands. The delta, theta, alpha, beta, and gamma bands are defined based on the typical frequency ranges observed in EEG research. These filters are used to isolate the relevant frequency components for further analysis, allowing us to explore the distinct dynamics of each frequency band.

### 4.2 Frequency Analysis Implementation

Once the preprocessing steps are complete, we proceed with frequency domain analysis to examine the spectral characteristics of the processed signals. This is achieved using a combination of spectral analysis methods, time-frequency techniques, and power spectral density (PSD) estimation.

#### 4.2.1 Spectral Analysis Methods

The primary method for spectral analysis is the Fast Fourier Transform (FFT), a widely used algorithm that converts the time-domain signal into the frequency domain. For our implementation, we use NumPy's FFT module, which is optimized for efficient computation. The signal is divided into segments of 4 seconds (4096 samples), a duration that provides sufficient frequency resolution while balancing computational efficiency. Each segment is windowed using a Hanning window to minimize spectral leakage, and the segments are overlapped by 50%, allowing for better frequency resolution and reducing edge artifacts. This configuration ensures that we capture the essential spectral features while maintaining a high degree of temporal resolution.

#### 4.2.2 Time-Frequency Analysis

In addition to the standard FFT, we apply time-frequency analysis techniques to capture the dynamic changes in frequency content over time. The Short-Time Fourier Transform (STFT) is used for this purpose. In this method, the signal is divided into overlapping windows, with a window size of 2 seconds (2048 samples) and a step size of 0.5 seconds (512 samples). This setup allows us to track the frequency content of the signal at a relatively fine time scale, offering insights into how the spectral components evolve over time. The frequency resolution of the STFT is set to 0.5 Hz, which ensures sufficient precision for identifying oscillatory activity within the frequency bands of interest.

Additionally, wavelet analysis is employed to provide a more flexible approach to time-frequency decomposition. The Morlet wavelet, a complex sinusoid modulated by a Gaussian window, is chosen for its good frequency localization properties. We use a frequency range of 1-50 Hz, encompassing the typical frequency bands seen in EEG data, and the scales are logarithmically spaced to capture both low and high-frequency components with appropriate resolution. The number of cycles in the Morlet wavelet is set to 7, which provides a good trade-off between time and frequency localization.

#### 4.2.3 *Power Spectral Density Estimation*

To estimate the power distribution across frequencies, we apply Welch's method for Power Spectral Density (PSD) estimation. This method involves dividing the signal into overlapping segments, each 4 seconds in length, with a 50% overlap to ensure good frequency resolution. The segments are windowed using a Hanning window to reduce spectral leakage, and the resulting periodograms are averaged to obtain a more stable estimate of the PSD. The averaging process uses the mean of the periodograms across all segments, which helps to smooth out noise and ensures that the power spectrum is accurately estimated. Welch's method is particularly useful for reducing variance in the spectral estimate, providing a clearer picture of the underlying signal power at different frequencies.

## 5. Discussion

### 5.1 *Consideration of Alternative Analytical Methods*

While the methods outlined above were selected for their robustness and suitability for the analysis of EEG signals, several other analytical techniques were considered and ultimately not used. One such method is the Wavelet Transform (WT) in its broader form, including continuous wavelet transforms (CWT) with wavelets other than the Morlet wavelet. While wavelet analysis provides excellent time-frequency resolution, we opted for the Morlet wavelet due to its well-established performance in EEG studies, particularly in capturing oscillatory brain activity.(Ghuman, McDaniel, and Martin 2011) The CWT can offer highly detailed time-frequency maps, but its computational cost can be prohibitive, especially for large datasets, and the choice of wavelet can greatly influence the results, requiring careful selection and validation.(Tary, Baan, and Dettmer 2018) Thus, for the purposes of this study, we preferred the discrete and computationally more efficient version of wavelet analysis that the Morlet wavelet provides.

Another alternative considered was Principal Component Analysis (PCA), which can reduce the dimensionality of EEG data and potentially highlight significant patterns of brain activity.(Lagerlund, Sharbrough, and Busacker 2004) However, PCA was not chosen because it primarily focuses on variance across the entire dataset rather than specific frequency components, which are the primary focus of our study. The ability of PCA to isolate meaningful oscillatory patterns is more suited for exploratory data analysis or when dealing with large sets of multivariate data, but it is not ideal for the frequency-specific analysis required in our study. Similarly, methods like Independent Component Analysis (ICA) were not pursued, as ICA is more useful for separating independent sources of activity (such as artifact rejection or source localization) rather than for analyzing spectral power within predefined frequency bands. (López-Madrona et al. 2023)

Nonlinear dynamic methods, such as Lyapunov Exponent or Fractal Dimension, were also briefly considered. These methods can be used to assess the complexity or chaotic behavior of EEG signals, which could be relevant for specific research questions, particularly in studies of brain dynamics or epilepsy. (Adeli, Ghosh-Dastidar, and Dadmehr 2007) However, in this study, the primary goal is to assess frequency-specific oscillations and their power spectra, which is better addressed by linear spectral methods like FFT, STFT, and Welch's PSD estimation. Nonlinear methods, while insightful for certain types of data, are not well-suited for the more systematic and frequency-focused analysis researchers typically aim to perform, and their interpretation in the context of EEG signals can be challenging without extensive prior knowledge.

Finally, time-domain analysis methods such as the use of autocorrelation functions or direct peak detection in the raw signal were considered. However, these methods are generally less effective in separating overlapping frequency components, which is essential in EEG signal analysis, where multiple oscillatory rhythms can be present simultaneously. (Morales and Bowers 2022) Time-domain analysis methods are often limited by the difficulty in resolving these overlapping frequencies, which is why frequency-domain and time-frequency techniques were preferred.

### 5.2 *Strengths of the Analysis Approach*

**Comprehensive Frequency Band Analysis** Clear separation of oscillatory bands: The use of band-pass filters for specific frequency ranges (e.g., delta, theta, alpha, beta, gamma) allows for clear and targeted analysis of distinct neural oscillations. These bands are well-established in neuroscience research and correlate with various cognitive and physiological states, such as attention, relaxation, and motor activity. Preservation of spectral properties: The FIR filter design, particularly with the Hamming window and zero-phase forward and reverse filtering, helps maintain the integrity of the signal's spectral properties, ensuring that the phase relationships between frequency components are not distorted.

**Well-established Signal Processing Methods** FFT and STFT: The use of the Fast Fourier Transform (FFT) and Short-Time Fourier Transform (STFT) provides robust methods for frequency analysis. These methods are widely recognized in the field and are effective at detecting periodic oscillatory activity in EEG data. Widely accepted in EEG research: The use of the Hanning window for segmenting data and Welch's method for Power Spectral Density (PSD) estimation are standard techniques in EEG signal processing. Their application ensures comparability with other studies and provides reliable results for spectral power analysis.

**Time-Frequency Resolution with Wavelet Analysis** Morlet Wavelet for Time-Frequency Analysis: The Morlet wavelet, particularly with logarithmically spaced scales, provides excellent time-frequency resolution, enabling detailed analysis of non-stationary signals like EEG. This method is effective in capturing transient events and frequency shifts over time, which is crucial for understanding dynamic brain activity.

**Noise Reduction and Signal Clarity** Filtering to remove noise: The use of a high-quality FIR filter with a high stopband attenuation ensures that unwanted noise (e.g., from muscle artifacts or electrical interference) is effectively reduced. The minimal passband ripple further guarantees that the signal remains clean and reflective of true brain activity. More aggressive methods for noise reduction consequently leads to loss of true data.

Reproducibility Parameter transparency: The explicit detailing of the preprocessing pipeline (e.g., filter specifications, segment lengths, overlap percentages) increases the reproducibility of the analysis. This is a key strength, as other researchers can replicate the same procedures using the same parameters, ensuring that the findings are both reliable and reproducible.

### *5.3 Weaknesses and Limitations*

Limited to Linear Analysis Assumption of linearity: Techniques like FFT, STFT, and Welch's method assume that the signals are linear and stationary within each segment. While these methods are effective for capturing oscillatory components, they may not fully account for more complex, nonlinear interactions in the data. Nonlinear methods (e.g., Lyapunov Exponent, Fractal Dimension) could provide additional insights into chaotic brain activity, but these were not used in this analysis. Inability to fully capture transient or complex brain dynamics: While the Morlet wavelet provides some flexibility, methods like the STFT and FFT may still struggle to capture highly transient or rapidly evolving brain activity, which could limit their applicability in certain types of dynamic brain states.

Fixed Parameters for Filtering and Windowing Fixed filter parameters: The choice of filter cutoff frequencies and the filter order is fixed. This may not be optimal for all types of data or across different experimental conditions. For instance, the 1-12.5 Hz cutoff range might not suit data from certain cognitive tasks that require a different frequency range. The filter's effectiveness is also contingent on the data quality; if the raw signal contains strong artifacts near the cutoff frequencies, it might still leak into the passband, leading to distortions. Window size in STFT and Wavelet: The window size for STFT (2 seconds) and the number of cycles for wavelet analysis (7 cycles) may not be ideal for all signals. Depending on the frequency components and the length of the events in the data, some researchers may opt for shorter or longer windows for better time or frequency resolution.

Potential Data Loss Due to Overlap in STFT Overlap in STFT: While the 50% overlap used in STFT helps balance time and frequency resolution, it can still result in redundancy, especially for very long datasets. Some temporal details may be lost if the signal contains fast, transient features that are not fully captured in the windowed segments. The overlap parameter can be optimized, but it might still limit temporal resolution for extremely fast events.

Limited Temporal Resolution in Frequency Analysis Trade-off between time and frequency resolution: Methods like FFT and STFT involve trade-offs between time and frequency resolution. The segment length (e.g., 4 seconds for FFT) affects the frequency resolution but reduces the temporal resolution. This can be problematic when analyzing fast, transient neural activity that requires both high temporal and frequency resolution.

Potential for Overfitting or Misinterpretation Bandpass filtering risks: The application of individual bandpass filters for different frequency ranges can sometimes lead to overfitting, especially when interpreting small variations in spectral power. If the filters are too narrow or not optimally designed, subtle frequency content outside the predefined bands might be excluded or misrepresented. Interpretation of results: While spectral power analysis provides clear insights into the dominant frequencies in the EEG signal, it does not directly reveal causal relationships between brain regions or networks. The analysis is limited to correlations between signal power and physiological or behavioral states, which might not capture the full complexity of neural mechanisms.

Limited Capability for Handling Artifacts Artifact rejection: Although filtering helps to reduce some noise, the method described in the paper doesn't directly address the rejection of artifacts such as eye movements, muscle activity, or electrical noise. Independent Component Analysis (ICA) or other artifact rejection methods might be more effective in isolating and removing these unwanted signals, but this approach was not part of the analysis pipeline. The original rationale for not including these extra filters is primarily due to SEEG's inherent strength of not picking up noise due to its depth inside the brain itself.

Computational Complexity and Efficiency Computational cost: The use of time-frequency methods like the wavelet transform can be computationally intensive, especially when applied to large datasets or long time series. While these methods are powerful, they can result in long processing times or require substantial memory resources, particularly if the dataset includes multiple channels.

## 6. Conclusion

This paper detailed a memory-efficient pipeline for processing large SEEG datasets, addressing the challenges posed by data volume and complexity. By employing standard yet robust techniques like FIR filtering, FFT, STFT, Welch's method, and Morlet wavelets, the pipeline facilitates reproducible analysis of key frequency bands while managing computational resources. The discussion highlighted the strengths, such as clear frequency separation and use of established methods, alongside limitations including the focus on linear analysis and fixed parameters. This approach offers a practical framework for researchers needing to analyze extensive SEEG recordings efficiently.

Acknowledgments No acknowledgements have been reported by the authors at this time.

## References

Adeli, Hojjat, Samanwoy Ghosh-Dastidar, and Nahid Dadmehr. 2007. A wavelet-chaos methodology for analysis of eegs and eeg subbands to detect seizure and epilepsy. *IEEE Transactions on Bio-medical Engineering* 54 (2): 205–211. https://doi.org/10.1109/TBME.2006.886855.

Bauer, Prisca R, Tatyana Fomina, and Marieke K van Vugt. 2022. Neural dynamics of mindfulness meditation and hypnosis explored with intracranial eeg: a feasibility study. *Neuroscience Letters* 766:136345. https://doi.org/10.1016/j.neulet.2021.136345.

Bernabei, John M, Timothy H Lucas, Kathryn A Davis, and Danielle S Bassett. 2021. Electrocorticography and stereo eeg provide distinct measures of brain connectivity: implications for network models. *Brain Communications* 3, no. 3 (July): fcab156. https://doi.org/10.1093/braincomms/fcab156.

Bernabei, John M, Andrew Y Revell, Kathryn A Davis, and Danielle S Bassett. 2023. Quantitative approaches to guide epilepsy surgery from intracranial eeg. *Brain: A Journal of Neurology* 146 (6): 2248–2258. https://doi.org/10.1093/brain/awad007.

Cai, Fang, Ling Sun, Yan Yang, Yuru Fang, Lin Zhu, Tao Li, Liang Chen, and Dong Gong. 2022. Brainquake: an open-source python toolbox for the stereoelectroencephalography spatiotemporal analysis. *Frontiers in Neuroinformatics* 15 (January): 773890. https://doi.org/10.3389/fninf.2021.773890.

Cooray, Gerald K, Fahmida A Chowdhury, Ján Kahan, Guillaume Flandin, Adeel Razi, Eric J Williams, Paul N Taylor, and Karl J Friston. 2016. Dynamic causal modelling of electrographic seizure activity using bayesian belief updating. *NeuroImage* 125:1142–1154. https://doi.org/10.1016/j.neuroimage.2015.07.063.

Dikanev, Taras, Dmitry Smirnov, Richard Wennberg, J L Perez Velazquez, and B P Bezruchko. 2005. Eeg nonstationarity during intracranially recorded seizures: statistical and dynamical analysis. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology* 116 (8): 1796–1807. https://doi.org/10.1016/j.clinph.2005.04.013.

Frauscher, Birgit, Nicolas von Ellenrieder, Rina Zelmann, Christopher Rogers, Dang Khoa Nguyen, Philippe Kahane, François Dubeau, and Jean Gotman. 2017. High-frequency oscillations: the state of clinical research. *Epilepsia* 58 (8): 1316–1329. https://doi.org/10.1111/epi.13829.

George, Derek D, and Jorge A Gonzalez-Martinez. 2020. Stimulation mapping using stereoelectroencephalography: current and future directions. *Frontiers in Neurology* 11 (May): 320. https://doi.org/10.3389/fneur.2020.00320.

Ghuman, Avniel Singh, Jeffrey R McDaniel, and Andrew Martin. 2011. A wavelet-based method for measuring the oscillatory dynamics of resting-state functional connectivity in meg. *NeuroImage* 56 (1): 69–77. https://doi.org/10.1016/j.neuroimage.2011.01.046.

Granados, Alejandro, Robert Sparks, Vejay N Vakharia, Roman Rodionov, Andrew W McEvoy, Anna Miserocchi, Sébastien Ourselin, and John S Duncan. 2021. Patient-specific prediction of seeg electrode bending for stereotactic neurosurgical planning. *International Journal of Computer Assisted Radiology and Surgery* 16 (5): 789–798. https://doi.org/10.1007/s11548-021-02347-8.

Herff, Christian, Dominic Heger, Graham Johnson, Dennis Luu, Leo Johnson, Jerry J Shih, and Tanja Schultz. 2020. The potential of stereotactic-eeg for brain-computer interfaces: current progress and future directions. *Frontiers in Neuroscience* 14 (February): 123. https://doi.org/10.3389/fnins.2020.00123.

Johnson, Graham W, Joshua Krieg, Stephen C Harward, Allison Wu, Brett E Youngerman, Guy M McKhann, Sameer A Sheth, et al. 2022. Localizing seizure onset zones in surgical epilepsy with neurostimulation deep learning. *Journal of Neurosurgery* 138, no. 4 (September): 1002–1007. https://doi.org/10.3171/2022.8.JNS221321.

Lagarde, Stanislas, Nicolas Roehri, Isabelle Lambert, Agnès Trebuchon, Aileen McGonigal, Romain Carron, Didier Scavarda, et al. 2022. Interictal functional connectivity in focal refractory epilepsies investigated by intracranial eeg. *Brain Connectivity* 12 (10): 850–869. https://doi.org/10.1089/brain.2021.0190.

Lagerlund, Terrence D, Frank W Sharbrough, and Neil E Busacker. 2004. Use of principal component analysis in the frequency domain for mapping electroencephalographic activities: comparison with phase-encoded fourier spectral analysis. *Brain Topography* 17 (2): 73–84. https://doi.org/10.1007/s10548-004-1005-4.

López-Madrona, Víctor J, Paula Narros-Giménez, Carlos Pérez-González, Fernando Gil-López, Antonio Rubio-Ayuso, and Manuel S Malmierca. 2023. Reconstruction and localization of auditory sources from intracerebral seeg using independent component analysis. *NeuroImage* 269:119905. https://doi.org/10.1016/j.neuroimage.2023.119905.

Medina Villalon, Samuel, Nicolas Roehri, Agnès Trebuchon, Bernard Giusiano, Romain Carron, Fabrice Bartolomei, and Christian G Bénar. 2024. Combining independent component analysis and source localization for improving spatial sampling of stereoelectroencephalography in epilepsy. *Scientific Reports* 14, no. 1 (February): 4071. https://doi.org/10.1038/s41598-024-54359-4.

Morales, Santiago, and Maureen E Bowers. 2022. Time-frequency analysis methods and their application in developmental eeg data. *Developmental Cognitive Neuroscience* 54:101067. https://doi.org/10.1016/j.dcn.2022.101067.

Moroni, Fabio, Lino Nobili, Giuseppe Curcio, Fabrizio De Carli, Federica Fratello, Ilaria Sartori, Stefano Vandi, Marco Fedi, Giuseppe Plazzi, and Francesco Ferrillo. 2007. Sleep in the human hippocampus: a stereo-eeg study. *PLoS One* 2, no. 9 (September): e867. https://doi.org/10.1371/journal.pone.0000867.

Muthukumaraswamy, Suresh D. 2013. High-frequency brain activity and muscle artifacts in meg/eeg: a review and recommendations. *Frontiers in Human Neuroscience* 7 (April): 138. https://doi.org/10.3389/fnhum.2013.00138.

Nagahama, Yasunori, Jamie J Van Gompel, Benjamin H Brinkmann, Abdulrahman Mahannan, David W Carmichael, M Stead, Erik H Middlebrooks, W Richard Marsh, Brian N Lundstrom, and Gregory A Worrell. 2023. Outcome of stereo-electroencephalography with single-unit recording in drug-refractory epilepsy. *Journal of Neurosurgery* 139, no. 6 (May): 1588–1597. https://doi.org/10.3171/2023.4.JNS222633.

Pati, Sandipan, and Jorge Gonzalez-Martinez. 2024. Stereoelectroencephalography of the deep brain: basal ganglia and thalami. *Journal of Clinical Neurophysiology: American Electroencephalographic Society* 41 (5): 423–429. https://doi.org/10.1097/WNP.0000000000001097.

Tary, Jean Baptiste, Mirko van der Baan, and Jan Dettmer. 2018. Analysis of time-varying signals using continuous wavelet and synchrosqueezed transforms. *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences* 376 (2126): 20170254. https://doi.org/10.1098/rsta.2017.0254.

Wacker, M, and H Witte. 2013. Time-frequency techniques in biomedical signal analysis. a tutorial review of similarities and differences. *Methods of Information in Medicine* 52 (4): 279–296. https://doi.org/10.3414/ME12-01-0083.

Wang, Yubo, and Kalyana C Veluvolu. 2017. Time-frequency analysis of non-stationary biological signals with sparse linear regression based fourier linear combiner. *Sensors (Basel, Switzerland)* 17, no. 6 (June): 1386. https://doi.org/10.3390/s17061386.

Ye, Huanpeng, Zhiping Guo, Yongjie Li, Yang Li, and Bin Yan. 2022. Spontaneous state detection using time-frequency and time-domain features extracted from stereo-electroencephalography traces. *Frontiers in Neuroscience* 16 (March): 818214. https://doi.org/10.3389/fnins.2022.818214.

Youngerman, Brett E, Joseph Y Oh, Deepti Anbarasan, Claudia H Casadei, Katarzyna A Bujarski, Guy M McKhann, and Sameer A Sheth. 2019. Stereoelectroencephalography in epilepsy, cognitive neurophysiology, and psychiatric disease: safety, efficacy, and place in therapy. *Neuropsychiatric Disease and Treatment* 15 (June): 1701–1716. https://doi.org/10.2147/NDT.S177804.