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Synthetic EEG Signal Generator of Morphologies Associated with Epileptogenic Events

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Abstract. In recent decades, Electroencephalography (EEG) has undergone extensive analysis and study, seeking to improve the brain signals knowledge. Given the importance of having EEG data available in contexts where it is unfeasible to obtain them, this work presents a methodology for the synthetic generation of these signals. Techniques and algorithms are described to simulate EEG frequency bands, incorporate noise, and emulate specific EEG phenomena. Using Python libraries, key functions for simulating EEG signals with different characteristics and morphologies are detailed. A Python-based tool, implemented through Dash, allows controlled generation of these signals with export options in various formats. Evaluation using EEGLAB ensures the accuracy and consistency of the generated signals, underlining the relevance of external validation. This initiative has potential in the research, diagnosis, and analysis of neurological diseases such as epilepsy, by offering a realistic synthetic approach to EEG signals.

Keywords: EEG signals, sharp wave, slow wave, sharp-slow wave, rhythm bands, noise types.

1 Introduction

The Electroencephalogram (EEG) has been utilized over decades to probe into brain activity. When employed as a cerebral mapping tool, it can furnish spatiotemporal insights regarding brain function or dysfunction [1]. Its utility in combined research approaches, particularly with techniques like EEG-fMRI, is often undervalued, pushing EEG to ancillary roles, despite its potential for a comprehensive spatial analysis [1].

A seminal contribution of the EEG has been towards diagnosing and treating afflictions such as epilepsy. The EEG has facilitated the pinpointing of aberrant rhythms or transient wave patterns in cerebral regions, although certain constraints related to volume conduction and the inter-electrode distances persist [2]. Such localizations are paramount when ascertaining, for instance, the precise site of an epileptic lesion in the brain, thereby aiding in informed treatment decisions.

Advancements in digitization have augmented the interpretative capabilities of these signals, paving the way for intricate analyses that aim to discern intracranial sources and their interconnections [2]. Nonetheless, it warrants mentioning that electrode dimensions denote the integration of signals spanning 30–500 million neurons.

Furthermore, scalp connectivity might introduce distortions to the resultant estimates [3]. These perturbations often obfuscate the understanding of inherent cerebral interactions, necessitating sophisticated methods to decipher the underlying neural dynamics [4].

Intriguingly, the morphological diversity in EEG readings, even adhering meticulous measurement paradigms, correlates with factors like age and the specific cerebral activity being observed. Hence, it is predominantly perceived as a stochastic signal. Notwithstanding, within minimal variability bounds, recurring patterns become discernible, predominantly in pathological states. It is observed that the EEG embodies significant inter-individual and intra-individual variances over time [5].

While these morphological diversities are consequential, their primary significance lies in their representational capacity of concurrent cerebral events, rather than being focal points of intrigue per se. In the epoch of machine learning, such data heterogeneity became pivotal for algorithm training and validation processes [5]. Concurrently, an extensive EEG dataset repository becomes indispensable to ascertain the robustness of data processing [5].

Positioned against this backdrop, the current endeavor embarks on crafting an application tailored for the synthetic generation of EEG signals, encapsulating clinically discernible morphologies. Such a tool becomes indispensable in enriching and diversifying the EEG signal repository available for scientific inquiries and educational purposes.

This article is organized to first contextualize the significance of EEG in clinical diagnosis (Section 2) and then to detail the nature of EEG waves and their simulation (Section 3). The methodology of synthesizing EEG signals, including noise integration and the emulation of distinctive EEG phenomena, is presented in Section 4. Section 5 evaluates the tool's efficacy using EEGLAB, while Section 6 concludes with the study's key findings and future research directions.

2 Importance and Contextualization of EEG Signals in the Diagnosis of Neurological Disease

Electroencephalogram (EEG) signals serve a paramount role in deciphering and diagnosing an array of diseases associated with the central nervous system (CNS). This diagnostic modality draws its essence from correlating specific EEG patterns with CNS functionalities, anomalies, and pathologies. Within the clinical settings, harnessing EEG signals fortifies the empirical skill in diagnosing cerebral afflictions, including convulsive and metabolic disorders.

Such signals, emanating from extracellular potentials termed as field potentials, are the outcomes of both neuronal and glial activities. The CNS architecture comprises nerve cells or neurons, instrumental in electrical signal transmission, and glial cells. While glial cells don't initiate action potentials akin to neurons, their association with ionic flows allows them to influence extracellular potentials.

Field potentials, stratified by their type and frequency, demand a thorough comprehension of their origin—be it due to neuronal or focal activity—for an apt clinical and diagnostic elucidation [2].

Central to this discussion is the acknowledgment of the quintessential waves within EEG readings. Segregated based on frequency, amplitude, and morphology, these waves encompass diverse patterns: spike waves, sharp waves, spikeslow wave complexes, and sharp wave-slow wave constructs [6]. These characteristic waves play a pivotal role in determining if an EEG trace leans towards being normal or denotes pathology. Specifically, the presence or absence of distinct waves or complexes can hint at disparate cerebral anomalies [6].

A pressing challenge in EEG analyses remains the manual deciphering of signals. Undertaking this intricate endeavor mandates a profound understanding of typical EEG activities, contingent on the patient's age and clinical statuses. A meticulous identification of artifacts, technical anomalies, and borderline patterns is imperative. This discernment, demanding both time and specialized expertise, underlines the rigorous efforts EEG specialists investing reviewing and juxtaposing EEG traces, aiming for unerring diagnoses or to negate specific medical hypotheses [6].

2.1 Background

Within the biomedical domain, a large number of tools and simulators have been conceived for biosignal generation and simulation. When focusing on EEG signals, these generative platforms have been crafted with distinct objectives and diverse methodologies. What follows is a comparative scrutiny of these instruments, emphasizing their attributes and limitations, subsequently delineating the unique proposition our endeavor offers in this realm.

Table 1 illustrates the cardinal features of akin projects, offering insights that could potentially refine our current endeavor and/or corroborate the accurate generation of signals. Contrary to the previously discussed tools, this project focuses on the synthetic generation of EEG signals with notable morphologies. The use of Python as the main programming language to harness of the large number of available libraries, thereby creating an intuitive tool.

This tool grants users the flexibility to dictate morphological patterns, t heir frequency, and spatial positioning. Developed using the Dash framework in Python, the interface is not only user-friendly but also encompasses several unique benefits, such as exporting data in diverse formats and affording a high degree of flexibility in parameter configuration. Fig. 1 presents some of the outputs from the projects outlined in Table 1.

This initiative's uniqueness becomes more pronounced when juxtaposed other available solutions against. For instance, the Simulated EEG data generator from the University of Oxford [7] and the ECG Simulator from Data Science Automation [8], while invaluable, don't provide the same comprehensive set of features, especially concerning generating specific morphologies.

Table 1. Related works.

Name	Description	Characteristics	Institute	Type	Quote
Simulated EEG data generator	Generates EEG data based on two Event-Related Potentials (ERP) theories: classical and phase reset.	EEG; Simulated EEG data generation; Classical and phase reset ERP theories; Matlab; Language: English.	University of Oxford	Open source CC BY-SA 4.0 license	[7]
ECG Simulator	NI-DAQmx HW compatible to generate pre-recorded or template-based ECG signals.	ECG; ECG signal generation; Platforms: Windows 10, 8.1, 7; Language: English;	Data Science Automation (DSA)	Commercial (Price not specified)	[8]
Synthetic ECG Signals model	Proposes a math model to generate an artificial synthetic ECG signal based on real.	ECG Signals Generation of synthetic ECG signals Trigonometric functions and Gaussian monopulse.	University of Calabria, Italy	Academic research (Article)	[9]
Simulating brain signals	Synthetic EEG data using neuralbased generative models to enhance SSVEP classification.	EEG signals; Synthetic EEG signals for SSVEP classification; Neural-based generative models like GAN and VAE.	University Durham, UK.	Academic research (Article)	[10]
Generation of Synthetic Biosignals through Timevarying Fourier Series	Suggests a database encompassing synthetic biomedical signals based on real signal planes. Characterized by time-frequency features, intended to mimic authentic behavior.	Focus on cardiographic impedance signals; Uses Fourier series for modeling and synthetic signal generation.	Quantium Medical SL Department	Research document	[11]
EEGLAB	Offers an opensource, interactive environment for EEG data processing within MATLAB.	EEG (partial support for MEG and other); Signal analysis, visualization, preprocessing, source modeling, and statistical. Plugins and add-ons.	University of California San Diego.	Open source	[12]
MNE	Tool tailored for analyzing and visualizing Magnetoencephalography (MEG) and EEG data.	MEG and EEG; Signal analysis, preprocessing, visualization, source reconstruction, and statistics; Includes t/f analysis, ICA, CSP, dSPM, and others.	Collaborative; No central institution	Open source	[13]

Concurrently, platforms like EEGLAB [12] and MNE [13] augment and enrich our work. EEGLAB serves as a signal processing tool, facilitating the import and analysis of the generated signals, thus verifying their integrity. MNE, on the other hand, refines the data formatting and processing, making the generated images resonate more with real EEG data. This is achieved by incorporating MNE-style visuals and leveraging Plotly graphics in Dash to capture user-specific sections.

It's also worth noting that, diverging from certain research propositions rooted in mathematical modeling, this project could be used in generative models powered by neural networks [10]. Our methodology emphasizes the temporal integration of elements categorized in specific frequency bands that synergize to establish distinguishable patterns. This tactic is reminiscent of strategies employed in ECG [9] and the creation of synthetic biosignals [11], grounding them in authentic signal paradigms.

3 EEG Signals and Primary Characteristics

EEG captures brain dynamics through electrodes placed on the scalp. Conventionally, these electrodes are organized according to the 10–20 system or its extension, the 10–10 system, as described by Oostenveld and Praamstra [14]. In specific circumstances, electrodes can be positioned on the cerebral cortex, termed ECoG, or intracranially implanted. This approach yields less filtered, localized, and higher quality data.

Nonetheless, being invasive entails greater associated risks. Both scalp EEG and intracranial signals are assessed for discernible patterns like epileptic spikes and ongoing background activity [15].

3.1 Waves

In EEG recordings, the potential difference between two electrodes is termed a wave. These shifts in cerebral electrical activity are identified as patterns [6]. Proper EEG interpretation necessitates distinguishing between normal and abnormal characteristics [16].

Sharp Wave, Spike, Spike-Slow Wave, and Sharp Wave-Slow Wave Complexes:

- Commonly referred to as spikes, these are transient waves distinguishable from background activity, lasting between 20 ms to just under 70 ms [2]. Characterized by their high amplitude and sharp morphology, these spikes might represent an event of overly synchronous neuronal discharge [2].
- Sharp waves, on the other hand, are also transient with a duration ranging from more than 70 ms to less than 200 ms, distinguished from background activity by their sharp peak at conventional paper speeds [8]. For its part, the Slow Wave-Point pattern, comprising a combination of sharp wave followed by a slow wave in the EEG, is commonly observed in typical absences or petit mal, but can also manifest in other clinical and epileptological conditions. Sharp waves represent a brief, synchronous

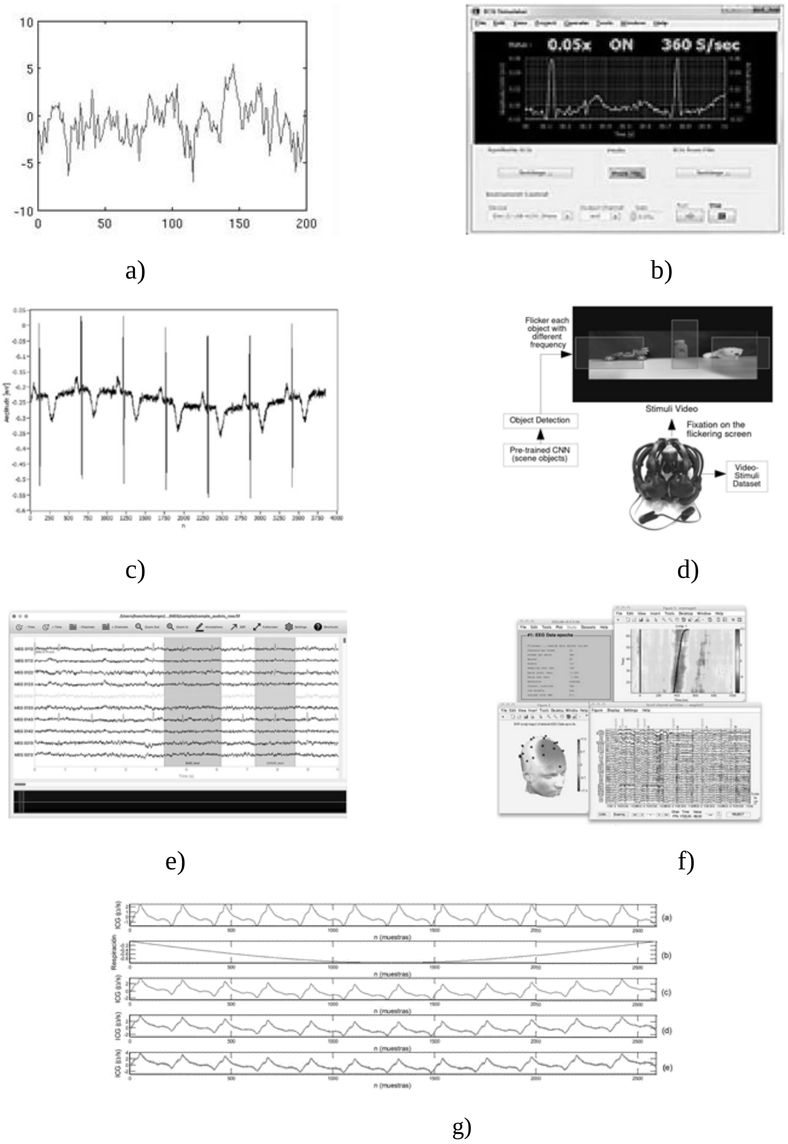


Fig. 1. a) Simulated EEG data generator [7]. b) ECG [8]. c) Model for generating simple synthetic ECG signals [9]. d) Simulating brain signals: creating synthetic EEG data via neural-based generative models for improved SSVEP classification [10]. e) MNE [11]. f) EEGLAB [12]. g) Generation of synthetic biosignals using time varying fourier series [10].

neuronal discharge, whereas slow waves may reflect the propagation of electrical activity through larger cortical circuits [9].

– Conversely, sharp waves are also transient, spanning over 70 ms but less than 200 ms. They stand out from the background activity due to their sharp peak [17]. The Spike-Slow Wave pattern, a sequence of a sharp wave followed by a slow one in the EEG, is often seen in typical absence seizures but can also be evident in other clinical and epileptologic situations. Sharp waves indicate a synchronous, brief neuronal discharge, whereas slow waves might suggest the spread of electrical activity through expansive cortical circuits [2].

– As per Niedermeyer and da Silva, slow waves are low-frequency, low-amplitude electrical discharges in the EEG, enduring typically between 200 and 500 milliseconds [2]. Although they might occasionally overlap with sharp waves, they're chiefly defined as waves persisting over 200 ms [16]. Morphologically, slow waves exhibit a variable amplitude and a gentler waveform when contrasted with sharp waves. Notably, slow waves can correspond with the synchronized activity of neuron groups, reflecting slow depolarization processes and cortical spread. Such waves are observed in diverse clinical and epileptologic states, including deep sleep and specific seizure disorders [2].

Fig. 2, showcases generalized interictal epileptiform discharges in EEG signals, underscoring the previously discussed features. The depicted complexes have a pronounced amplitude, roughly 200 uV, with the alpha rhythm and background retaining a standard amplitude. Yet, due to the vertical scaling chosen for optimal visualization of epileptiform discharges, the latter might seem of diminished amplitude. The signals originate from an EEG recording of a 16-year-old with a history of absence seizures, even though he presently exhibits no epileptic episodes. Technical specifications of the recording are (LFF 1 Hz, HFF 70 Hz) [17].

Transient Events and Wave Complexes: A complex is typified as "a series of two or more waves with a characteristic or consistently repeated shape, distinct from the background activity" [17].

Complexes can manifest as diphasic, triphasic, or polyphasic waves. Typically, the term denotes a wave with at least three distinctive waveform components. These complexes are identifiable by specific features in a singular EEG channel, less defined than patterns which are determined by additional factors like positioning and dispersion.

A transient event is demarcated as" an individual wave or complex, distinguishable from background activity" [17], marked by its pronounced disruption of the background activity and its duration.

3.2 EEG Frequency Characteristics

Clinical neurophysiology categorizes the EEG's background activity into various rhythmic bands, from the Delta rhythm (0-4 Hz) extending to exceptionally high EEG frequency components, seldom considered in regular clinical assessments [16].

3.2.1 Rhythmic Bands

– **Delta Band (*d*):** Ranging from 0.1 to 4 Hz with amplitudes exceeding 50uV, this band typifies children younger than three months and Phase III of physiological sleep. It predominantly features regular, sinusoidal, or sawtooth-like waveforms.

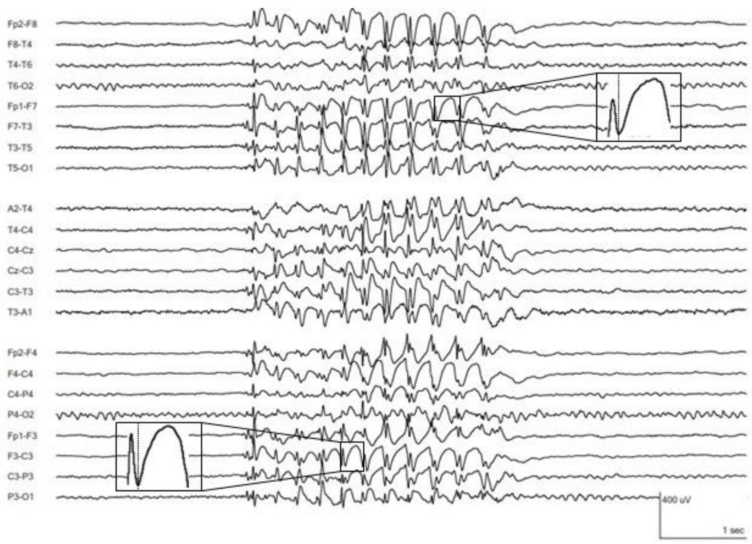


Fig. 2. Generalized interictal epileptiform discharges. Polyspikes precede the initial spike and the ensuing slow wave complex, with subsequent complexes also showcasing initiating polyspikes in individual channels. Edited from [17].

- **Theta Band (*theta*):** Frequencies between 4 and 7 Hz, this band manifests with amplitudes surpassing 40uV and is predominantly fronto-central. Its waves can display various morphologies and are typically low amplitude.
- **Alpha Band (*a*):** Located within 8 and 12 Hz, its amplitude is approximately 15µV, dominantly in the occipital region. A distinguishing feature is its cessation during eyelid opening and intense concentration.
- **Beta Band (*B*):** Characterized by regular waveforms lasting around 50 ms with a sinusoidal shape. As a faster variant of the Alpha rhythm, these waves usually have low amplitudes between 5-10 µV, though they can rise to 15-25 µV. Primarily found in the frontal and central regions, their frequencies are typically between 18-25 Hz, but always above 13 Hz.
- **Gamma Band (*Y*):** This represents the higher EEG frequencies, predominantly between 30-70 Hz.

3.2.2 The 1/f Statistical Behavior of EEG in the Noise Context and Its Types

Through its 1/f statistical behavior, EEG has elucidated how cellular discharge microscopic rules and synaptic activity result in a complex system spread across various temporal scales. The inverse correlation between oscillation classes and the extent of neuronal engagement offers valuable insights into the brain's large-scale, long-term operations.

A Fourier analysis, yielding a power spectrum across frequencies, presents a straight line on a log-log chart where the density logarithm is plotted against the EEG frequency logarithm, suggesting scale-free systems. This relationship is articulated as A ≈ 1/fa, where A symbolizes the amplitude (square root of power) and a is an exponent. This infers that the EEG mirrors the brain's internal noise, generated by both its active and passive components.

However, the 'one over f' power spectrum noise, or 'pink noise', is peculiar. It is essential to recognize that the mean frequencies of adjacent oscillatory groups are not integers relative to each other, making synchronization challenging and resulting in metastable or transient dynamics.

The log-log linear relationship gets disrupted below 2 Hz, possibly attributed in part to the high-pass filtering of the amplifiers utilized. Yet, extensive scalp recordings affirm a power-scaling behavior across all tested frequencies, lengthening the 1/f line's temporal scale past a minute. The EEG introduces three primary noise types:

– **Pink Noise:** Its power spectrum adheres to a 1/f relation, positioned between white and brown noise concerning predictability.
– **White Noise:** Exhibits no correlation between frequency bands, maintaining consistent power density across a limited frequency range. Its spectrum is flat, represented mathematically as 1/f0.
– **Brown Noise (Brownian Noise):** Pertaining to Brownian motion, this noise's power density diminishes with frequency (1/f2) quicker than pink noise. It's randomized over extended intervals but displays strong correlations over shorter spans.

The cerebral cortex, owing to its intricate architecture, emanates the most intricate noise recognized in physics. A pivotal query is the brain's rationale behind generating such intricate noise.

Several theories postulate that the brain oscillators aren't autonomous. Identical neurons and neuronal clusters orchestrate all rhythms. Oscillators at the cerebral level aren't merely swayed by noise; they might be spawning self-regulated collective patterns that sequentially influence the behavior of their constituent neurons [18].

4 Methodology

Over recent decades, the domain of Electroencephalography (EEG) has been intensely scrutinized, advancing the comprehension and characterization of cerebral signals. This progress has instigated the formulation of assorted tools and methodologies for the simulation and scrutiny of EEG data, particularly salient in scenarios where acquiring authentic signals is challenging or restricted.

Electroencephalographic (EEG) waves, stemming from cerebral electrical activity, are represented as voltage discrepancies between two electrodes. These transient patterns, termed waves, offer invaluable insights into cerebral dynamics. While the developed code in this project relies on established neurophysiological and mathematical principles, it is imperative to emphasize the balance between precision and realism in simulations. Inherent in any simulation is the abstraction from reality, which may not fully encapsulate the intricacies found in genuine EEG recordings.

Algorithm 1. EEG Signal Generation with Frequency Bands and Noise Integration.

```
Input: None
Output: eeg_signal (synthesized EEG signal)
    1: Enumerate EEG frequency bands.
    These bands denote specific EEG frequency delineations.
        1.1: delta_band ← [0, 4]
        Establish frequency range corresponding to deep sleep.
        1.2: theta_band ← [4, 8]
        Identify frequency range associated with relaxation and meditative states.
        1.3: alpha_band ← [8, 12]
        Denote frequency range typically correlated with relaxation and absence of visual stimuli.
        1.4: beta_band ← [12, 30]
        Demarcate frequency range linked to active cognition and focus.
        1.5: gamma_band ← [30, 70]
        Pinpoint frequency range affiliated with perceptual processes and cognizance.
    2: Establish signal parameters.
    These parameters ascertain signal duration, sampling rate, and     temporal vector.
        2.1: duration ← 10 sec
        2.2: sampling_freq ← 500 Hz
        2.3: num_samples ← duration × sampling_freq
        2.4: time ← array spanning from 0 to duration, incremented by 1/ sampling_freq
    3: Initialize eeg_signal with zero-valued array.
    This array serves as the foundational canvas for impending band and noise superpositions.
    4: generate_band(freq_range, amplitude, duration, sampling_freq) function :
    Constructs a sinusoidal waveform with frequency and phase values chosen from a given range.
        4.1: frequency ← random selection within freq_range
        4.2: phase ← random selection between 0 and 2*pi
        4.3: Return amplitude × sin (2*pi × frequency × time + phase)
    5: Incorporate variegated amplitudes from delta_band into eeg_signal
    This procedure amalgamates multiple sinusoidal signals onto the foundational signal.
    6: Construct and standardize pink_noise
    Pink_noise is noise characterized by a power spectrum that diminishes with frequency.
        6.1: pink_noise ← accumulation of random Gaussian-distributed values.
        6.2: eeg_signal ← eeg_signal + pink_noise
    7: Produce and regulate white_noise.
    White_noise manifests uniform intensity across disparate frequencies.
        7.1: white_noise ← random Gaussian-distributed values.
        7.2: eeg_signal ← eeg_signal + white_noise
    8: Synthesize and modulate brown_noise.
    Brown_noise (or Brownian noise) exhibits correlations between time-series values.
        8.1: brown_noise ← cumulative random Gaussian-distributed values.
        8.2: eeg_signal ← eeg_signal + brown_noise
    9: Standardize eeg_signal
    Adapt the amplitude of eeg_signal to fit within a predetermined range.
End of Algorithm
```

Fig. 3. Pseudocode illustrates the synthesis of an EEG signal through the combination of varied frequency bands, notably Delta, and three noise types: pink, white, and brown. The culminating signal undergoes normalization to maintain a specified amplitude.

As we move forward, collaborative validation with esteemed EEG specialists becomes pivotal. As the project transitions into a public phase, this collaboration will facilitate iterative feedback, ensuring that the simulations retain as much realism and accuracy as possible. This approach underlines the importance of balancing theoretical knowledge with practical insights from experienced professionals in the field.

4.1 Synthesis of EEG Signals

Enriching our proficiency in signal analysis and comprehension necessitates tools capable of simulating EEG data, mirroring genuine patterns. Such simulations furnish avenues for testing nascent theories, affirming analysis techniques, and refining real EEG interpretations.

This segment illuminates the methodology underpinning the synthetic generation of EEG signals, emphasizing their importance, simulation techniques, and plausible applications. Within this segment, we elucidate techniques employed for the synthetic simulation of Electroencephalogram (EEG) signals, leveraging mathematical functions and established Python libraries. The veracity of these simulated signals vis-`a-vis their genuine counterparts is also appraised.

4.1.1 Simulation of EEG Frequency Bands

EEG signals comprise various frequency bands, each indicative of distinct neural activities and states of consciousness. It is crucial to note that the simulations of these frequency bands are grounded in the information elaborated upon in Section 3.2. Each band is representative of specific neural patterns and consciousness states, as evidenced in prior studies [16, 18].

– **Delta Band:** Predominantly observed during profound sleep-in adults, these waves are contrived using sine waves oscillating between 0 and 4 Hz.
– **Theta Band:** Largely detected during phases of shallow sleep and contemplative states, simulated via sine waves fluctuating between 4 and 7 Hz.
– **Alpha Band:** Customarily linked to tranquility, these waves are simulated within the 8 to 12 Hz frequency range.
– **Beta Band:** Emblematic of vigilant states, these waves are derived from frequencies surpassing 13 Hz.
– **Gamma Band:** Pertaining to cognition and alertness, gamma oscillations are simulated within a 30 to 70 Hz range.

Central to this simulation is the generate-band () function from Algorithm 1, which facilitates sine wave creation based on stipulated parameters, encompassing frequency bands, amplitude, span, noise, and more.

4.1.2 Noise Integration

Given that authentic EEG is pervaded by multiple noise sources, it is essential to integrate noise within the simulations becomes.

– **White Noise:** Defined by its unwavering spectral density across all frequencies, it’s derived from the np.random.randn() function.

Algorithm 2. Synthesis of Spike-Wave Cluster in EEG Signals.

```
IIInput: sfreq (sampling rate), group_duration (optional, default 3 seconds)
Output: group_data (synthesized spike-wave cluster data)
    1: generate_spike(amplitude, duration, sfreq) function:
        1.1: Compute n_samples ← int(duration × sfreq)
        1.2: Formulate spike employing a Gaussian function with a standard deviation of
        n_samples/7
        1.3: Return amplitude × spike / max(spike)
    2: generate_slow_wave(amplitude_wave, duration, sfreq) function:
        2.1: Compute n_samples ← int(duration × sfreq)
        2.2: Configure time ← array spanning from 0 to n_samples, incremented by 1/sfreq
        2.3: Formulate slow_wave via a sinusoidal function with a 2 Hz frequency (Delta wave)
        2.4: Return amplitude_wave × slow_wave
    3: Initialize amplitude_spike and duration_spike with random values
    4: Initialize amplitude_wave and duration_wave with random values
    5: Compute n_samples ← int(group_duration × sfreq)
    6: Initialize group_data with a zero-valued array of size n_samples
    7: Calculate n_spikes using a random value between 9 and 12
    8: Set current_start_index ← 0
    9: For _ in range(n_spikes) execute:
        9.1: Refresh amplitude_spike and duration_spike with random values
        9.2: Fabricate spike employing generate_spike function 9.3: If a random number is below
        0.8, refresh amplitude_wave predicated on amplitude_spike;
        9.4: Refresh duration_wave with a random value
        9.5: Construct slow_wave via generate_slow_wave function
        9.6: If current_start_index + spike length + slow_wave length is \(\leq\) group_data length:
          9.6.1: Append spike to group_data at current position
          9.6.2: Append slow_wave to group_data at the subsequent position
          9.6.3: Update current_start_index
    10: Return group_data
End of Algorithm
```

Fig. 4. This algorithm emulates the emergence of spike-wave clusters, a phenomenon recurrently observed within EEG signals. Individual spikes and slow waves are synthesized and amalgamated, resulting in a group pattern.

– **Pink Noise:** Exhibiting a frequency-dependent diminishing power spectrum, it's the culmination of aggregated white noise.

– **Brown Noise (or Brownian Noise):** Symbolizing the integrated accumulation of white noise, it portrays stochastic fluctuations dependent on time.

Subsequently, Fig. 3 illustrates a code for generating synthetic EEG signals by integrating various frequency bands with noise. For those unfamiliar with coding paradigms, this code showcases the emulation of an authentic EEG signal, encapsulating potential "interferences" or inherent noises characteristic of authentic measurements.

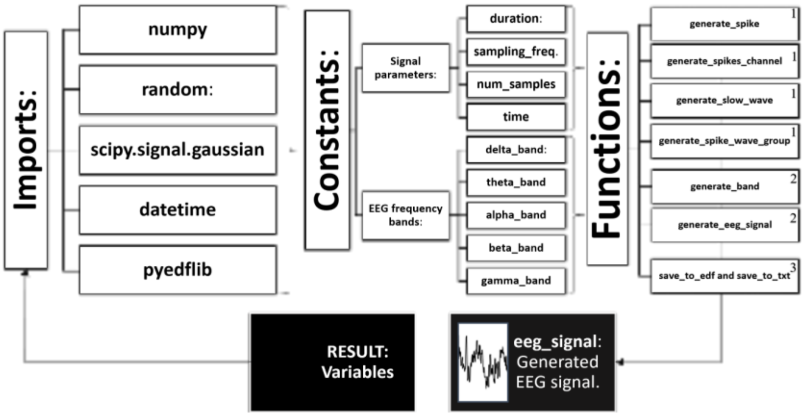


Fig. 5. An illustrative schematic of the signal-generator.py script.

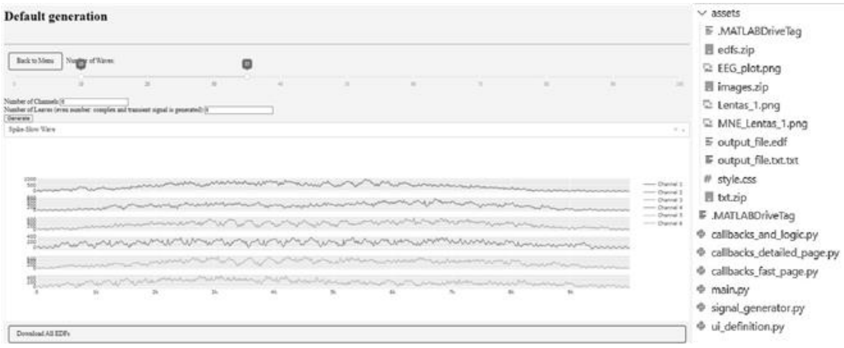


Fig. 6. Results stemming from the default generation paradigm. a) Generation interface showcasing Dash indicators. b) Real-time visualization of file generation within the assets directory.

4.1.3 Emulation of Distinctive EEG Phenomena

Recognizing and emulating distinctive EEG patterns, especially those concomitants with clinical manifestations, is paramount. The functions generatespike(), generate-slow-wave(), and generate-spike-wave-group() are indispensable for simulating spike waves, slow waves, and spike-slow wave clusters, respectively, in alignment with the theory previously delineated under ”EEG Signals and Key Features.”

Consequently, Fig. 4 emphasizes the emulation of a distinctive EEG phenomenon: the spike-wave cluster. This pattern is ubiquitously observed in EEG, particularly in certain disorders. The code synthetically renders this pattern, facilitating training and research endeavors.

4.2 EEG Synthetic Signal Generator

The signal generator module is quintessential in synthesizing EEG datasets. Previously delineated functions enabled the generation of EEG signals, each harboring unique characteristic.

For a detailed understanding, it is crucial to refer to the theoretical descriptions of these waveforms, definitions of EEG frequency bands, and a comprehensive explanation of the generating functions provided in Section 3.2.

The software design emphasizes three core elements—modularity, scalability, and consistency—essential for a robust and reliable implementation. These elements are manifest in the tool's architecture, which segregates specific functionalities into distinct modules: user interface (UI) definition, signal generation, and callback management. Fig. 5 provides a schematic representation of the script used for signal generation, highlighting the modular structure that incorporates essential libraries, constant parameters, and functions to produce a coherent and customizable EEG signal output.

The Python script outlined above and visualized in Fig. 5 is designed with a clear separation of concerns, allowing for independent development, testing, and maintenance of each component. The 'imports' section lists the essential libraries that provide the mathematical and signal processing functionalities required to generate EEG signals.

The 'constants' delineate the signal parameters and EEG frequency bands, which are fundamental to simulating the diverse aspects of EEG signals accurately. The 'functions' are a suite of tools developed to construct the EEG signal, incorporating various waveform patterns, such as spikes, slow waves, and their combinations, thus simulating complex neurological phenomena.

This structure not only aids in creating a clear and maintainable codebase but also ensures that the signal generation process is transparent and adaptable to changes in requirements or enhancements in EEG signal research.

4.3 Application Overview

Situated within the realm of EEG research, this endeavor is oriented towards the synthetic generation of EEG signals, manifesting distinct morphologies such as spike-waves, slow-waves, and spike-slow wave amalgamations. Engineered in Python, leveraging Dash, the application proffers two predominant operational modes:

– **Default Generation:** Here, users primarily define parameters like channel count for visualization, wave intervals per channel, and desired signal sheet count.

As depicted in Fig. 6, selection tools are available for waveform types, wave count per channel, sheet count (considering it generates complex and transient signals), and channel count. Additionally, an export functionality allows formats including ".txt", ".edf", and ".png". An integrated Plotly visualization offers real-time insights before exportation.

– **Detailed Generation:** This mode endows users with intricate control over generation parameters, as visualized in Fig. 7. Parameters encompass waveform amplitude, duration, sampling rate, and noise infusion.

Users can refine parameters: waveform selection, amplitude range in µV, signal duration in seconds, sampling frequency, and noise integration.

For compounded EEG signals, users have the flexibility to define frequency bands such as delta, theta, alpha, beta, and gamma, inclusive of noise conditions and EEG

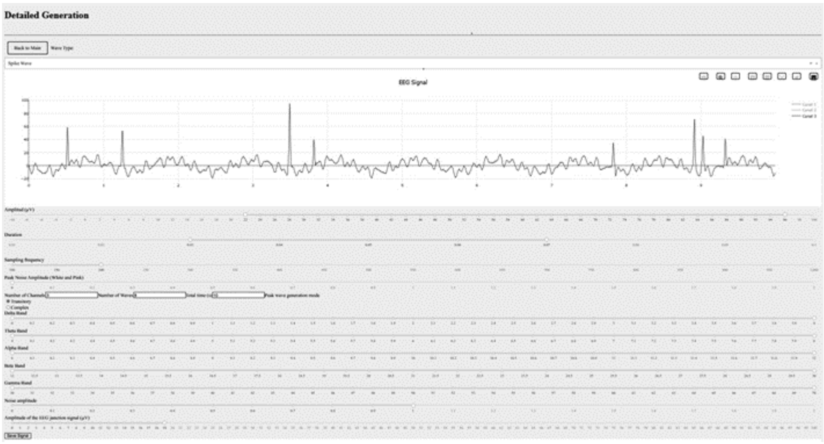
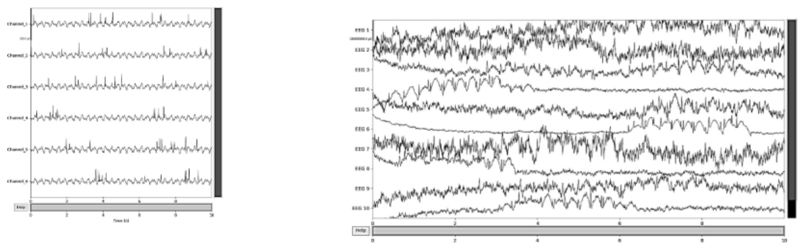


Fig. 7. Signal customization interface juxtaposed with a preliminary visualization of resultant signals.



(a) (b)

Fig. 8. Sample visual outputs in ".png" format, generated by the application. Visualizations encompass a) spike-wave formations, b) spike-slow wave configurations, rendered in an optimized MNE format for enhanced visualization.

amplitude in µV. Visual feedback is facilitated via an interactive Plotly dashboard, delineating both aggregated and channel-specific views, complemented by MNE formatted visual outputs for user convenience.

A hallmark feature of this platform is its adeptness in exporting the synthesized signals in a plethora of formats, namely ".edf", ".png", and ".txt". Examples of images generated by the application are shown in Fig. 8 below.

4.1.4 Evaluation

EEGLAB, a prominent tool in the neuroscience domain, offers an extensive range of functionalities for EEG processing. To ascertain the compatibility and usability of the synthetically generated signals with this tool, EEGLAB was employed for rigorous testing. Fig. 9 provides a comprehensive visual representation of how the signals, generated by our tool, integrate and perform within the EEGLAB environment.

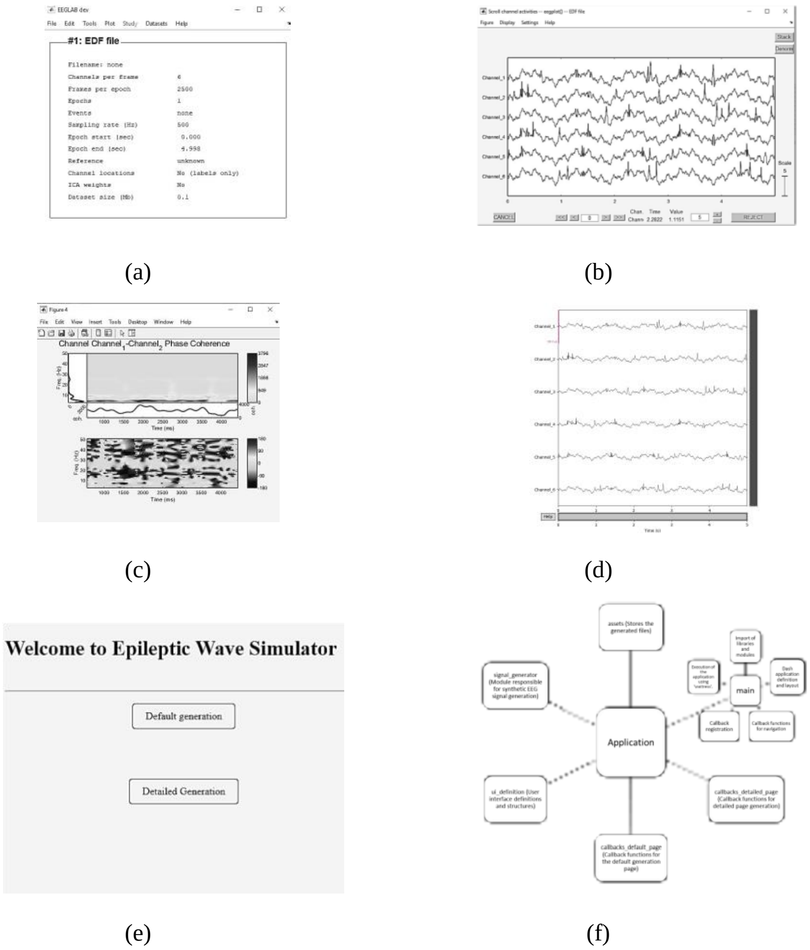


Fig. 9. a) Integration of the ".edf" file, synthesized within our application, into MATLAB's EEGLAB. b) Temporal channel display within EEGLAB. c) Validation of signal authenticity via coherence analysis in EEGLAB. d) Illustration of spike waveforms within a 6-second viewing window. e) Initial snapshot of the application, spotlighting both rapid and detailed generation facets. f) Conceptual diagram underlining the application's modular architecture.

In Fig. 9 the initial three illustrations (a-c) are derived from EEGLAB, showcasing the integration and analysis capabilities of this software with the signals generated by the "EEG signal generation tool for epiloptogenic morphologies". These sections demonstrate how the ".edf" file, synthesized by our application, is incorporated into EEGLAB followed by the display of temporal channel analyses and the validation of signal authenticity via coherence analysis.

Conversely, illustrations (d-f) represent various facets of the "EEG Synthetic Signal Generator for Epiloptogenic Morphologies" application. These include the portrayal of spike waveforms within a specific time frame, an initial snapshot of the application interface, and a conceptual diagram that delineates its modular structure. Together,

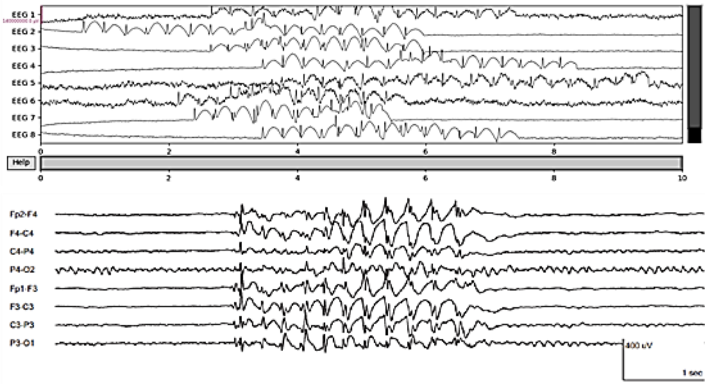


Fig. 10. A Comparative Display of Synthetically Generated EEG Signal (top) and EEG Images fragments from John M. Stern's "Atlas of EEG Patterns".

these elements highlight the application's versatility in EEG signal generation and its compatibility with EEG processing tools like EEGLAB. This integration underscores the potential of the tool to provide EEG signals with valuable information for processing, analysis and study, especially in the context of epiloptogenic morphologies.

4.2 Signal Generation Precision

Upon juxtaposition of signals exhibited within our application against those within EEGLAB, there emerges a notable uniformity. Such congruence predicates that resultant analyses on the signal are both valid and analogous across diverse platforms. Nonetheless, an exhaustive similarity analysis remains pending. Leveraging externalized tools, exemplified by EEGLAB, validates the simulator's congruence and compatibility.

Such synergies pave the way to amalgamate the proficiencies inherent in both platforms, ensuring that the system interoperates seamlessly within industry standards. This facilitates integration with various platforms, thereby spawning datasets that catalyze algorithmic development in EEG signal analysis. Fig. 10 illustrates the tool's ability to reproduce realistic EEG signal patterns, comparing a synthetically generated signal with a real.

4.3 Future Work

The next phase of development for this project is to undergo meticulous scrutiny by the medical fraternity. Such peer reviews are indispensable for affirming the authenticity of the generated signals and can unearth potential enhancements to the tool. Continuous feedback from medical experts remains vital to synchronize the tool with contemporary trends and revelations within the electroencephalography domain.

This process will not only validate the precision of the signal generation but also open avenues for its application in medical research and diagnostics. The goal is to establish the tool as a reliable resource for generating EEG data, particularly in areas where real data may be limited or inaccessible.

5 Conclusions

Electroencephalography (EEG) has steadfastly remained an instrumental paradigm in discerning cerebral dynamics. The meteoric advancements in analytical methodologies, coupled with integrated toolsets, have exponentially magnified EEG's pertinence. This endeavor endeavors to bridge the lacuna in synthetic EEG signal generation, facilitating the synthesis of waveforms mirroring genuine EEG morphologies. By harnessing mathematical paradigms and Python-centric programming, this tool has been meticulously engineered to simulate an array of EEG attributes, ranging from diverse frequency bands to specific events like spike waveforms.

An authentic EEG signal simulation mandates the infusion of noise, thereby ensuring data representation fidelity in real-world scenarios. The modular code architecture accentuates the project's adaptability and scalability, preemptively addressing prospective advancements in biosignal research. Its innate compatibility with renowned tools, such as EEGLAB, solidifies its prospective role in multi-platform integrations and expansive collaborations.

Importantly, the generation of synthetic EEG signals offers significant benefits, particularly in the realm of machine learning. Tools such as the one developed in this project contribute significantly to the training of intelligent systems, which require large datasets for effective learning. The synthetic signals generated can provide a rich, controlled variety of data, crucial for training robust machine learning models, especially in applications where real EEG data might be scarce or difficult to obtain.

In essence, while this initiative accentuates and augments the offerings of pre-existing platforms, it concurrently introduces a distinctive suite of features, poised to revolutionize EEG signal synthesis and simulation realms. Future directions encompass presenting this project to the medical domain, soliciting invaluable feedback to enhance signal precision and utility.

Potential extensions could also include a wide variety of default configurations tailored to medical requirements. This application, with its multifaceted offerings, could seamlessly integrate into the toolkit of EEG researchers, propelling the realm of EEG signal synthesis and simulations to unprecedented heights.

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