TECHNICAL NOTE

EEGg: Generating Synthetic EEG Signals in Matlab Environment

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Abstract

Purpose: Utilizing Electroencephalogram (EEG) is more than at any time in history, therefore we have introduced an open-source MATLAB function to provide simulated EEG which is as equivalent as viable to empirical EEG in a user-friendly way with ground truth that is not accessible in real EEG records.

This function should be versatile due to the requirements such as the number and orientation of sources, various noises, mode of activation function, and different anatomical structures.

Materials and Methods: We indicate all phases, modes, and formulas which constitute EEGg, EEG generator. This function supports selecting main sources locations and orientation, choosing SNR with white Gaussian noise, electrode numbers, and mode of activation functions. Also, users have the option to use automatic or partly automatic, or fully automatic EEG construction in EEGg. This function is ready to use at https://github.com/Avayekta/EEG.

Results: EEGg is designed with several parameters that users have chosen. Hence, users can choose different variables to inspect the time and frequency aspects of synthetic EEG.

Conclusion: EEGg is a multi-purpose and comprehensive function to mimic EEG but with ground-truth EEG data and adjustable parameters.

Keywords: Simulated Neuro-Electrical Data; Ground-Truth Networks; Electroencephalography; Simulation; Evaluation; Brain-Computer Interface.

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1. Introduction

In biomedical, one of the most popular ways to observe brain activity is Electroencephalogram (EEG) [1]. EEG has a temporal resolution in the order of milliseconds, moreover, it is relatively cost-efficient, non-invasive, portable, and available [2]. Brain activity imaging such as EEG can be used to: i) feedback control for medical rehabilitation devices and help to adjust rehabilitation strategies, ii) source localization, iii) to map the regions and networks involved in focal epileptic seizure generation, iv) for detecting brain wave signals that are characteristic of delirium [3], v) useful in brain-computer interface applications [4], vi) movements and pre-movements EEG detection [5], and vii) medical diagnosis [6]. However, a spatial resolution of EEG is insufficient since a single electrode records the normal activity of up to a billion neurons, and likely never below 10 million neurons [7]. A great number of strategies have been created over these years to extract characteristics from the recorded EEG. Although there was not any easy access platform for validating their accuracy, one major trouble in creating strategies for EEG investigations is that no ground truth depicts the precise brain activities, also no procedure exists to calculate such reference estimation. In addition, the gold standard for evaluating spatial analysis of EEG is a synchronous record of functional Magnetic Resonance Imaging (fMRI) and EEG which is expensive, immobile, and time-consuming. Therefore, there is not any convenient platform for analyzing source localization methods such as Linearly Constrained Minimum Variance (LCMV), minimum norm, Low-Resolution Electromagnetic Tomographic Analysis (LORETA), Focal Underdetermined System Solver (FOCUSS), and recursive Multiple Signal Classification (MUSIC) [8, 9] unless we generate pseudo-EEG in a platform which the user can define location and orientation of sources and their exact electric signal.

Pseudo-EEG is called toy data. This simulated EEG has frequently been utilized to test methods. The preliminary version of platforms for simulating EEG was constructed by linear combinations of several independent signals without any practical brain source locations. However, more advanced versions have included spatial conditions to the recreation [10-13], but still, they are neither user-friendly nor free for the public. Another toolbox named SIFT, which is the shortening of Source Information Flow Toolbox is an available platform and one of its features is providing ground truth. It is an EEGLAB-dependent simulation toolbox [14]. This feature, however, is confined in limited data construction of EEG [15]. Also, the phantom head device was invented which considers the effects of the subject motions on brain sources but this invention is not versatile for extended applications, moreover, its sharing is not as easy as software programs [16].

SEREEGA is the contraction of the first letters of these words: Simulated Event-Related EEG. Therefore, it is obvious that it generates an event-related EEG, beginning with a forward model (from source to EEG) with determining locations and orientations for sources but five choices for activation function, followed by five prepared lead fields and resulting in EEG which is the projection of these sources on scalp [17]. SEREEGA can be introduced as an open-access MATLAB Toolbox. In addition, SEED-G is made up of the initial letters of these words Simulated EEG Data Generator for Testing Connectivity Algorithms, taking a closer look at its name, it is evident that the produced EEG is custom-made for connectivity approaches. This toolbox is public and user-friendly, too. This platform enables users to manipulate time series and connectivity characteristics. Adjustable properties are the length of EEG records, Signal-Noise Ratio (SNR), external noise, and the number of brain sources [18].

SimMEEG is a public toolbox that was introduced to imitate simple and complex interactions between sources that can be parameterized by users. Users can characterize some signal variations (e.g., frequency, amplitude, phase interactions, and phase-amplitude correlations) to simulate brain signals that approximate Electroencephalography (EEG) and Magnetoencephalography (MEG) signals. The ground truth is untold in human-recorded EEG/MEG data because of the ill-posed inverse problem, thus data with ground truths can be practical to confirm the analysis approached prior to use it in analyzing human-recorded EEG/MEG. So the intent for releasing the SimSignals was to mimic EEG/MEG signals by users' choices to evaluate (having known ground truths) their analysis. Therefore, researchers can be more confident about the reported conclusions of bio-recorded EEG/MEG data [19]. Although, the parameters of this project are limited to frequency, amplitude, phase interactions, and phase-amplitude correlations. Also, you cannot customize the other variables.

SimBCI is another free software package that is capable of synthesizing EEG but only with a few tunable parameters such as head model. This package added spatial filters for various tests [20].

Despite significant progress in previous EEG simulations, there was a lack of some critical features which are:

i. Imposing the user's lead field

ii. Defining specific orientation that users need for each source

iii. Including internal noise which is inevitable in recording as their origins are normal background brain functions (background noise)

iv. Various external noise

v. Enabling any activation function for sources

vi. Multi-mode for sensor configuration

vii. Full automatic, semi-auto, and full manual modes for EEG production

All of these seven options have been added to EEGg, moreover, it is free, MATLAB function is easy to use, ground-truth, and upgradeable.

2. Materials and Methods

2.1. Architecture and Functionality

EEGg is a MATLAB function that asks the user for assigning inputs to specialize pseudo-EEG that is going to be generated. Inputs include the number of dominant active/background active/inactive sources, orientation, the activation function of each source, and the number of electrodes in the recording procedure. Moreover, a user can define the duration of EEG, sampling frequency ratio, and rate of attenuation for all background sources. Also, EEGg can add white Gaussian noise with a variety of SNR, confine Euclidean distance between two background noises to a definite number, and calculate the rank of the EEG output matrix by definable tolerance.

2.1.1. Principles of EEG Simulation

In order to simulate the EEG matrix, we are going to talk about the steps taken:

i. lead field computation

ii. Source Selection and Orientation

iii. Number of channels in recording EEG

iv. Signal characteristics

v. Equations for creating a pseudo-EEG matrix

2.1.2. Lead Field Computation

To simulate signals that have been transmitted from the source level to the sensor level, EEGg requires an interface matrix called a Lead field matrix [21]. Therefore, initiating the forward problem by importing MRI imaging. FieldTrip can be used to generate a lead field matrix from our head model. The computation of the Lead field from MRI by FieldTrip consists of:

I. Creating mesh: segmentation of geometrical features of MRI

II. Creating head model: combine mesh with tissue connectivity

III. Creating source model: allocating positions to sources in gray matter

IV. Handling sensors: defining the number of sensors and their locations

A lead field not only does consist of propagation coefficients that illustrate the relation of any electrode and source, but it also contains information about how sources' signals will scale through the recording EEG.

As of now, EEGg backs two modes to utilize a lead field: it could import an available, pre-produced lead field, or the user's exclusive lead field can be imported as a manual lead field. Right now, four pre-generated lead fields are ready to use. Each of these lead fields includes 2052 sources spaced in an almost 1×1×1 mm grid and the difference is in electrode numbers (16, 32, 64, and 128).

2.1.3. Source Selection and Orientation

EEGg enabled us to choose the number of dominant sources and background noises as input. After that, EEGg will ask about the position of these sources. Additionally, the magnitude of attenuation is in your hand. Therefore, you can tune it to resemble your intended EEG.

We have used perpendicular orientation for the default orientations of sources, however, orientations can be modified by the user. These pre-defined orientations relate a 3-component number (x,y,z) to each source of the brain. For instance, simulating the brain by 2052 sources including perpendicular orientation matrix with 2052×3 dimension. For manual allocation of direction, first, you will define the number of sources that you are changing their orientations as input for EEGg then regarding your input, EEGg will ask for source positions and the orientations in radian.

2.1.4. Number of Channels in Recording EEG

EEGg is compatible with 4 common electrode arrangements, including 16, 32, 64, and 128 sensors. Each of these arrangements has its sensor position, source position, and lead field for each source are accessible in EEGg.

2.1.5. Signal Characteristics

Generally, EEGg has two modes of activation signal for sources: sinusoidal and independent components of real EEG

Sinusoidal mode: if you have chosen this mode, EEGg asks you to type the frequency of the sinusoidal source signal in Hertz (Hz). As a result, your activation function is Equation 1.

$$af_{sin} = A\sin(2\pi f) \tag{1}$$

Independent component of real EEG: we have datasets that include ICA components of real acquisition of EEG with movement tasks. EEGg uses this mode for background noises either, but by multiplying attenuation. If this mode is chosen by the user, each source has its special signal. In other words, each source will produce its unique signal. EEGg includes almost 3000 exclusive signals.

2.1.6. Equations for Creating a Pseudo-EEG Matrix

EEGg structure for producing EEG will differ according to user demands, although the equation held in common is Equation 2.

First of all, EEGg will pose a mode of activation signal to each of the user's dominant sources by considering the pre-defined or manual orientation. The same process will go on to background sources by joining these two EEGs. Subsequently, our pseudo-EEG will occur.

$$eeg_n = eeg_{n-1} + LF(source_n) \times ori^T(source_n) \times att \times af \tag{2}$$

eeg_n: *eeg by considering source 1 to n*
eeg_{n-1}: *eeg by considering source 1 to n − 1*
$LF(source_n)$: *lead field matrix for* $source_n$
$ori^T(source_n)$: *transpose of orientation matrix for* $source_n$
af: *activation function signal that each source generates*

2.2. Automatic Mode

Our automatic mode is a straightforward production of EEG. This mode has a perpendicular orientation for sources and automatically will produce a full-rank EEG matrix with background noise. The only parameters that should be defined are the number of dominant sources and the mode of the activation signal.

2.3. Code

2.3.1. EEGg Description

```
EEGg sample generation:
[eeg,rtbg,rmain,orimainIDX,afbs,mainsourceIDX,afms,bsIDX,bsoriIDX,grid] =
EEGg(Fs,n_channel,t_end,n,na,nb,att,toler,range,report,NOISE_SNR,af,normaliz)
Inputs:
Fs: sampling frequency ratio of EEG
n_channel: number of EEG channels (acceptable values are 16, 32, 64, and 128)
n_t: duration of EEG (in seconds)
n: number of sources that you want to have specific NOT perpendicular orientations
na: number of main active sources
nb: number of background noises
att: ratio of attenuation
toler: The EEG may be generated by some element of small absolute value. So toler
```

```
will calculate the rank of the matrix by tolerance of 'toler' value.
**if you do not have any idea you can choose '-1' for toler. So the default value will be 'toler=0.1'**
range: limit the difference between two background sources. If you want default mode, insert range=-1. The default value is range=30.
report: It is a logical value (0 or 1). If you choose 1, you will have a report of the sources' index, activation functions, and orientations.
NOISE_SNR: if you want to add white Gaussian noise, import the SNR. If you do not, insert NOISE_SNR =-1.
af: define your activation function mode ('ICA' or 'sin') you want ICA component of real EEG or sin wave as signals of your sources.
normaliz: normalization is a logical variable if you insert 1, it will normalize the source signal and if you press 0, it will utilize the real value
```

```
Outputs:
eeg: eeg matrix that has been produced
rtbg: rank of eeg with toler
rmain: rank of produced EEG
orimainIDX: orientation of main sources
afbs: activation function of background sources
mainsourceIDX: indexes of main sources
afms: activation function of main sources
bsIDX: indexes of background sources
bsoriIDX: orientation of background sources
grid: this output includes the position of sources, their lead fields, and electrode labels.
```

2.3.2. EEGg Sample Code

```
Sample 1:
Fs=512;n_channel=64;t_end=20;n=0;na=1;nb=0;att=20;toler=-1;lim=-1;range=-1; report=1;NOISE_SNR=-1;af='sin';normaliz=-1;
Sample 2:
Fs=512;n_channel=64;t_end=20;n=0;na=4;nb=0;att=20;toler=-1;lim=-1;range=-1; report=1;NOISE_SNR=-1;af='ICA';normaliz=-1;
Sample 3:
Fs=512;n_channel=64;t_end=20;n=0;na=1;nb='default';att=20;toler=-1;lim=-1;range=-1; report=1;NOISE_SNR=-1;af='ICA';normaliz=-1;
Call your function:
[eeg,rtbg,rmain,orimainIDX,afbs,mainsourceIDX,afms,bsIDX,bsoriIDX,grid] = EEGg(Fs,n_channel,t_end,n,na,nb,att,toler,range,report,NOISE_SNR,af,normaliz)
```

2.4. Three Dimensions Visualizing

Firstly, we have used fieldtrip for visualization of the brain and the electrode positions in Figure 1. A second purpose is to visualize our main or background sources exclusively and to indicate their orientations in Figure 2. Moreover, the sources alone could be illustrated in Figure 3. Finally, Figure 4 shows the active, background, and inactive sources by distinctive colors. All codes are available at https://github.com/Avayekta/EEG.

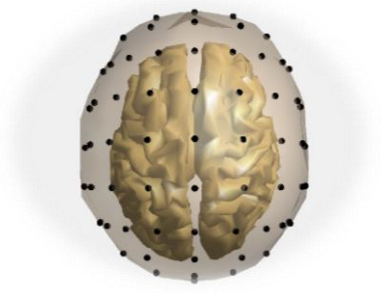

Figure 1. Visualization of the brain and the electrode positions

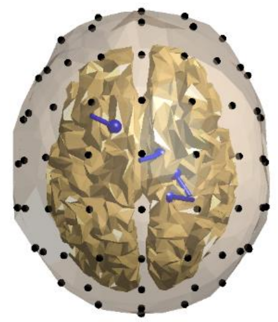

Figure 2. Exclusive visualization of our main or background sources and indicating the orientation

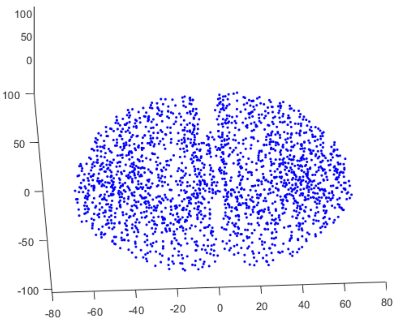

Figure 3. The sources alone could be illustrated

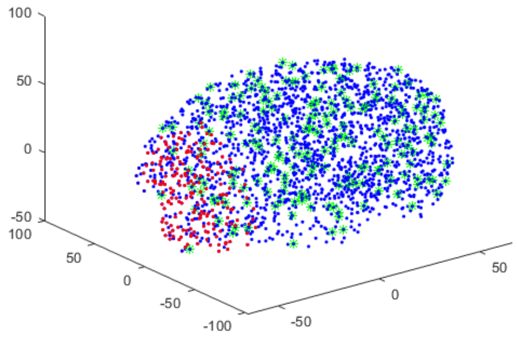

Figure 4. Indicates this distinction between active (red), background (green), and inactive sources by colors

3. Results

The simulated EEG was subjected to several standard analyses such as part1, part2, and part3 which will introduce to indicate their applicability and present the EEG itself. For testing features of EEG, we are going to introduce a MATLAB function named 'reportResult' which is accessible at https://github.com/Avayekta/EEG.

For each raw signal of EEG:

Absolute means of values:

For calculating the absolute means of each row in generated EEG, we sum up all absolute values of the elements and then divide them by the number of elements in each row (Equation 3).

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N}|X_n| \tag{3}$$

$N = Number\ of\ samples$
$|X_n| = Absolute\ value\ of\ EEG\ sample\ in\ n^{th}\ sample$
μ_x = Absolute means of values

Standard deviation:

Calculation of standard deviation is occurred by Equation 4.

$$\sigma_x = \frac{1}{N}\sum_{n=1}^{N}(X_n - \mu_x)^2 \tag{4}$$

$N = Number\ of\ samples$
$X_n = EEG\ sample\ in\ n^{th}\ sample$
$\sigma_x = Standard\ deviation$

Power:

For acquiring the power of a produced EEG, we utilize Equation 5.

$$p = \sum_{n=1}^{N}\|X_n\|^2 \tag{5}$$

$N = Number\ of\ samples$
$X_n = EEG\ sample\ in\ n^{th}\ sample$
$p = Power$

Variance:

Variances are calculated by Equation 6.

$$\sigma_x^2 = \frac{1}{N-1}\sum_{n=1}^{N}(X_n - \mu_x)^2 \tag{6}$$

$N =\ Number\ of\ samples$
$X_n = EEG\ sample\ in\ n^{th}\ sample$
$\sigma_x^2 = Variance$
$\mu_x = Means\ of\ values$

Skewness:

Skewness is calculated by Equation 7.

$$skewness = \frac{\sum_{n=1}^{N}(X_n - \mu_x)^3}{(N-1)\sigma_x^3} \tag{7}$$

$N =\ Number\ of\ samples$
$X_n = EEG\ sample\ in\ n^{th}\ sample$
$\mu_x = Means\ of\ values$
$\sigma_x = Standard\ deviation$

Kurtosis:

Kurtosis is calculated by Equation 8.

$$kurtosis = \frac{\sum_{n=1}^{N}(X_n - \mu_x)^4}{(N-1)\sigma_x^4} - 3 \tag{8}$$

$N =\ Number\ of\ samples$
$X_n = EEG\ sample\ in\ n^{th}\ sample$
$\mu_x = Means\ of\ values$
$\sigma_x = Standard\ deviation$

The frequency domain of each EEG generated is going to be evaluated with the assistance of the fast Fourier transform. As we have five kinds of EEG signals and each of them has its frequency domain, namely, Delta between 0.5 and 4 Hz, Theta is between 4 and 8 Hz, Alpha is between 8 and 12 Hz, Beta is between 12 and 35 Hz, and Gamma is above 35 Hz [22]. We consider Gamma waves from 35 Hz to 100 Hz. These frequencies from 0 to 100 Hz are the criteria for EEGg acceptable frequency [23].

The conditions of generating pseudo-EEG time series with:

- 20 seconds EEG signal with 512 Hz frequency sample
- 64 channel number

- All sources have the perpendicular orientation
- 1, 3, 5, and 10 main sources
- Manual background noise (20 sources) or automatic background noise
- Attenuation coefficient of background noise (attenuation=10, 50, 100)
- No noise, white noise with predefined SNR=10, and SNR=20

3.1. Properties of EEGg in Different Conditions

Part 1: Attenuation coefficient =10, 50, 100-- 1, 3, 5, and 10 main sources, 'auto background'

In the part 1 condition, by inspecting Figure 5 we understood that:

From an overall perspective, it is clear from the evidence in Figure 5 that regardless of the number of sources standard deviation, variance and power have risen if the attenuations rise. In addition, kurtosis stays constant. Whereas, acceptable frequencies drop when attenuations rise. Also, the skewness fluctuates in limited bonds.

- Acceptable frequency range: in Figure 5, it is apparent that the number of main sources has not had any effect on the acceptable frequency rate which appears in constructed EEG. Although, increasing the attenuation rate reduces the acceptable rate in this state.

- The means of absolute value in produced EEG was not affected by the number of main sources significantly. The growth in means of absolute value is proportional to the attenuation ratio.

- The standard deviation of generated EEG was not influenced by the number of main sources. But increase in attenuation, rising the value of standard deviation.

- The variance rate of constructed EEG was not affected by the number of main sources. But an increase in attenuation, rising the value of variance.

- The kurtosis rate is invariable when we modify the number of sources and attenuation rate

- The power of produced EEG was not altered remarkably by the number of main sources significantly. The growth in powers of absolute value is proportional to the attenuation ratio.

- The skewness rate fluctuated by a small margin and there is not any specific behavior.

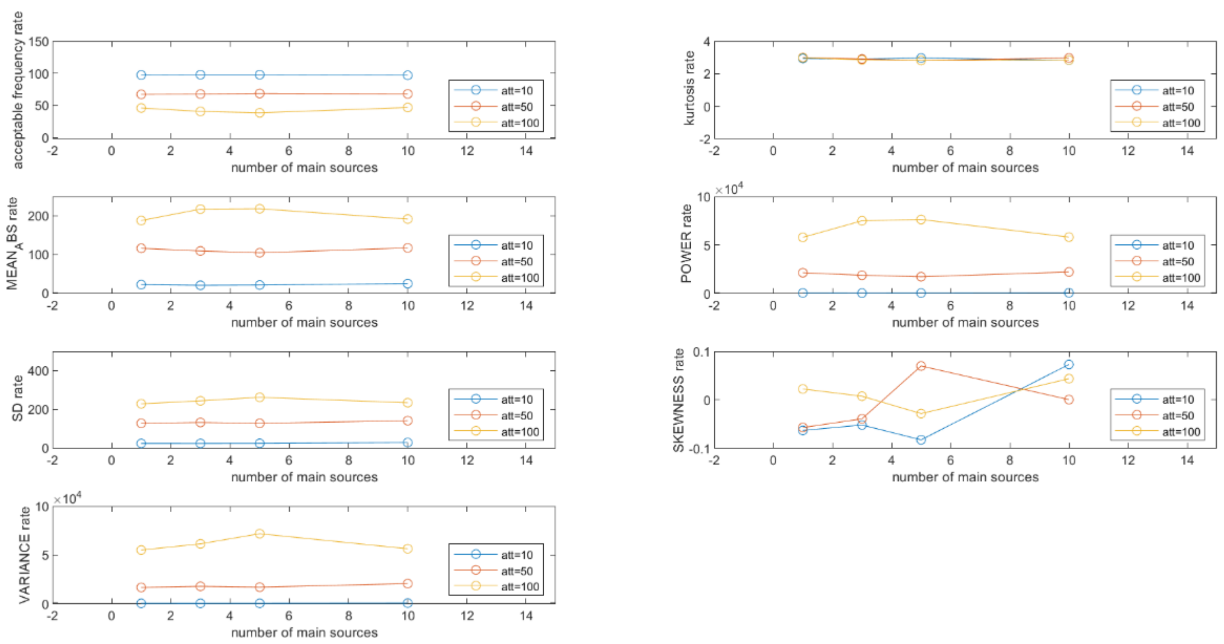

Figure 5. Plot of acceptable frequency, mean, standard deviation, variance, kurtosis, power, and skewness of generated EEG by a different number of main sources (1, 3, and 5) and also different attenuations (10, 50, and 100). All of the produced EEGs are full rank by background noise and the attenuation rate is mentioned (auto background sources)

Part 2: 5 main sources, 20 background sources, attenuation coefficient =10, 50,100

In the part 2 condition, by inspecting Figure 6 we understood that:

Overall, mean, standard deviation, variance, and power have risen if the attenuations rise. However, acceptable frequency and kurtosis are roughly stable. Also, the skewness is fluctuating.

- Acceptable frequency rates of generated EEG remain unchanged when the attenuation rises
- The means of the absolute rate will grow if the attenuations increase
- Standard deviation will grow when attenuations get higher
- Variance increases by the growth of attenuations
- Kurtosis grows slightly when attenuation increases
- *Sk*ewness fluctuates in a small margin

Part 3: 5 main sources, Attenuation coefficient =10, 50, 100, SNR=10, 20 'auto background'

In the part 3 condition, by inspecting Figure 7 we figured out that:

At first glance, there is not any obvious modification by doubling SNR.

Taking a closer look, it is evident that white Gaussian noise does not have any effect on acceptable frequency, mean, standard deviation, variance, kurtosis, and power ratio, whilst skewness decreases when SNR increases.

4. Discussion

In this article, we tried to illustrate the functions and infrastructure of EEGg which is accessible publicly at https://github.com/Avayekta/EEG. This EEG generator provides a platform for freely modeling the brain, including modifiable: background activity of the brain, exclusive/custom-made lead field with adjustable orientation in any direction, imposing external noise with various SNR (Signal-Noise Ratio), variable sample ratio, definable number of EEG channels for recording (acceptable values are 16, 32, 64, and 128) despite former studies [24], time domain features, number of main active sources that user requires, number of background noises and their changeable attenuation rates, activation function modes, ground truth signal of each source, and fully automatic or semi-automatic or complete manual mode. By imitating EEG properties, the improvement of novel EEG investigation strategies or the approval of existing ones gets more viable, realistic, and comprehensive due to the fact that it can validate numerous circumstances for each hypothesis. Therefore, the outcome is more reliable and accurate.

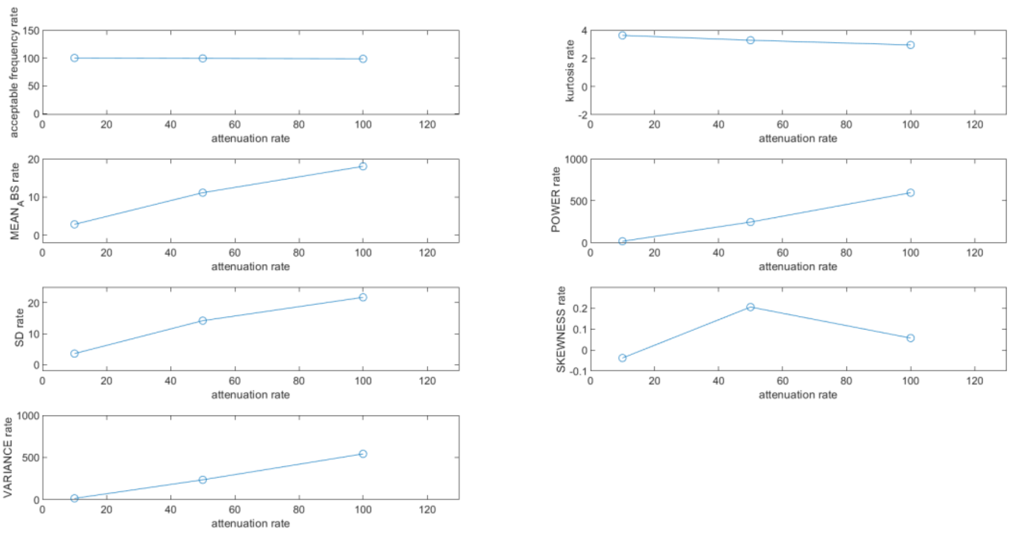

Figure 6. Plot of acceptable frequency, mean, standard deviation, variance, kurtosis, power, and the skewness of generated EEG by five main sources and different attenuations (10, 50, and 100) for 20 background sources

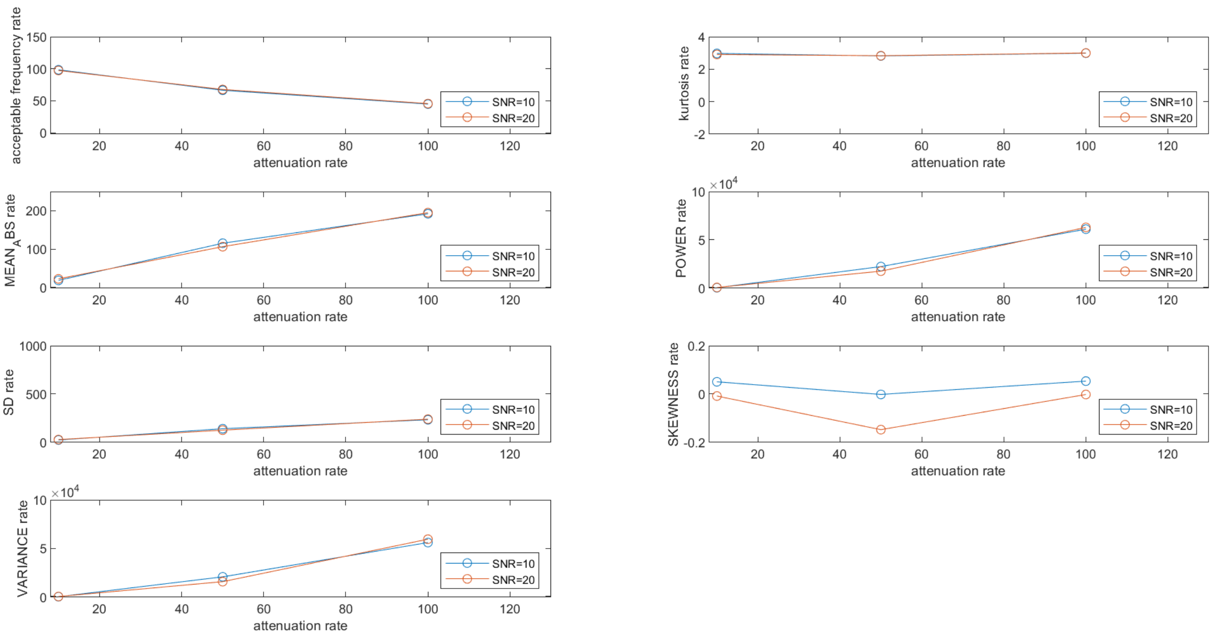

Figure 7. Plot of acceptable frequency, mean, standard deviation, variance, kurtosis, power, and the skewness of generated EEG by five main sources and different attenuations (10, 50, and 100) for auto background sources. The signal-to-noise rates, however, are 10 and 20 dB. (White Gaussian noise)

If the synthetic EEG Data Generation toolbox wants to simulate as similar to real EEG, it must include noises. EEG noises have three primary origins. Firstly, external noise which roots back to external factors such as 50–60 Hz power line interference, however, causes of advanced recording electric devices, omitting this noise during trials is acceptable. Secondly, sensor-level noise can be mimicked by white Gaussian noise. This sensor-level noise has been considered in EEGg. Finally, one of the significant noises is the background activity of the brain during tasks which should be considered as an unwanted signal which is recorded. This disturbing signal which has not been canceled yet is contemplated in EEGg. As a result, this function provides a platform to enhance and accelerate the analysis and improvement of any research which are in EEG fields. How much noises' statistical features are realistic directly affects the results. In a previous study, frequencies were simplified to restrict to the range of $[\frac{1}{f}\ \frac{1}{f^2}]$. Variable f annotated the frequency of EEG [25]. Though this presumption is not sufficient and precise enough to represent empirical EEG noises. As a consequence, in EEGg, we endeavor to employ real EEG noises. In addition, users can insert their demanded noise.

Meeting the requirements of researchers are essential for constructing desired signals as they will be able to produce any favorable signal in any configurations, any noise circumstances, and any sources with arbitrary orientation. These are not feasible in real labs owing to the limitations but applicable in EEGg, so the trial and error method in this open architecture of EEGg is low-cost and flexible despite using real subjects and equipment. Since EEGg provides data that imitates EEG with a reference signal in several conditions, leading to the same result in experiments with actual EEG. Accordingly, simulated EEG outcomes will have outcomes close to results that are turning out from real EEG. This fact is the facilitator of transformation and implementation. Also, all the steps for generating EEG are transparent thus users can manipulate algorithms underlying. Nevertheless, users have to be careful about their assumptions which must be compatible with reality when they are testing their hypothesis. Imagine, the 2 main active sources with an ideal pulse signal without any other activities, this is not an adverse option for the first trial but an unrealistic choice for a broad deduction. Hence, making smart choices is vital for valid inference.

EEGg auto-mode only has movement tasks activation functions which have been constructed by imposing ICA algorithm to real EEG data and some preprocessing to be as real as possible. This procedure can be done in other tasks, too. Real-time demonstration of constructed EEG can allow online algorithms researchers to utilize this toolbox which is not accessible till now.

The connections and networks of human brain models which are incorporated in the lead field are limited in this toolbox, the non-adults lead field is ignored in our auto mode which can be extended in subsequent work. These aspects have the potential to be more advanced in future works.

We have established EEGg which is more developed than the toolboxes mentioned in the introduction part. To acquire a lead field matrix from MRI, however, FieldTrip toolbox is required [21].

With the stunning growth of EEG usage in diagnosis, prediction, BCI, and rehabilitation, the requirement for an EEG toolbox is increasing, we suppose that EEGg will assist and equip researchers in this particular area.

5. Conclusion

EEGg function was programmed to assist researchers in fields, namely: neuroscience, EEG signal processing, EEG forward and inverse problem, and brain-computer interface by various automatic, semi-automatic and full manual experimental conditions. The future of this free function can be more comprehensive by inserting numerous activation functions. For instance, emotional signals or epilepsy signals. Also, other electrode arrangements could be inserted. Furthermore, adding a visual toolbox definitely will enhance its functions for general users. The wider options, the better research, and evaluation will occur.

Acknowledgments

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Appendix

Table 1 show Results file name and their descriptions.

Table 1. Results file name and their descriptions

File Name	Description
3_10_-1.MAT	3 main sources (auto full rank), att=10, NOISE_SNR=-1;
5_10_-1.MAT	5 main sources (auto full rank), att=10, NOISE_SNR=-1;
10_10_-1.MAT	10 main sources (auto full rank), att=10, NOISE_SNR=-1;
5_10_-1-b.MAT	5 main sources, 20 background noise, att=10
5_10_10.MAT	5 main sources, SNR=10, att=10, (auto full rank)
5_10_20.MAT	5 main sources, SNR=20, att=10, (auto full rank)
1_10_-1.MAT	1 main source, (auto full rank), att=10, NOISE_SNR=-1;
3_50_-1.MAT	3 main sources, (auto full rank), att=50, NOISE_SNR=-1;
5_50_-1.MAT	5 main sources, (auto full rank), att=50, NOISE_SNR=-1;
10_50_-1.MAT	10 main sources, (auto full rank), att=50, NOISE_SNR=-1;
5_50_-1-b.MAT	5 main sources, 20 background noise, att=50
5_50_10.MAT	5 main sources, SNR=10, att=50, (auto full rank)
5_50_20.MAT	5 main sources, SNR=20, att=50, (auto full rank)
1_50_-1.MAT	1 main source, (auto full rank), att=50, NOISE_SNR=-1;
3_100_-1.MAT	3 main sources, (auto full rank), att=100, NOISE_SNR=-1;
5_100_-1.MAT	5 main sources, (auto full rank), att=100, NOISE_SNR=-1;
10_100_-1.MAT	10 main sources, (auto full rank), att=100, NOISE_SNR=-1;
5_100_-1-b.MAT	5 main sources, 20 background noise, att=100
5_100_10.MAT	5 main sources, SNR=10, att=100, (auto full rank)
5_100_20.MAT	5 main sources, SNR=20, att=100, (auto full rank)
1_100_-1.MAT	1 main source, (auto full rank), att=100, NOISE_SNR=-1;
ResultPart1.MAT	Result of part 1 tests
ResultPart2.MAT	Result of part 2 tests
ResultPart3.MAT	Result of part 3 tests

References

1- B Venkata Phanikrishna, Paweł Pławiak, and Allam Jaya Prakash, "A Brief Review on EEG Signal Pre-processing Techniques for Real-Time Brain-Computer Interface Applications." (2021).

2- Suprijanto Suprijanto, Masitoh Masitoh, Finda Dwi Putri, and Ayu G Risangtuni, "Future Trend of EEG Source Localization for Quantifying Repetitive Motor Activity as feedback for Rehabilitation Device." in *2021 International Conference on Instrumentation, Control, and Automation (ICA)*, (2021): *IEEE*, pp. 12-15.

3- Takehiko Yamanashi *et al.*, "Topological data analysis (TDA) enhances bispectral EEG (BSEEG) algorithm for detection of delirium." *Scientific reports*, Vol. 11 (No. 1), pp. 1-9, (2021).

4- Siqi Cai, Peiwen Li, Enze Su, Qi Liu, and Longhan Xie, "A Neural-Inspired Architecture for EEG-Based Auditory Attention Detection." *IEEE Transactions on Human-Machine Systems*, (2022).

5- Rasmus L Kæseler, Tim Warburg Johansson, Lotte NS Andreasen Struijk, and Mads Jochumsen, "Feature and Classification Analysis for Detection and Classification of Tongue Movements From Single-Trial Pre-Movement EEG." *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 30pp. 678-87, (2022).

6- Amjed S Al-Fahoum and Ausilah A Al-Fraihat, "Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains." *International Scholarly Research Notices*, Vol. 2014(2014).

7- Paul L Nunez and Ramesh Srinivasan, Electric fields of the brain: the neurophysics of EEG. *Oxford University Press, USA*, (2006).

8- Munsif Ali Jatoi, Nidal Kamel, Aamir Saeed Malik, Ibrahima Faye, and Tahamina Begum, "A survey of methods used for source localization using EEG signals." *Biomedical Signal Processing and Control*, Vol. 11pp. 42-52, (2014).

9- Nasser Samadzadehaghdam, Bahador Makkiabadi, Sadegh Masjoodi, Mohammad Mohammadi, and Fahimeh Mohagheghian, "A new linearly constrained minimum variance beamformer for reconstructing EEG sparse sources." *International Journal of Imaging Systems and Technology*, Vol. 29 (No. 4), pp. 686-700, (2019).

10- E Giraldo, AJ den Dekker, and G Castellanos-Dominguez, "Estimation of dynamic neural activity using a Kalman filter approach based on physiological models." in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, (2010): *IEEE*, pp. 2914-17.

11- Stefan Haufe, Ryota Tomioka, Guido Nolte, Klaus-Robert Müller, and Motoaki Kawanabe, "Modeling sparse connectivity between underlying brain sources for EEG/MEG." *IEEE transactions on biomedical engineering*, Vol. 57 (No. 8), pp. 1954-63, (2010).

12- Stefan Haufe, Vadim V Nikulin, Klaus-Robert Müller, and Guido Nolte, "A critical assessment of connectivity measures for EEG data: a simulation study." *Neuroimage*, Vol. 64pp. 120-33, (2013).

13- Geertjan Huiskamp, "Interindividual variability of skull conductivity: an EEG-MEG analysis." *International Journal of Bioelectromagnetism*, Vol. 10 (No. 1), pp. 25-30, (2008).

14- Arnaud Delorme and Scott Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis." *Journal of neuroscience methods*, Vol. 134 (No. 1), pp. 9-21, (2004).

15- Sheng-Hsiou Hsu, Tim Mullen, Tzyy-Ping Jung, and Gert Cauwenberghs, "Online recursive independent component analysis for real-time source separation of high-density EEG." in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, (2014): *IEEE*, pp. 3845-48.

16- Anderson S Oliveira, Bryan R Schlink, W David Hairston, Peter König, and Daniel P Ferris, "Induction and separation of motion artifacts in EEG data using a mobile phantom head device." *Journal of neural engineering*, Vol. 13 (No. 3), p. 036014, (2016).

17- Laurens R Krol, Juliane Pawlitzki, Fabien Lotte, Klaus Gramann, and Thorsten O Zander, "SEREEGA: Simulating event-related EEG activity." *Journal of neuroscience methods*, Vol. 309pp. 13-24, (2018).

18- Alessandra Anzolin, Jlenia Toppi, Manuela Petti, Febo Cincotti, and Laura Astolfi, "SEED-G: simulated EEG data generator for testing connectivity algorithms." *Sensors*, Vol. 21 (No. 11), p. 3632, (2021).

19- Anthony T Herdman, "SimMEEG software for simulating event-related MEG and EEG data with underlying functional connectivity." *Journal of neuroscience methods*, Vol. 350p. 109017, (2021).

20- Jussi T Lindgren, Adrien Merlini, Anatole Lecuyer, and Francesco P Andriulli, "simBCI—a framework for studying BCI methods by simulated EEG." *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 26 (No. 11), pp. 2096-105, (2018).

21- Robert Oostenveld, Pascal Fries, Eric Maris, and Jan-Mathijs Schoffelen, "FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data." *Computational intelligence and neuroscience*, Vol. 2011(2011).

22- Eduardo Lattari *et al.*, "Corticomuscular coherence behavior in fine motor control of force: a critical review." *Rev. Neurol*, Vol. 51 (No. 10), pp. 610-23, (2010).

23- Hailong Liu, Jue Wang, Chongxun Zheng, and Ping He, "Study on the effect of different frequency bands of EEG signals on mental tasks classification." in *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, (2006): *IEEE*, pp. 5369-72.

24- Manuela Petti *et al.*, "Effect of inter-trials variability on the estimation of cortical connectivity by Partial Directed

Coherence." in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, (2015): *IEEE*, pp. 3791-94.

25- Claude Bedard, Helmut Kroeger, and Alain Destexhe, "Does the 1/f frequency scaling of brain signals reflect self-organized critical states?" *Physical review letters,* Vol. 97 (No. 11), p. 118102, (2006).