A Versatile Validation Framework for ERP and Oscillatory Brain Source Localization Using FieldTrip

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ABSTRACT

The use of electroencephalography (EEG) continuously expanded during the last century leading this recording technique to be the standard in various domains. Considering its poor spatial resolution, many researchers have developed methods to reconstruct cortical source activations from scalp signals, but the lack of ground truth brain activity makes the reconstruction algorithms difficult to validate. To deal with this issue, simulated EEG data can be used to evaluate the reliability of the reconstructed sources. In the literature, benchmark frameworks are proposed to evaluate the reconstruction on fixed pseudo-EEG and other tools allow the user to generate custom data. However, to the best of our knowledge, none of the available pipelines proposes a uniform way to validate a reconstruction method from custom pseudo-data. We therefore present our versatile validation framework for EEG-based source localization. This new tool is an all-in-one validation pipeline aiming to evaluate source localization from pseudo-EEG data as close as possible to the experimental environment of the researcher. This paper presents the 5-step framework from the configuration to the evaluation and template data that can be used for benchmarking purposes. By using our uniform region-based evaluation method, researchers will be able to compare their reconstruction method on different configurations that fit their own experimental data. All the codes, template data and configuration description have been made available through ***https://github.com/numediart/ValidEEG.git***.

CCS CONCEPTS

• **Applied computing** → Life and medical sciences; Health informatics;; • **General and reference** → Cross-computing tools and techniques; Validation.

KEYWORDS

Validation, EEG, Source reconstruction/localization, Benchmark, Simulation, ERP, FieldTrip

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1 INTRODUCTION

Nowadays, electroencephalography (EEG) is one of the most used recording techniques in human brain research due to its easiness, non-invasive nature, high temporal resolution and relatively low cost compared to other imaging techniques such as magnetic resonance imaging. However, EEG presents low spatial resolution as each electrode senses the activity of millions of neurons through their average electrical field considering the relatively high distance between the EEG cap and the actual cortical sources. Moreover, the problem of volume conduction i.e., the spreading of a single source's electrical field to multiple electrodes, makes the brain source activity even more difficult to be localized. Multiple methods have been developed to face the problem of source reconstruction such as common spatial pattern [1] or independent component analysis [2]. Nevertheless, the reliability of those algorithms is difficult to evaluate as there is no available ground truth describing the source activity of a specific EEG recording.

The need of a reliable way to evaluate source reconstruction methods is the reason why we propose a novel tool to validate the accuracy of source localization from EEG signals for Event-Related Potential (ERP) and oscillatory source activity. As the source signals highly vary from an experiment to another, we pay particular attention to the adaptable aspect of the proposed framework.

In order to make our tool as accessible as possible, we based our code on one of the most used toolboxes for EEG analysis: FieldTrip [3]. This choice results of a trade-off between ease-of-use and ease of modification.

2 RELATED WORK

The question of source reconstruction method evaluation has been addressed since the late 90's with Phantoms studies controlling inverse method accuracy with highly detailed volume conduction models [4], [5]. Then, EEG simulation took a growing importance for the validation of source reconstruction in the literature [6], [7]. Most of the evaluation methods are custom-made and relies on different hypotheses (linear model, spatial dependencies, etc.) or have been designed for some specific cases such as the *Source Information Flow Toolbox* (SIFT) [8] for connectivity and blind source separation evaluation or *simBCI* for studying Brain Computer Interface (BCI) methods [9]. Haufe and Ewald [10] proposed a more general benchmark framework for EEG-based source localization and connectivity, but they restricted their analysis to only two activated sources and only eight brain regions (octants). This evaluation is therefore not sufficient to ensure the reliability on a specific source reconstruction pipeline. Moreover, they do not give the opportunity to the users to customize the generated pseudo-EEG signal, limiting the analysis to oscillatory signals in the alpha band.

To fulfill the lack of custom EEG data simulation tools in the literature, Krol *et al.* [11] proposed the *Simulating Event-Related EEG Activity* (SEREEGA) toolbox whose purpose is to generate custom pseudo-event related EEG data. This tool allows the users to generate EEG signals with known ground truth according to their own signal patterns, head model, source localizations and event timestamps.

However, there is still a gap between signal generation and validation. We therefore aim to fill this gap with our versatile validation framework. On top of SEREEGA, we provide additional features to propose a complete validation framework:

- **Artifacts** generation
- **Evaluation** method for source localization
- Versatile **region**-based ground truth

Those features offer the opportunity to the users to evaluate their source reconstruction pipelines on realistic signals with the desired precision according to the chosen atlas.

To ensure standardization, this framework is developed on Matlab as most of the major toolboxes for EEG data analysis are based on this platform. As we want our framework to be accessible to the largest audience possible, we provide an easy configuration through a json file as well as our open-source FieldTrip-based codes for more specific analyses.

3 PROPOSED METHOD

The goal of our work is to provide an easy-to-configure validation framework for brain source localization. The versatile aspect allows the users to validate their pipelines on pseudo-data closer to their own use case. The framework is divided into 5 steps:

- **Parameters selection**: the custom parameters are defined in a configuration (.json) file allowing the user to design the framework with specific considerations such as the number of pseudo-sources (*n_dipoles*) or the number of trials within one session (*n_trials*).
- **Source selection**: *n_dipoles* are selected from the predefined atlas so that the region corresponding to each dipole is not a neighbor of the other selected dipole's regions.
- **Pseudo-source signal generation**: a signal containing *n_trials* occurrences of the desired pattern (ERP or oscillatory) is generated for each of the selected sources.
- **Pseudo-EEG data generation**: the final pseudo-EEG data are first generated through FieldTrip functions and some artifacts are further added as well as noise.
- **Performance evaluation:** the *n_dipoles* non-neighboring reconstructed regions with highest power are considered as the source regions and the score for each dipole of each session is given as follow:
- 1 if reconstructed source region = pseudo-source region.
- 0.5 if reconstructed source region is the neighbor of a pseudo-source region.
- 0 if reconstructed source region is the second neighbor (neighbor of neighbor) of a pseudo-source region.
- -1 otherwise.

The final score is the mean of each individual score through all sessions.

3.1 Parameters Selection

The parameters have been chosen as a trade-off between controllability (enough parameters to fit a specific analysis) and simplicity (limited number of parameters allowing an easy handling). Those parameters can be classified in 4 types

- **General pipeline**: definition of the number of sessions/dipoles/trials over which we want to generate the pseudo-source signal. The session and trial lengths are also defined there as well as the number of artifacts we want to introduce in the final EEG pseudo-data. An event file can also be defined there to control the appearance time of each trial.
- **Pseudo-source definition**: selection of the source type (ERP or oscillatory) and their main features (e.g., specific peaks for ERP and frequency bands for oscillatory signals). The desired atlas is also defined there. A dipole file can be specified to control the dipole locations for each session.
- **Pseudo-EEG definition**: selection of the head model and the electrodes with respect to FieldTrip requirements.
- **Artifacts and noise**: Template artifacts and signal-to-noise ratio (SNR), for source and EEG signals, are defined in this section.

3.2 Source Selection

Each source is defined as a 3-dimensional dipole with specific position and orientation. The dipole position is the position of a randomly chosen dipole among those of a predefined atlas. The atlas, given as a parameter, is a FieldTrip mesh structure where each dipole's region is defined. Importantly, the atlas mesh must be aligned to the head model and the electrodes. Templates of the required data are provided (template atlas is the Automated Anatomical Labeling (AAL) MNI atlas [12]), but custom atlas can be obtained through the function *prepare_atlas*. The orientation of each dipole is defined as a random unitary vector.

To ensure the selected dipoles are not part of the same region or neighboring ones, we designed a neighboring matrix of the atlas regions (cf. Figure 1). This matrix fulfills 2 conditions:

- A region from one hemisphere cannot be a neighbor of one of the other hemisphere.
- If 2 regions are neighbors in one hemisphere, their corresponding regions in the other hemisphere must be neighbors too.

3.3 Pseudo-Source Signal Generation

The pseudo-source signal is generated as a series of base signal trials around a baseline (cf. Figure 2). This base signal is either an event-related potential (ERP) or an oscillatory signal (OSCIL) depending on the *type* parameter. The trial samples are defined through the *event* parameter. We used the SEREEGA toolbox [11] to generate the base signals as follow:

- ERP

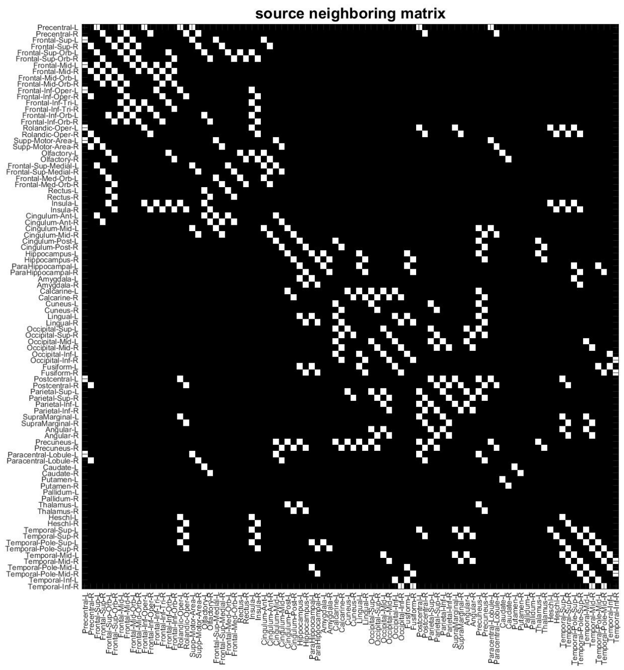

Figure 1: source neighboring matrix. For each region in row, neighbors are defined with a white square.

An ERP trial is a series of positive and/or negative peaks defined as normal probability density function around the specified latency (e.g., P300 is a positive peak appearing 300ms after the beginning of a trial) with the corresponding *width* covering 6 standard deviations and the maximum amplitude being the corresponding *ampli* parameter. To introduce variability between trials, we defined a latency deviation varying between +/-50ms, a width deviation of half the desired width and an amplitude deviation of a fifth of the corresponding amplitude. An additional parameter introduces the habituation to the stimulus along the session through a decaying slope in amplitude. This slope leads the last trial amplitude to be a fourth of the initial amplitude. To consider the polarity inversion between anterior and posterior brain regions [13], signals on anterior source are reverted. The last step is the addition of pink noise. This colored noise, inversely proportional to the frequency, is generated following Zhivomirov method [14] with respect to the *snr_source* parameter. *An* example of a 3-dipoles pseudo-ERP source signal is given in Figure 2A.

- OSCIL

An oscillatory trial is defined as an event-related spectral perturbation (ERSP) [15]. This signal is obtained by band-pass filtering a uniform white noise in a predefined frequency band (*freq* parameter) using a Kaiser window-based finite impulse response filter [16] with a specific amplitude (*ampli* parameter) and a random phase. Finally, pink noise is added to the signal with respect to the snr *source* parameter. An example of a 3-dipoles pseudo-oscillatory signal is shown in Figure 2B.

3.4 Pseudo-EEG Signal Generation

The pseudo-EEG signal generation consists of 2 steps: the first one creates the EEG signal on each channel as a FieldTrip *raw* structure through the *ft_dipolesimulation* function, the second step introduces artifacts within the data.

3.4.1 From source to EEG.. FieldTrip offers the opportunity to simulate channel-level time-series data from one or multiple dipole signals considering a specific volume conduction model, that geometrically defines the head model and carry information about the different tissues through which the electrical signal will spread (i.e., white/grey matter matters, cerebro-spinal fluid, skull, and scalp) as given by *ft_prepare_headmodel* function, and a particular electrode montage as defined by *ft_read_sens*. White noise with a relative level to data signal corresponding to *snr_eeg* parameter is also added to the generated pseudo-signal. The resulting EEG data are then normalized. An example of FieldTrip-generated EEG data is shown in Figure 3A. To give a better idea of what does the signal look like, we performed a timelock analysis of these FieldTrip-generated signals (cf. Figure 3B).

3.4.2 Artifacts generation. On top of the FieldTrip-generated EEG signal, we introduce artifactual signals. Those artifacts have been chosen within the annotated corpus of Hamid *et al.* [17]. This dataset consists of 310 EEG recordings in which every artifact has been annotated as one of the five following types: electrode, eye movement, muscle, chewing or shiver artifacts. We decided to only use the first three types in our pseudo-data as chewing and shiver artifacts are so rare that their effect on the result of timelock-based source reconstruction algorithms is negligible. We have extracted

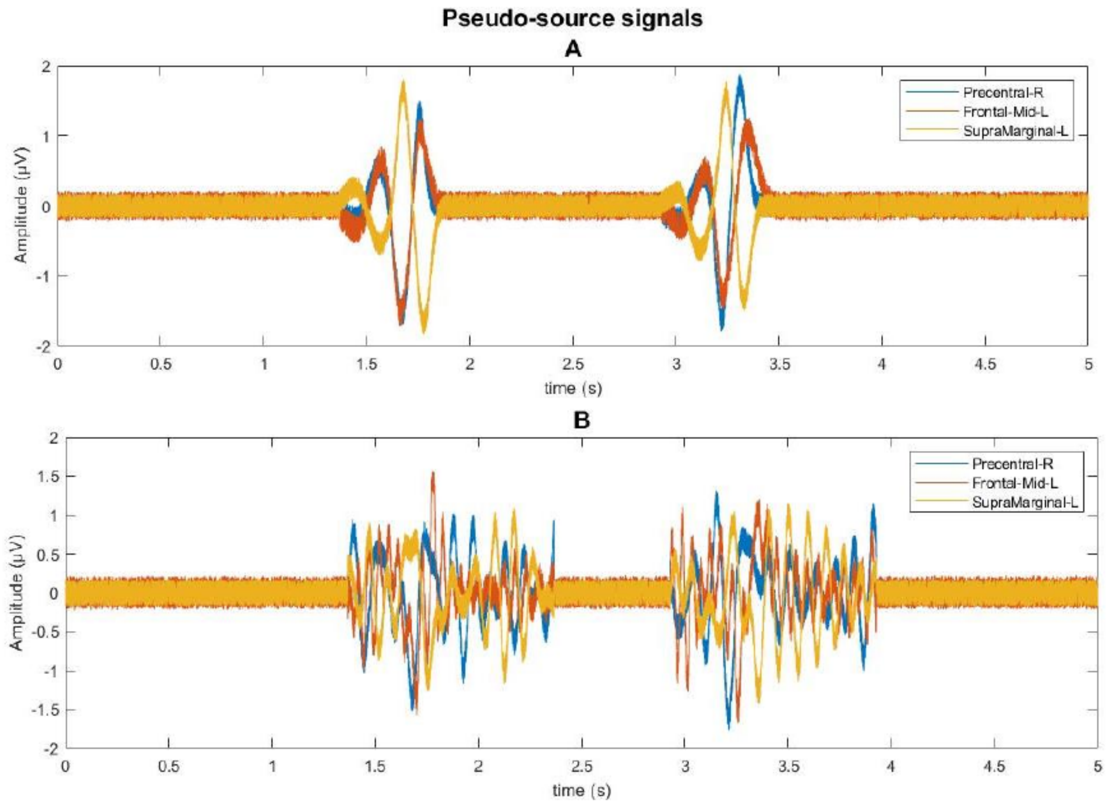

Figure 2: Example of 3-dipoles pseudo-source signals with the 2 first dipoles being on anterior regions and the 3rd once on the posterior region. A: pseudo-ERP defined as a series of P100, N200, P300 and N400. B: pseudo-oscillatory signal with frequency band of each dipole defined as: 8-12Hz (blue), 16-24Hz (orange), 9-13Hz (yellow).

all the artifactual segments from recordings of the patient number 100 to represent our template artifacts.

The artifact trials, being recorded with a sampling rate of 256 Hz on a 19-channel set-up, are first linearly interpolated to the pseudo-EEG sampling rate. Then, a second interpolation is conducted to generate artifact signals on channels of the pseudo-EEG set-up that are not present in the template artifact dataset. This latter interpolation is based on a neighboring matrix computed from the pseudo-EEG channel positions similarly to Figure 1. Every missing channel signal is computed as the mean of the neighbor's signals. Finally, the artifact trials are normalized in order to keep comparable scales between pseudo-EEG and artifact signals.

Following the chosen configuration, *n_artifacts* are randomly selected from the adapted trials and added to the pseudo-EEG signals at random timestamps. An example of the final pseudo-EEG data is shown in Figure 3C.

3.5 Performance Evaluation

We propose a qualitative evaluation of the performance of a timelock-based source reconstruction algorithm applied to the pseudo-EEG signals of each session. This evaluation is based on the closeness of reconstructed regions with highest root mean square values to the ground truth regions (i.e., regions to which the pseudo-source belongs). To avoid a dipole to be considered twice, we ensure the selected regions not to be neighbors using the previously computed source neighboring matrix. For each session, once the *n_dipoles* highest power regions selected, we compare each ground truth region with the selected regions and a qualitative score is assigned as follow: if one of the reconstructed region is the same as the ground truth, the score is 1; if one region is a neighbor of the ground truth, the score is 0.5; the score is 0 if one of the selected regions is a neighbor of the ground truth's neighbors; otherwise, the score is -1. This simple qualitative assignment gives the opportunity to be less penalized if the ground truth dipole is at the limit of several regions while greatly penalizing totally wrong reconstruction. The score is therefore represented by an *n_session***n_dipoles* matrix with the global mean being the final score. Figure 4A shows how the evaluation is represented in our framework through an example.

As the ground truth dipole positions and regions are automatically saved during generation, the users can visualize the reconstructed vs. ground truth sources on their atlas source model as shown on Figure 4B.

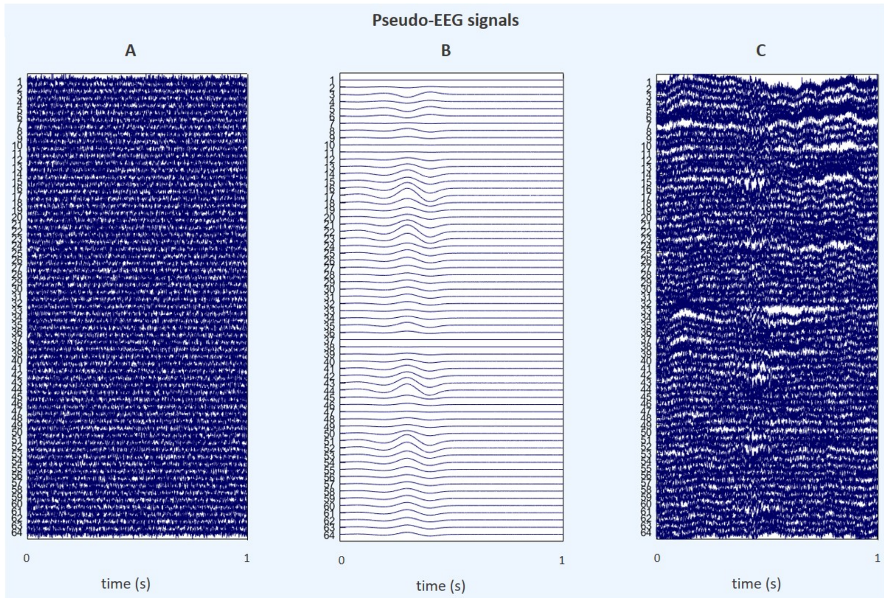

Figure 3: Example of a 3-dipoles pseudo-EEG signal. A: 64-channels EEG generated through *ft_dipolesimulation* function from a 3-dipoles pseudo-ERP signal. B: timelock analysis of signals in A. C: final pseudo-EEG signals after having added muscle artifact to the signal in A.

4 BENCHMARK

As we provide template data and configuration, the proposed validation framework can be used as a benchmark generator. The chosen template configuration is a 10-sessions 3-dipoles pseudo-source signals carrying, within each session of 15 minutes, 200 one-second trials and 400 artifacts, lasting less than 10 seconds, with a sampling rate of 2048 Hz. The artifact trials were randomly chosen among a set of 184 artifact segments composed of 13 electrode artifacts, 54 eye movement artifacts and 117 muscle artifacts. The template electrode is the 10/20 standard set-up from FieldTrip template over which we only kept 64 electrodes with respect to the 10/20 standard. The template volume conduction model (i.e., head model) were built following FieldTrip pipeline from their standard MRI template head model that we have segmented using five tissue types (gray matter, white matter, cerebro-spinal fluid, skull, and scalp) using the S*imBio* finite element method to build the forward model. The template atlas is the AAL MNI atlas provided by FieldTrip from which we kept only the 90 first regions as the cerebellum and the vermis are not part of our head model. We then realigned the electrodes, head model and atlas together with respect to the CTF coordinate system. The pseudo-ERP template is a 4 peaks ERP composed of P100, N200, P300 and N400 with corresponding amplitudes of 0.2, 0.4, 1 and 0.8 microvolt and widths of 300, 300, 200 and 200 milliseconds, respectively. The pseudo-oscillatory template is defined by a specific frequency band for each dipole: 8-12 Hz (dipole 1), 16-24 Hz (dipole 2) and 9-13 Hz (dipole 3) with a maximum amplitude of 1 microvolt for all of them. The source SNR is set to 1, while the EEG SNR is set to 2.

We encourage the users to provide the final evaluation of their source reconstruction pipeline applied to this template pseudo-ERP or oscillatory EEG data to progressively build a robust benchmark dataset.

5 DISCUSSION

From EEG simulation to localization evaluation, the proposed framework offers the possibility to customize multiple features so that the users can validate their method in a very specific way to fit their experimental data. The provided configuration file gives an easy way to modulate the framework while the open-source FieldTrip-based code allows more sophisticated analyses.

The addition of artifacts makes the generated signals closer to real EEG data. We therefore offer a large set of artifactual segments composed of electrode, eye movement and muscle artifacts, but expert Matlab users will easily be able to select specific artifacts from the dataset provided by Hamid *et al.* [17].

The evaluation process is based on neighboring matrices computed on source and sensor domains. Those matrices can be adapted to the desired accuracy through the available *eeg_neighbmat* and *source_neighbmat* functions. The chosen atlas also influences the way the validation is performed. Our template atlas is composed of 90 regions, but some users may want to work with different brain regions. For this purpose, two different functions can be used: 1) *select_roi* function allows one to combine and/or remove regions from an existing atlas; 2) *prepare_atlas* function transforms an atlas in *NIfTI* format to the required FieldTrip-like source model atlas while realigning it to the selected volume conduction model and the EEG-cap to CTF coordinates. Importantly, the final reconstructed source activity must be given as one signal per region with regions order corresponding to the chosen atlas.

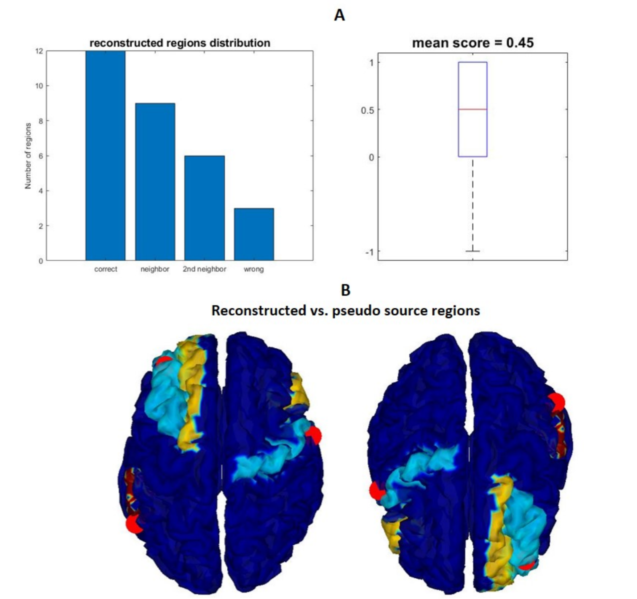

Figure 4: Example of the evaluation of a 10-sessions 3-dipoles source reconstruction of pseudo-EEG signals. A: distribution of the correctness of reconstructed regions through their relative position to the initial pseudo-regions (i.e., correct, neighbor, second neighbor or wrong position) (left) and the corresponding score statistics (right). B: occipital (left) and frontal (right) views of reconstructed regions (yellow) from one session in comparison with the ground truth pseudo-dipoles (red spheres) and their corresponding region (light blue). The region in red is a properly reconstructed source.

Although benchmarking is not the main purpose of our work, we offer a template configuration set to pave the way for benchmark building. So, we encourage users to run their analysis on template ERP and/or oscillatory data and provide their final score on future related publications.

The main limitation of the proposed framework is that it is restricted to source localization. Neither connectivity nor causality analyses can be evaluated here. Further implementations will be developed in the future to add those missing components. To that end, we will use the autoregressive signal generation proposed by Haufe and Ewald [10] and reimplemented into SEREEGA [11] to generate dependent source activities with specific directionality.

6 CONCLUSION

In this paper, we present an all-in-one framework as a tool to validate a wide range of EEG-based source reconstruction pipelines in a fashionable way. The proposed framework consists of 5 steps: 1) specific parameters are defined through a configuration file; 2) the targeted source location and orientation are set; 3) the pseudo-source signal is generated as ERP or oscillatory activations; 4) the pseudo-EEG data are created with respect to the predefined volume conduction model, EEG cap, sources definition and specific artifactual events; 5) the localization accuracy of the reconstructed sources from the previously generated pseudo-EEG is evaluated through a brain region-based score.

With this validation framework, we offer an accessible way to validate specific methods of EEG-based source localization and pave the way for the creation of a robust benchmark dataset.

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