Introduction

EEG experiments require careful preparation. You need to prepare the participants, spend some time on setting up the equipment and run initial tests. You certainly do not want your EEG experiment to fail mid-test, so before carrying out a full study with 100 participants start small and run some pilot sessions in order to check if everything is working properly. Are the stimuli presented in the right order? Are mouse and keyboard up and running? Do participants understand the instructions? Do you receive signals? Once you have crossed those questions off your list, you are all set to start with the actual data collection and analysis.

To this day, there is no algorithm that is able to decontaminate poorly recorded data, and you simply cannot clean up or process data in a way that magically alters the signal. Therefore, always start with properly recorded data. EEG systems generally offer soft- or hardware-based quality indicators such as impedance panels where the impedance of each electrode is visualized graphically. Green colors and low impedance values imply high recording quality (low impedances indicate that the recorded signal reflects the processes *inside* of the head rather than artifactual processes from the surroundings). Clean data allows clean responses to your research questions.

EEG data can be recorded and analyzed in a near-infinite amount of different ways, and not only the [processing steps](http://www.researchgate.net/post/What_are_the_preprocessing_methods_to_enhance_EEG_data_for_general_purpose) themselves but also their sequence matters. All signal processing techniques alter the data to some extent, and being aware of their impact on the data definitely helps to pick the right ones. The phrase “making informed decisions” is the key –if you are hesitant about which methods to choose, check out existing literature. Most certainly, you will find valuable advice in scientific research papers or even in the “lab traditions” of your team. By making sure that the methods of choice return the desired outcomes, you are able to maximize scientific research standards such as [objectivity, reliability, and validity](https://imotions.com/blog/measure-human-behavior/).

EEG data contains relevant and irrelevant aspects. What is signal to one EEG expert might be noise to another (and vice versa). For example, one might be interested in event-related potentials time-locked to the onset of a specific visual stimulus. If the participant blinks in that very moment, the EEG might not reflect the cortical processes of seeing the stimulus on screen. As an EEG expert, you might tend to exclude this trial from the analysis since the EEG data does not contain relevant information. However, if blinking occurs systematically during stimulus onset throughout the experiment, this might tell an interesting story. Maybe the participant avoids seeing a potentially threatening picture. Rejecting all trials where blinks occur basically results in a drastic reduction of data (it very well could happen that only 10 trials out of 100 are left – imagine this!). Therefore, attenuation procedures based on [statistical](https://imotions.com/blog/statistical-tools/) procedures such as regression or interpolation (e.g., the method proposed by [Gratton, Coles & Donchin, 1983](http://www.sciencedirect.com/science/article/pii/0013469483901359" \t "_blank)) or [Independent Component Analysis](http://journals.cambridge.org/action/displayAbstract?fromPage=online&aid=28723&fileId=S0048577200980259) might be more appropriate. In this case, contaminated data portions are replaced with interpolated data using surrounding data channels or time points (in the image above the red lines represent the corrected signal). Unfortunately, the discussion on whether artifacts should be attenuated or rejected is ongoing in the scientific community, and you might have to evaluate which procedures return the desired output signal of interest. However, combining scalp EEG with other sensors such as [eye trackers](https://imotions.com/blog/eye-tracking/), [EMG or ECG](https://imotions.com/ecg-emg/) electrodes helps to collect physiological processes such as blinks and muscle movements of limbs or the heart through other modalities, making it easier to identify their intrusion into the EEG data.

When designing and analyzing an EEG experiment, it is always recommendable to base your procedures on known material. You certainly will find it easier to explain the observed effects if you are able to link your results to existing publications where a comparable statistical procedure has been used. As mentioned above, making informed decisions also applies in the context of selecting the right statistical procedures. In case you intend to investigate event-related potentials ([ERPs](http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3016705/)), you might want to have a closer look into the latencies and amplitudes of the peaks in the ERP waveforms at certain electrode locations. By contrast, if you are interested in frequency-based measures such as theta, alpha, beta band power, you rather focus on the examination of the peak frequency within the band of interest. EEG metrics such as “cognitive load” ([Advanced Brain Monitoring B-Alert](http://www.advancedbrainmonitoring.com/xseries/)) or “frustration” ([Emotiv EPOC](https://emotiv.com/epoc.php" \t "_blank)) are either premised on time- or frequency-domain features of the EEG data, and can also be analyzed in view of peak amplitudes or latencies with respect to the onset of a certain event. Analysis techniques comprise simple t-tests and more complex ANOVAs ([Analysis of Variance](http://www.cambridge.org/de/academic/subjects/statistics-probability/statistical-theory-and-methods/design-comparative-experiments?format=HB)) as well as non-parametric procedures such as [bootstrapping or randomization techniques](http://openwetware.org/wiki/Mass_Univariate_ERP_Toolbox). The latter are particularly useful when you would like to examine the data in an explorative way without specifying the expected effect with respect to electrode site, latency or amplitude.

Parametric Analysis of Oscillatory Activity as Measured With EEG/MEG

The problem analysis of Oscillatory Activity as EEG is discussed in the article “Parametric Analysis of Oscillatory Activity as Measured With EEG/MEG”. The conventional approach to quantify transient, nonphase–locked responses is estimated data with using narrow-band filtering or a time–frequency decomposition of single trial responses. Morlet wavelet transform (MWT), the Hilbert transform applied after bandpass-filtering the data. Narrow-band filtering and Morlet wavelet transform (MWT), the Hilbert transform are largely equivalent. Any of the three transforms can be used to estimate instantaneous power, at each time point, by computing the sum of squares of the convolved data.

The STFT is a classical approach to time–frequency decomposition and has been applied to EEG data by Makeig. The idea of STFT is to apply the Fourier transform to windowed periods of the data. The STFT can be formulated as a convolution, at each frequency, with a complex kernel consisting of two windowed sinusoids of frequency *f*0 Hz. One sinusoid is phaseshifted, relative to the other, by π*/*2.



The Morlet wavelet transform has been used to compute the instantaneous power and phase of EEG signals. As with the STFT, the MWT is a convolution of the data with a windowed, complex sinusoid. What makes the Morlet transform popular is that the width of the Gaussian window is coupled to the center frequency *f*0. This reduces the window width at higher frequencies to ensure the number of cycles under the Gaussian is the same.



The Hilbert transform is used typically to compute the analytic signal. One application of the analytic signal is to estimate the instantaneous power and phase of a signal. The (continuous) Hilbert transform is a convolution of the data with the kernel The Fourier transform of this , where  is the signum function. The Hilbert transform is equivalent to altering all phases of the original signal components by π*/*2. The analytic signal is a complex function given by:



All three transforms, as described above, are convolutions of the data and effectively equivalent. This means that it does not matter which transform is used to compute a time–frequency decomposition. The key parameter is the window length (assuming a Gaussian or a similar shape) one chooses at each frequency.

The synthetic EEG data to show that parametric tests are valid tests and retain sensitivity. Subsequent analyses of real data are provided to illustrate operational details. The data were generated by drawing from a multivariate normal distribution estimated from 80 trials. EEG data were simulated by drawing from an empirically defined multivariate Gaussian distribution with the sampled ERP mean. The covariance was computed using only the first 15 eigenvectors of the sampled covariance matrix. The restriction to the principal components of EEG variability biased the nonspherical variation, in simulated data, towards physiological as opposed to measurement sources of variance. In simulations addressing sensitivity it was added additional oscillations to the null data.

In the first simulations, it was generated data without (additional) oscillations to sample from the null distribution of parametric statistics. The null distribution of *P*-values of T-statistics were computed. It was based on power and their log- and sqrt-transforms. It should be based on transformed data.

In the second simulations it was generated synthetic data as above. This time it is tested baseline-corrected averages. The log- and sqrttransform result in a valid and exact test. The test based directly on the differences is slightly conservative. The results are displayed on a log-log-scale and the deviation from an exact test, at low *P*-values, is very small. This correspondence suggests the transform may not be necessary in some settings.

In the last simulations, it was added an oscillatory activation with random phase to one of the trial types. The activation was a windowed sinusoid with a center frequency of 40 Hz. It was compared a commonly used nonparametric statistic. The results it has shown the nonparametric statistic is the least sensitive approach. The parametric tests have better and similar sensitivity. the test based on differences is nearly as sensitive as the tests based on the log-transform. This allows one to use parametric statistics on differences of average power, under normal assumptions, while retaining maximum sensitivity

The parametric and nonparametric tests to analyze induced oscillations in the gamma range (30–80 Hz) was calculated. To compare the parametric method with an established nonparametric approach.

Furthermore, under Gaussian assumptions parametric tests are, in expectation, more sensitive than nonparametric tests.

To compare parametric and nonparametric tests it was used the same epoched data. The resulting data were then subject to parametric and nonparametric tests.

For the parametric test, it was derived a *t*-statistic to test for a difference in power between conditions. The lower *P*-value of the nonparametric statistic does not contradict found parametric statistics. Also it was performed single subject analyses on all subjects to compare the parametric two-sample *t*-test to the Wilcoxon rank sum test (*P*-values not reported). It was found that subject-wise parametric and nonparametric *P*-values were very close to each other. This suggests that parametric tests are appropriate for these data.

It can be concluded that The STFT and the MWT can be made equivalent, at a specific frequency, by choosing a Gaussian window for the STFT with the appropriate width. How evoked and induced power it have shown can be analyzed using parametric statistics. A nonlinear transform it have shown can be used to render the data normal. It allows one to make inferences using a standard parametric framework. The validity and sensitivity of parametric tests was established with using simulated and real EEG data.

The STFT and the MWT can be made equivalent, at a specific frequency, by choosing a Gaussian window for the STFT with the appropriate width. The equivalence of the BP/HT can be seen by noting that the convolution operator is linear. In other words, instead of applying the Hilbert transform to bandpass-filtered data. One can also convolve the data with the Hilbert transformed bandpass filter kernel. The first kernel is the bandpass filter kernel.

A further difference is that the window of the MWT is Gaussian, whereas the STFT and the bandpass filter can be applied with arbitrary forms. For instance, between-subject variability calls for averaging of power over frequencies. This averaging is likely to obscure any differences arising from the filter shape. If it is assume that an FIR filter with a Gaussian window is sufficient to analyze induced oscillations, the key parameter will the window width.

**A Wavelet-Like Filter Based on Neuron Action Potentials for Analysis of Human Scalp Electroencephalographs**

The article “A Wavelet-Like Filter Based on Neuron Action Potentials for Analysis of Human Scalp Electroencephalographs” describes the development and testing of a wavelet-like filter, named the SNAP. The SNAP created from a neural activity simulation and used, in place of a wavelet, in a wavelet transform for improving EEG wavelet analysis, intended for brain-computer interfaces. The SNAP was compared to standard wavelets by measuring Support Vector Machine-based EEG classification accuracy when using different wavelets/filters for EEG analysis. Classification using the SNAP was more accurate than that with any of the six standard wavelets tested. Phenomena it have shown to explain why the SNAP appears to have promise for improving EEG wavelet analysis.

Human scalp electroencephalographic measurements (EEGs) are one way to peer into the activity of the brain. There are several distinct neural rhythms found in EEGs which are created by subsystems of different sizes. Accurate interpretation of EEGs is critical for such applications as brain-computer interfaces (BCIs). There is often a characteristic waveform can be recognized, if many trials are averaged together. The original goal of this research was to create an EEG-classification algorithm for eventual use in a BCI. The EEG-classification algorithm used for employs the discrete wavelet transform (DWT) for signal analysis. The wavelet transform’s output can be significantly affected by the choice of wavelet (the basic waveshape) with which the signal is analyzed. As a result, the choice of wavelet can also have a significant impact on the quality of the results with regard to the classifier. The classifier takes the wavelet coefficients as input features. There is no standard method for selecting the best wavelet. Therefore, it was necessary create a filter that matches the neural activity underlyingthe neuroelectric events. Such a filter could possibly produce superior classification performance across many different tasks and their associated neuroelectric events.

The filter developed is created from a simple model of neural activity. It is not wavelet shape manipulation. It is designed to correspond with a general oscillation of neuronal activity, presumed to be a basic underlying component of EEGs. The waveshape generated by the model of neural activity was, after minor adjustments, a wavelet-like filter usable in the Matlab DWT.

Before using the algorithm described as a platform for comparing wavelets, it was necessary to validate its ability to classify EEGs with reasonable accuracy regardless of the wavelet used. The algorithm first performed signal analysis on the data using a wavelet transform. Once the signals are analyzed using a wavelet transform, a subset of the wavelet coefficients is selected for input into the classifier. In this EEG-classification algorithm, the criterion is discriminability. Discriminability is a standard statistical measure of how well a feature indicates which class the EEG signal belongs to; it measures the relative overlap of the two classes’ distributions of values for that feature. It is defined in



The selected features from the signal analysis are then used to train the classifier.

Finding or creating the optimal wavelet for EEG analysis have been the subject of much investigation. Therefore, the method was created. This method involves the construction of a Meyer wavelet. DWT high- and low-pass filters are derived from the constructed wavelet such that any signal can be analyzed with this matched Meyer wavelet using the DWT. It should be most appropriate for signals with waveforms similar to the waveform the wavelet was originally made to match. The method presented in this paper differs in that, instead of constructing a wavelet that matches a particular signal’s waveform, a wavelet is designed to match the underlyingactivity of neuroelectric waveforms (and thus less specific to any one type of waveform).

Others have constructed wavelets using fractal interpolation functions or by creating “super-wavelets” from linear combinations of standard wavelets. It was demonstrated that super-wavelets can be produced with waveshapes very closely matched to those of the signal being analyzed. Note that these super-wavelets do not necessarily conform to the requirements of a filter usable in the DWT.

The matching pursuit technique is another method for decomposing a signal using waveforms that are similar to those of the signal being analyzed. This technique finds the weighted combination of waveforms (or “atoms”) that is closest to the input signal using a predefined waveform library. Instead of using one waveform may be used any waveform in the library. If the dominant activity in any particular signal is noise, the library waveform that most closely resembles that noise will likely dominate the output of the analysis.

Other approaches to the problem of choosing or creating a wavelet include the examination of the wavelet’s properties.

There is a wide variety of signal analysis methods currently in use in BCI-oriented EEG-classification algorithms. These methods have a large effect on the overall performance. For example, Autoregressive (AR) model parameters, Principal Component Analysis (PCA), Independent Component Analysis (ICA), common spatial pattern analyses, temporal filtering, power spectral density, temporal and spatial filtering, and wavelet analysis. Once the signals are analyzed using the signal analysis method(s). It is often necessary to select a subset of the analysis’s output for input into a classifier. For instance, a learning vector quantizer (LVQ) has been used to select electrodes and frequency bands. Also in the BCI literature, many different methods have been used for classification.

A model was built to approximate the simplest underlying activity in the brain. It based on the hypothesis that this most basic underlying neural activity was a propagating wave of depolarization through a population of neurons. The model was constructed with consideration for how such activity would be measured by EEG electrodes. It was hypothesized that, from the EEG electrode’s perspective, a wave of activity would first appear when the summation of postsynaptic potentials created dipoles and triggered action potentials from the apical dendrites on the outer range of the electrode’s region of sensitivity. This wave would stimulate the surrounding neurons in the network, which would stimulate even more neighbors, until it grew into a peak of activity and then eventually died away, the wave of activity having passed on to another region of the brain.

The normal distribution was chosen because the actual distribution was not known, and the normal distribution is often assumed when that is the case. For each random number, a simulated neuron action potential was added to an array, its position in time determined by the random number’s value. The result was a sum of ten thousand simulated neuron action potentials.

The SNAP filter is designed to correspond with a general oscillation of neuronal activity. Since there are several distinct neural rhythms found in EEGs that are created by subsystems of different sizes, this filter may perform well regardless of scale.

There are many ways of evaluating a wavelet’s appropriateness for a specific type of signal, because was used a very direct method. A classifier was trained and tested to differentiate between EEG signals from two different classes. The classifier identified the class of an EEG signal based upon its wavelet coefficients. By training and testing the classifier was used a different wavelet. It is possible to compare how effective the wavelets are.

For feature selection was selected a subset of the wavelet coefficients as input for the classifier. The coefficients were rank-ordered by discriminability. The classifier was trained on the coefficients with highest discriminability, where was determined by the grid search method. There was no threshold for the discriminability of selected coefficients. In order to visualize the discriminability values, signals were analyzed with the continuous wavelet transform (CWT). The resulting coefficients can be arranged in a matrix and plotted as an image in which the coefficients’ discriminability values are mapped to a color map. It produces a “discriminability map” across frequency and time. Although the clarity of creation of CWT discriminability maps, DWT discriminability maps were not made.

The features were ranked by discriminability. The classifier, a polynomial SVM, was trained and tested using tenfold cross- validation on the data. Cross-validation was performed for every combination of values within set ranges for parameters.

Even though wavelets it was shown to be constrained to having the same shape for every scale. Variations of the neuronal model may be particularly applicable to certain scales of EEG decomposition and analysis. Therefore, one could construct a filter bank, where each scale is analyzed using a filter specifically designed for that time scale. The successful creation of new filters and filter banks may be a way to further probe the neuronal mechanisms behind the EEG.

**Detecting clinically relevant eeg anomalies using discrete wavelet transforms**

In this section it is discussed detecting clinically relevant eeg anomalies using discrete wavelet transforms. Also it will tell about EEG, a variety of cognitive and pathologies in specific EEG signatures, automatically detect of cognitive and pathologies in specific EEG signatures. In addition, this section will explain how automatically detect of cognitive and pathologies in specific EEG signatures is happened.

An EEG is a recording of the electrical signals produced by activity within the brain. A variety of cognitive and pathologies yield specific EEG signatures, which are diagnostic of the condition. As a clinical EEG may contain non-stationary signals, we have employed a Daubechies wavelet to automatically detect embedded signals. The experimental results indicate that its system is able to identify anomalous signals embedded in a standard EEG data-stream.

The human brain is obviously a complex system and exhibits rich spatiotemporal dynamics. Among the non-invasive techniques for probing human brain dynamics, electroencephalography (EEG) provides a direct measure of cortical activity with millisecond temporal resolution. EEG is a record of the electrical potentials generated by the cerebral cortex nerve cells. There are two different types of EEG depending on where the signal is taken in the head: scalp or intracranial. For scalp EEG, the focus of this research, small metal discs, also known as electrodes, are placed on the scalp with good mechanical and electrical contact. Intracranial EEG (EcoG) is obtained by special electrodes implanted in the brain during surgery. In order to provide an accurate detection of the voltage of the brain neuron current, the electrodes are of low impedance (<5 kΩ). The recorded EEG provides a continuous graphic exhibition of the spatial distribution of the changing voltage fields over time. EEG signals involve a great deal of information about the function of the brain. But classification and evaluation of these signals are limited. Visual analysis of EEG signals in time domain may be insufficient. Routine clinical diagnosis needs to analysis of EEG signals. Therefore, some automation and computer techniques have been used for this aim. These signals are not deterministic and they have no special formation like electrocardiogram (ECG) signals. Because of this, in the analysis of EEG signals, statistical and parametric analysis methods are used (such as time–frequency analysis, self relation, crosswise relation, wavelet transform). They also provide the determination of the time of frequency rhythm analysis of periodic EEG signals. EEG signals are treated as complex signals. But these signals may be decomposed into typical sample periods analytically.

Spectral analysis of the EEG signals is performed using the short-time Fourier transform (STFT), in which the signal is divided into small sequential or overlapping data frames and fast Fourier transform (FFT) applied to each one. This approach is based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands–delta (< 4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz). The output of successive STFTs can provide a time–frequency representation of the signal. In order to analyse the whole signal, the window is translated in time and then reapplied to the signal. Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Parametric power spectrum estimation methods such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution. But, since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals.

Wavelet’s feature extraction and representation properties can be used to analyze various transient events in biological signals. The discrete wavelet transform (DWT) developed for recognizing and quantifying spikes, sharp waves and spike-waves. It used wavelet transform to analyze and characterize epileptiform discharges in the form of 3-Hz spike and wave complex in patients with absence seizure. Transient features are accurately captured and localized in both time and frequency context through wavelet decomposition of the EEG records. The capability of this mathematical microscope to analyze different scales of neural rhythms is shown to be a powerful tool for investigating small-scale oscillations of the brain signals. The Discrete Wavelet Transform (DWT) is a versatile signal processing tool that finds many engineering and scientific applications. One area in which the DWT has been particularly successful is the epileptic seizure detection. WT analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions called scaling functions and wavelet functions. Selection of suitable wavelet and the number of levels of decomposition is very important in analysis of signals using DWT. A better understanding of the dynamics of the human brain through EEG analysis can be obtained through further analysis of such EEG records. Neural networks and statistical pattern recognition methods have been applied to EEG analysis. The time frequency characteristics of spontaneous brain rhythms have been investigated.

In this section, it is present the results of a preliminary study that autonomously extracts an embedded signal. The embedded signal was extracted using a Daubechy DWT level 9 and band-passed filtered. The resulting signal extraction algorithm was able to detect the embedded signal with 100% sensitivity. It will investigate the automated detection of additional phenomena that frequently appear in clinical EEG recordings. In addition, its system will be adapted to be able to automatically detect relevant neurophy-siological conditions that have an EEG signature such as petite mals, cortical spreading depression, migraine aura and other related phenomena.

**NeuralAct: A Tool to Visualize Electrocortical (ECoG) Activity on a Three-Dimensional Model of the Cortex**

In this section it is discussed a tool to visualize electrocortical (ECoG) activity on a three-dimensional model of the cortex. Also it will tell about the visualization of neurophysiological data on anatomical structures, Electrocorticography (ECoG) records neural signals, a three-dimensional model of the cortex. In addition, this section will explain creating a tool to visualize cortical activity on a 3D model of the cortex.

Electrocorticography (ECoG) records neural signals directly from the surface of the cortex. ECoG has emerged as a valuable new tool in acquiring cortical activity in cognitive and systems neuroscience. Many studies using ECoG visualized topographies of cortical activity or statistical tests on a three-dimensional model of the cortex, but a dedicated tool for this function has not yet been described. In this section, it is describe the NeuralAct package that serves this purpose. This package takes as input the 3D coordinates of the recording sensors, a cortical model in the same coordinate system and the activation data to be visualized at each sensor. It then aligns the sensor coordinates with the cortical model and renders the resulting activations in color on the cortical model. The NeuralAct package can plot cortical activations of an individual subject. It is capable to render single images as well as sequences of images. The software runs under Matlab and is stable and robust. It here provide the tool and describe its visualization capabilities and procedures. The provided package contains thoroughly documented code and includes a simple demo.

The visualization of neurophysiological data on anatomical structures is a critical vehicle in communicating research in cognitive and systems neuroscience.

The recent increase in the application of electrocorticography (ECoG) as a recording modality has been paralleled by an increased need for visualization of the resulting data. This visualization faces important challenges that in part are unique to ECoG. As with EEG and MEG, the functional imaging space is different than the anatomical space. In contrast to EEG/MEG, the spatial resolution of ECoG is higher than the typical inter-electrode distance.

A meaningful visualization of ECoG data must consist of three steps. First, it is necessary to estimate the locations of the implanted electrodes by co-registering them within a model of the cortical surface. This can be performed using commercial software or tools produced by the academic community. Because the coordinates of the recording electrodes are typically devised using a different imaging methodology. It is the anatomical surface of the brain the co-registered electrode locations are typically located within up to several millimeters above or below the surface of a cortical model. This  
would lead to inaccurate and in certain cases possibly even misleading visualization results. To address this issue, it is necessary to perform a second step. In this step, the estimated electrode coordinates are projected onto the model of the cortical surface. Finally, in the third step, the topographies associated with neural activity or a particular statistical analysis of the neural data (“activations”) must be visualized at those projected electrode locations. This step poses a conceptual problem: the cortical signals are inherently sampled only at the locations of the electrodes. Only the locations of the electrodes would convey activation information to the reader. This would produce a very sparse plot that is difficult to interpret. The third step addresses this problem using spatial interpolation. Specifically, NeuralAct offers the researcher to convolve the activation data at each electrode with a spatial kernel. The NeuralAct tool it is described to receive its input from procedures that perform the first step. It then submits this input to the second and the third steps, which produce the desired activation images.

NeuralAct has been used for this purpose over the past several years. This tool has not been formally described, and has not been made publicly available. To extend the benefit of this tool to the wider neuroscientific community. It here describe the challenges associated with the visualization of data such as those acquired using ECoG. It is discuss how these challenges are addressed in NeuralAct, apply NeuralAct to an exemplary ECoG dataset. It is provide the software in a downloadable package along with a description of its function. The procedure is robust, simple to use, the code is thoroughly documented and contains a demonstration script that highlights the most important functions.

The “NeuralAct” tool it was developed to visualize cortical activations on a three-dimensional model of a brain surface. The tool is written in Matlab. The tool has been tested with Matlab versions 7 and higher, on both Windows and Linux Matlab distributions.

NeuralAct takes three inputs: 1) a 3D model of the cortical surface; 2) 3D coordinates of the recording sensors; and 3) the activation data for each of the sensors. The first input to NeuralAct is a 3D model of the cortical surface. In NeuralAct, the model consists of triplets of vertices that define the elementary triangles that build the cortical surface. NeuralAct includes a model of a pial cortical surface in the Talairach coordinate space. This cortical surface model is derived from the AFNI SUMA package. This default model is loaded into Matlab using the command load pial talairach. The model can subsequently be visualized by invoking the command viewBrain(cortex).

It is desirable to extract a model of the cortical surface individually in each subject.

The second input to NeuralAct are the 3D coordinates of the recording sensors. The 3D coordinates of each electrode from lateral skull radiographs is estimated with using a simple procedure. A more complex and rigorous procedure are performed to extract the 3D coordinates of the implanted electrodes. This and other methods rest on pre-operative magnetic resonance (MR) images and on post-operative computed tomography (CT) images. In NeuralAct, the 3D coordinates of each channel are specified. It is to note that the estimation of the 3D coordinates of the electrodes can be a significant source of inaccuracy. NeuralAct does not by itself perform this step and is therefore free of this source of error.

The third input is the value of cortical activity (“activation”) that results from a particular statistical analysis at each individual sensor. An example of such an analysis may be the average power of ECoG activity in the gamma band, or the value of the ECoG raw potential at a particular latency relative to sensory stimulation or motor output. In NeuralAct, activations are specified as a *n*-by-1 vector subj.activations.

NeuralAct allows researchers to visualize activations that are averaged over subjects. NeuralAct must first project the electrode coordinates onto the surface of the cortical model.

The electrode coordinates are then projected onto the resulting cortical surface. This procedure is described in detail in this section. Finally, the activations are visualized on the cortical surface as color maps.

NeuralAct provides researchers working with ECoG the means to visualize cortical activity on 3D models of the cortex. It has used NeuralAct to visualize data acquired primarily using ECoG. the tool may also be applied to data recorded with other modalities, such as the EEG. In the case of the EEG, for instance, the 3D Talairach coordinates of EEG channels in various montages can be obtained using Loreta software. EEG electrodes are positioned relatively far from the cortex, extra care should be exercised.

NeuralAct has been used to produce sequences of images of neural activity evolving in time. This functionality is demonstrated in the demo included in the NeuralAct package. The package includes the default cortical template and the code that implements the individual steps. In addition to the description provided in this section. It includes detailed comments about the purpose and parameters of each function in the package. Also it is provided comments on the individual lines of the code. Within the package directory, the command demo demonstrates the basic NeuralAct functionality.

It is provided a tool to visualize cortical activity on a 3D model of the cortex. The tool has proven valuable in visualizing data acquired using ECoG. Scientists using other modalities in which sensors are located near the cortical surface (EEG, MEG, diffuse optical tomography (DOT)). It may also find useful. The tool is robust and easy to use, and should therefore benefit a wide range of researchers in these areas.

**Conclusions**

In the last two decades, a considerable amount of experimental evidence was gathered that supports the notion that EEG/MEG signals can provide relevant insights into dynamic brain processes responsible for specific cognitive functions. We may distinguish three main functional roles of brain oscillations: (1) coding specific information, (2) setting and modulating brain attentional states, and (3) assuring the communication between neuronal populations such that specific dynamic workspaces may be created.

This perspective on brain functions is essentially dynamic and nonphrenological. The critical issue is not simply to localize cognitive functions to some site in the brain but to find out the patterns of dynamic interaction between different brain systems underlying a cognitive process; indeed, to unravel these processes it is essential to understand the dynamics of the workspaces that constitute the material core of any cognitive process. For instance, a given conscious perception does not depend exclusively on the activation of a well-localized cortical area, but it emerges from the dynamic interaction between several neuronal populations. This process includes intertwined changes of neuronal activities that enable information processing to take place by (1) the process of focal attention and suppression of distracters (as displayed by the suppression and the enhancement of α oscillations, respectively), and (2) the emergence of information carriers, as, for example, in the form of packets of γ oscillations that entrain neighboring networks and can be broadcast to distant populations, particularly nested with θ oscillations, by feedforward and recurrent connections. To grasp these dynamic cognitive processes that evolve at high speed, in a few tens of milliseconds, the fine time resolution of EEG/MEG is invaluable, and powerful analytical methods to estimate functional and effective connectivity are indispensable. The shortcoming of the limited spatial resolution of these signals can be, to some extent, compensated by advanced spatial dynamical mapping techniques. Methodologies to perform better integration of EEG/MEG with fMRI are being actively developed and are opening up novel exciting perspectives for the study of the dynamics of brain functions with respect to cognitive processes.

In short, brain oscillations should be considered as neural mechanisms underlying cognitive processes and not as simple correlates.

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