FACULTY OF PSYCHOLOGY
AND EDUCATIONAL SCIENCES

CASE STUDIES IN THE ANALYSIS OF EXPERIMENTAL DATA

EEG

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Introduction

The human brain consists of a network of connected pathways. Via synchronized electric brain activity along fiber tracts there can be communication between all these pathways. Synchronized activity of a significantly large population of neurons within this neural network can give rise to large electric field oscillations with an accompanying magnetic field, which can be detected by **EEG (Electroencephalography)** and **MEG (Magnetoencephalography)** respectively. MEG measures the ionic current flow inside a neuron (i.e. primary currents) whereas EEG measures the return of the volume currents outside a neuron (i.e. secondary currents). Both techniques have an excellent temporal resolution and are therefore optimal to calculate connectivity (Bowyer, 2016). MEG and EEG are only partially independent and their spatial resolutions are about the same on the cortex. Generally, recording both of them can give additional information on the bioelectric activity of the brain. Both methods have some unique properties that make either of them more suitable, more beneficial in a certain application (e.g. EEG is better for whole head recording while MEG is better for small region recording) (Malmivuo, 2012).

The synchronized activity cannot only be detected, it can also be imaged using network **connectivity analysis**. Brain connectivity analyses make it possible to map out the communication networks that are needed for the brain in order to function properly. Neuroimaging brain studies have shown that there are specific brain regions that are specialized for the processing of certain types of information and that these regions are all connected and in communication with each other. **Coherence** is one mathematical method that can be used to determine if two such brain regions (or two sensors) have similar neuronal oscillatory activity. Coherence quantifies the frequency and amplitude of the synchronicity of neuronal patterns of oscillating brain activity. When using EEG, coherence quantifies the neuronal patterns of synchronicity between separated scalp electrodes. When using MEG, this is between coils. Coherence estimates the consistency of relative amplitude and phase between signals that are detected in electrodes or coils within a set frequency band. If signals in a sensor space are in phase, their amplitudes will add up while they will subtract if they are out of phase (possibly reducing the coherence value). Next to the sensor space, there is also information in the source space: the amplitude of the underlying source can be used to determine the connectivity's strength. When using source space, a localization is first performed using an inverse solution which removes the current that may have spread into the MEG coil or the EEG electrode which provides a specific region from which the coherent frequencies may be coming. This coherence method at the source level is helpful since it can overcome fundamental problems with localization and interpretation for coherence analysis at the sensor level. So coherence is a linear math method in the frequency domain for calculating neuronal networks. The result is a symmetrical matrix providing no information on directionality. However, coherence is the most commonly used measure to determine whether different brain areas are generating signals that are significantly correlated (i.e. coherent) or not. So actually coherence is a statistic that can be used to determine the relationship between two datasets (i.e. two electrodes or coils). If measured signals are identical, they have a coherence value of 1 (the more dissimilar the signals are, the more the coherent value will approach 0).

So in short, EEG and MEG are recording techniques that can be used for functional connectivity analysis, which does not determine the specific direction of information flow in the brain but rather shows that regions have similar signal content and are therefore most likely connected (Bowyer, 2016).

In the current study I first looked at how to compute coherence in source spacing using an MNE inverse solution (and more specifically between a seed in the left auditory cortex and the rest of the brain using single-trial MNE-dSPM inverse solutions). Then I wanted to compare the outcomes of this dataset using MEG versus EEG. So I added a dataset that contained both MEG and EEG data and adjusted the code in such a way that it was possible to compute coherence for EEG as well (cf. infra). Finally, I checked if other source locations next to the left auditory hemisphere were included in the data. This was the case, there were a total of four different possible source locations: left auditory hemisphere (Aud-lh), right auditory hemisphere (Aud-rh), left visual hemisphere (Vis-lh) and right visual hemisphere (Vis-rh). For this paper, I chose to discuss the right visual hemisphere (cf. infra).

So all together the goal of the current study was to use two different recording techniques (MEG and EEG) to find the vertex with the most observed power (an anatomical brain region or a collection of neurons) in those four different source locations and to compare the (possibly different) results of the two recording techniques regarding coherence for a location of choice (Sporns, 2007)

Materials and methods

Dataset and software

In the original dataset by Martin Luessi, the sample MEG data for computing coherence between channels were first read in and converted into epochs to compute the event-related coherence. The dSPM method was used here, but this could have been MNE or sLORETA as well. Next, the channel sources were calculated and the most active vertex was found in the left auditory hemisphere, which would later be used as seed for the connectivity computation. In this step, the inverse solution was computed for each epoch which made it possible to compute the coherence without having to keep all source estimates in memory. Then, the coherence in the alpha (8-12 Hz) and beta (13-30 Hz) frequency band could be computed (Michels et al., 2010). Finally, a SourceEstimate was generated with the coherence (which was simple since a single seed was used) and plotted on the brain.

The data of Olaf Hauk and Alexandre Gramfort that were imported into this dataset did not only include MEG data but also EEG data (/MEG/sample/sample_audvis-**eeg**-oct-6-fwd.fif) and were adjusted in such a way that it was possible to compute source coherence just as in the original (MEG only) dataset.

Regarding software, all data were analyzed in Python (version 3.7) using MNE-software (Gramfort, Strohmeier, Haueisen, Hämäläinen, & Kowalski, 2013), version 0.18.

Choice of location, vertex index and event id for this paper

In the beginning of the code it is possible to indicate the location, vertex index and event id (i.e. left versus right stimulation) of your choice. For this paper, I chose to discuss respectively the right visual hemisphere, vertex index 2 (cf. infra) and event id 1 (corresponding to left stimulation).

EEG analysis

First the data were loaded and the MEG samples were dropped so that only the EEG samples remained. I controlled for the location I wanted to analyze (Vis-rh in this paper) by assigning the variable 'location' to a label name. To make sure the data loaded properly, it was necessary to read in a forward solution (7498 sources, 60 channels, free orientations), a 366 x 366 noise covariance matrix and evoked data for information. I decided to remove the so called 'bad' channel [EEG 053] before picking the EEG channels which resulted in a total of 59 EEG channels. However, the removal of this EEG channel is free for interpretation (and easily made undone). Epochs were extracted from the data starting from -0.2 seconds before the event until 0.5 seconds after the event.

The goal here was trying to find the number and the index of the vertex with the most observed power for the chosen location. Next, the lower and upper frequency of interest were defined together with the sampling frequency. Also, a function was carried out that gave information about computed connectivity measures, frequency points at which the connectivity was computed, time points for which the connectivity was computed and the number of epochs needed (see Python notebook for more detail). Finally the coherence was visualized using the plot method.

MEG analysis

The only differences with the EEG-analyzation were loading in the data (e.g. no forward solution), the removal of [MEG 2443] in this case (again if desired) resulting in the picking of 306 MEG channels. It is interesting to know that these 306 MEG channels are composed out of 203 gradiometers (GRAD) and 102 magnometers (MAG) – two fundamental classes of MEG sensors – and 1 electrooculography (EOG, often recorded to detect artifacts that are caused by eye movements or blinks) (Mohseni et al., 2012; Quax, Dijkstra, van Staveren, Bosch & van Gerven, 2019).

General analyses

Both for EEG and MEG, the computed coherence for the chosen location and vertex index were saved. Afterwards, the previously computed data could be loaded and analyzed for a comparison between e.g. here the vertex index with the most observed power in the right visual hemisphere using EEG vs that same vertex index and location but using MEG. Therefore the EEG- and MEG-data of both frequency bands (alpha and beta) were plotted. First EEG and MEG were plotted together (with connection on x-axis and coherence on y-axis) per frequency band. Then the same information was plotted again but in different sub-plots through a separation of the EEG and the MEG analysis. Finally some simple statistics were generated for both frequency bands.

Results

Vertex indices with most power

In table 1, the vertex index with the most power is presented for every recording technique (EEG and MEG) and every location (Aud-lh, Aud-rh, Vis-lh, Vis-rh). Apparently the most powerful vertex indices are the same for both recording techniques in the left- and the right visual hemisphere.

Plots

The plots of the MEG and EEG data together (see figure 1) and separately (see figure 2), show that the vertices around the vertex under observation have the highest coherence values. The average coherence is higher on the alpha band for EEG vs MEG, this is also the case on the beta band. Also, in both frequency bands the variance is higher for EEG vs MEG (cf. infra for detailed numbers).

Visualizations

When computing the coherence between the vertex index with most observed power (i.e. 2) and the rest of the brain, this is very similar for both frequency bands when using EEG (see Figures 3 and 4). The colors represent the coherence with white being the strongest coherence. Comparing both frequency bands using MEG (Figures 5 and 6), the only observable differences are a slightly larger scatter of strong coherence in the right visual cortex and some little (weak) coherence in the left visual cortex on the beta band compared to the alpha band. Most importantly when comparing EEG vs MEG, the (strong) coherence is less spread out when using MEG. This is in line with the smaller variance we noticed for MEG on the plots.

Some simple coherence statistics

Figure 7 shows some simple statistics for both recording techniques (EEG and MEG) and both frequency bands (alpha and beta): average, standard deviation, median, minimum, maximum and variance. Most importantly the average coherence is higher in EEG vs MEG for both frequency bands and the same is true for the variance. (Further statistical analyses could show whether or not the differences are significant).

Discussion

The goal of this paper was to compare two recording techniques (EEG and MEG) when computing coherence between the vertex index with the most observed power (here vertex index 2) in a certain brain location (here Vis-rh) and the rest of the brain. It was found that in general both recording techniques present more or less the same core of strongest coherence. However, EEG shows coherence in a wider area than MEG does. When considering only the example comparison discussed in this paper, it is not possible to prefer one method over the other. On the contrary, both methods can complement each other. Moreover, the code makes it possible to easily look into different locations, vertex indices and event id's using both recording techniques in order to gain more coherence information and to find out whether one recording technique might be more useful than the other.

One interesting remark I would like to add to this concise discussion is that these results were all for event id 1. But if one would wish to look more into left-right asymmetry, it is possible to also look at all the same results but for event id 2 (right stimulation) instead of event id 1 (left stimulation). However, for the example discussed in this paper it is not so interesting to compare these results because the vertex index with the most observed power in the right visual hemisphere is not the same for event id 1 and 2. According to table 2 it would be more interesting to additionally check this out for the left visual hemisphere, if desired according to the research question.

References

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Tables and figures

Table 1. *Vertex index with most observed power per recording technique and source location (for event id 1).*

	Aud-lh	Aud-rh	Vis-lh	Vis-rh
EEG	7	2	10	2
MEG	2	5	10	2

Legend: EEG = electroencephalography, MEG = magnetoencephalography, Aud-lh = left hemisphere of auditory cortex, Aud-rh = right hemisphere of auditory cortex, Vis-lh = left hemisphere of visual cortex, Vis-rh = right hemisphere of auditory cortex

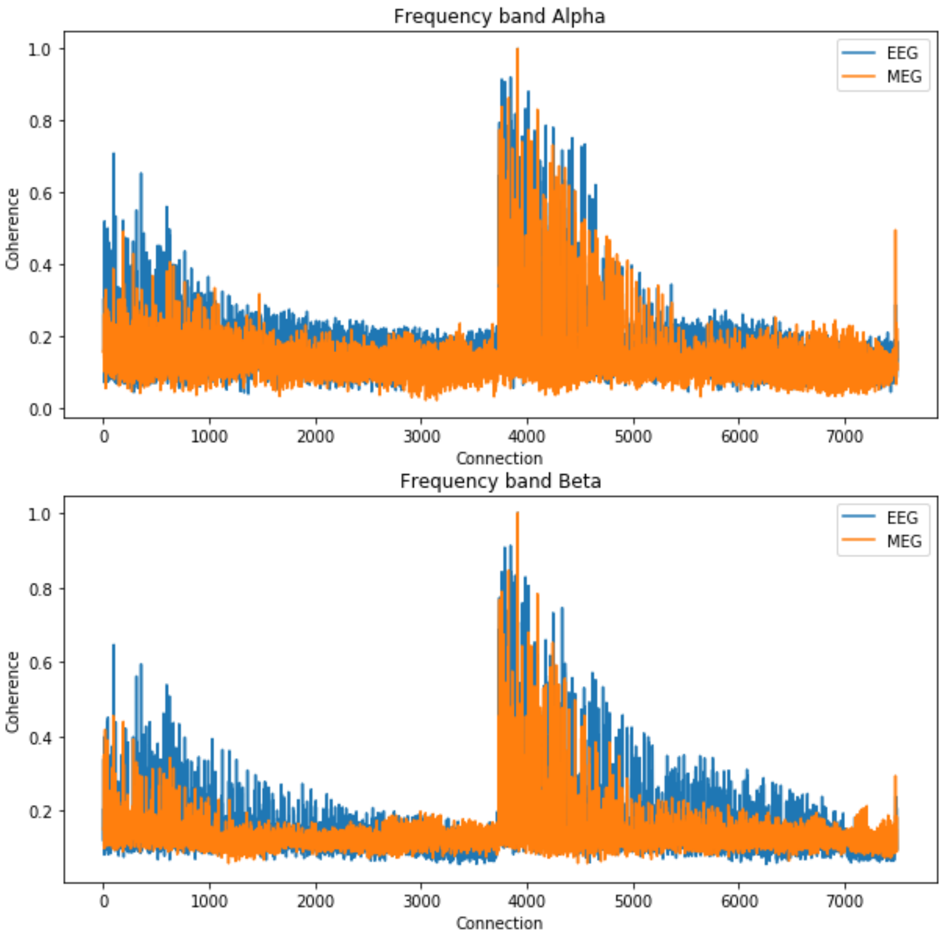

Figure 1. Plots of MEG and EEG data together on both frequency bands (alpha and beta).

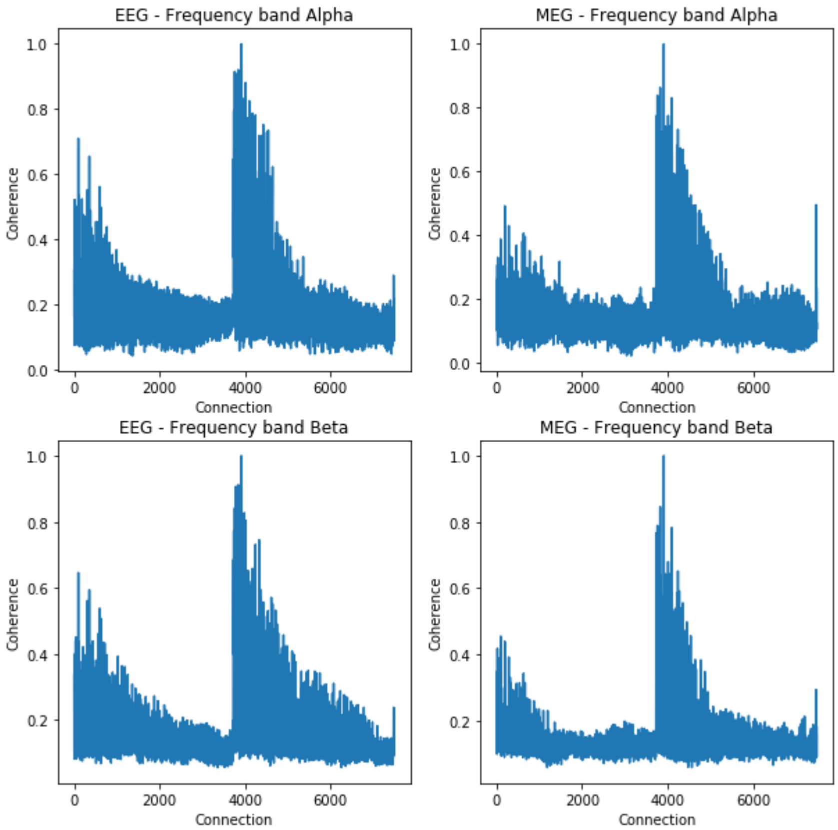

Figure 2. Plots of MEG and EEG data separately on both frequency bands (alpha and beta).

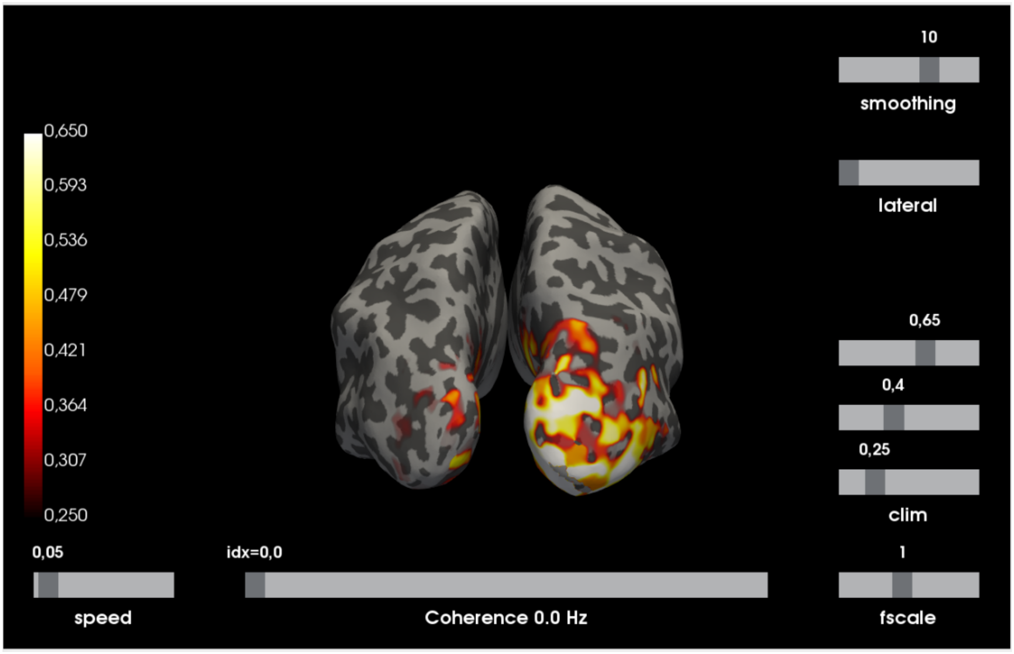

Fig 3. Visualization of the coherence between vertex index 2 of Vis-rh and the rest of the brain, on the alpha band, using EEG and looking at event id 1.

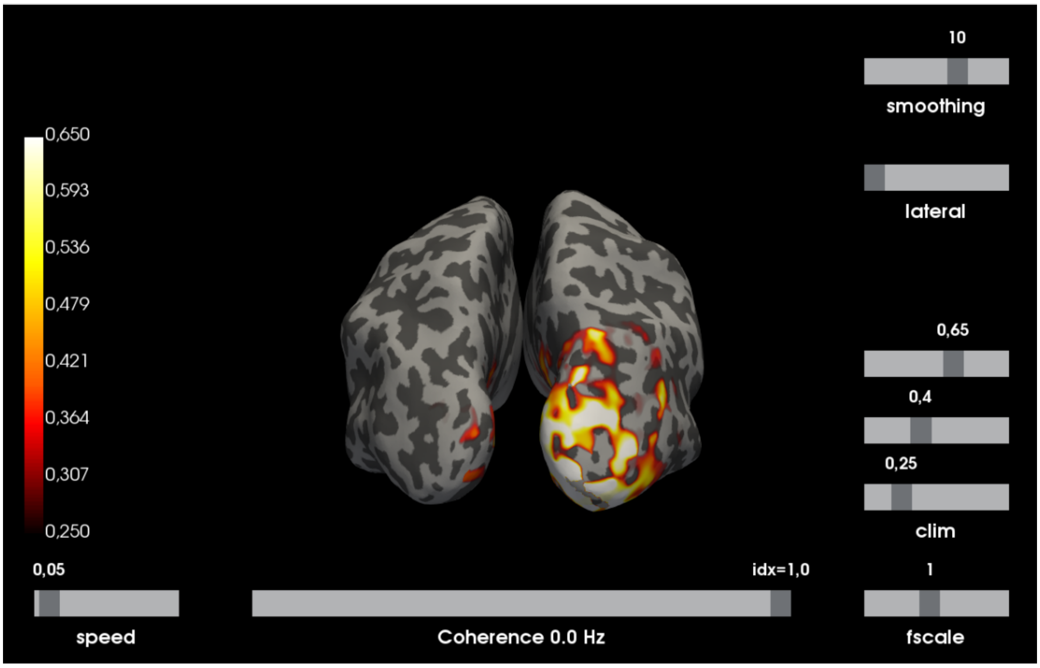

Fig 4: Visualization of the coherence between vertex index 2 of Vis-rh and the rest of the brain, on the beta band, using EEG and looking at event id 1.

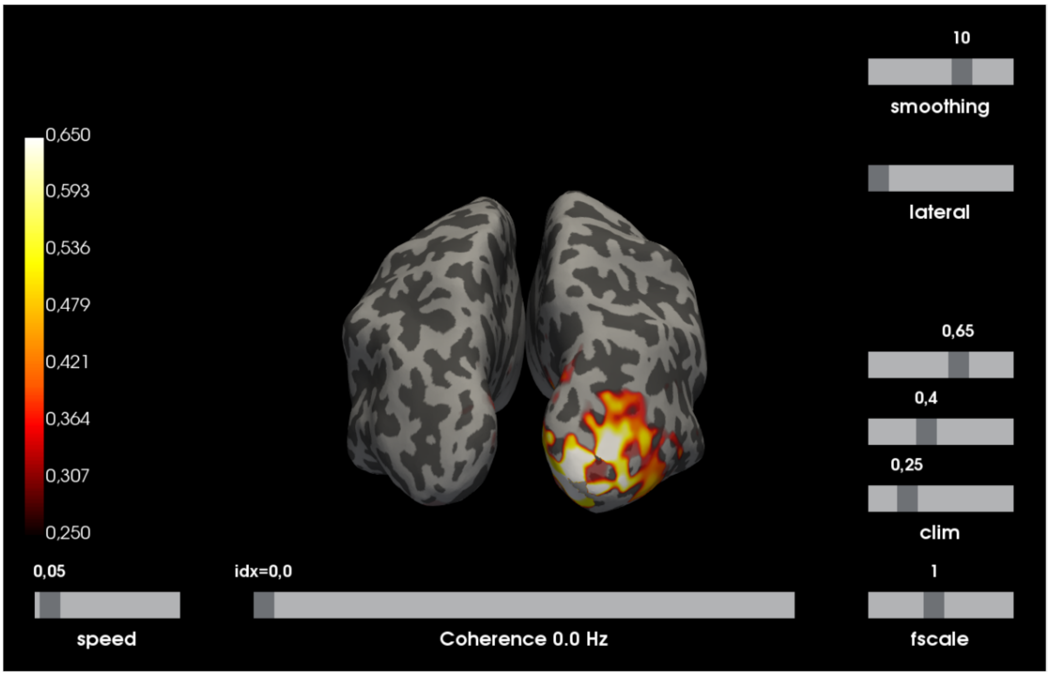

Fig 5: Visualization of the coherence between vertex index 2 of Vis-rh and the rest of the brain, on the alpha band, using MEG and looking at event id 1.

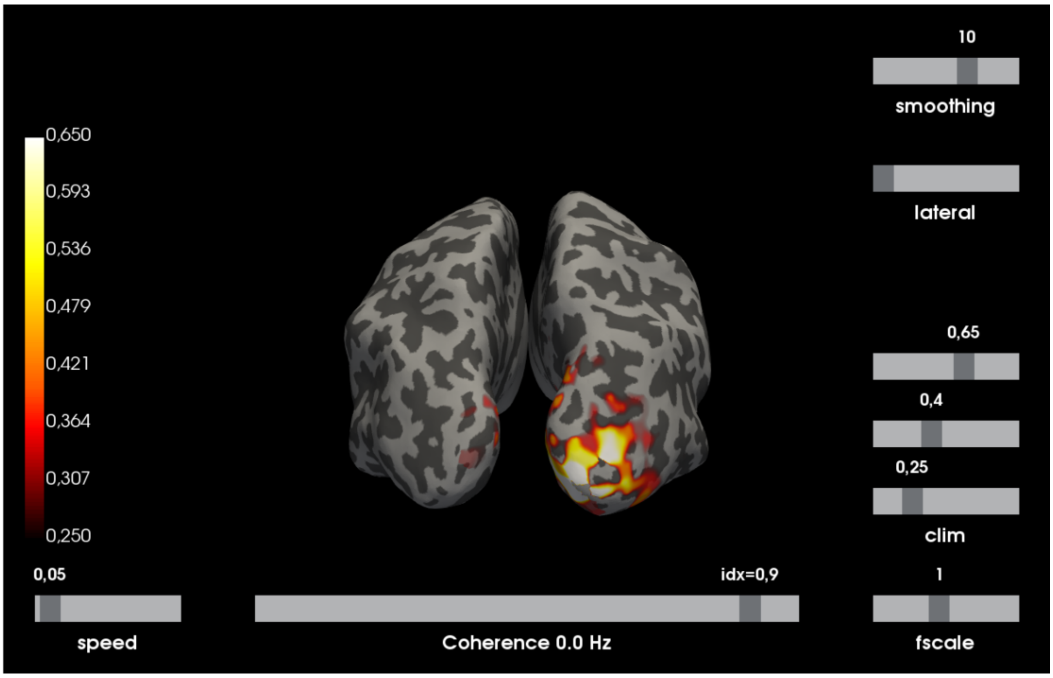

Fig 6: Visualization of the coherence between vertex index 2 of Vis-rh and the rest of the brain, on the beta band, using MEG and looking at event id 1.

```
Statistics frequency band Alpha (EEG first, MEG second)
        average: 0.1763747654137534
        median: 0.16288028031830898
        variance: 0.008122024607295702
        max value: 0.9454440140865529
        min value: 0.040355718595889004
        std value: 0.09012227586615698


        average: 0.1391061567331032
        median: 0.12491814312278797
        variance: 0.005547969624946319
        max value: 0.8633381303342487
        min value: 0.022784453766834214
        std value: 0.07448469389711096


Statistics frequency band Beta (EEG first, MEG second)
        average: 0.15106593254729725
        median: 0.12888033472846758
        variance: 0.007214565108404427
        max value: 0.9174168953891804
        min value: 0.05686782735493929
        std value: 0.08493859610568347


        average: 0.13702897082035048
        median: 0.12627290086987983
        variance: 0.0030639332879593586
        max value: 0.8456673932608147
        min value: 0.05945284526150862
        std value: 0.055352807408110376
```

Fig 7. Some simple coherence statistics for both recording techniques and both frequency bands.

Table 2. *Vertex index with most observed power per recording technique and source location (for event id 2).*

	Aud-lh	**Aud-rh**	**Vis-lh**	**Vis-rh**
EEG	7	7	7	0
MEG	2	7	7	3

Legend: EEG = electroencephalography, MEG = magnetoencephalography, Aud-lh = left hemisphere of auditory cortex, Aud-rh = right hemisphere of auditory cortex, Vis-lh = left hemisphere of visual cortex, Vis-rh = right hemisphere of auditory cortex