A Specialized Interactive Data Application for EEG- Based Sleep Studies

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ABSTRACT

In this paper we present an approach for multimodal visualization of a subject's EEG recordings, specialized for sleep studies. A web application was developed and a real test case from asleep study with a clinically-anxious child (age 7, male) were exploited in order to showcase the operation and use of the tool.

CCS CONCEPTS

• **Human-centered computing → User interface programming**; **Scientific visualization**; **Visualization systems and tools**;

KEYWORDS

Data visualization, EEG, Sleep Study

1 INTRODUCTION

In the context of analyzing data from scientific experiments, the need for visualization of a specific subject recordings often arises. For a sleep study, visualizing the spectrum of each subject during critical epochs (e.g., the transition from wake to sleep) might reveal patterns otherwise overlooked in statistical group comparisons. To this end, a way to derive and visualize the recordings and the spectral power of each subject is proposed, using the open source language R. The framework includes visualization of the time series of each electrode, filtering in the most common EEG bands, computation of the mean spectral density for each channel during specific epochs, as well as an interactive visualization of the brain's spectral activity in each channel before and after the onset of sleep. This solution, apart from providing technical ideas as to how to visualize the data in order to assist experts in making inferences, also provides also base form for every experimenter to follow and enrich, in order to produce a meaningful data app that will assist

a researcher's individual claims and hypothesis. It can thus be considered a basic guide for reproducible research, in the sense that everyone interested can use this framework after publication of a relevant experimental study to reproduce and inspect the analysis online.

2 IMPLEMENTATION

The data application was constructed solely based on the R language and the web framework Shiny[1] . Several open source libraries were exploited both for the processing of the EEG signals as well as for the visualization. Below we separate between the development of the modules that implement these two tasks.

2.1 Processing

EEG is a very complex biosignal, mainly due to the obscurity that surrounds the human brain and its operations, as well as the nature of the electromagnetic signal itself. More specifically, since the signal is recorded in the surface of the scalp, noise removal needs to take place and artifacts often need to be removed in order to retrieve a signal that represents pure neural activity (e.g., free of muscle movement, etc.). To this end, the user can exploit the preprocessing in this application to filter in certain frequency bands, and estimate the spectral density and independent component analysis.

2.1.1 Filtering. The most common transformation used in EEG studies revolve around filtering the EEG signal based on a particular bandwidth, in order to remove artifacts and reveal certain patterns [4] Crucial frequencies used for EEG-based Brain Computer Interfaces [9] as well as for clinical EEG analysis are generally considered [1] [3].

- Delta (0.5-3.5 Hz)
- Theta (4-7 Hz)
- Alpha (8-12 Hz)
- Sigma (12.5-16 Hz)
- Beta (16.5 – 30 Hz)
- Gamma (30.5 – 60 Hz)

These frequencies are the options we included in the app for the signal filtering of each channel. The package used for this task is the "signal"[2] package. To evaluate the correctness of the methods in the library, we also used the respective methods in MATLAB. For filtering, a forward and reverse passband Butterworth filter was applied to retrieve the signal in the given bandwidth.

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[1]http://shiny.rstudio.com/
[2]https://cran.r-project.org/web/packages/signal/signal.pdf

2.1.2 Spectral Density Estimation. Computing the power of the EEG signal in the frequency domain (e.g., spectral density) is also a mainstream way of analyzing biosignals [9]. Findings suggest that this step is also meaningful in the context of sleep studies [8]. The frequencies used are the same as in the filtering process.

2.1.3 Independent Component Analysis. Apart from filtering and spectral density estimation, we added another transformation that has proven to enhance the efficiency of EEG signal analysis [5]. Independent component analysis [7] is a computational method that uses information theory to decompose a set of dependent signals. Unlike factor analysis and PCA, which are also common techniques to decompose a set of entangled signals into uncorrelated components, the ICA uses higher order criteria to determine independence. Since the EEG inherently detects signals that are composed of the superposition of multiple signals stemmed from intracranial sources, ICA aspires to separate the signals into the ones produced by these initial sources. We used the package âĂIJFastICAâĂİ[3] to compute the transformation in the data app. It should be noted that the independent components produced cannot be exactly assigned to a specific channel, but rather, represent the activity of one of the sources inside the brain. That said, the correspondence between processed signal and tallied channel in the application might differ in different runs of the app.

2.2 Visualizations

Four types of visualizations are proposed. The first is based on the filtered signal in each epoch. The second is a boxplot of two channelsâĂŹ signal before and after the onset of sleep. The third is a table containing the mean spectral densities, and the last one is a 3D head showing the power spectrum in each channel before and after falling asleep. The two first visualizations are based on the recordings values while the latter two on their spectral power. The data recordings we use have two 30 second epochs immediately before the onset of sleep and the ten immediately after. The sampling rate of each recording channel was 200Hz. These are static for the current framework, but these quantities can be defined as variables and adjust dynamically for a different study.

2.2.1 Filtered Signal by Epoch. A simple plot of each channelâĂŹs signal, filtered in the indicated frequency. The user can choose which channel to visualize and switch through the tabs to change between the epochs of the signal. Package âĂIJggplot2âĂİ[4] was used for that case.

2.2.2 Channel Boxplots. Boxplots are considered one of the most efficient ways to compare distributions. In this visualization, the user can compare the values of a channel before and after sleep as well as between two different channels.

2.2.3 Table. A table containing the mean spectral density estimation for each epoch and each channel, as well as a mean estimation through channels and epochs. This serves as a manifestation of the subjects exact spectral EEG in that particular frequency band and allows for detailed quantitative comparisons.
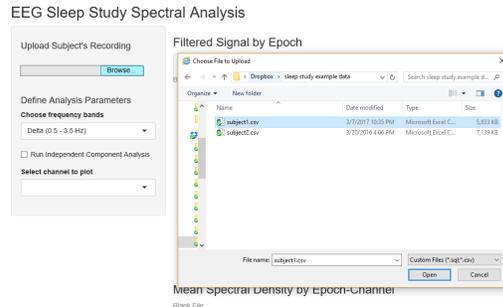

Figure 1: Example of Loading File.

2.2.4 3D depiction of channel spectrum. An interactive 3D head with colored indications on each channelâĂŹs locations. The color is determined by the mean spectral density of the frequency band chosen by the user, amongst the respective epochs. The left one uses the first two epochs (epochs before the onset of sleep) and the right one uses the remaining ten (after the onset of sleep). The channels are sorted based on their mean spectral density and assigned variations of red based on their position (the higher their order the more vivid red becomes). The user can rotate and zoom the 3D image using their mouse. Packages âĂIJRGLâĂİ[5] and âĂIJeegkitâĂİ[6] were used for that task.

3 USE CASE

The data application is accessible in shinyapps [7] .In addition, example datasets from a real study with EEG recordings of anxious children and the code can be found on github[8]. The left panel is devoted to the userâĂŹs input. One can choose either of the two example datasets from above and upload using the âĂIJChoose FileâĂİ button.

Then there is a waiting phase for the dataset to be uploaded and the first computations to take place (filtering in the default band which is Delta, and spectral density estimation). To perform exploratory analysis using this visualizations, one has to start with the less detailed visualization, which is the 3D heads. Filtering in the delta frequency reveals no difference between before and after sleep mean spectral density. However, filtering in the theta frequency reveals a change in spectral activity distribution, from central channels before sleep to frontal channels after (Figure 2) (the color density is higher in frontal after sleep). Theta frequency has been associated with the first stages of sleep [2]. The swift from central to frontal activity also partially agrees with other research [1], which states that though normally there is a decrease in activity in anterior cingulate and orbitofrontal cortex (the frontal channels) during NREM, this may not be the case for people with subjective insomnia, who may often feel anxious before sleep. Since our recordings come from anxious children, this contradiction with the norm may indeed agree with the aforementioned findings.

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[3]https://cran.r-project.org/web/packages/fastICA/fastICA.pdf
[4]http://ggplot2.org/

[5]https://cran.r-project.org/web/packages/rgl/index.html
[6]https://cran.r-project.org/web/packages/eegkit/index.html
[7]https://georgepanagopoulos.shinyapps.io/sleepeeg/
[8]https://github.com/GiorgosPanagopoulos/Data-app-for-sleep-EEG-analysis

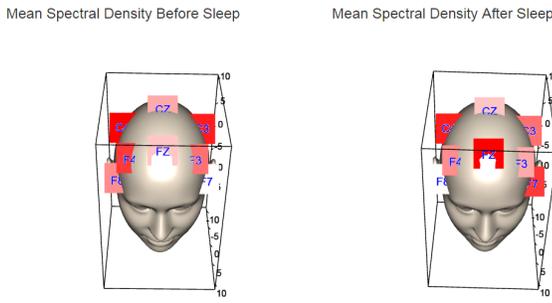Mean Spectral Density Before Sleep   Mean Spectral Density After Sleep

Figure 2: Mean Spectral Density Before and After Sleep.

Mean Spectral Density by Epoch-Channel

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	Mean
F3	372.22	566.300	567.850	231.720	264.480	186.82	242.960	218.880	244.180	210.260	252.330	289.710	303.98
F4	491.03	815.120	629.120	308.870	293.140	203.46	360.600	188.780	264.550	214.720	252.590	305.370	360.61
C3	596.96	760.980	708.090	291.430	341.320	219.86	311.340	234.380	243.640	193.430	248.200	307.370	371.42
C4	811.60	1488.750	787.740	847.690	346.890	304.82	483.500	117.810	197.870	96.190	121.080	161.270	480.43
O1	377.13	675.350	616.810	431.580	353.580	275.57	374.350	285.190	361.500	323.420	362.410	393.280	402.51
O2	262.39	467.710	454.420	349.410	262.230	205.30	252.220	169.170	187.100	233.710	218.750	210.860	272.77
Cz	347.59	453.370	488.340	337.820	290.870	242.16	234.980	202.670	207.800	204.140	220.630	218.910	287.44
Fz	411.89	510.530	512.320	451.910	472.740	495.82	469.680	469.850	462.540	632.980	489.060	497.790	489.76
F7	350.79	396.850	372.260	365.350	392.440	358.18	342.650	326.470	340.840	831.420	357.190	333.370	397.32
F8	312.78	606.760	541.430	227.250	284.690	170.21	226.460	186.920	235.590	195.860	255.950	283.640	293.96
Mean	433.44	674.172	567.838	384.303	330.238	266.22	329.874	240.012	274.561	313.613	277.819	300.157	366.02

Figure 3: Mean Spectral Density by Epoch and Channel.

Diving deeper into the analysis, we can compare the exact values of the density, using the table, to identify patterns or evaluate the hypothesis we came up with. One can easily observe that almost all channels suffer a steep decrease in spectral density after epoch E3, except from Fz and F7. This also agrees with the findings suggested above. Moreover, by observing the mean spectral density for each epoch in Delta and Theta frequencies, we can certify that the overall activity declines during sleep time in the low frequencies. By examining the table in other frequencies, we see that higher frequencies are more prone to increase after sleep, which is also suggested in [8] and buttresses some of the claims in [6]. Apart from the spectral realm, however, we should evaluate whether there are any indications supporting the hypothesis on the values of the signal in the time domain. We can focus on the Fz channel, which represents mostly activity stemming from the prefrontal cortex. By comparing the boxplots of Fz with the rest of the channels, filtered in Theta, we can easily conclude that Fz has significantly more variance than any other channel during this frequency (e.g., Figure 4). Note that if we change the frequency filtering, the same comparison changes completely (Figure 5), making clear that the activity in the frontal lobe is dominant in theta frequencies.

The same outcome can be revealed through plotting the filtered signal itself. Figure 5 shows Fz filtered in theta for Epoch E3 (first of sleep) while Figure 6 and Figure 7 shows O2 and O1 (which represent more central activity) during the same epoch.

This work is subject to several limitations. First, these examples are based on date from one subject. Moreover, there are multiple
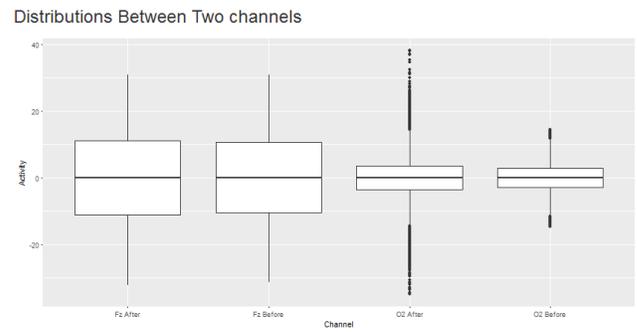
Distributions Between Two channels

Figure 4: Distribution Comparison Between Fz and Oz (Theta filtering)

Distributions Between Two channels

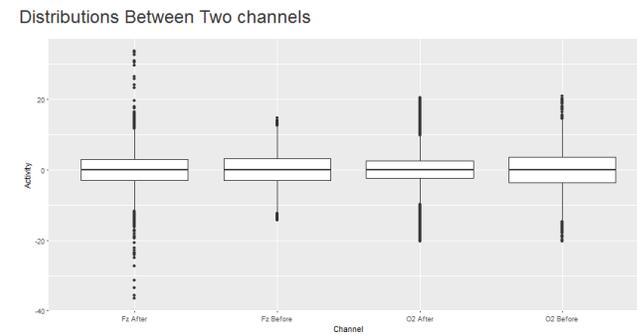**Figure 5: Distribution Comparison Between Fz and Oz (Alpha filtering)**

Filtered Signal by Epoch

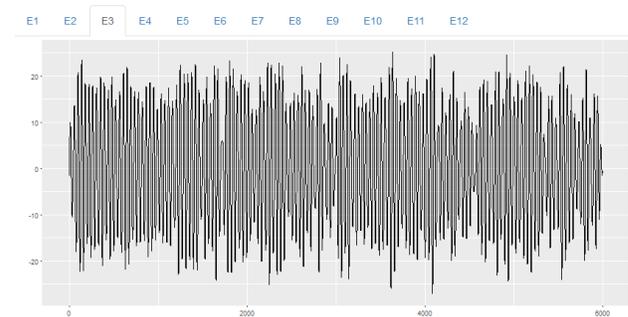E1   E2   E3   E4   E5   E6   E7   E8   E9   E10   E11   E12

Figure 6: Distribution Comparison Between Fz and Oz (Alpha filtering)

assumptions that our exploratory analysis is based on (e.g.,Fz represents localized frontal activity, etc.). However, the purpose of this tool is to provide detailed visualizations, for specific cases, in order to provide specific evidence when drawing conclusions from research studies. In case of evaluating interindividual differences across subjects and drawing conclusions for certain populations,
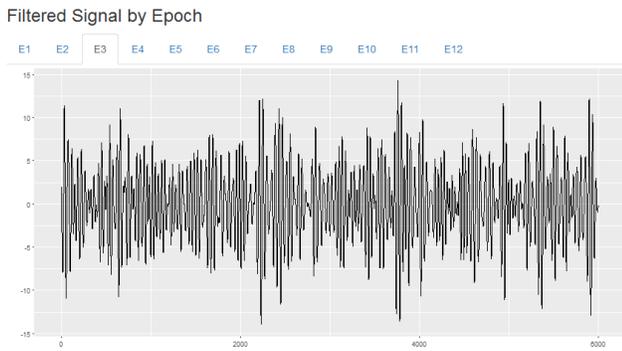
Figure 7: Plot of O1 activity during Epoch 3 filtered in Theta
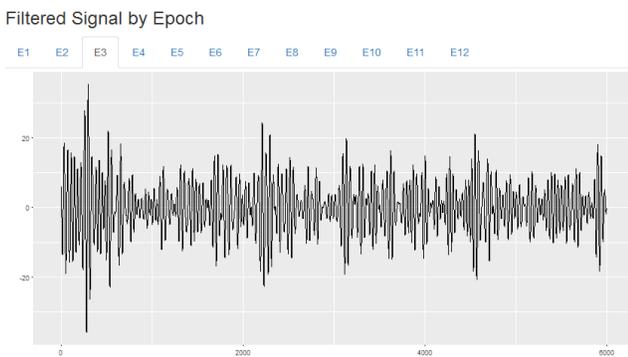
Figure 8: Plot of O2 activity during Epoch 3 filtered in Theta

the data application can be adjusted accordingly to have an analogous input and evaluate statistical tests, plot population differences, etc.

4 CONCLUSIONS AND FUTURE WORK

The application is flexible enough to be enriched with further functions or completely modify the ones present, as the analysis proceeds in depth. For example, deriving further transformations or extra plots to present something possibly crucial for the outcome of a specific study is quite feasible and can be easily added to the data app. In this way, the current framework serves simply as a base for relevant research, and individual researchers can use this mechanisms to investigate their own hypotheses. This continuous interaction between the domain expert and the computational tool augments the focus and efficiency of the exploratory analysis, in disjunction to studies where difficulties arise due to lack of background knowledge on the analyst side or technical skills on the expertsâĂŹ side. Following this paradigm during an experimental study will result at the end of the analysis to a web application where everyone interested can reproduce the analysis step by step, examine the results and access the exact code used to produce them. We use R because it is open source and popular amongst quantitative as well as qualitative scientists, ensuring that everyone can rerun or adapt/edit the analysis, deriving further conclusions. This,

along with the public availability of the study's data, will ensure the total transparency and reproducibility of the given research, thus massively enhancing its robustness.

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