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Visualising a multi-modal neuroimaging dataset

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Abstract

This document contains the documentation for the project of the *Information Visualisation* course, taught by Prof. Beat Signer for the Master of Science in Applied Sciences & Engineering: Computer Science, at the Vrije Universiteit Brussel (VUB). The project's goal is to adequately visualise a large dataset of choice. In our case, the dataset is a multi-modal neuroimaging dataset.

1 Introduction

Recent advances in the area of Brain-Computer Interfaces (BCI; Rashid et al., 2020; Saha et al., 2021) have popularised neuroimaging, resulting in large standardised neuroimaging datasets (Wakeman & Henson, 2015; Kaya et al., 2018; Schoffelen et al., 2019; Rathee et al., 2021). Consequently, a variety of online databases that host and validate such datasets have emerged (e.g., OpenNeuro[1] and StudyForrest[2]). These phenomena bode well for the neuroimaging community as BCIs are a promising application of neurological data, however, they are not the only one. Neurologists diagnose patients through neuroimaging and they can learn new patterns from neuroimaging datasets which they can then teach to students. For these purposes, neurological data needs to be adequately visualised. In addition, even for BCIs, visualising the neurological data is important. To ensure that the machine learning algorithms that steer BCIs do not learn irrelevant patterns from the data, it is often preprocessed using a variety of techniques (Burgess, 2003; Turnip & Junaidi, 2014; Ngoc et al., 2015). A simple but fundamental example of such a technique is visualising the data and letting a domain expert, i.e., a neurologist, look for artefacts. These artefacts can then be removed from the data, allowing the algorithms to learn from less noisy data. Overall, it is clear that visualising neurological data can be very useful and therefore investigating new ways of graphically representing neurological data is a worthwhile undertaking, hence, our choice for this subject.

Particularly interesting in the context of visualisation is the use of multi-modal data. It is often the case that doctors revise multiple different types of neuroimaging before diagnosing a patient. In fact, the BCI research field has noticed this and has begun research into algorithms that can make use of two types of neurological data to make more accurate predictions (Hinterberger et al., 2004; Deshpande et al., 2017; Corsi et al., 2019). Consequently, the usefulness of multi-modality has resulted

[1] `https://openneuro.org/`
[2] `http://www.studyforrest.org/`

in a variety of multi-modal neuroimaging datasets (Wakeman & Henson, 2015; Schoffelen et al., 2019). The dataset that we chose for this project is one of these datasets, namely, Wakeman and Henson's (2015) "A multi-subject, multi-modal human neuroimaging dataset".

For this project, we chose to emphasise on within-subject multi-modality. The dataset contains three types of functional neurological data, namely, electroencephalography, electrical recordings from the brain (EEG; Berger, 1938; Haas, 2003), magnetoencephalography, magnetic field recordings from the brain (MEG; Singh, 2014), and functional magnetic resonance imaging, blood flow recordings from the brain (fMRI; Glover, 2011; Menon & Crottaz-Herbette, 2005). While fMRI is interesting in the context of visualising, its form is inherently different from EEG and MEG, which are both oscillating signals. Therefore, we chose to focus on creating a visualisation that allows for a simultaneous view of the EEG and MEG recordings of the dataset. The initial aim of the visualisation was to provide neurologists with a single view that shows both the EEG and MEG data. In the neuroimaging field, the dataset is seen as an Event-Related Potentials (ERP) dataset. This means that the subjects from which the data was recorded were asked to perform simple cognitive tasks during the recording of their neurological activity. By investigating the recorded signals at the times where the tasks were performed, insights can be gained into the workings of the brain. Adding multi-modality to this paradigm, we find it interesting to create a visualisation where both EEG and MEG recordings can be seen in a single view where the signals are aligned and events are highlighted. Complementary to such a visualisation are a variety of possible operations such as windowing around the events and depicting the average window as well as power spectral density analysis.

The dataset is preprocessed using a standard neuroimaging preprocessing pipeline that consists of the following three steps: frequency filtering, downsampling, and Independent Component Analysis (ICA) to remove artefacts originating from irrelevant activity. The visualisation consists of two phases. In the first phase, users can select a subject based on a number of data fields. The focus lies on multi-modality within a single subject, not between subjects, hence the choice for this separate first phase. In the subsequent second phase the chosen subject's EEG and MEG signals are shown, aligned on the events and with the aforementioned optional operations. Users can choose to show (or hide) signals by selecting (or deselecting) groups of recording channels, which are three-dimensionally visualised and grouped per brain lobe. The visualisation is qualitatively validated by means of a discussion with a domain expert, i.e., a Professor in neuroscience. Overall, the results of the validation are positive. However, according to the validator, the visualisation is more tailored to the needs of a neurology researcher than to those of a clinical neurologist. Hence, from that point, the focus of the visualisation was thus shifted towards neurology researchers.

The rest of this document is structured as follows. Section 2 gives a description of the dataset as well as a brief introduction into EEG and MEG. Section 3 explains the preprocessing that was performed. Section 4 describes the visualisation. Section 5 summarises the validation process. Finally, Section 6 concludes the document with a discussion on the conclusions that can be drawn.

2 Data

The dataset that is visualised is Wakeman and Henson's (2015) "A multi-subject, multi-modal human neuroimaging dataset". As its name suggests, this dataset consists of multiple functional and structural neuroimaging modalities. In the context of this project, the focus lies on the functional modalities. The dataset consists of data from 19 healthy subjects. However, due to recording issues, in the latest version of the dataset (v1.0.0[3]), the data of 3 subjects is dropped, resulting in a dataset of 16 subjects. For each subject, the functional modalities consist of EEG, MEG, and fMRI, recorded while they performed multiple runs of hundreds of trials of a simple perceptual task on pictures of familiar, unfamiliar, and scrambled faces during two visits to the laboratory. As mentioned, the focus lies on the EEG and MEG data, as they are similar in form. The fMRI data is excluded. Since the subjects'

[3] `https://legacy.openfmri.org/dataset/ds000117/`

neurological activity is recorded while being asked to perform certain tasks, the dataset is an ERP dataset. The visualisation is designed accordingly. The following three paragraphs give descriptions of the three types of data that are extracted from the complete dataset, i.e., the EEG data, the MEG data, and the metadata.

Electroencephalograpy EEG signals consist of voltage fluctuations in the brain resulting from the flow of ionic current during the firing of synapses in the neurons of the brain (Baillet et al., 2001). The actual recorded signal corresponds to the difference in voltage between the active and reference electrode, over time. EEG amplitudes generally range from -100 to +100 microvolts ($1 \times 10^{-6}\,\mathrm{V} = 1\,\mu\mathrm{V}$). Research has shown that EEG (and MEG as well) signals can be categorised into frequency bands, each of which can be linked to particular functions. On top of that, irregularities in these frequencies can be used for the diagnosis of certain disorders (Fisch, 2003). To record EEG, a number of 1 to 256 electrodes are attached to the scalp. Numerous types of electrodes are used. A distinction is made between *wet* and *dry* electrodes. The former of which is the most common. Aside from the type of the electrode, its placement on the scalp is also an important factor. Most often, the internationally recognised '10/20' system is implemented, with the values 10 and 20 indicating that the distances between adjacent electrodes are either 10 % or 20 % of the total front-back or right-left size of the skull. Wakeman and Henson (2015) record EEG data through 70 dry electrodes on an Easycap[4] EEG cap with electrode layout conforming to the extended 10–10 % system (Jurcak et al., 2007). Since the shape of the head of the subject can mold such caps quite easily, they use a 3D digitizer to determine the estimated locations of the electrodes (Wakeman & Henson, 2015).

Magnetoencephalograpy MEG signals consist of measurements of the magnetic field produced by the brain's electrical currents. The sensors that are used to record MEG are called magnetometers. MEG amplitudes can vary significantly when compared to EEG, down and up to, respectively, -100000 and 100000 femtotesla ($1 \times 10^{-15}\,\mathrm{T} = 1\,\mathrm{fT}$). Note that the origin of the magnetic fields are exactly those electrical currents that are measured through EEG. Electrical currents are always associated with a magnetic field and it is exactly that field that is measured through MEG. A significant advantage of MEG over EEG is that magnetic fields pass through the skull without any distortion. MEG also provides better spatial resolution than EEG, with a difference of almost 5mm. MEG recording equipment consists of a dewar[5] that contains multiple sensor coils that do not touch the subject's head. Wakeman and Henson (2015) record MEG data (simultaneous with the EEG data) in a light magnetically shielded room using an Elekta Neuromag Vectorview 306[6] system, which consists of 102 magnetometers. Unlike EEG electrodes, the magnetometers have a fixed position and are thus the same for every subject.

Metadata Aside from the actual neuroimaging data, three types of metadata are extracted from the dataset. Firstly, Wakeman and Henson (2015) store the age and sex of each of the subjects. Two filters for these data fields will allow users to look for suitable subjects. Secondly, the locations of the EEG electrodes are extracted, as mentioned, these are subject specific. Lastly, the locations of the MEG sensors are extracted, these are equivalent for all subjects.

3 Preprocessing

A traditional neuroimaging preprocessing pipeline is used to clean the extracted data. The following paragraphs discuss each of the steps of the pipeline. All preprocessing is implemented using the *Python*

[4] `https://www.easycap.de/`

[5] *noun*: a double-walled flask of metal or silvered glass with a vacuum between the walls, used to hold liquids at well below ambient temperature. Definition by Google's English Dictionary.

[6] `https://www.mrn.org/collaborate/elekta-neuromag`

MNE library (Gramfort et al., 2013). Due to the size of the dataset, all preprocessing was ran on the VUB Hydra HPC cluster[7].

Downsampling Downsampling is a signal preprocessing technique that is intended to reduce the size of the dataset. This can be needed as, for example, when EEG recording apparatus with 32 channels and a sample rate of 0 Hz, i.e., 400 samples per second, represents each sample as a 32-bit float, the EEG data would consist of $32 * 400 * 32$ bits per second of recording, which is approximately 50kB/s. Reducing this can be done through downsampling, which consists of simply selecting every nth sample and dropping the rest. Downsampling must be done with extreme care as, through a phenomenon called aliasing, it can introduce new artefacts to the data. Important to keep in mind when downsampling is the Nyquist-Shannon sampling theorem (Shannon, 1949), which states that if the sampling rate is R_1, then any signal with a frequency $R_2 \geq R_1 + \frac{R_1}{2}$ will be perceived as a signal with a lower frequency. This means that, for example, when trying to detect certain frequency bands in an EEG signal, the sampling rate must at least be double the higher bound of the frequency band and thus downsampling can have a significant effect on the information in EEG data. In the case of the dataset that is used here, the EEG and MEG signals were originally sampled at 1100 Hz. In the context of this project, they are downsampled to 145 Hz, meaning that frequencies up to $\frac{145\,\text{Hz}}{2} = 72\,\text{Hz}$ should be detectable from the resulting signals. This corresponds to the upper bound of the 'high gamma' frequency band and thus all relevant frequency bands are captured, see Table 1 of Kawala-Sterniuk et al. (2021).

Frequency filtering EEG and MEG signals often contain electrical noise with frequencies depending on the outlet. In Europe outlets have frequencies around 50 Hz. Additionally, in most cases, only certain frequency ranges are of interest. In these cases, frequency filtering can be used to filter out frequencies that are not part of the chosen frequency bands. Frequency filtering can be done in multiple ways: low-pass filters, which filter out high frequencies above a certain threshold, high-pass filters, which do the opposite, band-pass filters, which do both, and notch filters, which remove a single frequency. The exact mathematics are not explained here, but in general they consist of applying some transformation function to each of the data points of a signal, with the possibility of having recursive transformations (Burgess, 2003). In the case of the dataset that is used here, the EEG and MEG signals were originally frequency filtered with a low-pass filter at 350 Hz and no high-pass filter. In the context of this project they are further frequency filtered with a 1 Hz to 70 Hz band-pass filter and a 50 Hz notch filter, thereby removing electrical noise and isolating the relevant frequency bands.

Artefact cleaning When artefacts only span a single frequency or when they span a frequency range that does not contain relevant information, frequency filtering can be used to filter out these frequencies and with that remove the artefacts. However, when artefacts span multiple frequencies and these frequencies can not just be filtered out, other techniques must be used to get cleaner data. The technique that is used in the case of this project is an artefact correction technique. This means that the technique transforms the signals in such a way that the part of the signal that is the artefact is removed and the relevant information is kept. A general assumption that is made when correcting signals is that if two signals are statistically independent and they are combined into a single signal, that signal can also be separated again into into statistically independent components. This process of separation is called *source decomposition* and algorithms that are used to do this are often based on Independent Component Analysis (ICA; Sun et al., 2005; Turnip & Junaidi, 2014), Principal Component Analysis (PCA; Turnip & Junaidi, 2014), or Signal Space Projection (SSP; Uusitalo & Ilmoniemi, 1997). It is important to note that ICA and PCA are both techniques that separate independent signals that have been combined, but generally, ICA is assumed to be the better one since it does not assume orthogonality between the individual signals. Both PCA and SSP do make

[7] `https://hpc.vub.be/`

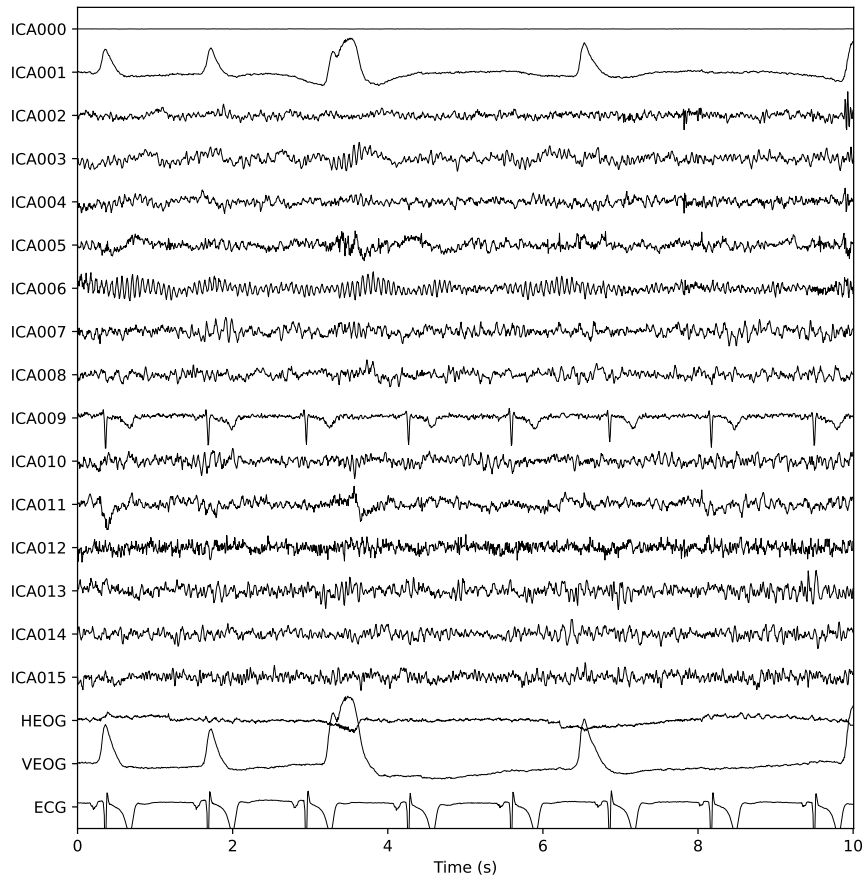

Figure 1: The first 10 s of 16 ICA components derived from the EEG data of the first run of the first subject in the dataset. Additionally, the datasets' EOG and ECG channels are shown.

this assumption, which is unrealistic for EEG and MEG data. Once signals have been separated into components, selecting which ones are artefacts and which ones are not can be done in two ways. Figure 1 shows 10 s of 16 ICA components derived from the EEG data of the dataset that is visualised in this project. Some artefacts, like those that originate from eye movements or heartbeats, have known patterns and can be recognised manually. In Figure 1, component 1 clearly captures the subject's eye blinks. On the other hand, component 9 clearly captures the subject's heartbeats. Datasets often include three complementary modalities on top of their EEG and/or MEG data. Firstly, two electrooculography (EOG) channels, one vertically oriented and another horizontally oriented, which capture a subject's eye blinks. Secondly, a single electrocardiography (ECG) channel, which captures a subject's heartbeat. The dataset that is used here contains such complementary channels, represented in Figure 1 by 'HEOG' and 'VEOG', and 'ECG', respectively. By calculating the similarity between these channels and each of the components, the process of finding and correcting noisy components can be automated. It is exactly this process of artefact correction that is applied here, using 16 components calculated through ICA and the provided EOG and ECG channels.

4 Visualisation

The design of the visualisation followed the principle of 'Function First, Form Next' (Munzner, 2014). Firstly, we focused on developing the functionalities that the target user would need for the task we are trying to address with the visualisation. Only after implementing these, more visual aspects were taken into account. Therefore, reflecting the design process, the description of our visualisation is separated into two subsections. In the first subsection, we elucidate which functionalities are provided and why these are important. The subsequent subsection clarifies the visual design choices that were made.

Finally, the last subsection briefly mentions the frameworks that were used to build the visualisation. The source code for the visualisation can be found on GitHub[8], for instructions on how to boot the visualisation, the reader is referred to the `README.md` file. For a demonstration of the visualisation in the form of a walkthrough, the reader is referred to the `demo/demo.mp4` file.

4.1 Function

Traditionally, a certain workflow is followed when analysing EEG and MEG data. Once the signals have been preprocessed to remove as many artefacts as possible, neurologists and neurology researchers often start by getting a general overview of the subjects' runs. Whether they have a specific category of subjects in mind for a certain research question, or whether they simply want to analyse as many subjects as possible, the first thing that is usually done is looking at a subject's complete run and at the accompanying event offsets. When doing so, the signals of individual electrodes/sensors can be interesting, more so in the case of clinical neurologists. On the other hand, researchers are often more interested in generalising over certain brain areas. Hence, they will want to be able to at least distinguish between brain lobes. If more fine-grained distinctions are possible, all the better. Once the neurologists/researchers have a general idea of what happens in the time-domain, they will want to investigate the frequency-domain. As mentioned, neural activity recorded by EEG and MEG falls into certain frequency bands and thus, by investigating a signal's frequency densities, neurologists/researchers can get insight into what types of neural activity the subject's brain was performing, all throughout a run. To be able to do this, a transformation that transforms signals from the time-domain to the frequency-domain is required. Most often, a power spectral density analysis (PSD; Bascil et al., 2016; Chakladar & Chakraborty, 2018) is performed. After investigating a complete run, dataset-specific questions are addressed. In the case of the dataset that is visualised here, i.e., an ERP dataset, a neurologist/researcher will want to investigate what happens at the event offsets. To do so, they will often calculate an average window starting a certain amount of time before the event offsets and ending a certain amount of time after. Naturally, to make such an average window meaningful, a baseline correction needs to be performed, usually with respect to the time before the event offset. A baseline correction consists of subtracting the mean value of a certain period in a window from the entire window. When analysing such an average window, once more, neurologists/researchers will want to be able to distinguish between brain lobes, as here, they can really learn which brain lobe is active for which type of event. Additionally, calculating and analysing a PSD for such an average window can result in insight regarding which type of neural activity these brain lobes are performing.

While the corpus of functionalities that neurologists and/or researchers require are in no way restricted to those that are mentioned here, in the context of this project, the functionality that is addressed is limited to that which is mentioned above. The development of a visualisation that handles all possible neurologist and/or researcher needs would require time and resources beyond the scope of this project. Examples of frameworks that are working on this are the Python MNE library (Gramfort et al., 2013) and the FieldTrip package (Oostenveld et al., 2010).

4.2 Form

Before delving deeper into the more form-related design choices we made for our visualisation, we want to acknowledge that the ideas presented in this section are heavily based on lectures given by Prof. Beat Signer in the Information Visualisation course at the VUB. The lectures in question are in turn based on Munzner's (2014) *Visualization Analysis & Design* and Few's (2006) *Information Dashboard Design: The Effective Visual Communication of Data.*

To visualise the dataset and provide the aforementioned functionalities, we developed a single-page application consisting of two screens. The first screen provides a subject selection panel, while the

[8] `https://github.com/RobinDHVUB/info-vis-project`

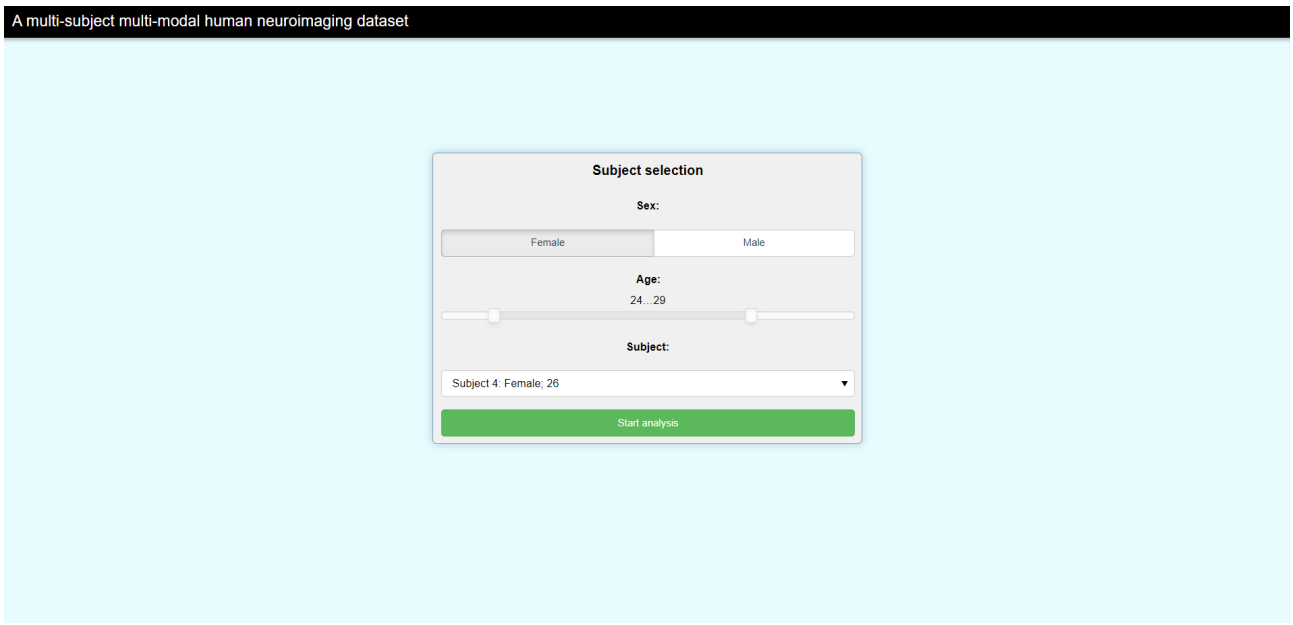

Figure 2: Screenshot of the first screen of the visualisation, which focuses on subject selection.

second screen provides the needed views and operations that allow interaction with and exploration of the selected subject's data. The choice to use separate screens was made for two reasons. First and foremost, the dataset to be visualised, even for a single subject, is very large, which might impact loading time. Secondly, in our opinion, a clear distinction between the subject selection phase and the data exploration phase will incline the user to first think about which subject's data they want to explore, before moving to the next screen where they can then further interact with the data in a responsive manner.

When booting the visualisation, a start screen (shown in Figure 2) that contains two components is loaded. Firstly, a link to the original dataset is presented in a navigation bar at the top. Secondly, a subject selection frame is depicted in the center. The link to the dataset is positioned visibly in the top left corner of the screen as it provides important context regarding what the user is exploring. Nevertheless, the main focus lies on the subject selection panel. The emphasising central position and size of this panel is expected to quickly attract the user's attention. Although the number of subjects in the dataset is rather limited, the choice was made to provide filtering options. Finding and selecting a specific subject is thereby made easier. Additionally, it allows for some scalability in the number of subjects. Currently, filtering can be done on the biological sex and the age of a subject, using, respectively, toggle buttons and a range slider. These filtering options reduce the number of subjects to choose from in the underneath dropdown selection box. If there had been a larger collection of patients, a search bar accompanying the dropdown selection box might have been useful. However, large patient collections are rather rare in neuroimaging datasets. Once the user selects a subject, clicking the 'Start Analysis' button loads in that single subject's data and renders the second screen where this subset of data can be analysed. Since this transition can take some time, visual feedback is provided through the use of a spinner to inform the user that the button's action is being executed.

The second screen (shown in Figure 3) contains the analysis-related visualisations. The link to the dataset in the left top corner is replaced by the details of the selected subject, i.e., subject ID, age and sex. These details have been added in light of the 'Eyes Beat Memory' principle. By showing these details, the cognitive load on the user is reduced by removing the need to remember their selection from the previous screen. Furthermore, this is contextual information that is actually important to the user in this screen while, at this point, having access to the original dataset is unneeded. Returning to the previous screen is not an important action so it could be placed in the de-emphasised region at the bottom right corner. However, the choice was made to place it in the top right corner, since the

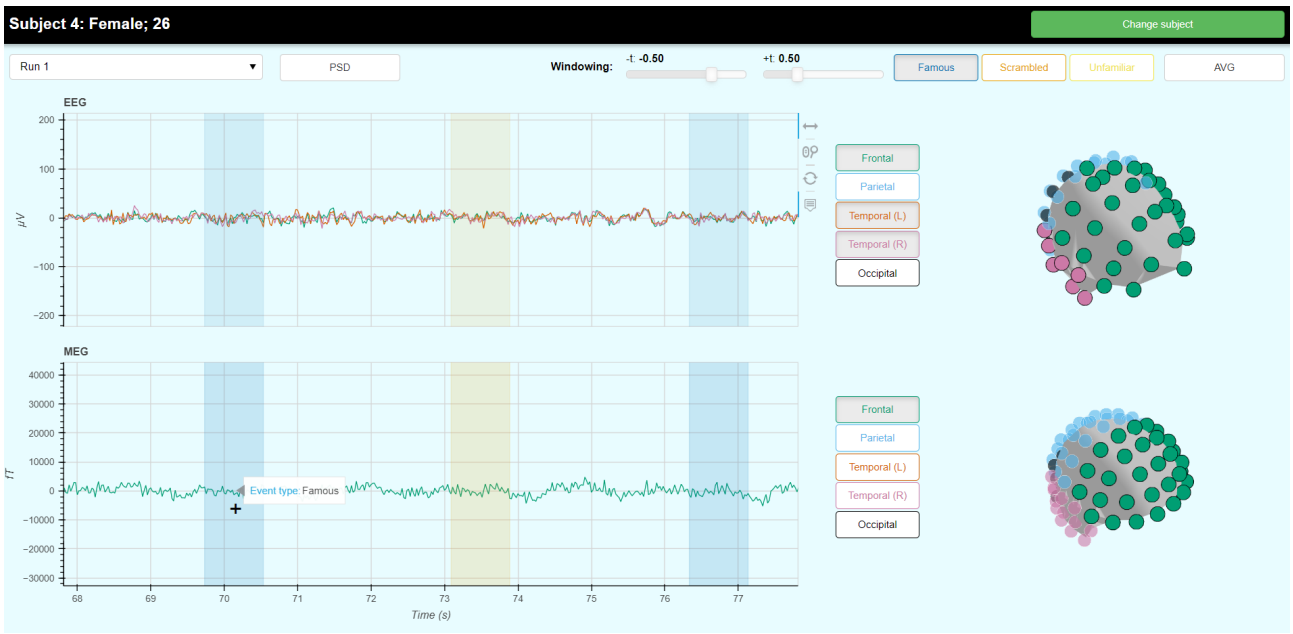

Figure 3: Screenshot of the second screen of the visualisation, which focuses on signal analysis.

action of changing a subject is somewhat related to the currently selected subject whose information is summarised at the top.

The main content of the second screen consists of a row of controls at the top with linked EEG and MEG plots underneath. Although interaction controls should generally not be given a prominent location, positioning them at the top instead of at the bottom is a good choice in this case. These controls perform important operations and transformations and do not serve as mere filters or selectors. In addition, they also partially serve as legends for the events through colour linking. Furthermore, the main EEG and MEG line graphs draw enough attention due to the large amount of space they cover. It should be noted though that the colour linking provided by the event buttons can serve as a legend, but it is actually not required. To prevent forcing eye movement between the main graphs and the coloured event buttons, information about the events is also displayed when hovering over them. Moreover, some control actions are only possible when certain other controls are activated, which is made clear to the user by providing visual feedback in the form of lightening or darkening the button when they are, respectively, enabled and disabled. Ideally, an additional tooltip would be shown, briefly explaining why the action is currently disabled. However, this functionality is currently unsupported in the used framework.

The rectilinear layout with superimposed, coloured line charts seemed like a fitting presentation for the continuous quantitative signal data of EEG and MEG. The line charts allow easy detection and comparison of trends and up to twelve distinguishable bins are available within the colour channel. Since we only have five lines (for signal groups) and three types of regions (for events), the colour channel is a good choice to identify these eight categories. The colour scheme is based on three requirements. Firstly, colour blind people should be able to effectively make use of the visualisation. Secondly, sensory overkill and unintended 'pop out' of lines for non-colourblind people should be avoided by using milder colours. Thirdly, there should be an adequate contrast between the colours of the plot and the background. As it fulfills these three requirements, the colourblind palette provided by the Bokeh framework was chosen as colour palette. Furthermore, the opacity of the event areas is decreased such that they have a lower saturation, ensuring the signal lines remain dominantly visible. The data shown in the line charts will be modified to show window averaged or PSD data if these operations are performed, but this remains quantitative signal data for which the aforementioned remarks are still valid. Spinners will make it visually clear to the user which visualisations are being updated during the operation. Screenshots of PSD and window averaged visualisations can be found

in Appendix C.

Besides the linked colour channels, the user is further supported in the comparison of EEG and MEG signals by arranging them vertically. In this case, a vertical sequential arrangement is better than a horizontal one as these types of signals are generally compared around the same period or frequency. A single shared horizontal axis further emphasises this intended manner of comparison. Moreover, all navigation actions are linked between the two plots.

Navigation actions are required because the signal data is extensive and being able to change the visible frame reduces the amount of cognitive processing that the user needs to do. Currently, three possible navigational actions are provided: horizontal panning, geometric zooming and view resets. Panning allows users to filter their view to a certain time or frequency window that they can simply translate to the left or right when needed. Constraining panning to the minimum and maximum possible values would have been preferable, however, in the used framework this makes the zoom behaviour less user-friendly. Constrained panning causes zooming out completely to only be possible if you first pan to the middle of the signal. To mitigate this unconstrained navigation and to avoid that the user gets stuck in a space without data, the view reset option is added. This action resets the view to its initial state that shows the start of the signals. Geometric zooming allows the user to easily zoom out and to find interesting regions that contain events and then zoom in again to see more details. Ideally, the tick frequency on the horizontal axis is modified while zooming, preventing them of becoming illegible when completely zoomed out. However, in the visualisation that is presented here, this behaviour is not problematic as the user will generally only zoom out to find an interesting region and then zoom in again. Being able to read all ticks when completely zoomed out can therefore be seen as more visually pleasing but not functionally important.

The five buttons to the right of the EEG and MEG plots provide a double function. Firstly, they serve as a legend since their labels and colours are linked to the lines in the graph. This is also the reason that they are positioned right next to the graph. Secondly, they provide selection actions that hide or unhide the signals in the graphs. Only the signals of the lobes whose buttons are active, are shown. This allows the user to more easily focus on the signals they are interested in. Since it is plausible that a user wants to compare EEG and MEG signals of different lobes, the selection buttons are not shared between EEG and MEG.

Although the selection buttons represent brain lobes that are expected to be well-known by neurology researchers, three-dimensional views of the EEG and MEG electrode/sensor placements are provided as well. These three-dimensional views serve three functions. Firstly, they visually show novice researchers where certain lobes are located. Secondly, since the channel's name is displayed on hovering, a researcher noticing unexpected behaviour in a specific signal can easily investigate whether it could be due to the exact placement of an electrode/sensor. The EEG electrode placements can vary per subject, thereby influencing recordings. Which is exactly why using three-dimensional visualisations is justified in this particular case. The data is inherently three-dimensional. Although there are some costs like occlusion and the need for navigation through rotation, the benefits outweigh them. A two-dimensional projection would result in less clear analytic insight due to distortion effects. The third and final function of these three-dimensional views is providing visual feedback. The selection buttons are both linked to the graphs and the three-dimensional electrode/sensor location views. When lobes are selected through the buttons, they are shown in the graph but also highlighted in the three-dimensional views, thereby allowing for more easily understanding which electrodes/sensors are currently shown in the graphs. The visual popout for highlighting mainly happens through the size and saturation channels. When a lobe is selected, the semi-transparent channel elements become opaque and increase in size.

Finally, the visual display of the visualisation is made more attractive without cluttering it with useless decoration. The overall colour scheme used in the main visualisations and controls should not disturb the user. A barely discernible light blue background instead of pure white is used to provide a more soothing experience and a bit less contrast. Lastly, the same legible 'Arial' font with a decent font size is used consistently throughout the visualisation.

4.3 Frameworks

The visualisation integrates multiple components from three Python frameworks, namely, Bokeh (Bokeh Development Team, 2018), Plotly (Plotly Technologies Inc., 2015), and Panel (Bednar et al., 2020). The Panel framework is a high level framework intended for developing interactive dashboards and web applications that support almost all major plotting libraries. Bokeh and Plotly both provide a multitude of options for the development of rich and interactive plots.

The EEG and MEG line charts are made through the Bokeh framework. Considering the large amount of signal data to be visualised, a framework based on websockets with support for data streaming seemed like a good choice to ensure responsiveness. Since the Plotly framework has broad support for a variety of interactive three-dimensional plots, this framework is used for the three-dimensional representations of the electrode/sensor space. These plots need less data, which makes the absence of websockets unproblematic. The Panel framework is used to build the general layout of the application and all UI. This framework is chosen because it allows for a dynamic layout based on screen size. Additionally, it allows for an easy integration of both Bokeh and Plotly plots.

5 Evaluation

The evaluation of the visualisation followed an iterative process that can be divided into three iterations. The first iteration was focused on our own research of the domain and validation by friends and family who are active in the medical field. The second iteration mostly included approximative algorithmic validations. The third iteration consisted of a qualitative review with Prof. Dr. Guy Nagels, a clinical neurologist, researcher, and engineer. Throughout these iterations the validations were based on the formal framework proposed by Munzner (2014). This framework splits visual design validation up into four different levels: domain situation, data/task abstraction, visual encoding/interaction idiom and algorithms. The following three sections describe each of the three validation iterations as well as the changes they resulted in.

5.1 First iteration

Since the visualisation is problem-driven, the design followed a top-down process. Therefore, the first iteration mostly focused on validation on the level of 'domain situation', 'data/task abstraction' and 'idiom validation'. In the context of domain validation, we defined our target users and performed some research and self-study to better understand their field. At this point, we assumed the target users to mostly consist of neurologists that would use the visualisation for diagnosis as well as researchers that can use it to gain general insight into neurological data. We could also envision the visualisation being used in an educational setting or by domain experts in the context of artificial intelligence, although it should be noted that the visualisation would not be optimised for these purposes. After selecting a useful dataset, we tried to improve our understanding of the field and regarding the target users' needs. Firstly, we refreshed our theoretical knowledge in the field of signal theory, as the chosen dataset is largely composed of signals. Secondly, we performed a superficial study of neurology, focusing on how EEG and MEG data is generally used in this field. Wakeman and Henson (2015) note that comparing EEG and MEG data can prove to be very useful, hence, our choice for the main task we would try to address. Furthermore, operations such as windowing, averaging and Fourier transforms seemed important. We also discovered that, in text books, electrode positions are often presented by a top-down projection on a two-dimensional representation of a human head. Thirdly, we looked at tools that are currently used such as the Python MNE library (Gramfort et al., 2013) and the FieldTrip package (Oostenveld et al., 2010). Lastly, we informally interviewed a number of friends and family that are studying or practising medicine.

As was already clear from the validation of the domain, our data mostly consists of signal data, i.e., quantitative time series. The comparison tasks and proposed operations can therefore be abstracted to

this type of data and tasks. Subject selection and selection of electrodes/sensors on a two-dimensional representation, similar to selection on a map, can be trivially abstracted as well.

Most of our encoding idioms have already been given a detailed justification in Section 4.2, as our encoding idioms have mostly remained throughout. The biggest difference at this point is that we decided to use a two-dimensional projection of electrode/sensor positions, since it seemed to be the standard textbook way of presenting this data and we expected users to be more familiar with it. It would prevent problems such as occlusion, but give a distorted view. However, the electrode/sensor positions we saw in textbooks were almost perfect, which made it seem easy for a user to understand where they are placed even with a distorted view.

At the end of this iteration we created a mock-up of our visualisation, consisting of three main screens: a screen for subject and channel selection, a screen for signal analysis in the time domain and one for signal analysis in the frequency domain. The mock-up screens can be found in Appendix A.

We presented this mock-up to the friends and family we interviewed before to ensure that we correctly understood the users' needs. We extended the validation of our mock-up by also showing it to friends that are active in the field of neuroimaging, as the third screen was mostly focused on supporting these types of users. They informed us that the information on this screen is mostly useful for machines but would generally not be read by humans. Therefore, we removed the third screen from our design. No other modifications had to be made after this qualitative validation of our mock-up.

5.2 Second iteration

After the validation of the mock-up, we made an initial implementation of the two-screen visualisation consisting of a single-page Flask application that switched between the two screens. All interactions and visualisations on the first screen were completely JavaScript based using the D3 framework (Bostock, 2011) for user and electrode/sensor selection. The web development framework Bootstrap 5 (Bootstrap Development Team, 2021) was used in combination with HTML templates to obtain a responsive layout. The second screen was built using Bokeh (Bokeh Development Team, 2018). AJAX calls were used to switch between the screens in a user-friendly way, without navigation between multiple pages in the browser.

During the implementation, validation mostly happened on the level of visual encoding idioms and the algorithmic level. With regard to the visual encoding, we noticed that the two-dimensional projection of the electrode/sensor positions brought more distortion than we had anticipated. Although visualisations of electrode positions seemed to work well in textbooks, more realistic data clearly had less perfect positioning. An EEG cap is placed manually on a person's head and both head size as well as electrode positioning can vary a lot. When showing the visualisation to friends and family, they found the two-dimensional encoding to be unclear. Therefore, we found it justified to replace them with three-dimensional plots constructed with the Plotly JavaScript framework (Plotly Technologies Inc., 2015).

On the algorithmic level, we performed a lot of performance measurements with regard to loading time and responsiveness. The first insight we gained was that the loading time of the second screen could be as long as 60 seconds, depending on the selection that was made in the first screen. This was unacceptable, which was the reason we decided to only load part of the data and then stream the rest of the data on the background. Since the graphs only show part of the data at once to reduce cognitive load, the user would not notice that not all data is available from the start. This reduced the loading time between the two screens to 10 seconds, which was found to be acceptable as long as some sort of progress indication is shown during the transition. The second insight we gained was that the large amount of data also caused certain interactions, such as linked panning, to take up to one second to be performed. This level of responsiveness was too low, which is the reason we decided to aggregate the data for now to then later add the possibility to show details on demand. Screenshots of the visualisation resulting from this iteration can be found in Appendix B.

5.3 Third iteration

As a final validation of our tool, we considered using the well-known User Experience Questionnaire (UEQ; Laugwitz et al., 2008). This questionnaire provides a number of Likert scale questions regarding the innovation, utility, and overall user experience of interactive applications. A quantitative analysis of the results could then be made. However, we eventually decided a qualitative review with an expert user would be more useful as most questions from the UEQ are rather irrelevant for our specific use case. Furthermore, a large-scale survey among people that realistically cannot be considered plausible end users seemed unproductive.

We contacted Prof. dr. ir. Guy Nagels who is head of the department of Neurology at UZ Brussels, works as a clinical neurologist, and is a neurology researcher. He proposed to have a video conference in which we demonstrate the visualisation. As general feedback he indicated that the visualisation reflects a good understanding of the data and the tools needed to analyse it. However, he stated that clinical neurologists generally have a lot of additional specific needs to be able to come to a reliable diagnosis such as viewing individual electrodes, setting up montages, performing computationally heavy operations, and having extremely detailed views. All of this would be infeasible to implement for a small team in a period of months. The commercial packages that were developed for this purpose took years to build. In contrast, neurology researchers would benefit a lot from a visualisation like ours, both in the context of neurology research and in the context of artificial intelligence. Furthermore, neurology researchers are often more interested in groups and averages, while clinical neurologists need more individual details. Based on these remarks, we decided to no longer consider clinical neurologists as potential end users but instead narrow down our focus to supporting neurology researchers.

Professor Nagels concluded his feedback with some final practical remarks. Firstly, he found that it would be nice to have the three-dimensional electrode/sensor placement plots next to the signal graphs on the analysis screen. This would make it easier to actually know what you are looking at in the graphs. Secondly, he remarked that the average overview we show is a common way to show a complete run because the human eye can not differentiate between sampling frequency differences. It is only the calculation of the windows and power-spectral densities that must be done using the higher sampling rate data. Thirdly, after we inquired about the usefulness of the power-spectral density feature, he assured us that this functionality is indeed useful. It clearly shows which frequencies show the most activity, allowing researchers to relate this to the frequency bands.

After this validation, not many functional changes had to be made. Streaming the data, however, became redundant as we now only focused on providing an overview averaged for groups of signals instead of individual signals. Moving the three-dimensional electrode/sensor plots to the analysis screen, however, proved to be more difficult than expected. The JavaScript Plotly app could not be placed inside the embedded Bokeh app. After careful consideration and taking the remarks of Prof. Nagels into account, the decision was made to convert the Flask application with embedded JavaScript Bokeh and Plotly apps to a purely Python based application using Panel, Bokeh, and Plotly. Two downsides of this decision were the loss of informative tooltips on disabled buttons and some loss of web responsiveness. However, researchers in the domain generally know why certain actions are impossible. The tooltips are therefore less important, although they would still have been a user-friendly addition. The fact that the visualisation could not be viewed on a mobile phone seemed irrelevant as adequately researching EEG and MEG signals on a small screen would be cumbersome either way. It should be noted that Panel does ensure that the visualisation stretches to fill the complete screen on reasonable screen sizes, ranging from tablets to large desktops.

After the conversion, a colour scheme was decided on, which we then presented to colourblind and non-colour blind people to ensure that the chosen colours were distinguishable and comfortable. This final version of the visualisation corresponds to the version that was described in Section 4.

6 Conclusion

A visualisation of Wakeman and Henson's (2015) "A multi-subject, multi-modal human neuroimaging dataset" that allows for a comparison between EEG and MEG data is presented. The iterative validation-adaptation process that was followed to design the visualisation is discussed. All throughout this process, the principles and concepts that were taught in the course are followed and applied as much as possible. The process starts with preliminary research, getting to know the neuroimaging field, and refreshing knowledge regarding signal theory. Discussions regarding the target users and the functionality to be implemented result in clear delineations of what these will be. A mock-up is created as a first design for the visualisation. Said mock-up serves as a blueprint for what is to be developed. However, before starting development, the mock-up is evaluated through informal discussions with people who are in some way related to the field. This first evaluation results in a number of changes in the mock-up, before it is actually developed. A first version of the visualisation results in insights regarding performance, frameworks to use, and general design. At this point, feedback of a target user is required to further improve the visualisation. A qualitative review with a neurology researcher who is also an engineer results in the confirmation of the majority of the design. A number of specific comments allow for improving the visualisation towards the final design. Additionally, a number of possible future functionalities come to light. Examples are functionality that would allow clinical neurologists to set up montages and functionality to allow inter-subject comparisons. Once the last changes are made and thus the expert validator's remarks are integrated, keeping in mind their confirmations of our design, we conclude that the end result conforms to the functionalities that were established at the beginning of the project and that it is an adequate visualisation of the chosen dataset, which was the goal of the project.

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Appendices

A Mock-up

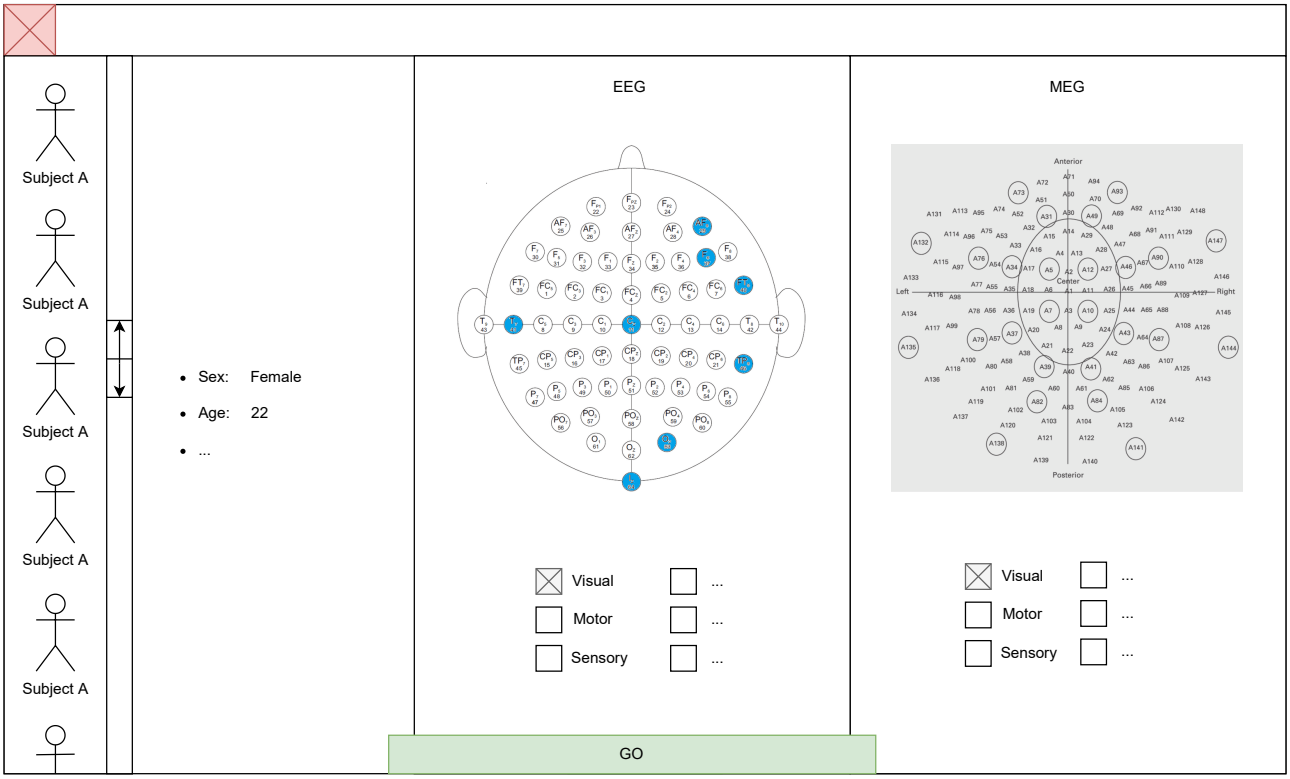

Figure 4: Mock first page of the initial visualisation design.

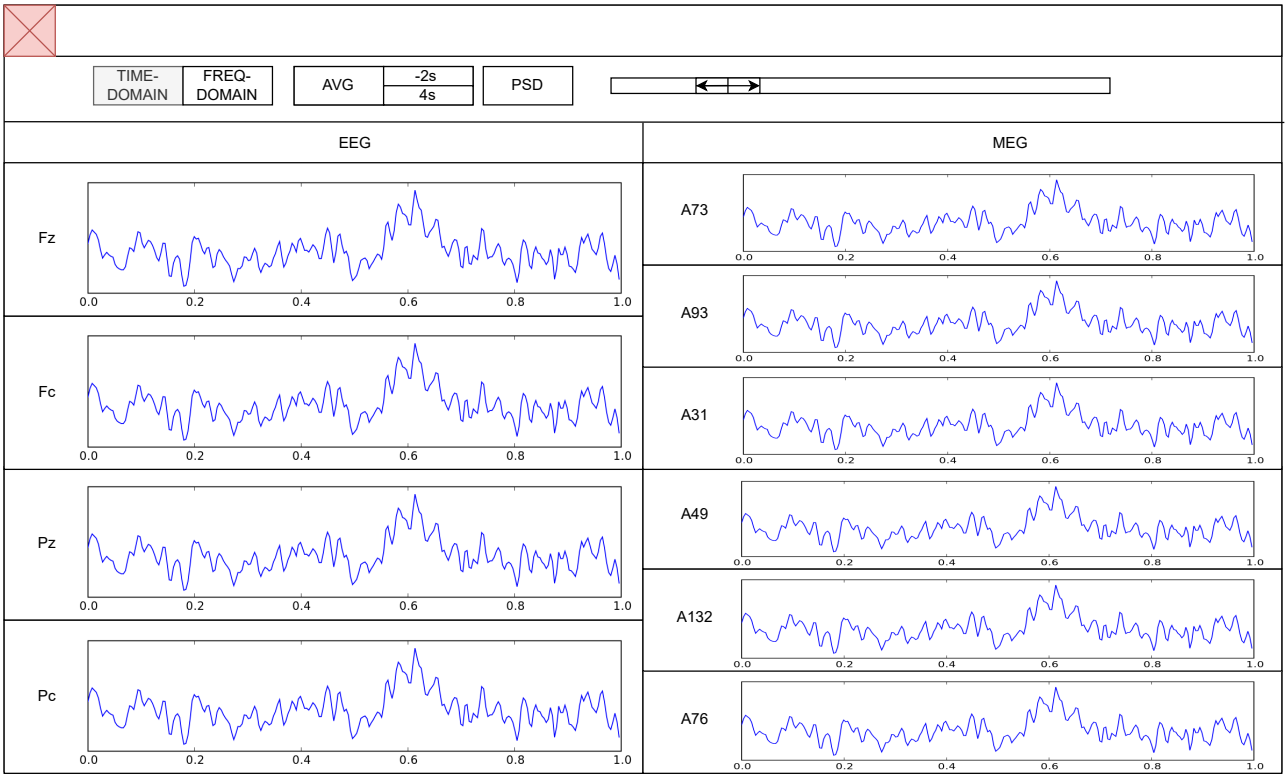

Figure 5: Mock time-domain page of the initial visualisation design.

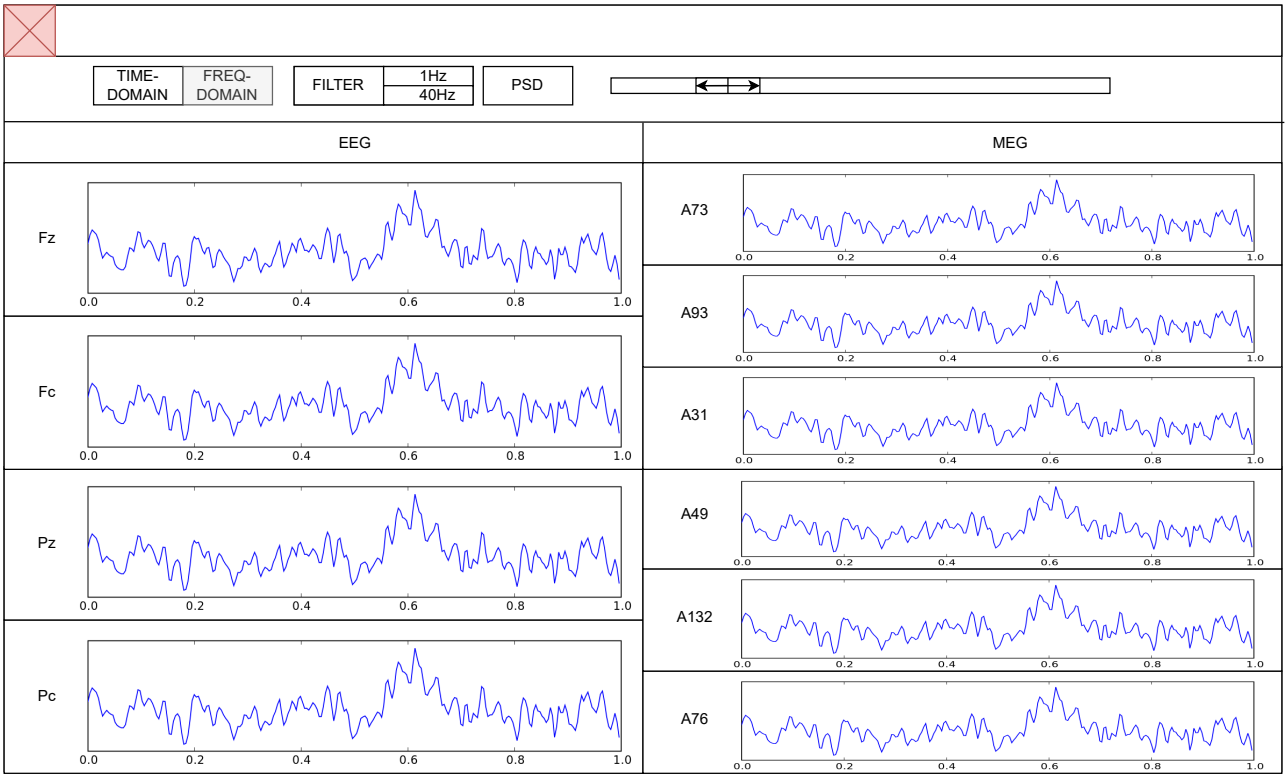

Figure 6: Mock frequency-domain page of the initial visualisation design.

B Screenshots of the second iteration

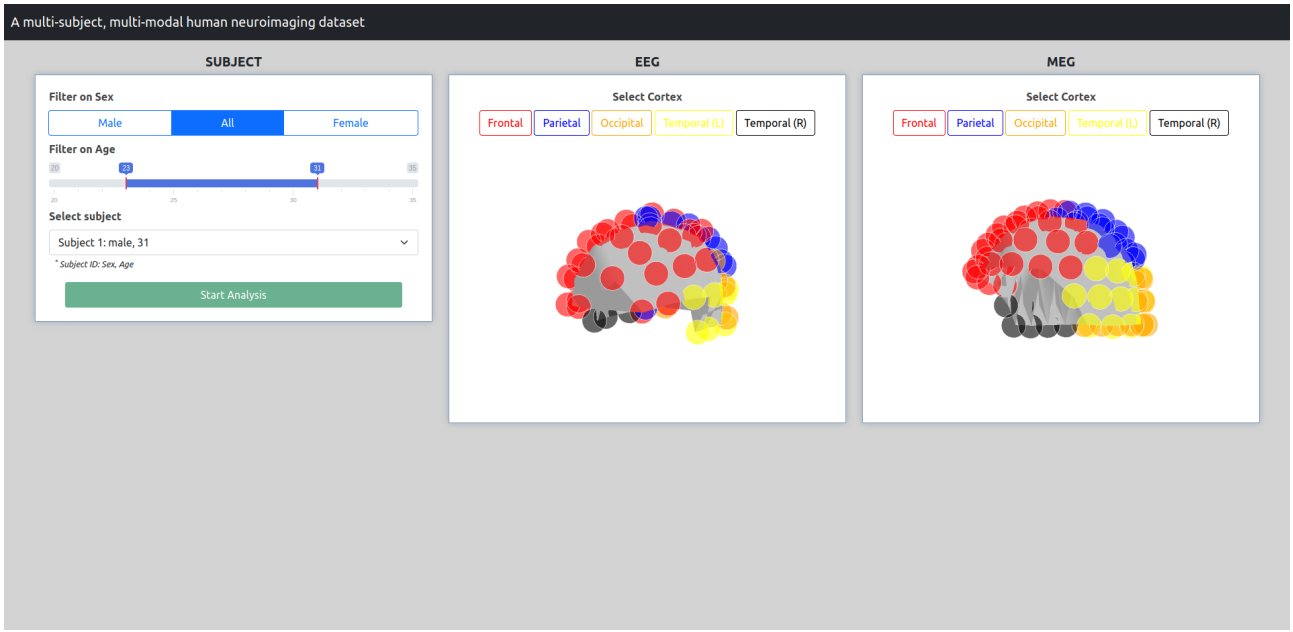

Figure 7: Selection screen of the visualisation from the second design iteration.

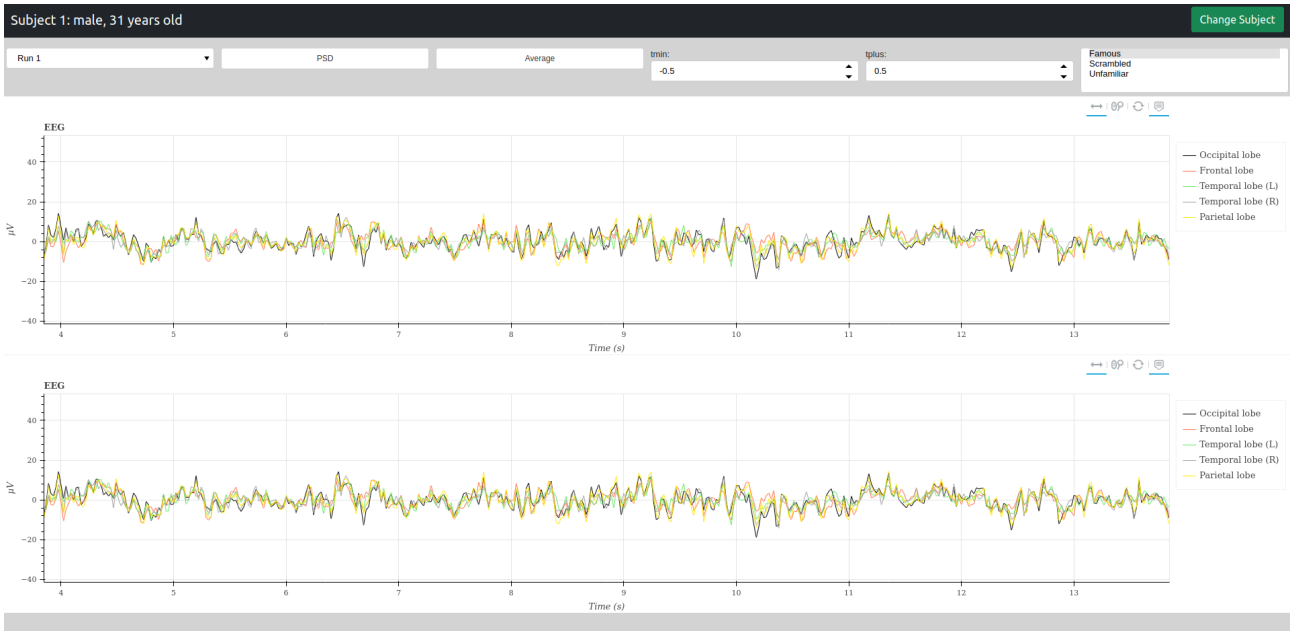

Figure 8: Analysis screen of the visualisation from the second design iteration.

C Additional screenshots of the final version

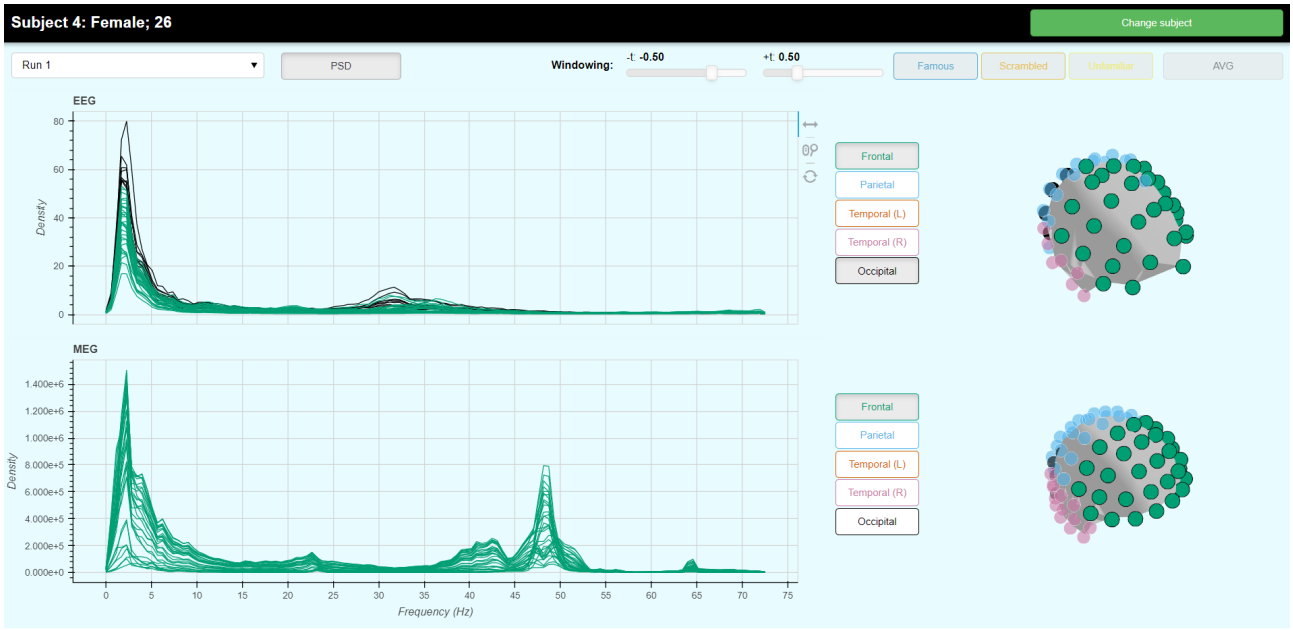

Figure 9: Screenshot of the PSD graphs on the final visualisation's analysis screen.

Figure 10: Screenshot of the average window graphs on the final visualisation's analysis screen.