Multichannel EEG Visualization

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Chapter 5

Discussion

5.1 Summary & Conclusions

Electroencephalography (EEG) is the oldest noninvasive functional neuroimaging technique and is still going strong, despite the more recent development of magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI). Since its development in the 1920s, visual inspection is most commonly used for EEG analysis. Traditional EEG visualizations are not tailored for the two major technological improvements which lie at the basis of this thesis. First, the number of EEG electrodes that can be attached to the human scalp increases, improving the spatial resolution. Second, improving computers increase automated signal processing possibilities. This thesis introduces new visualizations designed for the improved EEG.

Chapter 1 provides background information on EEG and visualization. It briefly describes how electrical brain activity leads to the measured scalp potentials referred to as EEG. Further, it mentions how this brain activity can be influenced by external stimuli. In this thesis, EEG visualization is dedicated to the time domain and the frequency domain, which is restricted here to time-varying multivariate data and relational (coherence) data, respectively. Basic visualizations for those data types are discussed.

We introduce a visualization for time-varying multichannel EEG, referred to as *tiled parallel coordinate (TPC) map*, in Chapter 2. The novel TPC map employs a two-dimensional tiled organization of parallel coordinates which schematically preserves electrode positions, representing one electrode by one tile. In our opinion, the power of the TPC method lies in the combination of parallel coordinates with contextual (temporal and spatial) information.

The tiled parallel coordinate (TPC) map is assessed by both a qualitative evaluation and a user evaluation. Contrary to other methods, the TPC map is able to visualize the combination of a large number of electrodes and many time steps. Although the TPC map does not have an explicit natural time order, a linked view displays temporal information on a time axis. In a user evaluation, identical tasks were performed with typical EEG assessment elements using both the TPC method and an existing clinical EEG visualization method (standard method). Participants were students, EEG researchers, and clinical experts. The TPC map was on average about 40 % faster than the standard method, without a loss of information, even though the TPC method used a single page and the standard method four pages. Opinions on the TPC map were positive and generally agreed with opinions on the standard method. However, participants considered the

TPC map to be more simple than the standard map. Further, especially symmetry assessment was regarded to be easier with the TPC map. Interactivity was a feature missing in both the TPC map and the standard visualization.

Chapter 3 first discusses existing connectivity visualizations for the three noninvasive functional neuroimaging techniques (EEG, MEG, and fMRI), mainly concerning graph layouts. For both EEG and MEG coherence analysis, most approaches are hypothesis-driven, whereas existing data-driven approaches would not be suitable for the use of a large number of sensors. For fMRI connectivity studies, graph clustering is commonly applied. Many graph visualizations do not preserve vertex locations or lead to clutter. As an alternative to the hypothesis-driven approach, we propose a data-driven visualization of multichannel EEG coherence based on *functional units (FUs)*. An FU is a data-driven region of interest (ROI) consisting of electrodes recording pairwise significantly coherent signals. In a graph representing EEG coherence, an FU is represented by a spatially connected clique, i.e., a spatially connected set of electrodes recording pairwise significantly coherent signals. Three FU detection methods are employed. Our first method, maximal clique based (MCB) FU detection obtains FUs as large as possible, because larger FUs are associated with stronger EEG source signals. A more efficient method is based on the method of choice for image segmentation in the field of mathematical morphology, the watershed transform. Our watershed based (WB) method detects FUs in a greedy way. Its oversegmentation problem is strongly reduced by our improved watershed based (IWB) method, which merges FUs if they are spatially connected and if their union is a clique. The IWB FUs are very similar to the MCB FUs which are considered as the gold standard. Because the IWB method is much more efficient than the MCB method, whereas the differences in FU clustering between both methods is small, the IWB method is our choice for FU detection.

For individual dataset analysis, a so-called *FU map* visualizes size and location of each FU and coherence between FUs, while preserving electrode positions. In comparison with other data-driven visualizations of EEG coherence, the FU map strongly reduces visual clutter.

Between individual datasets, FU maps may differ strongly. Therefore, two group maps are employed. A *group mean coherence map* preserves dominant features from a collection of individual FU maps. A *group FU size map* visualizes the average FU size per electrode across a collection of individual FU maps. FUs in the group mean coherence map generally correspond to FUs in the majority of the individual FU maps. Sometimes, an FU appears in an area in a group mean coherence map without a corresponding FU in most individual FU maps. This is probably due to a combination of high sub-threshold and super-threshold coherences in that area, which is an effect inherent to group analysis. However, because such an FU is generally not connected to other FUs, it is considered to be less important for brain connectivity studies.

Our new multichannel EEG coherence visualization method for individual dataset and group analysis is applied to two case studies. The first case concerns a study of aging, meant to illustrate our method (Chapter 3). For this case, a hypothesis-driven approach was available from the literature. The second case concerns a mental fatigue study for which no strong hypotheses could be based on related studies (Chapter 4). For both case studies, our method for individual and group analysis shows decreasing FU sizes and a decreasing number of longer-distance coherences for increasing frequencies. This is in accordance with the general finding that global coherence is associated with lower EEG frequencies and local coherence with higher EEG frequencies. For the aging study (Chapter 3), younger adults have smaller FUs than older adults, indicating lower coherence for younger adults than older adults, in agreement with conventional results. For the mental fatigue study (Chapter 4), differences between non-fatigued and fatigued participants are generally small. However, the area where the largest FUs reside is different for non-fatigued and fatigued participants in the lowest frequency band. A difference between non-fatigued and fatigued participants in the lowest frequency band is not surprising, because lower frequencies are associated with higher-level cognitive processes, which are expected to be affected by mental fatigue.

Contrary to hypothesis-driven approaches, our data-driven method leads to a selection of FUs and coherences of interest between these FUs which always matches the spatial resolution of the actual data acquisition. Obviously, a hypothesis-driven approach may miss significant (average) coherences, such as the interhemispheric anterior-posterior coherences of interest indicated by our data-driven method for both case studies. Altogether, our FU method summarizes extensive experimental results efficiently.

5.2 Perspectives

This thesis has discussed EEG visualizations for time domain and frequency domain EEG analysis, and some basic visualizations related to the corresponding data types. We presented two new visualizations tailored for multichannel EEG. For time domain visualization, we proposed the TPC map. For frequency domain visualization, we introduced functional unit maps for individual analysis, in combination with two group maps.

A future improvement of the TPC map would be an interactive visualization with linked temporal and spatial brushing, as desired by the participants of the user evaluation. In fact, some participants would prefer to have all available visualization components at their disposal, from both the TPC map and the standard clinical visualization. Apparently, they appreciate ‘converging evidence’. Because it takes more time to study a larger number of different visualizations and because the visual space on a screen is limited, a selection of visualization techniques should be made carefully.

The combination of multiple methods is not only an issue in visualization. For EEG analysis, a combination of multiple measures is also advocated for frequency domain (Nunez *et al.* 1997) and time-frequency domain (Zhan *et al.* 2006) analysis. Our method for frequency domain analysis is not restricted to coherence, but is also suitable for other measures with similar properties.

Frequency analysis of EEG is often restricted to the generally recognized frequency bands, even though there is no consensus on the boundaries of those bands (Section 1.1.4). Results could improve when those frequency bands are refined in a data-driven fashion. If there are no automated signal processing routines available for this purpose, an interactive visual adaptation of the frequency band for coherence analysis can be accomplished on the basis of efficient FU visualizations (Section 3).

Time-frequency domain analysis is not explicitly discussed, but can be considered as a temporal sequence of frequency domain analyses (Section 1.1.6). To our knowledge, existing time-frequency visualizations are straightforward combinations of other techniques described here.

For example, a time-frequency plot for a single electrode is technically the same as an EP image (Fig. 2.5, p. 23), setting out frequency instead of EP trials along the rows of a tabular visualization (with time along the columns). For multiple electrodes, time-frequency plots can be mapped (schematically) to the corresponding electrode positions (Graimann *et al.* 2002), similar to the organization of conventional time-series in a topographic array (Fig. 2.4, p. 22).

As indicated before (Chapter 4), higher-level cognitive mechanisms are associated with activity at lower frequencies and a more global synchronization, whereas lower-level mechanisms are associated with activity at higher frequencies and a more local synchronization (Nunez *et al.* 1997, von Stein and Sarnthein 2000). For the study of this synchronization, further research may adopt a hierarchical approach across multiple EEG frequency bands.

Nowadays, it is also possible to simultaneously record fMRI and EEG. A fusion of both data types is a future challenge, due to the different resolutions in space and time.

Apart from functional neuroimaging, other fields with a temporal and spatial data component include seismology, meteorology, geographical information systems (GIS), astronomy, and electrocardiographic imaging (ECGI). EEG visualization can benefit from new developments in these areas as well.