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Visualizing and Exploring Dynamic Multichannel EEG Coherence Networks

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Abstract

An electroencephalography (EEG) coherence network represents functional brain connectivity, and is constructed by calculating the coherence between pairs of electrode signals as a function of frequency. Visualization of coherence networks can provide insight into unexpected patterns of cognitive processing and help neuroscientists to understand brain mechanisms. However, visualizing dynamic *EEG coherence networks is a challenge for the analysis of brain connectivity, especially when the spatial structure of the network needs to be taken into account. In this paper, we present a design and implementation of a visualization framework for such dynamic networks. First, requirements for supporting typical tasks in the context of dynamic functional connectivity network analysis were collected from neuroscience researchers. In our design, we consider groups of network nodes and their corresponding spatial location for visualizing the evolution of the dynamic coherence network. We introduce an augmented timeline-based representation to provide an overview of the evolution of functional units (FUs) and their spatial location over time. This representation can help the viewer to identify relations between functional connectivity and brain regions, as well as to identify persistent or transient functional connectivity patterns across the whole timewindow. In addition, we modified the FU map representation to facilitate comparison of the behavior of nodes between consecutive FU maps. Our implementation also supports interactive exploration. The usefulness of our visualization design was evaluated by an informal user study. The feedback we received shows that our design supports exploratory analysis tasks well. The method can serve as an preprocessing step before a complete analysis of dynamic EEG coherence networks.*

CCS Concepts

•***Applied computing*** → ***Life and medical sciences;*** •***Human-centered computing*** → ***Information visualization;***

1. Introduction

A functional brain network is a graph representation of brain organization, in which the nodes usually represent signals recorded from spatially distinct brain regions and edges represent significant statistical correlations between pairs of signals. Currently, increased attention is being paid to the analysis of functional connectivity at the subgroup level. A subgroup is defined as an intermediate entity between the entire network and individual nodes, such as a community or module which is comprised of a set of densely connected nodes (Ahn *et al.* [APS14]). Such a group of nodes can represent a certain cognitive activity that requires brain connectivity.

Data-driven visualization of functional brain networks plays an important role as a preprocessing step in the exploration of brain connectivity, where no *a priori* assumptions or hypotheses about brain activity in specific regions are made. This type of visualization can provide insight into unexpected patterns of brain function and help neuroscientists to understand how the brain works. An important goal of visualization is to facilitate the discovery of groups of nodes and patterns that govern their evolution (Reda *et al.* [RTJ*11]). Recent techniques mostly focus on the visualization of *static* EEG coherence networks. Here we focus on the evolution of groups of nodes over time, i.e., *dynamic* communities, which has received less attention so far in the neuroscience domain. Although some visualization approaches have been developed for dynamic social networks, these approaches cannot be directly applied to brain networks, since they do not maintain the spatial structure of the network, that is, the relative spatial positions of the nodes. Visualization approaches which do not take into account the physical location of the nodes make it hard to identify how the functional pattern is related to brain regions.

An EEG coherence network is a 2D graph representation of functional brain connectivity. In such a network, nodes represent electrodes attached to the scalp at multiple locations, and edges represent significant coherences between electrode signals [HRA*95, MSvdHdJ06]. Traditional visualization of multichannel (64 or 128 electrodes) EEG coherence networks suffers from a large number of overlapping edges, resulting in visual clutter. To solve this problem, a data-driven approach has been pro-

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posed by ten Caat *et al.* [tCMR08] that divides electrodes into several *functional units* (FUs). Each FU is a set of spatially connected electrodes which record pairwise significantly coherent signals. For a certain EEG coherence network, FUs can be derived by the FU detection method [tCMR08] and displayed in a so-called *FU map*. An example is shown in Figure 1. In such a map, a Voronoi cell is associated to each electrode position, cells within one FU have the same color, circles overlayed on the map represent the barycenters of FUs, and the color of the line connecting two FUs encodes the average coherence between all electrodes of the two FUs. An extension of this method to resting state fMRI networks was presented by Crippa *et al.* [CR11].

In this paper, we provide an interactive visualization methodology for the analysis of dynamic connectivity structures in EEG coherence networks as an exploratory preprocessing step to a complete analysis of such networks. Experts from the neuroscience domain were involved in our study in two ways. First, they provided a set of requirements for supporting typical tasks in the context of dynamic functional connectivity network analysis. Second, we carried out an evaluation of our tool with a (partially different) group of experts from the neuroscience domain. One of the main requirements coming from the domain experts is that spatial information about the brain regions needs to be maintained in the network layout, a feature which is not present in most existing network visualization methods.

The main contribution of this paper is a combination and adaptation of existing techniques to visualize functional connectivity data in the neuroscience domain. In particular we provide:

- an augmented timeline representation of dynamic EEG coherence networks with a focus on revealing the evolution of FUs and their spatial structures;
- the detection of dynamic FUs to detect persistent as well as transient FUs;
- a sorted representation of FUs and vertices per timestep to facilitate the tracking of the evolution of FUs over time and the identification of brain regions that the FU members belong to;
- a time-annotated FU map, which is an extended FU map for detailed comparison of FU maps at two consecutive timesteps;
- an online interactive tool that provides an implementation of the above methods.

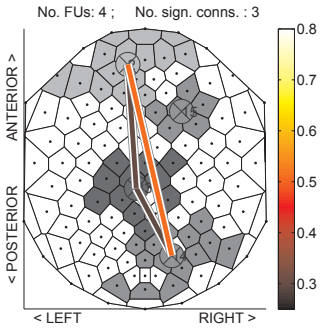


Figure 1: *Example of an FU map [tC08] as obtained during an oddball task (see also subsection 5.1).*

2. Related Work

Many techniques for visualizing dynamic networks have been developed; these are reviewed by Beck *et al.* [BBDW14]. These techniques can be classified into three categories: animation, timeline-based visualization, and hybrid approaches. The most straightforward method is animation (Archambault *et al.* [APP11]). When an animation is used to visualize the evolution of networks, the changes are usually reflected by a change in the color of the nodes. However, network animation is limited to a small number of timesteps [RFF*08, RTJ*11]. When this number becomes large, the users have to navigate back and forth to compare networks since it is hard to memorize the states of networks in previous timesteps, see Bach *et al.* [BHRD*15]. Some work has been done to help users easily capture network changes. These approaches aim to preserve the abstract structural information of a graph, called the mental map (Diehl *et al.* [DGK01], Misue *et al.* [MELS95]).

An alternative to animation is the timeline-based representation. A typical approach is the application of small multiples, in which multiple networks at different points in time are placed next to each other [BHRD*15]. This approach is limited by the size of the display screen: it is very hard to display entire graphs at once when the dataset becomes large. Networks can be shrunk in size, but the corresponding resolution and detail are reduced [BHRD*15]. Besides, this type of small multiples makes it hard to track the evolution of networks, because corresponding nodes in different multiples have to be identified visually.

Interactive visual analysis of temporal cluster structures in high-dimensional timeseries was studied by Turkay *et al.* [TPRH11]. They presented a cluster view that visualizes temporal clusters with associated structural quality variation, temporal signatures that visually represent structural changes of groups over time, and an interactive visual analysis procedure. Van den Elzen *et al.* [vdEHBvW16] presented a visual analytics approach for the exploration and analysis of dynamic networks, where snapshots of the network are considered as points in a high-dimensional space that are projected to two dimensions for visualization and interaction using a snapshot view and an evolution view of the network. However, in both approaches the spatial nature of the data did not play a role or was absent from the beginning.

An extension of the timeline-based representation has been developed for visualizing the evolution of communities that is widely used for dynamic social networks (Sallaberry *et al.* [SMM13], Vehlow *et al.* [VBAW15], Liu *et al.* [LWW*13]). In this representation, nodes are aligned vertically for each timestep and are connected by lines between consecutive timesteps. For a certain timestep, nodes in the same community form a block. As time progresses, lines may split or merge, reflecting changes in the communities. This visualization is based on the flow metaphor, as is used in Sankey diagrams (Riehmann *et al.* [RHF05]) or flow map layouts (Phan *et al.* [PXY*05]), where users can explore complex flow scenarios.

Specifically, the communities and nodes are sorted to reduce the number of line crossings, which can improve the readability of the graph [SMM13, VBAW15]. In addition, the color of the nodes usually reflects the temporal properties of a community, e.g., the stability of a dynamic community or the node stability over

time [VBAW15]. To allow interactivity, the order of the nodes can be manipulated by the user [RTJ*11]. However, this approach cannot be applied to dynamic brain networks directly since it visualizes the dynamic network while ignoring the spatial information of the network nodes, which is a crucial factor in the analysis of brain networks.

3. Design

In this section we first introduce the tasks that neuroscientists want to perform in the context of functional connectivity network analysis, then formulate the design goals that take into account the requirements following from the task analysis, and describe the decisions we took when designing the visualization.

3.1. Requirements

We used a questionnaire to collect requirements from a small group of researchers who regularly employ brain connectivity analysis. Eight participants were involved in the requirements collecting stage, consisting of master and PhD students, a postdoc, an associate and a full professor. The median age of the participants was 35 years. Their experience in working with brain data ranged from 0.5 year to 30 years (with a median of 12 years). The goal of the questionnaire was to understand the general problems the researchers are facing when analyzing their data, the specific needs regarding network analysis, and the role of visualization in their data analysis.

Although the way of acquiring neuroimaging data may vary among researchers, the common underlying data representation for different types of connectivity and the methods of analyzing data are similar. Therefore, our questionnaire was not limited to the analysis of EEG data, but also addressed fMRI data. In our study, we restricted ourselves to graph representations, especially focusing on dynamic structures present in the data. We analyzed the feedback of the respondents and compiled the following list of tasks that are of interest to them to explore brain connectivity, and for which visualization tools are not readily available:

- **Task 1** Provide an overview of coherence networks across time.
- **Task 2** Identify the state of each coherence network, that is, indicate significant connections between signals recorded from distinct locations.
- **Task 3** Discover how functional connectivity is related to spatial brain structure at each timestep.
- **Task 4** Explore the evolution of functional connectivity structures over time. That is, determine at which time step and in which brain areas the connections and their spatial distribution change, to find the areas of interest in which connections are stable or strongly changing, as a starting point for further study.
- **Task 5** Compare coherence networks between individuals or conditions. That is, indicate the differences between coherence networks of, e.g., patients and healthy individuals, or the differences of coherence networks between task conditions for single individuals. This can help neuroscientists to predict diseases or explain differences in human behavior.

3.2. Design

In this section we discuss our choices for representing the evolution of coherence networks over time, and the visual encodings adopted in the representation, that meet the requirements set out above.

Visualizing dynamic coherence networks requires that the changes of connections are shown. As mentioned in section 2, animation or a timeline-based representation can be used to visualize dynamic coherence networks.

Given the limitations of animation, we have chosen to base our method on the timeline representation for visualizing the evolution of communities in dynamic social networks (see Figure 2), because it can not only provide an overview but also the trend of changes in coherence networks over time (**Task 1**).

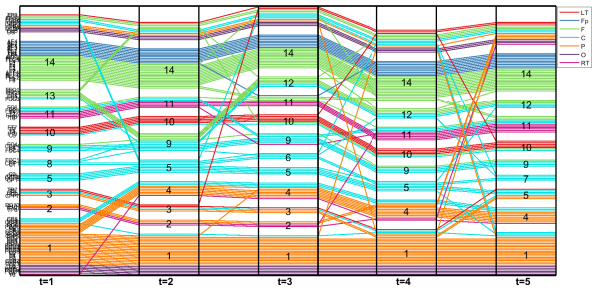
In this timeline-based representation, electrodes are represented by lines (Figure 2(a)). For each timestep, to reflect the connections between electrodes and also consider their spatial information (Figure 1), we use the FUs proposed by ten Caat *et al.* [tCMR08]. This approach has been used to analyze coherence networks derived from an oddball EEG experiment (ten Caat *et al.* [tCMR08]), as well as to study the influence of mental fatigue on coherence networks (Lorist *et al.* [LBtC*09], ten Caat *et al.* [tCLB*08]). Later it was extended to the analysis of functional fMRI networks by Crippa *et al.* [CR11]. An FU, which can be viewed as a region of interest (ROI), is a set of spatially connected electrodes in which each pair of EEG signals at these electrodes is significantly coherent. In the timeline representation, FUs are represented by blocks of lines (Figure 2). The blocks are separated by a small gap to distinguish different FUs (**Task 2**).

Since the representation based on FUs maintains the spatial layout of electrode positions, it is more intuitive compared to other representations when exploring the relationship between spatial structures and functional connectivity. For each FU in the timeline representation, we use the color of the line to indicate which brain region the corresponding electrode originates from (Figure 3). In addition, to provide the exact location for each FU we provide a *partial FU map* for each block of lines in the timeline representation (Figure 2(b)). A partial FU map for a block of lines is a map where the electrodes included in this block are colored black and the rest of the electrodes are colored white (**Task 3**).

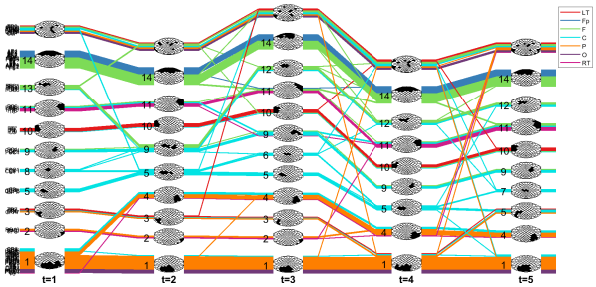
To help users identify the persistent or transient functional connectivity and to simplify the tracking of connections over time, we first preprocess the coherence networks to detect *dynamic FUs*. A dynamic FU is a set of similar FUs detected at consecutive time steps (a precise definition is provided in subsection 3.3, Figure 4). A dynamic FU which persists across a wide span of consecutive timesteps is a stable state across time (Figure 7(a)). Dynamic FUs which only exist for a small range of timesteps are referred to as transient dynamic FUs (**Task 4**).

The last main goal is to compare coherence networks between different conditions. To achieve this goal, we use a *time-annotated FU map* to demonstrate the differences between two consecutive FU maps (Figure 5). In this time-annotated FU map, we adopt a division of each cell into an inner and an outer region, such that the information of the previous/current state is encoded in the color of the inner/outer cell, where the dynamic FU from each coherence

network is mapped to the color of the corresponding region. We consider this approach to be useful since it does not obscure the graph layout structure and it can provide details about changes of the node states (**Task 5**).



(a) Timeline-based representation without partial FU map.



(b) Augmented timeline-based representation with partial FU map.

Figure 2: *Examples of the timeline-based representations. Both representations represent the evolution of dynamic FUs across five timesteps for coherence in the frequency band 8-12 Hz. For each timestep, FUs are ordered by their barycenter and within each FU brain regions are ordered as follows: LT, Fp, F, C, P, O, RT (see Figure 3). The labels of 119 electrodes are arranged vertically on the left. The line color reflects the location of electrodes (see legend). The number at the center of a block corresponds to the dynamic FU, and the top block (labeled 15) represents electrodes that do not belong to any FU whose size is above the size threshold. (a) Timeline-based representation, providing an overview of the time evolution of FUs. (b) Augmented timeline-based representation, providing an overview of the time evolution of FUs, including partial FU maps. Details about the implementation of these visualizations are provided in section 4.*

3.3. Data Model and Dynamic FU Detection

In our visualization framework, we define a *dynamic EEG coherence network* as a sequence $S = (G_1, G_2, ..., G_N)$ of consecutive coherence networks, where N denotes the number of such networks, and $G_t = (V, E_t)$ $(1 \leq t \leq N)$ is a coherence network at timestep t defined by a set of vertices V and a set of edges $E_t \subseteq V \times V$. Each coherence network has the same vertex set V since the electrode set, and therefore the vertex set, is constant over time. In contrast, the edge sets E_t change over time as coherences change over time.

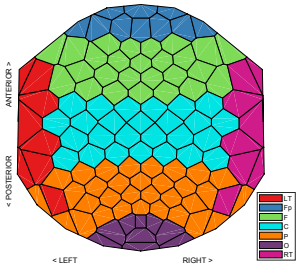


Figure 3: *Schematic map of the scalp on which electrodes have been attached (nose on top). Electrodes, represented by Voronoi cells, are divided into seven regions based on the EEG electrode placement system: LT (Left Temporal), Fp (Fronto-polar), F (Frontal), C (Central), P (Parietal), O (Occipital), RT (Right Temporal). Each region has a unique color (see the color legend on the right-bottom).*

3.3.1. FUs and FU map

For exploring the network while taking its spatial structure into account, the node-link diagram is considered to be more intuitive compared to other representations since its layout is based on the actual physical distribution of electrodes. However, the node-link diagram suffers from a large number of overlapping edges when the number of nodes exceeds a certain number. Therefore, the FU map can be used to better understand the relationship between connections and spatial structure (Figure 1).

The FU map was proposed to visualize EEG coherence networks with reduced visual clutter and preservation of the spatial structure of electrode positions. An FU is a spatially connected set of electrodes recording pairwise significantly coherent signals. Here "significant" means that their coherence is equal or higher than a threshold which is determined by the number of stimuli repetitions [tCMR08]. For each coherence network, FUs are displayed in a so-called FU map which visualizes the size and location of all FUs and connects FUs if the average coherence between them exceeds the threshold.

For each timestep, FUs are detected by the method proposed by ten Caat *et al.* [tCMR08]. We denote the set of FUs detected at timestep t by $P_t = \{C_{t,1}, C_{t,2}, ..., C_{t,n_t}\}$, where n_t is the number of FUs at time t.

3.3.2. Dynamic FU

To track the evolution of FUs, we introduce the concept of *dynamic FU*. Connecting FUs across timesteps, a set of L dynamic FUs $\{D_1, D_2, ..., D_L\}$ is derived from the dynamic EEG coherence network S as follows. Each dynamic FU D_l is an ordered sequence $D_l = \{C_{t_l,l_1}, C_{t_{l+1},l_2}, ..., C_{t_{l+k_l},l_{k_l}}\} \in P_{t_l} \times P_{t_{l+1}} \times ... \times P_{t_{l+k_l}}$, where t_l is the timestep at which D_l first appears, k_l is the number of timesteps during which D_l lasts, and each C_{t_{l+i},l_i} is an FU at timestep t_{l+i} (Figure 4). That is, each dynamic FU D_l is an FU whose members (i.e., included electrodes) are evolving over time as a result of the changing coherences between signals recorded by electrodes.

The key problem of detecting dynamic FUs is how to connect

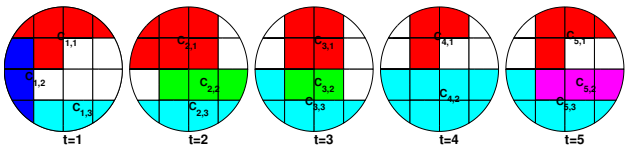


Figure 4: *Synthetic FU maps with five dynamic FUs tracked over five timesteps. Each cell corresponds to an electrode. Cell colors indicate different dynamic FUs: red represents D_1 : $\{C_{1,1},C_{2,1},C_{3,1},C_{4,1},C_{5,1}\}$, blue represents D_2 : $\{C_{1,2}\}$, cyan represents D_3 : $\{C_{1,3},C_{2,3},C_{3,3},C_{4,2},C_{5,3}\}$, green represents D_4 : $\{C_{2,2},C_{3,2}\}$, and magenta represents D_5 : $\{C_{5,2}\}$; the white cells represent electrodes belonging to small FUs with size less than two.*

FUs at consecutive timesteps. Similar to Greene's work [GDC10], we do a pairwise comparison of the FUs between consecutive timesteps and put the most similar FUs into the same dynamic FU. Here, we define the similarity between FUs C_1 and C_2 as a weighted sum of Jaccard similarity $J(C_1,C_2) = \frac{|C_1 \cap C_2|}{|C_1 \cup C_2|}$ and spatial similarity $E(C_1,C_2)$:

$$sim(C_1,C_2) = \lambda J(C_1,C_2) + (1-\lambda)E(C_1,C_2) \quad (1)$$

where the weight factor λ satisfies $\lambda \in [0,1]$. $E(C_1,C_2)$ is defined as one minus the 2D Euclidean distance between the barycenters of C_1 and C_2. Note that this 2D Euclidean distance is normalized to the interval [0, 1] by scaling it to the maximum possible distance in an FU map. If $sim(C_1,C_2)$ is equal or higher than a threshold $\theta \in [0,1]$, then we consider these two FUs similar. Our similarity measure is inspired by Crippa *et al.* [CMLR11], but note that they used a dissimilarity measure rather than a similarity measure. Standard values of the parameters were chosen in our experiments, following the literature: $\lambda = 0.5$ [CMLR11] and $\theta = 0.3$ [GDC10].

Pseudocode of the dynamic FU identification process is given in Algorithm 1, see also Figure 4 for a synthetic example. This identification algorithm maintains the following dynamic structures:

- D_l: a set of FUs representing the dynamic FU D_l.
- a dynamic label $L(C_{t,i})$ that equals l when $C_{t,i}$ belongs to dynamic FU D_l.
- com_l: a set of the common nodes of the FUs $C_{t_{l+i},l_i}, i = 1,\ldots,k_l$ that are part of the dynamic FU D_l.
- $nodes(C_{t,i})$: a set of nodes contained in the FU $C_{t,i}$.
- a queue containing all similarities in decreasing order between FUs at consecutive timesteps.

Algorithm 1 contains the following steps:

1. Initialization: a dynamic D_i is created for each FU detected in the coherence network at the first timestep (lines 1-5).
2. For each subsequent time $t > 1$, the following steps are performed. First, all similarities $sim(C_{t-1,j},C_{t,i})$ $(1 \le j \le |P_{t-1}|$, $1 \le i \le P_t)$ between FUs in P_{t-1} and P_t are inserted in the queue in descending order (line 11). Then,

   a. While the queue is not empty, the highest similarity $sim(C_{t-1,j},C_{t,i})$ is removed from the queue (lines 12-13). If $sim(C_{t-1,j},C_{t,i})$ is equal or higher than the threshold θ, $C_{t,i}$ has at least one node in the common nodes set $com_{L(C_{t-1,j})}$, and $C_{t,i}$ has no label, then (line 14),

   - $C_{t,i}$ is added to the dynamic FU $D_{L(C_{t-1,j})}$ (line 15).
   - $C_{t,i}$ receives label $L(C_{t-1,j})$ (line 16).
   - $com_{L(C_{t-1,j})}$ is replaced by its intersection with the nodes in $C_{t,i}$ (line 17).

   Otherwise, nothing is done.

   b. When the queue is empty, it is checked whether FU $C_{t,i}$ has no matching dynamic FUs, in which case a new dynamic FU containing $C_{t,i}$ is created (lines 20-27).

From the pseudocode the algorithm can be expected to have quadratic complexity in the number N of timesteps. For the data considered in this paper this did not present a problem. The FU detection was carried out as a preprocessing step. For a data set of 119 electrodes and 5 timesteps the computing time was in the order of 7 seconds on a modern laptop.

Algorithm 1 Dynamic FU Detection

Require: $P_t (1 \le t \le N)$; $sim(C_{t-1,j},C_{t,i}) (2 \le t \le N, 1 \le j \le |P_{t-1}|, 1 \le i \le |P_t|)$; similarity threshold θ.

Ensure: D_l is dynamic FU l consisting of a series of similar FUs; $L(C_{t,i})$ indicates the dynamic FU that $C_{t,i}$ belongs to; L_{max} is the number of dynamic FUs.

1: **for** $i = 1$ to $|P_1|$ **do**
2: $D_i = \{C_{1,i}\}$
3: $L(C_{1,i}) = i$
4: $com_i = nodes(C_{1,i})$
5: **end for**
6: $L_{max} = |P_1|$
7: **for** $t = 2$ to N **do**
8: **for** $i = 1$ to $|P_t|$ **do**
9: $L(C_{t,i}) = 0$
10: **end for**
11: add all similarities $sim(C_{t-1,j},C_{t,i})$ $(1 \le j \le |P_{t-1}|$, $1 \le i \le |P_t|)$ between FUs in P_{t-1} and P_t to *queue* in descending order
12: **while** *queue* $\neq \emptyset$ **do**
13: $sim(C_{t-1,j},C_{t,i}) = dequeue(queue)$
14: **if** $sim(C_{t-1,j},C_{t,i}) \ge \theta$ **and** $|nodes(C_{t,i}) \cap com_{L(C_{t-1,j})}| \ge 1$ **and** $L(C_{t,i}) = 0$ **then**
15: $D_{L(C_{t-1,j})} = D_{L(C_{t-1,j})} \cup C_{t,i}$
16: $L(C_{t,i}) = L(C_{t-1,j})$
17: $com_{L(C_{t-1,j})} = nodes(C_{t,i}) \cap com_{L(C_{t-1,j})}$
18: **end if**
19: **end while**
20: **for** i = 1 to $|P_t|$ **do**
21: **if** $L(C_{t,i}) = 0$ **then**
22: $L_{max} = L_{max} + 1$
23: $L(C_{t,i}) = L_{max}$
24: $D_{L_{max}} = \{C_{t,i}\}$
25: $com_{L_{max}} = nodes(C_{t,i})$
26: **end if**
27: **end for**
28: **end for**

4. Dynamic Network Visualization

Our visualization design provides an interactive exploration of dynamic coherence networks. As discussed in section 3, our design aims for helping users to understand the states of coherence networks, how these states are related to brain spatial structure, how the states change over time, and where the differences occur between coherence networks at different timesteps or under different conditions.

To this end, we employ three views: an FU map, a timeline-based representation, and a time-annotated FU map. The FU map has already been described in subsubsection 3.3.1. The timeline-based representation provides an overview of the evolution of FUs including both the changes in its composition and spatial information. The time-annotated FU map reveals the detailed content of the vertices and location of FUs, to facilitate the assessment of vertex behavior in two consecutive FU maps and the comparison of FU maps obtained under different conditions.

4.1. Augmented Timeline-based Representation

The timeline-based representation has already been used in other contexts to visualize dynamic communities [SMM13, RTJ*11, LWW*13]. In this representation, time is mapped to the horizontal axis, while the vertical axis is used to position vertices represented by lines. We extended this representation to show the evolution of FUs. For a certain timestep, lines grouped together represent corresponding electrodes forming FUs. Thus, the width of the grouped lines is proportional to the size of the FU in question, similar to what is done in Sankey diagrams or flow map layouts [RHF05,PXY*05]. The grouped lines are separated by a small gap to distinguish different FUs. The lines running from left to right represent the time evolution of the states of the coherence networks. When the grouped lines separate, this means that the corresponding FU splits, while the electrodes start to form an FU when lines forming different groups are joined together in the next timestep. Thus, this split and merge phenomenon helps to investigate the evolution of FUs over time.

4.1.1. Including spatial information

To incorporate spatial information in such a timeline-based representation, we provide two methods. First, we encode the spatial information into the color of the lines. To achieve this, we use an EEG placement layout based on underlying brain regions showing the location of electrodes. In this layout, electrodes are partitioned into several regions based on the EEG electrode placement system (Oostenveld and Praamstra [OP01]), and each region has a unique color generated by the Color Brewer tool [HB03] (Figure 3). In the timeline-based view (Figure 2), the lines are colored in the same way as the corresponding electrodes in the EEG electrode placement system of Figure 3, thus providing a mapping of each timeline to a specific spatial brain region.

However, the color of the lines only provides rough spatial information (one of the seven brain regions). To assess the dynamics of a small number of coherence networks in more spatial detail, we augment the timeline-based representation by combining the evolution of FUs with *partial FU maps* through a method inspired by Vehlow *et al.* [VBAW15]. In a partial FU map, only one FU is displayed with its cells colored black, while the cells of all other FUs are colored white. For a given timestep, each FU is visualized by a block of lines, followed by the corresponding partial FU map. For example, in Figure 2(b) each block of lines (labeled 1, 2, ..., 14) represents an FU, except the top block (labeled 15) which represents electrodes that do not belong to any FUs because their size is below the size threshold. Each block is followed by a partial FU map in which the corresponding electrodes in this FU are colored black and the rest are white.

In Figure 2, dynamic FUs are tracked over five time steps and it can be seen that a total of fourteen dynamic FUs are detected. The larger FUs included in dynamic FUs D_1, D_2 (labeled in the figure by "1" and "2", respectively) are located in the fronto-polar and parieto-occipital regions (cf. Figure 3). The dynamic FUs D_1, D_2, D_3, D_5, D_6, D_7 exist for all timesteps. Dynamic FU D_1 splits at timestep 2, creating a new dynamic FU D_{11} in addition to D_1. Dynamic FU D_3 significantly changes at timestep 3: the electrodes colored in yellow disappear while other electrodes (colored green) become part of it; at timestep 4, D_3 returns to the original state. This is also happening for D_7, which changes a lot at timesteps 2 and 3, but returns to the original state at timestep 4.

4.1.2. Ordering of FUs and vertices

To help users easily track the evolution of FUs and their locations in the brain, FUs need to be ordered in such a way that the position of FUs in the timeline-based view does reflect their locations in the FU map. Within each FU, lines representing electrodes should be ordered in such a way that it is easy to find the electrode distribution within this FU.

To this end, we first order FUs based on the y-coordinate of their corresponding barycenters for each timestep (Figure 2). The FUs with larger y-coordinate are placed above the FUs whose y-coordinates are smaller. If any FUs have the same y-coordinate, they are ordered based on their corresponding x-coordinate from left to right. Because FUs exchanging many electrodes over time usually are close to each other in the FU map, this ordering also makes for a stable layout to some extent. To allow the viewer to understand the electrode distribution within each FU, we have chosen to order the vertices of an FU based on their location in the EEG placement layout (Figure 3). Within each FU, vertices are ordered based on the brain parts to which they belong. Vertices from the same brain regions are placed together, and they are ordered as follows: vertices from LT are placed on the top of the FU, and then vertices from Fp, F, C, P, O, RT. Vertices from RT are placed at the bottom of the FU. Thus we do not optimize the view for minimum line crossing, since earlier experiments have shown that optimizing the layout for minimum line transition often resulted in local layouts where some areas suffer from excessive crossings [RTJ*11]. In our case, the optimized layout for minimum line crossing would make it hard to understand the spatial distribution.

4.2. Time-annotated FU map

The timeline-based view provides an overview of the evolution of FUs over time, and the changes of states between consecutive

timesteps can be inferred from the line transitions. These transitions provide a rough indication of the difference between states at consecutive timesteps. To focus on specific changes in the states of coherence networks between consecutive timesteps, it is necessary to provide more detail about the behavior of electrode signals. To achieve this, we provide a *time-annotated FU map* to facilitate the comparison of states of vertices between two consecutive FU maps. An exa

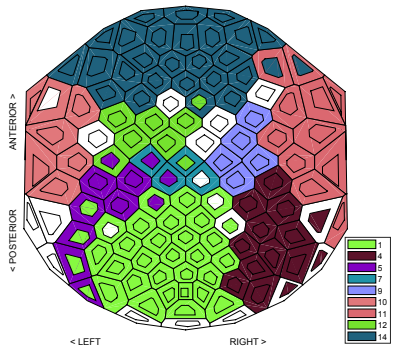


Figure 5: *Time-annotated FU map at timestep 5 (see Figure 2). Cells are divided into an inner and outer part. The outer cell color indicates which dynamic FU (see the color legend on the right-bottom) the electrode belongs to at timestep 5 while the color of the inner cell represents the state in the previous timestep 4. The white cells belong to FUs with size smaller than four.*

Here, we employ a technique, inspired by the work of Alper *et al.* [ABHR*13]. Cells are divided into an inner and outer part; for simplicity, we will speak of "inner cell" and "outer cell". The information of the previous state is encoded in the color of the inner cell, the information of the current state is encoded in the color of the outer cell. Before we do this, each dynamic FU is assigned a unique color to distinguish different dynamic FUs. This method preserves the FU map's structure, and it is intuitive to infer changes from the colors of the inner and outer cells. For the first timestep, the color of the inner cell is the same as that of the outer cell. For an FU at a given timestep $t > 1$, if the color of the majority of inner cells is the same as their outer cells' color, it means that this FU is relatively stable during these two consecutive timesteps. Note that this time-annotated FU map is not limited to comparison of consecutive FU maps, but can also be used to compare FU maps obtained under different conditions, e.g., to compare the states between healthy individuals and patients.

4.3. Interaction

To support the interactive exploration of the states of coherence networks and their evolution over time, our visualization approach also incorporates brushing-and-linking techniques that help users to focus on a particular coherence network or dynamic FU of the dynamic coherence network. A prototype application was developed for this purpose (https://DynCohNetVis.github.io/). A screenshot of the user interface is shown in Figure 6.

Users can find a timestep of interest in the timeline representation and click on the timestep (the blue area in Figure 6(f)) where they want to get more detail, so that the corresponding FU map at that timestep is displayed in Figure 6(b). Clicking on a particular FU in the timeline view, FUs belonging to the same dynamic FU will be highlighted in the timeline view, and the corresponding dynamic FU index also will be highlighted in Figure 6(d). Linked views are used for synchronous updating of the timeline representation and the FU map. This can help users to track the evolution of dynamic FUs. Following Vehlow *et al.* [VBAW15], the highlighting is accomplished by using a 100% opacity for the selected item and a smaller opacity for the remaining items. Clicking on the white space between blue areas in Figure 6(f), the time-annotated FU map is displayed so that the user can compare the corresponding two consecutive FU maps. Within the timeline view itself, we also allow for zooming and panning techniques to investigate the evolution of larger coherence networks.

5. User study

To evaluate the usefulness of our visualization design, we conducted an informal user study in which the participants explored the use of the dynamic coherence network visualization methods. During exploration, we collected online and offline feedback from the participants on the current and potential utility of our framework. Specifically, our goal was to assess how our visualization methods can help neuroscientists to analyze domain problems related to the identified tasks described in section 3.

Five PhD students (three female and two male) participated in the study. The mean age of these participants was 30 years. Four participants regularly analyzed EEG data; one used brain connectivity analysis while the others analyzed event-related potential (ERP) data. One participant was a computer scientist familiar with general visualization techniques and some familiarity with EEG data visualization. The first author met the participants at their research institutes, and carried out an evaluation interview. Please note that the participants in the evaluation stage were not the same as the participants in the requirements collecting stage. We believe that the use of two different groups helps to remove a potential bias in the evaluation.

5.1. Evaluation Procedure

During the interview, the purpose of the visualization method as well as the use of the implementation were explained first. Then, the participants were asked to explore data derived from an EEG experiment with four tasks and discuss their observations freely. These data were recorded from an oddball detection experiment in which participants (N.B.: not the same participants as those in our user study) were instructed to count target tones and ignore standard tones and were used before for FU analysis [tCMR08]. After the experiment, each participant had to report the number of perceived target tones. In our data, brain responses to 20 target tones were analyzed in $L = 20$ segments of 1 second, sampled at 1000 Hz. We first averaged over segments and then divided the averaged segment into five equal time intervals. For each time interval, we calculated the coherence network within the [8, 12] (alpha) Hz frequency band and detected FUs following the procedure described by ten Caat *et al.* [tCMR08]. We focused on this band as its related FU maps were interesting [tCMR08].

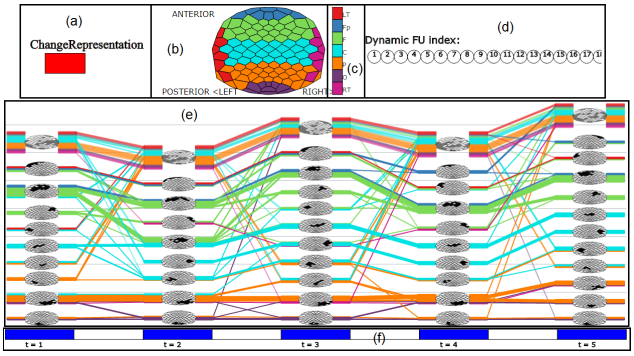


Figure 6: *(a) red bar that can be clicked to change the timeline representation with or without partial FU maps; (b) electrode placement layout for reference purposes; (c) color legend for regions; (d) dynamic FU index window: after selecting a circle a specific dynamic FU is highlighted; (e) main window for displaying the timeline representation; (f) time ticks: by selecting a blue area the associated timestep is highlighted, while by selecting a white area between blue areas the time-annotated FU map is displayed.*

The tasks the participants of our user study had to execute were based on the requirement analysis as reported in section 3:

1. to explore the state of the coherence network at a certain time step;
2. to explore the relation between functional connectivity and brain regions;
3. to explore the evolution of coherence networks over time;
4. to compare consecutive FU maps of interest using the time-annotated FU map.

At the end of the session, each participant completed a questionnaire. Each session took approximately 60 minutes and was audiotaped. The interface of our visualization prototype is illustrated in Figure 6. All participants used the online version of our tool.

5.2. Results

We collected both the observations of participants during exploration and their feedback in the form of a questionnaire that was completed after they finished the exploration.

5.2.1. Results during exploration

We observed that in general, participants were able to quickly find the more connected areas from the thickness of the blocks and identify the stable FUs from the dynamic FUs (task 1). However, participants were mostly interested in the change of connections within regions and transient dynamic FUs (they called these "striking"). With respect to tasks 2 and 3, one participant remarked that she could get a first impression from the timeline representation and then use the interactive techniques to investigate more details of changes in dynamic FUs and regions. Another participant stated that connections in F and C regions change a lot over time (the green and light blue lines) while the connections in Fp and O regions were more stable (the blue and purple lines), see Figure 6.

Transient dynamic FUs are those that only exist for a few timesteps or exist at one particular timestep only. Two participants who regularly used ERP analysis were particularly interested in the second and third timesteps (tasks 1 and 3). One of them observed that dynamic FU D_{11} appears at the second timestep (see Figure 7(a)), but found it more interesting that at this timestep the electrodes of this dynamic FU come from two regions, F and C regions (green and light blue lines), while in the following time steps the electrodes of dynamic FU D_{11} only are from the C region (light blue lines), except for the third timestep at which there is still one electrode of D_{11} that is from the F region (the thin green line branching of from the thick light blue line). We can interpret these changes in inter-region connections as reflecting changes in the functional brain connectivity between these two regions. A similar phenomenon was observed by another participant: dynamic FU D_{10} appears at the second timestep, and the electrodes in this dynamic FU mostly come from the C region except at the third timestep at which two electrodes come from the F and P regions.

Another participant chose to compare FU maps at the first and second timestep (see Figure 7(b)). She stated that electrodes changed their state mostly near the boundary between F and C regions, since the color of the inner cells and outer cells corresponding to these electrodes are different (task 4).

In summary, participants are mostly interested in stable or transient dynamic FUs, and dynamic FUs appearing at a specific time step. These observations can serve as the starting point for further analysis.

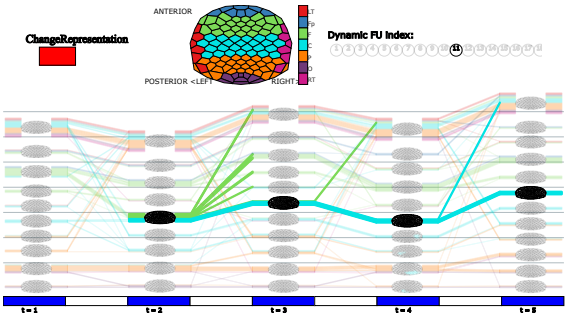
5.2.2. Observations from questionnaires

After free exploration, a questionnaire was used to collect additional feedback from the participants using the following five questions:

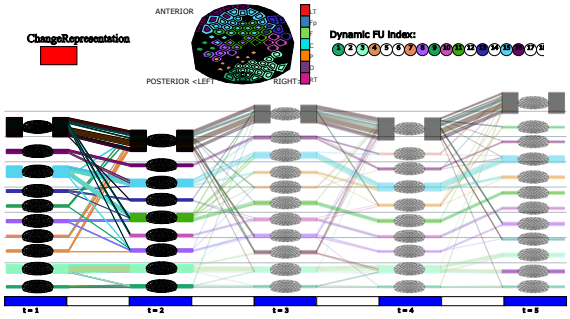
1. How does the visualization reflect the coherence network at a certain moment in time? (Easy to understand / Insightful / I would be able to use it)
2. What do you think about the connections in the timeline representation? (Clear / Relevant)
3. What do you think about the relation between the grouped lines and their underlying spatial brain structure in the timeline representation? (Easy to understand / Insightful / I would be able to use it)
4. What do you think about the visualization of changes over time in the timeline representation? (Easy to understand / Insightful / I would be able to use it)
5. What do you think about the time-annotated FU map to facilitate the comparison of FU maps? (Easy to understand / Insightful / I would be able to use it)

Responses were collected on a Likert scale (fully disagree; disagree; neutral; agree; fully agree).

When asked about how the visualization reflects the coherence network at a certain moment in time, four of the participants (fully) agreed that it is easy to understand and insightful, while three of them agreed they would be able to use it. When considering the properties of the connections in the timeline representation, all participants agreed that it is clear and three of them agreed it is rel-



(a) The evolution of dynamic FU D_{11}.



(b) Comparison of FU maps at first and second timestep.

Figure 7: *In (a) the dynamic FU D_{11} is selected and the evolution of dynamic FU D_{11} is highlighted in the timeline representation window. The dynamic FU D_{11} starts at the second timestep at which green lines represent electrodes coming from the F region while light blue lines represent electrodes coming from the C region. Then, it splits into several FUs at the third timestep at which only one green line remains while the remaining lines are light blue. At the fourth and fifth timesteps, only light blue lines remain in this dynamic FU. In (b) the time-annotated FU map is displayed in the electrode placement layout to compare FU maps at the first and second timesteps. For each inner cell, its color represents the dynamic FU to which the electrode belongs at the first timestep while the outer-cell color represents the dynamic FU at the second timestep. In the timeline window dynamic FUs appearing at the first and second time steps are highlighted. Dynamic FUs are distinguished by the colors of blocks. Colors of dynamic FUs are highlighted in the window of the dynamic FU index.*

evant. For the relation between the grouped lines and their underlying spatial brain structure in the timeline representation, four of them agreed that it is easy to understand and all agreed it is insightful. Furthermore, all agreed that it is easy to understand the changes over time in the timeline representation and that it is insightful. Finally, when asked about the time-annotated FU map to facilitate the comparison of FU maps, all of them agreed that it is easy to understand and four of them agreed that it is insightful. Regarding the usability, the majority of the participants agreed that they would be able to use it; however, for each task there was one "disagree" response. The second part of the questionnaire contained open-ended questions that invited participants to give both positive and negative comments. One participant, when asked what kind of information she could gather from these representations, said: "functional connectivity within groups of electrodes (Functional Units), their distribution, and location and changes over time with respect to the previously mentioned." Most participants thought the representations were useful and some stated that they can be used to interpret the data, for presentation purposes, to compare several participants simultaneously, and to investigate the dynamics in ERP experiments.

To address the change of states of electrodes, one participant suggested that the time-annotated FU map could be improved by not displaying the inner-cell shape for electrodes whose state does not change, since the inner cell and outer cell have the same color for this situation. Another participant suggested that the color assignment for dynamic FUs could be improved. When the number of dynamic FUs is large, the color for several dynamic FUs may be comparable, making it harder to distinguish them (Figure 7(b)). One participant stated it would also be useful to see the actual ERP at each timestep for each cluster to be able to interpret the data.

In summary, the feedback we received from the user study was generally positive, which indicates the application potential of our method for visualizing dynamic EEG coherence networks. Some suggestions for further improvement have been made.

6. Conclusions and future work

Requirements for supporting typical tasks in the context of dynamic functional connectivity network analysis were obtained from neuroscience researchers. We designed an interactive method for visualizing the evolution of EEG coherence networks over time that meets the requirements. With this visualization, a user can investigate the relationship between functional brain connectivity and brain regions, and the time evolution of this relationship. In addition, we provided a time-annotated FU map which can be used to facilitate the comparison of consecutive FU maps.

The user study suggests that our visualization method is potentially useful for dynamic coherence network analysis. However our visualization method still has some limitations. First, the coherence between FUs at a certain timestep is not reflected in the timeline-based representation. Therefore, a future improvement is to develop effective visual encodings to reflect the connections between FUs at a certain timestep.

Another concern for our visualization method is its scalability. The order of electrodes and FUs at a certain timestep is based on regions to which electrodes belong and barycenters of FUs. The ordering of electrodes will benefit the recognition of members for each FU, while the ordering of FUs will benefit the tracking of the evolution of dynamic FUs. However, for a dynamic coherence network in which there are many electrodes that switch their state often, the number of line crossings in the timeline-based view increases, especially when the number of electrodes increases. This makes the representation less readable. One potential solution is to provide some interaction techniques that allow users to interactively reorder electrodes and FUs. Third, for a large dataset, the number of dynamic FUs also increases, potentially making the colors hard to distinguish between dynamic FUs (as was remarked by

one participant in our user study). Finally, although the dynamic FU detection is carried out as a preprocessing step it may still become time-consuming as the number of timesteps increases.

As future work, we therefore intend to further explore the incorporation of the coherence between FUs in the timeline representation, to reduce the number of line crossings, to improve the color assignment for larger datasets, to provide access to the original EEG signals, and to find an approximation to the dynamic FU detection algorithm of lower complexity.

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