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Visual Analysis of Evolution of EEG Coherence Networks employing Temporal Multidimensional Scaling

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Abstract

The community structure of networks plays an important role in their analysis. It represents a high-level organization of objects within a network. However, in many application domains, the relationship between objects in a network changes over time, resulting in the change of community structure (the partition of a network), their attributes (the composition of a community and the values of relationships between communities), or both. Previous animation or timeline-based representations either visualize the change of attributes of networks or the community structure. There is no single method that can optimally show graphs that change in both structure and attributes. In this paper we propose a method for the case of dynamic EEG coherence networks to assist users in exploring the dynamic changes in both their community structure and their attributes. The method uses an initial timeline representation which was designed to provide an overview of changes in community structure. In addition, we order communities and assign colors to them based on their relationships by adapting the existing Temporal Multidimensional Scaling (TMDS) method. Users can identify evolution patterns of dynamic networks from this visualization.

CCS Concepts

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

1. Introduction

Networks are generally used to model interactions between objects, and play an important role in various disciplines, such as biology, social science, mathematics, computer science, and engineering. In mathematics, networks are often referred to as *graphs*, where objects are represented by vertices (nodes) while their interactions are indicated by edges (links). Most of these networks have an inherent community structure, i.e., vertices can be organized into groups, which are referred to in various ways, such as communities, clusters, cliques, or modules [For10].

In many application domains, the relationship between objects in a network changes over time, resulting in a *dynamic* network [GDC10]. The community structure (the partition of a network), as well as the corresponding attributes (the composition of communities and the relationships between communities) are then dynamically changing over time [vLKS*11, HET13]. Visualizing the evolution of networks in dynamic networks can facilitate the discovery of evolution patterns of communities and can help researchers propose hypotheses to explain these patterns for further study.

In this paper we focus on *dynamic* EEG coherence networks that represent functional brain connectivity, in which nodes represent electrodes which are used to record electrical activity of the brain

and edges represent coherences between pairs of signals recorded by electrodes. As the starting point, we consider the existing visualization method for *static* EEG coherence networks based on functional unit maps (FU maps) by ten Caat *et al.* [tCMR08]. An example of such a static EEG network is shown in Figure 1(a). The FU-map method clusters electrodes based on their relative spatial position and corresponding coherence values. The resulting clusters for the example in Figure 1(a) are shown in Figure 1(b) and compose an FU map, in which electrodes represented by polygon cells are divided into several groups, each of which is an FU, that is, a spatially connected set of electrodes recording pairwise significantly coherent signals. Each FU is assigned a gray color for distinguishing between FUs and the color of lines connecting two FUs indicates the corresponding inter-FU coherence.

To visualize the evolution of dynamic EEG coherence networks, Ji *et al.* proposed a visualization framework based on a timeline representation [JvdGMR17]. This representation assists users in identifying the temporal evolution of FUs and their corresponding location on the scalp. However, this approach only shows the change of community structure and composition of FUs, but it does not consider how the relationships between FUs change. Also, existing visualization methods either focus on the change of network attributes or the change of community structure [vLKS*11]. For example, some methods have been proposed to depict the evolu-
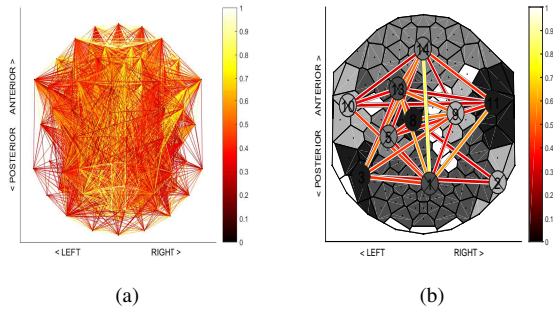
(a)   (b)

Figure 1: *Example of a static EEG coherence network. (a) Layout of a coherence network (the EEG frequency band is 8-12 Hz). Vertices represent electrodes, and edges represent coherences between electrode signals, where only coherences of at least 0.2 are plotted. The color of the edge indicates the coherence value. (b) FU map based on the coherence network in (a). Spatial groups of similarly colored (in gray scale) cells correspond to FUs with a size of at least four, while the white cells are part of smaller FUs. Circles overlayed on the cells represent the barycenter of the FUs and are connected by lines whose color reflects the inter-FU coherence calculated as the average coherence between all electrodes of the FUs (see colorbar).*

tion of community evolution *structure*, such as splitting or merging of communities [RTJ*11, VBAW15], where the attributes of the connections between these communities are ignored. On the other hand, some methods have been designed to show the change of attributes of individual nodes or edges instead of at the group level [BBDW16]. However, there is no single method that can optimally show graphs that change in both structure and attributes.

Therefore, we here propose a combined visualization approach taking both the community structure and the relationships between communities into account to support the identification of evolution patterns of dynamic EEG coherence networks. First, following [JvdGMR17] we use an initial timeline representation to show significant events for community evolution in EEG coherence networks. Additionally, we adapt the temporal Multidimensional Scaling (TMDS) method which was developed for multivariate data [JFSK16] to order and assign colors to network communities for each time step based on relationships between them. The ordering and assignment of color makes that similar communities are spatially close in the representation and have similar colors, so they can be identified efficiently.

Summarizing, our main contributions include:

- a combination of a timeline representation for dynamic EEG coherence networks and TMDS for visualizing evolution patterns of community structure and relationship between communities;
- a color assignment method for communities;
- a color design for transition edges connecting communities that belong to the same dynamic communities.

2. Method

Our method aims to overcome the drawback of a previously proposed visualization method for EEG coherence networks by Ji *et al.* [JvdGMR17]. The drawback of that approach is that it focuses only on the changes of state of dynamic FUs and ignores the changes in relationships between FUs. The solution we propose here for incorporating the attribute changes in the visualization is based upon the TMDS method of Jäckle *et al.* [JFSK16].

Once the dynamic FUs have been detected and inter-dynamic FU coherences have been calculated, we can model the relationships between dynamic FUs at a certain time step t as an undirected weighted graph $G_t = (V, E_t)$ in which $v_i \in V$ represents a dynamic FU and $e_{ij} \in E_t$ represents the inter-dynamic FU coherence between v_i and v_j. A dynamic graph, more precisely the sequence graph $\mathcal{G} := (G_1, ..., G_N)$, then is defined as a sequence of N ordered graphs of which each observes the structure of a system at N moments [HET13]. The inter-dynamic FU coherence at a certain time step is the inter-FU coherence which is calculated as the average coherence between all electrodes in the corresponding FUs. Note that after dynamic FU detection, the number $|V|$ of dynamic FUs is a constant, but any FU may exist for a limited period of time only instead of for all time steps.

The main idea of our approach is as follows. For a given dynamic coherence graph with the derived dynamic FUs and a given color space, we embed the dynamic FUs at each time step into the specified color space using the TMDS method (without using the sliding window approach) so that users can recognize the evolution patterns of inter-FU coherences from the changes in FU colors. In this approach, the distance between dynamic FUs in the color space should be inversely related to their similarity, as defined by their inter-FU coherence at each time step.

2.1. Timeline-based Representation

The timeline representation is a widely used visual metaphor for visualizing the evolution of communities in dynamic graphs [RTJ*11, VBAW15, JvdGMR17, TA08]. This visualization can track the progress of communities over time in a dynamic network, where each community is characterized by a series of significant evolutionary events [GDC10], such as two or more current FUs *merging* into one FU in the next time step, or one current FU *splitting* into two or more FUs in the next time step.

We here propose to use a coloring scheme to depict the evolution pattern of the relationship between dynamic network communities over time. Although there have been studies of the assignment of color to (dynamic) communities, most color schemes were designed in such a way that (dynamic) communities are easily distinguished in generic representations [JRFL09, DEG07, VBAW15, RTJ*11]. Instead, we propose a coloring solution using multidimensional scaling to assist users in recognizing the relationships between dynamic communities and explore the evolution of patterns of relationships between such communities over time.

2.2. Distance Function

For a given graph G_t at time step t, we define a distance measure for the set of dynamic FUs so that dynamic FUs with high inter-FU

coherence will have a small distance. In addition, we only incorporate coherences above a pre-defined significance threshold; in our case, we set the threshold to 0.2 [HRA*95, MSvdHdJ06, tCMR08]. Specifically, we use the following distance function with parameters a and b based on the coherence value e_{ij} between nodes i and j:

$$d_{ij} = \begin{cases} e^{a(1-e_{ij})} - 1 & e_{ij} \geq 0.2 \\ e^{a(1-e_{ij})} - 1 + b & \text{else} \end{cases} \quad (1)$$

We then embed the dynamic FUs into a color space using MDS as described in Section 2.3.

This exponential function has several properties. First, it decreases with increasing coherence so that dynamic FUs that have high inter-FU coherence will have a small distance and will be embedded closely together in the color space C. The parameter a can be used to adjust the rate with which the distance decreases. Second, inter-FU coherences that are below the threshold will be assigned a large distance, and will be separated far away from each other in the color space C. This is achieved by the additive constant b. When b is larger the distances between values below the threshold are larger. Third, the inter-FU coherence is limited to the interval [0, 1], which makes coherence values harder to distinguish, so by introducing the exponential function the coherence value domain is stretched out while the relative order of coherence values is preserved.

2.3. Multidimensional Scaling

Multidimensional scaling enables the analysis of high-dimensional data or relations (usually given as a similarity/dissimilarity matrix) between objects in a lower dimensional space [BSL*08, VHBV16, JFSK16]. It provides a visual representation of the pattern of proximities (i.e., similarities or distances) among a set of objects such that those objects that are very similar to each other are placed near each other, and those that are very different are placed far away from each other in the representation.

Our MDS approach is based on an adaptation of the temporal MDS approach in [JFSK16], in which a temporal 1D MDS plot is computed for each window separately and then sequentially aligned in the Cartesian coordinate system. The x-axis represents time and the y-axis represents the 1D similarity value derived from the MDS computation. In our case, we map dynamic FUs to a color space for each time step using MDS based on their inter-FU coherences which are included in the weighted graph G_t, such that FUs having higher inter-FU coherence also have more similar colors. The resulting colors are then assigned to dynamic FUs in the timeline representation.

The MDS layout for each time step (also referred to as an MDS "slice") is computed by the method proposed in [GKN05, XKH11]. In our implementation, the Matlab package of Xu *et al.* [XKH11] was used to calculate MDS for every time step.

2.4. Color Space Selection

The distance matrix obtained in Section 2.2 can be used to produce a 3D layout in a color space using MDS since usually the color is a
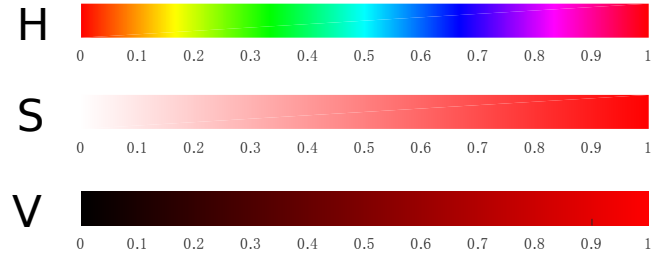
Figure 2: *HSV color components. Saturation and Value are varying on the condition of Hue is setting equal to 1. The Hue component has been normalized so that it lies in the interval [0, 1] instead of the interval from 0 to 360 degrees.*

combination of three components. It also can produce a 2D or 1D layout in a 3D color space when fixing the other one or two components. However, when vertices are mapped to 2D or 3D color space, the resulting color is very hard to interpret, and it requires a high cognitive load to compare colors. We chose to map vertices to the Hue component using 1D MDS rather than Saturation or Value component, because it is easier to recognize the color differences, since colors change gradually from red to yellow, green, blue and pink. Then colors that are close in the color space will be similar, and colors having a large distance in the color space will be perceived as very different (see Figure 2). In addition, the reason we have chosen the Hue component of the HSV model instead of one of the single-hue sequential color schemes as provided by Color Brewer (`colorbrewer2.org`) is that we are not aiming for an exact quantitative reflection of the distance or similarity between nodes. Instead, we focus on finding the general evolution pattern of clusters of nodes having a close relationship for a long time. The Hue component has the desired property of providing an intuitive visual representation of such clusters.

2.5. MDS Slice Flipping

We first normalize the MDS similarity values of all dynamic FUs to the interval [0, 0.9] instead of [0,1]. Hue has an intrinsic circularity property, meaning that the color at the left end of the interval is the same as at the right end (see Figure 2). By normalizing the MDS similarity values to [0, 0.9] we avoid the extreme condition that two blocks of lines with a large distance between them (therefore being placed at totally different positions) would get the same red color.

MDS is not invariant to rotation [JFSK16]. This property means that position can make the evolution of inter-FU coherence patterns hard to identify. Figure 3 gives an example of applying MDS to the first and second time steps, where Figure 3(a) and 3(b) show totally different orderings of dynamic FUs at the second time step, even though they share the same graph G_2. To solve this problem, we first compute the sum of the absolute differences $\sum |X_i[t] - X_i[t-1]|$ between positions of dynamic FUs i which are present at time step $t-1$ and t before and after flipping, respectively. If the value after flipping is smaller than before flipping, the position of dynamic FUs at time step t will flip; otherwise dynamic FUs will keep the original position computed by MDS.
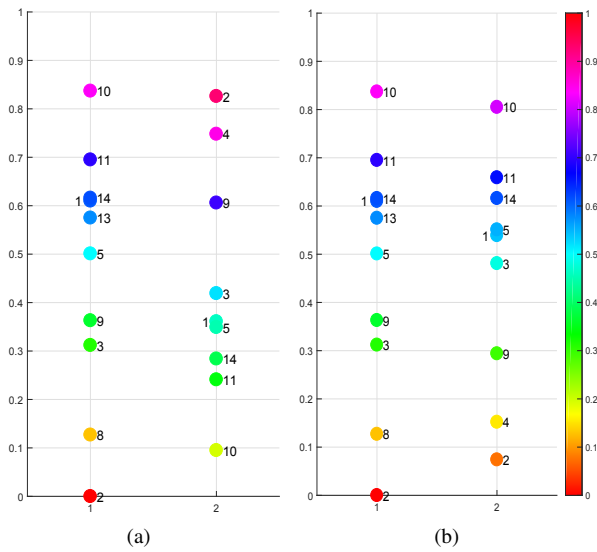
Figure 3: *1D layout computed by MDS for graphs at the first (1) and second (2) time step. (a) 1D layout before flipping the second time step. (b) 1D layout after flipping the second time step.*

3. Usage Scenario

We demonstrate the proposed method on dynamic coherence network data obtained from a single person [JvdGMR17]. The data were collected during an auditory oddball experiment, in which participants were instructed to count target tones of 2 kHz (probability 0.15) and ignore standard tones of 1 kHz (probability 0.85). After the experiment, each participant had to report the number of perceived target tones [MSvdHdJ06, tCMR08]. 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 performed the procedure described in [JvdGMR17] to detect dynamic FUs.

The goal of the analysis is to identify patterns of synchronization and how these relate to task conditions. Previous work focused on the synchronization between electrode signals *within* FUs, which cannot analyze synchronization *between* FUs [JvdGMR17]. In contrast, the combined approach can identify not only the change of dynamic FUs, but also the evolution of relationships between dynamic FUs over time.

Figure 4 is the result of a timeline representation in which the straight lines are rendered by the color derived from the proposed method described in Section 2. In 4(a), we ordered the FUs at each time step based on the location of their barycenter on the FU map, while the FUs in 4(b) are ordered based on their position on the H-axis in the HSV color space. To indicate the shift in relative positions of dynamic FUs along the H-dimension, we render the transition edges between neighbouring time steps with gradually changing colors using linear interpolation. For example, at the first time step, dynamic FU 1 that is located at around 0.61 is assigned

a blue color. At the second time step, dynamic FU 1 splits into two FUs: dynamic FU 1 and 4, where dynamic FU 4 is located at around 0.15 and assigned a yellow color. We then render the transition edges which reach from dynamic FU 1 in the first time step to dynamic FU 4 at the second time step with gradually changing color from blue to yellow (Figure 4(a)).
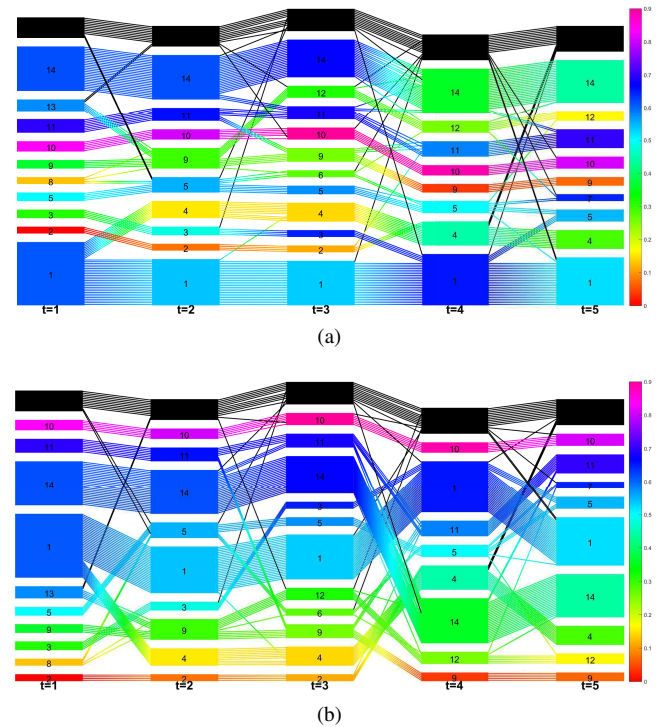

Figure 4: *Timeline representation of the evolution of dynamic FUs over time. Each block of lines represents an FU at each time step. The color of the lines at each time step represents the corresponding position of the dynamic FU on the H-axis in the HSV color space (see legend). The top block of lines (rendered in black) is the set of electrodes belonging to very small FUs. (a) FUs ordered by their barycenter on the FU map. (b) FUs ordered by their position on the H-axis in HSV color space.*

From Figure 4, it can be seen that dynamic FUs 1, 5, 11, 14 have a similar blueish color across time steps (this is especially clear in Figure 4(b)), except for the fourth time step at which dynamic FU 14 is green, but it shifts back to a blueish green color at the fifth time step. This means that there is rather constant high inter-dynamic FU coherence among them, but at the fourth time step dynamic FU 14 is less synchronized with the other FUs. In addition, these four dynamic FUs exist for all time steps and the size of most of them is large. Another observation is that even though dynamic FU 10 exists for all time steps, it is consistently far apart from all other dynamic FUs, meaning that it has low inter-FU coherence with these other dynamic FUs. This pattern changes at the fourth time step, at which dynamic FU 9 is far from the other dynamic FUs in the specified color space. Dynamic FU 4 has similar behaviour, it appears at the second time step and is a branch of dynamic FU

1. But it does not have a color close to that of dynamic FU 1 from $t = 2$ to $t = 5$. Similar to dynamic FU 9 and 14, it displays a big change of color at the fourth time step.

The dynamic FU 1 is located posteriorly while dynamic FU 14 is located anteriorly, dynamic FU 5 is located left-centrally, dynamic FU 9 is located right-centrally and dynamic FU 11 is located right-frontally [JvdGMR17]. These regions have a high synchronization during the cognitive processing task. Therefore, regions where dynamic FUs 1, 5, 9, 11, and 14 are located, as well as the change in behaviour at the fourth time step are particularly interesting for further targeted analyzes.

4. Conclusion

We have presented a combination of a timeline representation for dynamic graphs and the TMDS technique to visualize dynamic EEG coherence networks. The main goal of this study was to help users discover the evolution pattern of relationships between dynamic FUs over time. It does not only show the change in community structure of dynamic networks, but also the evolution patterns of relationships between communities. Therefore, the proposed method can act as a guideline for further analysis and has the potential for visual exploration of large data sets. It can be extended to analyze different types of networks. Many networks can be ordered by their similarity using algorithms such as developed by Van den Elzen *et al.* [VHBV16].

However, the proposed method has some limitations. First, the underlying visualization metaphor (timeline representation) has a limited scalability. In our application, there are 119 electrodes for each coherence network and 5 time steps. When this method is extended to other dynamic networks of thousands of nodes and hundreds of time steps, the scalability becomes an issue. In such cases, interactive methods may be helpful to facilitate users to explore the evolution patterns of dynamic networks, e.g., drilling-down abilities and more aggregated views. Second, the final assessment of similarity involves the composition of the similarity reduction from a high-dimensional space to 1D (hues) with the way humans perceive hues as being similar or not. As such, what MDS finds to be similar of different is not necessarily perceived in the same proportion by a human observer. Studying the precise effect of this composition is an interesting topic for future research.

5. Acknowledgements

References

[BBDW16] BECK F., BURCH M., DIEHL S., WEISKOPF D.: A taxonomy and survey of dynamic graph visualization. *Computer Graphics Forum 36*, 1 (jan 2016), 133–159. 2

[BSL*08] BUJA A., SWAYNE D. F., LITTMAN M. L., DEAN N., HOFMANN H., CHEN L.: Data Visualization with Multidimensional Scaling. *Journal of Computational and Graphical Statistics 17*, 2 (2008), 444–472. 3

[DEG07] DILLENCOURT M. B., EPPSTEIN D., GOODRICH M. T.: Choosing colors for geometric graphs via color space embeddings. In *Graph Drawing*. Springer Berlin Heidelberg, 2007, pp. 294–305. 2

[For10] FORTUNATO S.: Community detection in graphs. *Physics Reports 486*, 3-5 (2010), 75–174. 1

[GDC10] GREENE D., DOYLE D., CUNNINGHAM P.: Tracking the evolution of communities in dynamic social networks. In *Proceedings of the 2010 International Conference on Advances in Social Networks Analysis and Mining* (Washington, DC, USA, 2010), IEEE Computer Society, pp. 176–183. 1, 2

[GKN05] GANSNER E. R., KOREN Y., NORTH S.: Graph drawing by stress majorization. In *Graph Drawing*. Springer Berlin Heidelberg, 2005, pp. 239–250. 3

[HET13] HURTER C., ERSOY O., TELEA A.: Smooth bundling of large streaming and sequence graphs. In *2013 IEEE Pacific Visualization Symposium (PacificVis)* (feb 2013), IEEE. 1, 2

[HRA*95] HALLIDAY D., ROSENBERG J., AMJAD A., BREEZE P., CONWAY B., FARMER S.: A framework for the analysis of mixed time series/point process data—theory and application to the study of physiological tremor, single motor unit discharges and electromyograms. *Progress in Biophysics and Molecular Biology 64*, 2 (1995), 237–278. 3

[JFSK16] JÄCKLE D., FISCHER F., SCHRECK T., KEIM D. A.: Temporal MDS Plots for Analysis of Multivariate Data. *IEEE Transactions on Visualization and Computer Graphics 22*, 1 (2016), 141–150. 2, 3

[JRFL09] JIANU R., RUSU A., FABIAN A. J., LAIDLAW D. H.: A coloring solution to the edge crossing problem. In *Information visualisation, 2009 13th international conference* (2009), IEEE, pp. 691–696. 2

[JvdGMR17] JI C., VAN DE GRONDE J. J., MAURITS N. M., ROERDINK J. B. T. M.: Visualizing and Exploring Dynamic Multichannel EEG Coherence Networks. In *Eurographics Workshop on Visual Computing for Biology and Medicine (VCBM)* (2017), Bruckner S., Hennemuth A., Kainz B., Hotz I., Merhof D., Rieder C., (Eds.), The Eurographics Association. 1, 2, 4, 5

[MSvdHdJ06] MAURITS N. M., SCHEERINGA R., VAN DER HOEVEN J. H., DE JONG R.: EEG coherence obtained from an auditory oddball task increases with age. *Journal of clinical neurophysiology 23*, 5 (2006), 395–403. 3, 4

[RTJ*11] REDA K., TANTIPATHANANANDH C., JOHNSON A., LEIGH J., BERGER-WOLF T.: Visualizing the evolution of community structures in dynamic social networks. *Computer Graphics Forum 30*, 3 (jun 2011), 1061–1070. 2

[TA08] TELEA A., AUBER D.: Code flows: Visualizing structural evolution of source code. *Computer Graphics Forum 27*, 3 (may 2008), 831–838. 2

[tCMR08] TEN CAAT M., MAURITS N. M., ROERDINK J. B. T. M.: Data-driven visualization and group analysis of multichannel EEG coherence with functional units. *IEEE Transactions on Visualization and Computer Graphics 14*, 4 (2008), 756–771. 1, 3, 4

[VBAW15] VEHLOW C., BECK F., AUWÄRTER P., WEISKOPF D.: Visualizing the evolution of communities in dynamic graphs. *Computer Graphics Forum 34*, 1 (2015), 277–288. 2

[VHBV16] VAN DEN ELZEN S., HOLTEN D., BLAAS J., VAN WIJK J. J.: Reducing Snapshots to Points: A Visual Analytics Approach to Dynamic Network Exploration. *IEEE Transactions on Visualization and Computer Graphics 22*, 1 (2016), 1–10. 3, 5

[vLKS*11] VON LANDESBERGER T., KUIJPER A., SCHRECK T., KOHLHAMMER J., VAN WIJK J., FEKETE J.-D., FELLNER D.: Visual analysis of large graphs: State-of-the-art and future research challenges. *Computer Graphics Forum 30*, 6 (apr 2011), 1719–1749. 1

[XKH11] XU K. S., KLIGER M., HERO III A. O.: Visualizing the Temporal Evolution of Dynamic Networks. *Proc. 9th Workshop on Mining and Learning with Graphs* (2011), 2. 3