6

CONCLUSION

In this chapter, we will first provide a summary of this thesis. Subsequently, limitations of the methods proposed in this thesis are discussed and directions are indicated for future research. At the end, a final conclusion is presented.

6.1 SUMMARY

Brain functional connectivity analysis can be useful to improve the understanding of brain mechanisms underlying human behaviour. In addition to well-defined questions about the datasets, visualization techniques can aid to discover unanticipated patterns in the data. This thesis has focused on the development and investigation of visualization and analysis techniques for brain functional connectivity of multichannel EEG coherence networks. However, the methods introduced in this thesis are not limited to EEG coherence networks, but can be extended to explore other kinds of brain networks such as fMRI or PET functional networks.

There are many visual approaches for exploring brain connectivity, where each approach has its own purpose and is usually applied for a particular task. However, in practice the tasks will be varied and will depend on the researcher’s requirements. In Chapter 2, we introduced an interactive visualization methodology for the analysis of dynamic connectivity structures in multichannel EEG coherence networks as an exploratory preprocessing step to a complete analysis of such networks. This visualization framework was developed based on researcher requirements and evaluated by four domain researchers and one computer researcher. The feedback we received during the evaluation showed that our design supports exploratory analysis tasks well. We found that the timeline representation, which provides an overview of the evolution of dynamic networks, is effective in showing changes over time. This overview enables users to identify critical dynamic FUs, e.g., stable or striking dynamic FUs, and critical time steps. This overview achieves meeting the requirements R2, R3, R4 mentioned in the introduction of the thesis (see Section 1.3.4). In addition, the time-annotated FU map we introduced is useful for identifying changes of node states between successive EEG coherence networks (R1).

Dynamic EEG coherence networks based on functional units can be viewed as temporal multivariate data. For example, the FUs, including their composition and their mutual relationships, of a dynamic network are changing over time. In Chapter 2, the visualization only considered
the changes in the composition of FUs while ignoring the relationships between FUs. In Chapter 3 we improved upon this approach by proposing a method based on dimension reduction techniques to explore the evolution patterns of dynamic FUs. On the basis of the timeline-based representation introduced in Chapter 2, we encoded the colour and position of FUs by employing the multidimensional scaling technique such that similar FUs that have high inter-FU coherence are grouped together (R4). The application showed that the proposed method is able to identify the evolution patterns of dynamic FUs (R3). It allows researchers to identify dynamic FUs with high synchronization based on their position or colour. If dynamic FUs stay close to their position or colour, it means they have a stable high coherence with each other across time steps.

In Chapter 4 we proposed a method based on the earth mover’s distance (EMD) for quantifying differences between multichannel EEG coherence networks represented by functional unit maps (R1). We compared the proposed method to the inexact graph matching method. This method tries to find a one-to-one correspondence between FUs of two FU maps, but it does not use information across FUs. However, in brain connectivity networks the location and number of nodes are fixed for every network, so that the final detected FUs in distinct FU maps are not absolutely different even if they are not matched in the one-to-one matching method. In contrast, for the new method information across FUs is taken into account to compute the difference between FU maps. The application to EEG coherence networks obtained from an odd-ball experiment showed that the proposed method is able to measure the dissimilarity between EEG coherence networks and helps in quantifying the inter-subject variability during a cognitive experiment. It showed that the similarity between coherence networks decreases with increasing frequency band, both for young and old participants. Furthermore, there was a higher variability in FU maps between older participants than between younger participants.

Identification of regions of interest (ROIs) is a fundamental task in brain connectivity analysis. Most traditional methods are hypothesis-driven and depend on parcellation schemes. As an alternative, in Chapter 5 we proposed a data-driven method, built upon the maximal clique based (MCB) method and improved watershed based (IWB) method that were previously proposed for multichannel EEG coherence network analysis. The new method is referred to as the community clique-based (CCB) method. These three methods detect ROIs, that is, functional units (FUs), based on different criteria. A drawback of the MCB and IWB methods is that the analysis of local synchronization is difficult, since these methods detect maximal cliques, that is, groups of spatially-connected electrodes that are as large as possible. Specifically, the MCB method views coherences above or equal to the pre-defined threshold equally while the IWB method clusters electrodes based on
their neighbours which have the largest coherences with them, without considering how strongly the electrodes are connected to other members of the group. In contrast, the CCB method partitions electrodes into dense groups of spatially connected regions (R4). In the resulting FU maps, we not only showed the distribution and coherence between FUs, but also depicted the average coherence within FUs by employing a colour circle overlaid on the corresponding FUs. We applied our technique to the study of multichannel EEG coherence networks. The results showed that the proposed method could be used to detect highly synchronized areas from the colour of circles overlaid on the FUs.

6.2 LIMITATIONS AND FUTURE WORK

This thesis has mainly focused on EEG coherence networks, but it is not limited to it. It can be extended to other brain connectivity networks as derived from e.g. fMRI or PET data. When these methods are applied to other brain connectivity networks or temporal multivariate data, two major factors should be considered: the problems which researchers are facing, and the data dimensions.

To get a clear understanding of which problems researchers need to solve, it is important to have a strong collaboration with domain experts and to jointly formalize the final tasks. For example, in Chapter 2, users who participated in the user study suggested that these methods can be applied to the analysis of ERP signals. In addition, one of the limitations of dynamic FU detection is that neighboring FUs in the same dynamic FU must be appearing at successive time steps. This constraint ignores the reoccurrence of similar FUs. For future work, detecting dynamic FUs can take distant FUs into account which are not neighbors in the time sequence. Also, finding an approximation to the algorithm of detecting dynamic FUs with lower complexity can be studied. Another consideration for improving the method is reducing line crossings. In the cases we considered, there are only five time steps and 119 nodes per network in total. For further study, the number of nodes for each network and time steps may be much larger. For such cases, it may be difficult or even impossible to provide a global crossing reduction method. A potential method to solve this problem is to divide the whole time domain into several time windows, and reduce line crossings for each time window individually.

Another factor is the data dimension, i.e., the challenge of visualizing and analyzing high-dimensional data. Visualizing all dimensions simultaneously seems impossible. Dimension reduction techniques are necessary to simplify the original data. As an example, the method applied to FUs in Chapter 3 can be extended to networks. In that case, the color encoding should be redesigned, especially when the number of nodes is larger. Another example of analyzing high-dimensional data can be found in Chapter 4, where we considered the comparison of connec-
activity networks. The dataset itself has many properties which can be used when comparing FU maps. For example, the properties of FUs include location, average coherence, and inter-FU coherence with other FUs. The proposed method in Chapter 4 can be improved by taking the inter-coherence and average coherence of FUs into account.

Identifying regions of interest is also important in the analysis of brain connectivity. Graph clustering can be seen as a process of dimension reduction: putting nodes with the same specific property into the same group. There are many methods available for clustering nodes of networks for various purposes. For a further study on identifying ROIs, it is important to communicate with neuroscientists to find out what properties of data they are interested in. Then a decision about the interesting regions can be made and suitable clustering methods selected.

6.3 conclusion

This thesis has explored visual methods to study brain connectivity networks determined by EEG coherence data. The contributions of this thesis are promising for further understanding of brain mechanisms. The timeline representation was shown to be useful to find time steps and regions of interest. The time-annotated FU map and the method based on EMD are both useful to analyze the differences between FUs both qualitatively and quantitatively. Finally, dimension reduction techniques are important for identifying evolution patterns in dynamic networks.