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Graph averaging as a means to compare multichannel EEG coherence networks and its application to the study of mental fatigue and neurodegenerative disease

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ABSTRACT

A method is proposed for quantifying differences between multichannel EEG coherence networks represented by functional unit (FU) maps. The approach is based on inexact graph matching for attributed relational graphs and graph averaging, adapted to FU-maps. The mean of a set of input FU-maps is defined in such a way that it not only represents the mean group coherence during a certain task or condition but also to some extent displays individual variations in brain activity. The definition of a mean FU-map relies on a graph dissimilarity measure which takes into account both node positions and node or edge attributes. A visualization of the mean FU-map is used with a visual representation of the frequency of occurrence of nodes and edges in the input FUs. This makes it possible to investigate which brain regions are more commonly involved in a certain task, by analysing the occurrence of a FU of the mean graph in the input FUs. Furthermore, our method gives the possibility to quantitatively compare individual FU-maps by computing their distance to the mean FU-map. The method is applied to the analysis of EEG coherence networks in two case studies, one on mental fatigue and one on patients with corticobasal ganglionic degeneration (CBGD). The method is proposed as a preliminary step towards a complete quantitative comparison, and the real benefit of its application is still to be proven.

1. Introduction

Nowadays, many neuroimaging methods are available to assess the functioning brain, such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), electroencephalography (EEG) and magneto-encephalography (MEG). A recording with one of these imaging modalities provides a measurement of brain activity as a function of time and position. A more recent innovation is connectivity analysis, in which the anatomical or functional relation between different (underlying) brain areas is calculated [1]. Of particular interest is the *comparison* of functional brain networks under different experimental conditions, or comparison of such networks between groups of subjects. In the last decade a multitude of topological network measures has been developed [2–4] in an attempt to characterize and compare brain networks. However, such topological measures are calculated by thresholding, binarizing and symmetrizing the connectivity matrix of the weighted and directed brain network. Thus, spatial information is lost and only global network information is retained. For interpretation and diagnosis it is essential that local differences can be visualized in the original network representation [5,6]. This asks for the development of mathematical methods, algorithms and visualization tools for the *local comparison* of complex networks – not necessarily of the same size – obtained under different conditions (time, frequency, scale) or pertaining to different (groups of) subjects.

In this paper, we propose a basis for a local network comparison method for the case of EEG coherence networks. EEG is the oldest noninvasive functional neuroimaging technique. Electrodes, positioned on the scalp, record electrical activity of the brain. Synchronous electrical activity recorded in different brain regions is assumed to imply functional relations between those regions. A measure for this synchrony is EEG coherence, which is computed between pairs of electrode signals as a function of frequency [7,8]. Visualization aids the interpretation of the experimental results by transforming large quantities of data into visual representations. A typical visualization of an EEG coherence dataset is a two dimensional graph layout (the EEG coherence graph) where vertices represent electrodes and edges

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represent significant coherences between electrode signals. For multichannel EEG (at least 64 electrodes) [9,10] this layout suffers from a large number of overlapping edges and results in a cluttered layout. Reorganizing the edges or varying the attributes of the edges without reducing their number can lead to less cluttered visualizations [11,12]. Also, the positions of the vertices in the layout can be reorganized [13], but in the case of EEG this is not appropriate, because the electrodes have meaningful positions as they relate to brain activity in specific areas.

Another approach to simplify the EEG graph is based on the selection of a small number of electrodes as representative for all other electrodes in a certain region of interest (ROI), which are assumed to record similar signals because of volume conduction effects [9,14,15]. Several researchers have employed a hypothesis-driven selection of markers; this, however, neglects individual variations and does not make optimal use of the available information. An alternative is a data-driven approach where electrodes are grouped into functional units (FUs), which are defined as spatially connected cliques in the EEG graph, i.e., sets of electrodes that are spatially close and record pairwise significantly coherent signals [16]. A representation of the FUs in an EEG recording is called a FU-map; see Fig. 3 for a simple example. FU-maps can be used as a preprocessing step for conventional analysis.

In EEG research, several datasets are usually compared in a group analysis, for which several methods exist. Obviously, multiple FU-maps can be compared visually when displayed next to each other, but this method is limited as humans are notoriously weak in spotting visual differences in images. In this paper we propose a method for comparing several FU-maps which is more quantitative, although it still involves visual assessment to a certain degree. Our method is based on inexact graph matching for attributed relational graphs [17] and graph averaging [18]. In our work we introduce a modification of the algorithm proposed in [18] to obtain a mean FU-map, given a set of FU-maps corresponding to different subjects or different experimental conditions. The basic assumption underlying our work is that the position of the electrodes on the scalp is fixed for all the subjects and that the same projection is used to create the two-dimensional FU representations. Our approach gives the possibility to quantitatively compare individual FU-maps by computing their distance to the mean FU-map. Although our method was specifically designed for EEG coherence network comparison, we believe it to be of sufficient generality to be extended to other types of networks as well.

A preliminary version of this paper appeared in [19]. Here we expand on this by studying the robustness of the method for changes in parameters and by applying the method in two case studies, one on mental fatigue and one on patients with corticobasal ganglionic degeneration (CBGD). These case studies show the potential of our method for large datasets, and also reveal a number of limitations of the current method, which we discuss in Section 5.

The main contributions of this paper are:

- The definition of a graph dissimilarity measure for EEG functional unit maps, which takes into account both node positions and node or edge attributes.
- A definition of the mean of two attributed graphs representing FUs, following [18], and its extension to an arbitrary number of such graphs.
- An algorithm for computing the mean of a set of FU-maps, with a quantitative measure of dissimilarity between this mean FU-map and each of the input FU-maps.
- Visualization of the mean FU-map employing a visual representation of the frequency of occurrence of nodes and the average coherence between nodes in the input FUs.
- The applicability of the method is demonstrated in two case studies.

2. Related work

The principal concept in our approach is that of graph matching, that is, the problem to find a one-to-one mapping among the vertices of two graphs (graph isomorphism). This is a very challenging problem and several solutions are available in the literature. Graph matching is an NP-complete problem and thus exponential time is required to find an optimal solution. Approximate methods, with polynomial time requirements, are often used to find suboptimal solutions.

In many cases, exact graph matching is not possible, and one has to resort to inexact graph matching. Bunke and Allerman [17] proposed such a method for structural pattern recognition, where one has to find which of a set of prototype graphs most closely resembles an input graph. This requires some notion of graph similarity. They considered attributed relational graphs [20], where nodes and edges carry labels of the form (s,x) where s is the syntactic component and $x=(x_1,\ldots,x_n)$ is a semantic vector consisting of attribute values associated with s. Their similarity notion was defined in terms of graph edit operations (deletion, insertion, and substitution of nodes and edges) by which one graph can be (approximately) transformed to another one. The costs apply both to the syntactic and semantic part. The optimal inexact match was then defined as the inexact match with minimal graph edit distance. These notions were used by Bunke and Kandel [18] and Bunke and Günter [21] to define the *weighted mean* of a pair of graphs G,G' as a graph G'' such that $d(G,G'')=(1-\gamma)d(G,G')$ and $d(G'',G')=\gamma d(G,G')$, where $d(\cdot,\cdot)$ is the graph edit distance and $0 \le \gamma \le 1$. It was shown how to compute the weighted mean graph based on the algorithms for graph edit distance computation. Bunke and Günter [21] also introduced *median graphs*, which were further studied in [22]. Building upon this, Jain and Obermayer [23] proposed the sample mean of graphs.

Another area in which graph comparison plays a role is that of graph animation. For example, Diehl et al. [24] consider drawing of dynamic graphs where nodes can be added or removed in the course of time. This problem is simpler than ours since in graph animation a significant fraction of nodes and edges in different time frames do not change and can be identified *a priori*. So the graph matching problem does not arise here.

A different approach for comparing multiple FU-maps for EEG coherence was proposed in [16]. First a mean EEG coherence graph was computed, i.e., the graph containing the mean coherence for every electrode pair computed across a group. Then a FU-map was created for this mean EEG coherence graph just as for a single EEG graph. Such a mean-coherence FU-map is meant to preserve dominant features from a collection of individual EEG graphs. Nevertheless, this approach has some drawbacks. Most importantly, individual variations are lost in such a map. Hence one still would have to visually compare individual FU-maps to the mean-coherence FU-map, and so the need for a quantitative method for comparing FU-maps remains.

3. Methods

Given an EEG coherence graph, a functional unit (FU) represents a spatially connected set of electrodes recording pairwise significantly coherent signals (for the definition of significance, see [7]). The *intra-node coherence* of a FU is defined as the average of the coherences between the electrodes in the FU. Given two FUs, the *inter-node coherence* is the average of the coherences between all electrodes of the first FU and all electrodes of the second FU. FUs are displayed in a so-called *FU-map*. This is a derived graph, in which the nodes, representing FUs, are located at the barycenter of the electrodes in the FU, while edges connect FUs if the corresponding