EEG synchrony pattern segmentation for the exploratory analysis of cognitive experiments

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Abstract

Here we propose a methodology for the exploratory analysis of EEG synchrony data based on the segmentation of the time-frequency plane in regions with homogeneous synchrony patterns. This segmentation is performed by means of a region-growing algorithm with automatic seed selection, and a Bayesian regularization technique. To illustrate our method, we present the resulting maps from a figure categorization experiment.

1 Introduction

The study of oscillatory synchronization between different brain regions is currently one of the most active topics in neuroscience research. According to various authors [2] [6], several brain areas, which may be relatively distant, interact together during the execution of a complex task. These interactions are reflected in the EEG as some form of synchronization between electrode signals, over different frequency bands. Various measures have been proposed to quantify the degree of synchronization between pairs of electrode signals [4] [2] [1], all of which result in a high-dimensional field μ_{t,f,e_1,e_2} which corresponds to the degree of synchrony between electrodes e_1 and e_2, at time t and frequency f. This leads to a visualization problem which some authors avoid by focusing only on specific frequency bands or electrode pairs, or by averaging across a large time window. Here we propose a different solution, which consists on finding regions in time-frequency (TF) space where the interactions between electrodes are relatively constant. These regions are segmented using an efficient algorithm, which also assigns a representative interaction pattern to each region.

2 Methodology

We first compute a class field c_{t,f,e_1,e_2} which specifies, for each time, frequency, and electrode pair, if synchronization between the electrodes is significantly higher ($c = 1$), lower ($c = -1$), or equal ($c = 0$) than a baseline level corresponding to a neutral condition. The estimation of this class field is detailed in [1]. If one defines a *synchrony pattern* (SP) as an element from $\{-1, 0, 1\}^{N_s}$, where N_s is the number of non-redundant electrode pairs, then it is clear that the class field c can be seen as a multi-band image $c_{t,f}$ in TF space, where an SP is associated to each pixel. To segment this image, we use a seeded region growing algorithm where the seeds are points in the TF plane. The algorithm requires a distance measure d between two SP's, which in our case is given by:

$$d(p_1, p_2) = \frac{1}{N_s} \sum_{s=1}^{N_s} \left(1 - \delta(p_{1,s} - p_{2,s})\right), \tag{1}$$

where δ is the Kronecker delta function, and $p_1, p_2 \in \{-1, 0, 1\}^{N_s}$. One can also estimate the *average neighbor distance* $\hat{d}(t, f)$ defined as:

$$\hat{d}(t, f) = \frac{1}{|N(t, f)|} \sum_{(t',f') \in N(t,f)} d(c_{t,f}, c_{t',f'}), \tag{2}$$

with $N(t, f)$ a neighborhood of (t, f).

The actual region growing algorithm is as follows: given a set of N_k seeds (t_k, f_k), $k = 1, \ldots, N_k$,

1. Initialize a region label field $l_{t,f} = -1$ for all t, f. The value -1 indicates that the point t, f is yet unlabeled.
2. Assign a different label to each seed (t_k, f_k); e.g., let $l_{t_k,f_k} = k$ for $k = 1, \ldots, N_k$.
3. Let $r_k = c_{t_k,f_k}$ be the initial *representative SP* (RSP) for each region k.
4. Initialize a priority queue Q and insert each seed (t_k, f_k) in Q with priority given by $-\hat{d}(t_k, f_k)$.
5. While Q is not empty, do the following:
   (a) Pull the highest-priority point (t, f) from Q. Let $k = l_{t,f}$ be the region label assigned to this point.
   (b) For each $(t', f') \in N(t, f)$ such that $l_{t',f'} = -1$ and $d(r_k, c_{t',f'}) < \epsilon$ (where ϵ is a given threshold), let $l_{t',f'} = k$, and add (t', f') to the queue with priority given by $-\hat{d}(t', f')$.
   (c) If the region label field l has changed, re-compute the RSP for region k as the item-by-item mode of all SP's observed within the region; that is, $r_{k,s} = \mathrm{mode}_{(t,f):l_{t,f}=k} \{c_{t,f,s}\}$, for $s = 1, \ldots, N_s$.

One can obtain a fully-automated segmentation by cleverly choosing the seeds. An unlabeled pixel (t, f) is a good candidate for a seed if it is similar to its neighbors, and all of its neighbors are also unlabeled. This suggests the following seed selection algorithm:

1. Let C be the set of all unlabeled points (t, f) whose neighbors are also unlabeled.
2. Let $(t^*, f^*) = \arg\min_{(t,f)\in C}\{\hat{d}(t, f)\}$ be a new seed. Without resetting the label field l, grow the new seed and label the new region accordingly.
3. Repeat the procedure until some criteria is met (e.g., a maximum number of seeds is reached, or some percentage of the TF plane has been labeled).

The regions obtained with region-growing may contain holes (unlabeled points inside the region) or very rough edges, and thus require some kind of regularization. We have chosen to use a Bayesian classification approach with a prior Markov random field (MRF) model [5]. Specifically, l is assumed to be Markovian, with an associated energy function $U(l)$ given by:

$$U(l) = -\frac{1}{N_s}\sum_{t,f} L_{t,f}(l_{t,f}) + \lambda_t \sum_{t,f} V(l_{t,f}, l_{t+1,f}) + \lambda_f \sum_{t,f} V(l_{t,f}, l_{t,f+1}), \quad (3)$$

where λ_t and λ_f are, respectively, the time and frequency granularity parameters, $V(x, y) = 1 - 2\delta(x - y)$ is the Ising potential function, and $L_{t,f}(k)$ is a pseudo-log-likelihood function given by:

$$L_{t,f}(k) = \begin{cases} \log P_L(c_{t,f} \mid k) & \text{for } k \neq -1, \\ \frac{1}{N_k}\left[\sum_{k\neq -1} L_{t,f}(k)\right] - \max_{k\neq -1}\{L_{t,f}(k)\}, & \text{for } k = -1, \end{cases} \quad (4)$$

with $P_L(c_{t,f} \mid k)$ the probability of observing the SP $c_{t,f}$ given that (t, f) belongs in region k. These probabilities can be written as

$$\log P_L(c_{t,f} \mid k) = \sum_{s=1}^{N_s} \log p_{k,s}(c_{t,f,s}), \quad (5)$$

where $p_{k,s}(q)$, $q \in \{-1, 0, 1\}$ is the probability of observing class q for the electrode pair s, across region k, which can be estimated from the segmentation obtained from the region-growing algorithm simply by counting, for each region and each electrode pair, the number of occurrences of each class q. Note that, for $k \neq -1$, $L_{t,f}(k)$ represents a true log-likelihood, whereas $L_{t,f}(-1)$ measures the uncertainty of (t, f) belonging in some region (i.e., a pseudo-likelihood of (t, f) not belonging in *any* region).

Regularization of the label field l is achieved by minimizing $U(l)$. In particular, we use a Gibbs sampler algorithm with the region-growing segmentation as starting point.

3 Results

The procedure described above has been tested with real EEG data from a figure categorization experiment [3] using $\epsilon = 0.3$, $\lambda_t = 2.0$, $\lambda_f = 0.7$, 500 Gibbs

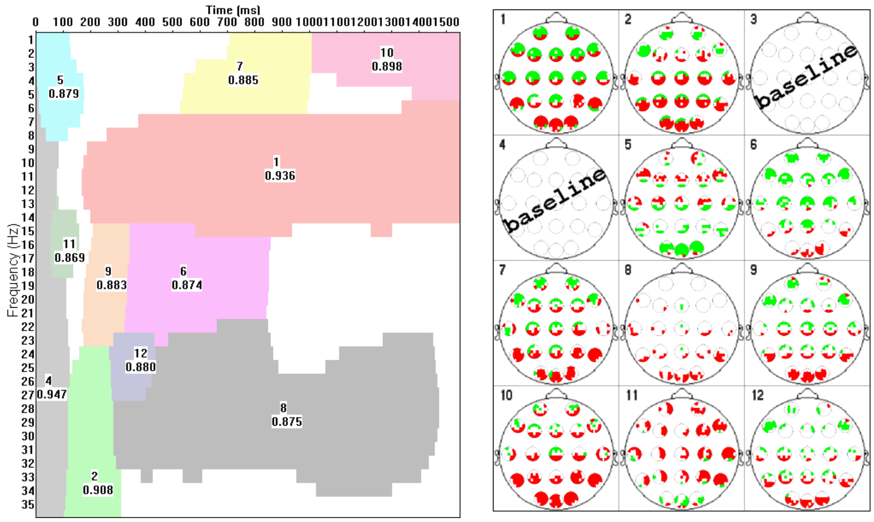

Figure 1: Regularized segmentation for the figure classification experiment: the time-frequency plane (left) is segmented in regions with homogeneous synchrony patterns (right). Each synchrony pattern represents the interaction between all electrode pairs: red and green areas represent significant increases and decreases, respectively, of synchrony with respect to a neutral condition (baseline).

sampler iterations, and 12 seeds. The resulting segmentation and representative SP's are shown in Figure 1. From a neurophysiological point of view, these SP's may be related to specific cognitive tasks; however, each of these patterns is statistically estimated from all SP's within the corresponding region, and thus have different degrees of confidence. One way to estimate the degree of confidence for each region k is by means of a homogeneity coefficient (HC) $H(k)$, which in our case is given by:

$$H(k) = 1 - \frac{\sum_{(t,f):l_{t,f}=k} \hat{d}(t,f)}{\sum_{(t,f):l_{t,f}=k} 1}. \tag{6}$$

The HC is also shown in Figure 1 for each region. It is worth mentioning that those regions with higher HC correspond to the first points obtained with the seed selection algorithm, which suggests that our selection criteria is adequate.

4 Conclusions

We have presented an automated EEG synchrony visualization methodology which provides a detailed description of the interactions between all electrode pairs for time-frequency regions where those interactions are relatively constant, and thus may be related to specific neural processes.

Perspectives for future work include: (1) a region-merging algorithm for regions with similar RSP's (e.g., regions 3 and 4, or regions 9 and 12, in Figure 1), (2) the use of segmented synchrony maps for the study of an psychophysiological EEG experiment.

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