Microstate analysis of the EEG using Local Global graphs

Kostas Michalopoulos and Nikolaos Bourbakis

Abstract— **The topography of the electrical field does not vary randomly with time but rather displays short periods of stable topographical configurations or spatial patterns, known as microstates. The search of such patterns takes place in the high dimensional electrode space with all the problems that comes with it. In this paper, we present a technique for the extraction, detection and representation of EEG microstates based on the Local Global graph(LG graph). We use the Local Global graph to represent the spatial configuration of the topographic map and use a LG graph matching approach to determine the different microstates.**

The proposed method was applied on the average, over trials, Event related potential recording presenting a positive peak known as P300. Five dominant microstates were identified using our methodology. During the whole period of the P300 peak there is one active microstate which presents frontal and parietal topography which is expected for the phase locked activations of the P300. The LG graph modeling of the EEG topography provides a flexible descriptor for the EEG topography and can be used for the efficient microstate segmentation of the EEG.

I. INTRODUCTION

Electroencephalogram (EEG) is a brain imaging technique that records the electrical activity of the brain. EEG presents unparalleled temporal resolution, to the millisecond scale and has been widely used for the study of brain functions and pathologies[9], [4], [6]. The measured electrical activity recorded is the the combined activation of large group of neurons synchronously activating. The produced electrical current propagates through the brain structures and the scull to the head scalp. Due to volume conduction the recorded electrical activity in the electrode is the summation of multiple sources activating at the same time. Therefore, we cannot directly derive the part of the brain that produced the recorded activity.

Event related potentials (ERP) are brain activities recorded as a response to a specific stimulus or event. In order to identify the activity associated with the given stimulus the experiment is repeated many times and the individual trials are averaged. The resulting waveform is examined at a specified electrode or electrodes and features like amplitude and latency of different peaks are extracted. ERP allows us to associate such EEG features with functional processing of the stimulus and other cognitive functions.[5].

Over time different signal processing techniques have been applied to extract information from the averaged waveform as well as the single trials[9], [18], [11]. Often, the analysis is restricted in a certain time window and electrode where the appearance of the brain response is expected. Different algorithms have been proposed in order to identify the optimal electrode and/or the most interesting segment of the EEG in time[14]. The problem with this approach is that these measures are dependent on the experimental setup. The choice of the reference electrode affects the amplitude and phase of the signals in the different electrodes and significantly impacts the statistical outcome of the analysis and its interpretation. Additionally, the a priori selection of an electrode and/ or time interval introduces bias in the analysis and may ignore other related components lying outside the predefined spatial and temporal regions.

Nevertheless, this approach has been proven to be quite successful and has provided useful insights in the brain functionality, but there is still the need to take full advantage of the provided EEG information. Towards this goal, an alternative methodology has been proposed that moves the EEG analysis from the temporal to the spatial domain and considers the electrical field in the electrodes at each time point[8], [17]. The main advantage of this approach is that the distribution of the electrical activity in the electrodes is independent of the reference electrode[8]. Topographic analysis of the EEG offers a different view in the EEG data and has provided new insights on the analysis of brain functionality [7], [12], [15], [16].

The basic idea is that a certain topographic configuration at a certain point in time is caused by a number of active sources in the brain [13] and subsequently a certain topography reflects a distinct brain functional state. It has been shown that the topography of the electrical field does not vary randomly with time but rather displays short periods (50-100 milliseconds) of stable topographical configurations followed by a period of instability before moving into a new stable configuration[8]. These stable topographic configurations, known as microstates are considered the basic elements that reflect the brain state over the given time interval that the EEG was recorded. Although the same topographic organization is not necessarily result of the same underlying sources it is reasonable to assume that different distributions of the electrical field in the scalp represent different brain states.

Each state can be mapped into the N-dimensional sensor space and then apply machine learning techniques in order to find formed classes of spatial maps in this N-dimensional space [15]. With denser electrode configurations and taking under consideration the volume conduction effect the dimensionality increases without a necessary increase in the descriptive power of the topographic map.

Kostas Michalpoulos and Nikolaos Bourbakis are with Computer Engineering and Computer Science, Wright State University. michalopoulos.2@wright.edu, nikolaos.bourbakis@wright.edu

978-1-4799-3163-7/13/$31.00 ©2013 IEEE

In this paper we present a new method for identifying stable topographic maps in the EEG. Our methodology uses the LG graph to model and represent the topographic activity at each time point of the EEG.In the next section we are going to present methods for the characterization of the spatial EEG information. Then, we proceed to describe the building blocks of our methodology and their application in the analysis of ERPs. Finally, results of our methodology in real EEG data are presented.

II. EEG MICROSTATES

The microstate model considers the EEG or ERP data as a series of momentary spatial distributions of the electrical field in the brain or as they are also known topographic maps. It has been noted in [8] that these maps remain stable for a certain period of time and then they change abruptly to a new configuration. The assumption made is that these time segments reflect parts of information processing or in other words functional microstates of the brain. Change from one stable microstate to another indicates an alteration of the functional state of the brain. Such microstates can be seen as the atomic elements of higher cognition [7]. The series of such microstates does not mean though that the information processing is sequential. Each state may encode different parallel processes acting in synchrony.[7].

Under this spatial-oriented approach a measure that is reference independent and describes the topography of the EEG, was proposed by Lehman, called Global Field Power(GFP). GFP can be considered as the standard deviation of the is defined as following:

$$GFP = \sqrt{\frac{\sum_{i=1}^{N}(v_i - \hat{v})^2}{N}} \tag{1}$$

where v_i is the measurement at electrode i and $\hat{v}$ is the mean over all electrodes. GFP is a measure of the flatness or hilliness of the topographic map. It takes high values when the map presents high peaks or valleys and low values when the resulting map is flat [13].

In order to identify periods of stable topographic configuration we need a measure of how similar or different two topographic maps are to each other. A similarity measure was proposed in [8] to compare different maps. The Global dissimilarity measure (GMD) defined the distance between two maps in the sensor space and is defined as following:

$$GDM = \frac{1}{N}\sum_{i=1}^{N} \frac{v_i - \hat{v}}{\sqrt{\frac{\sum_{i=1}^{N}(v_i-\hat{v})^2}{N}}} - \frac{u_i - \hat{u}}{\sqrt{\frac{\sum_{i=1}^{N}(u_i-\hat{u})^2}{N}}} \tag{2}$$

Where v_i and u_i represent the measurements in the elctrode i of the two maps respectively. Essentially, this measure represents the distance between two topographic maps by treating them as vectors. Also, TANOVA [13], a non parametric randomization test, has been proposed and used widely in order to identify significant different maps between conditions. These two measures, GFP and GDM can be treated independently in order to examine the topographic variations of the brain response over time.

As the EEG technology advances, the number of recording electrodes increases and so does the dimensionality of the problem. Down-sampling on the number of electrodes is a common method used in several studies [13].

In our approach we use a segmentation algorithm in order to identify the significant regions of activity in each map. Then we use the LG graph to represent the major characteristics of this map, while keeping the local information. This way we effectively transform the problem of microstate identification into a graph matching problem, a domain where the LG graph presents significant advantages, as we will see below.

III. METHODS

A. Segmentation

The first step is to obtain the topographic maps for each point in time from the multichannel EEG. We remove the mean from each channel and then for a given time point we colorcode the values in the electrodes, representing minimum with blue and maximum with red and the natural neighbor interpolation method is used to interpolate the values in the space between the electrodes [1], [3].

Our goal is to group channels into regions that present similar activations. The watershed segmentation algorithm uses the local minima in the image as initial points(seeds) and then the regions are growing from each seed, until the borders of one region reaches the limits of another [10]. In our case we use a slight modification of the algorithm where the background activity is marked with seeds, in order to avoid the regions to grow into areas with background(small) activity. Figure 1(c), displays the result of the watershed algorithm, while in Figure 2 we can observe the marked watershed results.

The main advantage of this algorithm is that it creates compact regions that represent similar activity without using any prior knowledge about the number of regions that we expect to produce. Since we are interested in the spatial structure of the electric field we normalize each map by its GFP before applying the watershed algorithm. The segmentation step provides a natural way to reduce the dimensions of our problem while remaining in the sensors space. Next we present the LG Graph and its application for the spatial analysis of the EEG.

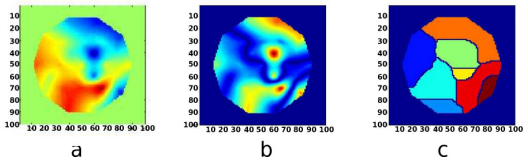

Fig. 1. The segmentation procedure and results. Figure 1a shows the GFP normalized topographic map. Figure 1b shows the absolute normalized map used for the segmentation. Figure 1c displays the segmentation result.

B. Local Global Graph

LG Graph (LG graph) is a well known technique that has found many applications in computer vision[2]. The

LG graph extends the information that the graph holds by attaching local information about each node. Initially, it was used for image understanding applications. The local graph is a graph describing the shape of the region and holds information characterizing the region, such as its color. Along with the centroid of each region, this local graph is used as a node of the greater graph representing spatial relations between segments of the image.

The relationships between the nodes represent the geometrical relationship between regions of the image. In order to further simplify the relationships between the regions of the image, a node can be arbitrarily chosen and only connections to this node can be taken under consideration. The idea behind this simplification is that we can full characterize the geometrical relations between nodes by keeping only their relations to a common reference and discard the redundant information. In the next section we provide the detailed steps for the calculation of each graph in the context of topographical maps.

C. Global Graph

Each region in the image is a node of the Global graph and is represented by its centroid. The centroid that characterizes each region is calculated as the center of mass of the region as following:

$$centroid(x,y) = \left(\frac{\sum_{x,y\in R} x * I(x,y)}{\sum_{x,y\in R} I(x,y)}, \frac{\sum_{x,y\in R} x * I(x,y)}{\sum_{x,y\in R} I(x,y)} \right) \quad (3)$$

where the $I(x,y)$ is the value at the point x,y belonging to the region R of the map. The centroid is directly affected by the field distribution in the given area and is representative of the underlying field. Therefore, changes of the field inside a region will be reflected in the centroid.

Analysis of the centroid has been used under the GFP context as it prove to be less sensitive to noise and encompass the information from the surrounding electrodes[17]. The main difference in our approach is that we do not limit our analysis only in the extrema of the negative and positive fields identified in the electrode map but we use all the regions identified by the segmentation step to construct the global graph. The proposed scheme can handle both local (region) and global (relative position of regions) information and can be represent the spatial distribution of the electric field in an efficient way.

When all the centroids of the image segments are calculated then the central electrode Cz is arbitrarily chosen as the reference node of the graph. This reference node is connected to all the centroids and the relative distance and angle between two consecutive centroids is calculated.

D. Local Graph

We use the local graph to model each region of the topographic map generated by the segmentation step. The local graph does not contain only point information derived by the location of the centroid but also the detailed region information. As we mentioned earlier, different types of information can be effectively described and queried by the local graph. In our case, since we are interested in the characterization of the microstates, each local graph keeps the number of electrodes included in the region, the amplitude and power of each electrode along with the amplitude and power of the whole region. The local graph therefore is defined by the local relations of the members of each region.

We can use this information to detect changes inside the region and provides a compact local descriptor of the topographic map.

IV. LG GRAPH SIMILARITY

Our goal is to detect and identify microstates that compose the time course of the multichannel EEG. Using the LG graph to characterize the topographic maps of multiple time points, we need a measure to quantify the similarity/ dissimilarity between two LG graphs. We approach this problem using a two level evaluation of the distance between maps. We use the global graph defined above to evaluate the structural similarity/ dissimilarity between topographic maps and then at a second level we can compare the individual local graphs.

A. Local similarity

The local graph is used to determine the corresponding regions/ nodes between the graphs. We determine the percent of overlap between two regions using the Jacard similarity measure as following:

$$S_{region} = \frac{region_a \cap region_b}{region_a \cup region_b} \quad (4)$$

This measure displays the degree of overlap between two regions. The amount of overlap is not enough to determine the similarity of two regions since we have to take into account the similarity of the two local electrical fields. Although the centroid gives an indication of the underlying field, we need to check the local graph to detect local regional changes in the field distribution. We use the cosine similarity to calculate the similarity between the field amplitude vectors of the common region of the two local maps, as following:

$$S_{field} = \frac{\sum_{i\in region} R_i^a * R_i^b}{\sqrt{\sum_{i\in edges} (R_i^a)^2} * \sqrt{\sum_{i\in region} (R_i^b)^2}} \quad (5)$$

B. Global similarity

The distance between two global graphs can be calculated by comparing the differences between the angles formed by the edges of the graph, connecting the reference node and each centroid. We move the center of the x-y axes to the Cz electrode and we calculate the angle of each edge from the positive x-axis. By comparing the re-referenced angles, we can calculate the distance between two global graphs and at the same time obtain the node correspondence between the two graphs. We construct the vector V which holds the angle, the distance from the centroid and value at the centroid in order to describe the global relation of each region. The structural similarity between the two graphs is calculated as the cosine similarity as in equation (5) This measure takes values from [-1,1] where 1 means that the two global graphs are reversed.

C. Comparing LG Graphs

To determine the total graph similarity we combine both local and global information. Recall, that we are using the centroid value as an indication of the field configuration for a given region, so a high global similarity reflects both the structural similarity of the topographic maps as well their field configurations. We weight the global similarity by the ratio w defined as $w = \frac{\text{\#matched nodes}}{max(nodes_{graphA}, nodes_{graphB})}$ derived from the matching of the local graphs. The following function is used to calculate the graph similarity for different values of the global graph:

$$S_{graph} = w * S_{global} \tag{6}$$

If we want to compare the behavior of specific regions the local graph provides the necessary flexibility to constrain the analysis in these regions.

V. Results

We applied the LG graph methodology in an ERP data set obtained from a single healthy subject performing an auditory oddball experiment. 27 channels were used to record the EEG and the data were sampled at 1024Hz. Each trial has 1300 samples and the auditory stimulus occurred at 600ms. We used 40 trials that correspond to the target stimuli in order to generate the average ERP in each channel. A detailed description of the full dataset can be found in[18].

We calculated the average ERP of the wide-band signal and for each time point we applied the LG graph methodology. A hierarchical clustering algorithm was employed in order to find stable topographic maps and perform a first evaluation of our methodology. We decided to keep 5 clusters. The merging distance fell bellow a certain threshold(t = 0.30) when merging further. The threshold was set empirically based on the current dataset. The fifth cluster was formed last and has members with low similarities that probably represent transitional states. The extracted graphs and can be seen in Figure 2-row a and b, where the maps and the resulting graphs are displayed accordingly. In Figure 2-row c, the explained GFP from each microstate is presented in time.

TABLE I
VARIANCE EXPLAINED BY MICROSTATES

variance explained %	Microstate 1	Microstate 2	Microstate 3	Microstate 4	Microstate 5
Prestimulus	36%	28%	7%	17%	12%
Poststimulus	29%	-	31%	19%	14%

During the pre-stimulus we can observe an interesting pattern where microstate 1(cyan) and microstate 2(magenta) alternate each other in frequencies that can be identified as theta band. Microstate 2 completely vanishes from the post-stimulus period, while the microstate 3(green) emerges right after the stimulus. Microstate 4(blue) is active for the period before the actual P300 peak that occurs around 950 -1100ms. More specifically, for the duration of the P300 peak only microstate 1 is active. This is in line with other studies on the same data, which indicated that the evoked activations, represented in the average ERP have frontal and parietal topographies[18]. Finally, microstate 5(red) is active for small periods of time both prestimulus and poststistimulus and probably reflect transitional states where the GFP is low.

Table I summarizes the microstates duration for the pre and post-stimulus period.

VI. Conclusion

We presented a new technique for the spatial analysis of the EEG using LG graphs. The LG graph provides an alternative representation of the spatial characteristics of the EEG that enables the identification of topographical patterns.

Modeling each segmented map using the LG graph methodology, we transform the problem to from the channel space to a LG graph matching problem. We take advantage of the hierarchical properties of the LG graph and we simplify the matching procedure significantly, without sacrificing the descriptive power of our features. A major advantage of this methodology is that the LG graph is flexible enough to incorporate different local and global measures at the same time, a fact that allows for different queries and views in our data.

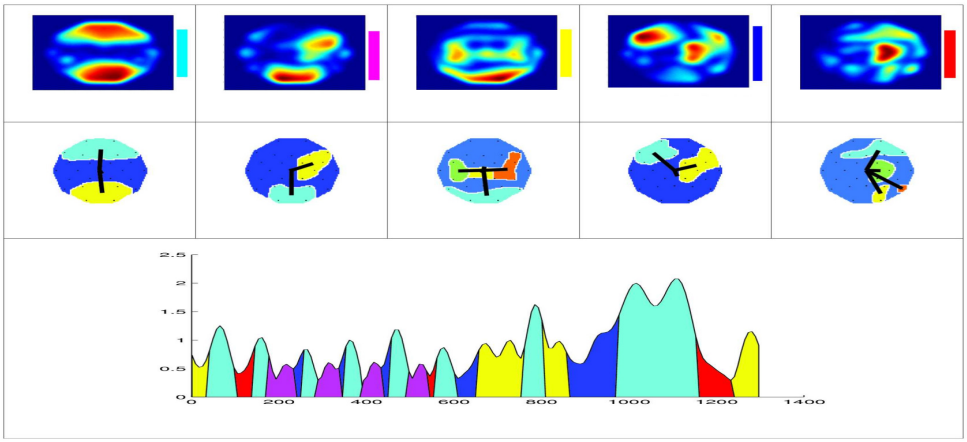

Fig. 2. Row a.Four stable maps identified in the average ERP. The nose is in the top of the figure. The bar next to each map represents their color label. Row b displays the corresponding LG graphs. Row c displays the distribution of the microstates in time.

Future work involves the further evaluation of the methodology and its application to single trials and incorporation of synchronization and time-frequency measures.

VII. Acknowledgment

The authors would like to thank Prof. Cristin Bigan at the Ecological University of Bucharest, Romania for providing the EEG dataset.

References

[1] Jean-Daniel Boissonnat and Frédéric Cazals. Smooth surface reconstruction via natural neighbour interpolation of distance functions. In *Proceedings of the sixteenth annual symposium on Computational geometry*, SCG '00, pages 223–232, New York, NY, USA, 2000. ACM.

[2] Nikolaos G. Bourbakis. Visual target tracking, extraction and recognition from a sequence of images using the lg graph approach. *International Journal on Artificial Intelligence Tools*, 11(04):513–529, 2002.

[3] Arnaud Delorme and Scott Makeig. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1):9–21, 2004.

[4] L. Dipietro, M. Plank, H. Poizner, and H.I. Krebs. EEG microstate analysis in human motor corrections. In *2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, pages 1727–1732, 2012.

[5] H J Heinze, T F Mnte, and G R Mangun. *Cognitive electrophysiology*. Birkhuser, Boston, 1994.

[6] B.W. Jervis, S. Belal, T. Cassar, M. Besleaga, C. Bigan, K. Michalopoulos, M. Zervakis, K. Camilleri, and S. Fabri. Waveform analysis of non-oscillatory independent components in single-trial auditory event-related activity in healthy subjects and alzheimers disease patients. *Current Alzheimer Research*, 7(4):334–347, 2010.

[7] Thomas Koenig, Leslie Prichep, Dietrich Lehmann, Pedro Valdes Sosa, Elisabeth Braeker, Horst Kleinlogel, Robert Isenhart, and E.Roy John. Millisecond by millisecond, year by year: Normative EEG microstates and developmental stages. *NeuroImage*, 16(1):41–48, May 2002.

[8] D. Lehmann, H. Ozaki, and I. Pal. EEG alpha map series: brain microstates by space-oriented adaptive segmentation. *Electroencephalography and Clinical Neurophysiology*, 67(3):271–288, September 1987.

[9] S. Makeig, M. Westerfield, T.-P. Jung, S. Enghoff, J. Townsend, E. Courchesne, and T. J. Sejnowski. Dynamic brain sources of visual evoked responses. *Science*, 295(5555):690–694, January 2002. PMID: 11809976.

[10] Fernand Meyer. Topographic distance and watershed lines. *Signal Process.*, 38(1):113–125, July 1994.

[11] K. Michalopoulos, V. Sakkalis, V. Iordanidou, and M. Zervakis. Activity detection and causal interaction analysis among independent EEG components from memory related tasks. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, pages 2070 –2073, September 2009.

[12] Christoph M. Michel and Micah M. Murray. Towards the utilization of EEG as a brain imaging tool. *NeuroImage*, 61(2):371–385, June 2012.

[13] Micah M. Murray, Denis Brunet, and Christoph M. Michel. Topographic ERP analyses: A step-by-step tutorial review. *Brain Topography*, 20(4):249–264, June 2008.

[14] R. Palaniappan, P. Raveendran, and S. Omatu. VEP optimal channel selection using genetic algorithm for neural network classification of alcoholics. *Neural Networks, IEEE Transactions on*, 13(2):486–491, 2002.

[15] R.D. Pascual-Marqui, C.M. Michel, and Dietrich Lehmann. Segmentation of brain electrical activity into microstates: model estimation and validation. *IEEE Transactions on Biomedical Engineering*, 42(7):658–665, 1995.

[16] Gilles Pourtois, Sylvain Delplanque, Christoph Michel, and Patrik Vuilleumier. Beyond conventional event-related brain potential (ERP): exploring the time-course of visual emotion processing using topographic and principal component analyses. *Brain Topography*, 20(4):265–277, June 2008.

[17] J. Wackermann, D. Lehmann, C.M. Michel, and W.K. Strik. Adaptive segmentation of spontaneous EEG map series into spatially defined microstates. *International Journal of Psychophysiology*, 14(3):269–283, May 1993.

[18] M. Zervakis, K. Michalopoulos, V. Iordanidou, and V. Sakkalis. Intertrial coherence and causal interaction among independent EEG components. *Journal of Neuroscience Methods*, 197(2):302–314, April 2011.