Atomic Decomposition of EEG for Mapping Cortical Activation

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Abstract. To improve the measurement and differentiation of normal and abnormal brain function we are developing new methods to decompose multichannel (electroencephalogram) EEG into elemental components or "atoms." We estimate EEG atoms using multiway analysis, specifically parallel factor analysis or PARAFAC for modeling. Activation sequences of EEG atoms can identify functional brain networks dynamically, with much finer time resolution than fMRI. For example, EEG atoms activate in specific combinations during the sequential operations of brain networks, such as Default Mode, Somatomotor, Dorsal Attention and others. Guided by the score values of the identified atoms we inferred the volumetric brain sources of the selected networks using the sLORETA pseudoinverse algorithm. To confirm network identities, we compared 2-D and 3-D functional network maps derived from EEG atoms to known functional neuroanatomy of the networks. We find that multichannel EEGs in most individuals can be accounted for by a set of five to six standard atoms, which parallel classical EEG bands, and have unique power spectra, scalp and cortical topographies. We discuss how we may use the activation sequences of these atoms to describe the dynamic interplay of functional brain networks.

Keywords: atomic decomposition of EEG, parallel factor analysis, low resolution brain electromagnetic tomography

1 Introduction

Despite extensive prior efforts to develop physiological methods for monitoring different brain state conditions, these methods are still unreliable in many practical aspects. For example, the performance of most methods is unduly influenced by day-to-day or subject-specific variability. Electroenheplaograms (EEGs) are considered to be the gold standard for objective detection of many functional brain states and currently may be recorded and analyzed in almost any occupational setting. However, EEGs are usually recorded as a high-dimensional time-space distributed data. Conventional 2-D decomposition techniques are not ideally suited to reveal the existing latent data structure of EEGs, because unfolding

2-D decompositions can be done in several ways, and interactions of dimensions are not modeled well in 2-D decompositions. Recently, promising results were achieved by applying multi-way decomposition models such as PARAFAC to EEG data [5, 6, 9].

Recent studies and analysis of functional magnetic resonance imaging (fMRI) during resting state conditions revealed a new challenging approach to explore the brain's functional organization [8]. This may not only lead to better understanding of brain functioning and organization, but also of altered conditions of this anatomical and functional organization due to neurological or psychiatric diseases, or even due to variability in mental and cognitive functioning.

The connection between resting state cortical processes and EEG activation at the scalp has been the subject of several recent studies [4]. However, in spite of great efforts in this direction, a clear answer and established methodology revealing this important cortico-scalp connection remains an open research question. Using multi-way decomposition models we analyzed EEG data recorded from participants in a study consisting of resting state conditions, neurofeedback training, continuous performance test (CPT) and the lateralized attention network test (LANT) [2]. In this study, we applied the PARAFAC model to EEGs recorded under resting and mentally active conditions and we identified a set of standard atoms corresponding to physiologically recognized EEG rhythms and topologies. Next, we used score values of these atoms to identify their levels of activation and used this information to select the corresponding EEG segments. Finally, we used low resolution brain electromagnetic tomography method (sLORETA [7]) to identify cortical activation corresponding to the selected EEG segments. This revealed elements of functional cortical networks and organization observed in other studies. This represents novel way of combining multi-way decomposition models with EEG-based cortical mapping methods.

2 Methods

2.1 Data acquisition and preprocessing

UCLA students were recruited for behavioral testing with EEG monitoring. Participants were randomly assigned to experimental groups differing in biofeedback training protocols and they spent approximately six hours across five testing sessions. Participants were seated in front of a computer. A BioSemi / ActiveTwo system was applied to each participant's head, and 66-channel EEG was recorded (64-channel QuickCap plus ear electrodes). Several minutes of resting baseline EEG was recorded prior and after the training. In this pilot study we analyzed only selected subsets of resting-state recordings with the aim of improving our approach before performing more thorough analyses.

The EEGs were originally sampled at 512 Hz and digitally down sampled to 128 Hz using appropriate acausal antialiasing filters.. Data were re-referenced using the average reference method. Next, the data were segmented into 1-s long windows with no overlap. For each segment the positive logarithmic power spec-

tral density (PSD) was computed using the fast Fourier method with Hann windowing. Frequencies in the range of 0 to 64 Hz were considered in this study. This procedure was repeated for each EEG channel separately and a three-dimensional matrix $\mathbf{X}(I \times J \times K)$ with I time segments, J electrodes and logarithmic PSD estimates at K frequencies was constructed.

2.2 The PARAFAC model

A three-way PARAFAC model was applied to data. PARAFAC can be seen as a generalization of PCA for dealing with multi-dimensional data [1]. However, the uniqueness of the obtained decomposition gives the PARAFAC model an unsurpassed advantage [1]. Three loading matrices, $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ with elements a_{if}, b_{jf}, and c_{kf} defines the model that can be mathematically described as $x_{ijk} = \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} + \epsilon_{ijk}$, where ϵ_{ijk} are the residual elements or errors and $\mathbf{F}$ stands for number of components or atoms that are considered. The loadings elements are then found by minimizing the sum of squares of the residuals ϵ_{ijk} [1], that is $min_{a_{if} b_{jf} c_{kf}} \| x_{ijk} - \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} \|$ For the analyses reported here we used proprietary Matlab codes developed by Pacific Development and Technology, LLC, and subroutines from the N-way toolbox for Matlab [3].

2.3 sLORETA

EEGs as measured on the scalp represent a collection of neuronal post-synaptic processes at the cortical level. sLORETA is a technique solving the inverse problem; that is, an estimate of cortical activation corresponding to the scalp EEG [7]. sLORETA estimates an image of cortical activation (inferred by current-source density estimates) for every sample time-point. To separate EEG into segments of specific spatial and frequency based scalp activation patterns we used multiway atomic decomposition of EEG and we defined segments of EEG based on the atomic score values. This allowed us to combine different atomic activations and to study the corresponding cortical patterns. For every set of EEG segments we computed sLORETA cortical activations and in the post-processing analysis we averaged these cortical activation values.

3 Results

We analyzed data from six subjects attending the protocol across five successive days. We used the PARAFAC model with a uni-modality constraint on spectral loadings and a non-negativity constraint on spatial and time loadings [1]. Each experimental condition (resting state eyes open and closed, biofeedback training, CPT and LANT) was considered separately. Visually inspecting spatial and spectral loadings of each extracted PARAFAC component we were able to identify five to six stable atoms including theta (4-7 Hz), alpha1 (9-11 Hz), alpha2 or senosrimotor rhythm (SMR) (12-15 Hz), beta1 (15 - 18 Hz) and beta2 (22-30). The topographical distribution and spectral characteristics of these atoms are

depicted in Fig. 1. The beta2 atom has a similar topological distribution to the beta1 atom but with spectral peak closer to 21 Hz.

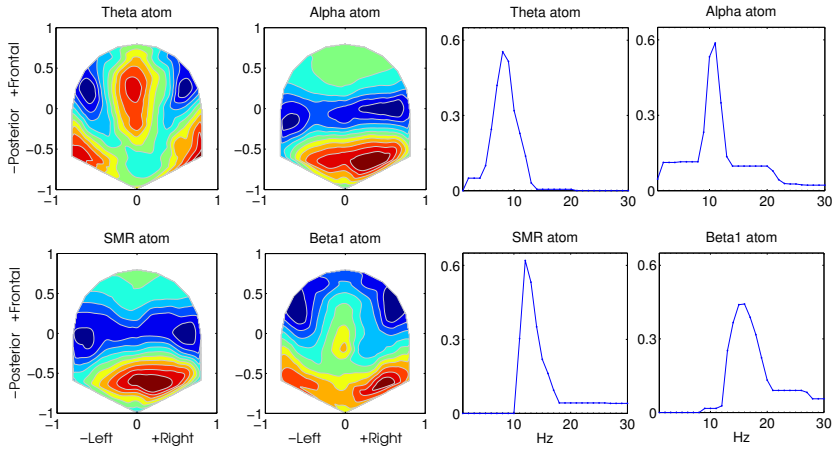

Fig. 1. *Left:* Topomap of the four extracted atoms. SMR - senosrimotor rhythm. *Right:* Spectral characteristics of the four extracted atoms.

Next, we selected segments of EEG corresponding to high or low score vectors of the extracted atoms or their combination[1] Using the sLORETA software [7] we estimated cortical activations corresponding to the selected segments. In Fig. 2 the cortical activation extracted during the low score (less than 0.25 of the rescaled score values into the 0 to 1 interval) and high (greater than 0.75) scores values of the alpha atom for eyes open condition during the resting state is depicted. This volumetric plot shows of strong cortical activation in the left superior frontal gyrus (Broadman area 11) for low scores values, while EEG segments during high score values correspond to strong activation in the right post central gyrus (Broadman area 5) presumably associated with stronger alpha oscillations in this resting state condition. By analyzing other experimental conditions, subjects and sessions we observed activation of cortical networks associated with resting or mentally active brain states closely matching results in literature.

4 Conclusions

We are presenting a new approach of combining multi-way atomic decomposition of EEG with cortical activation mapping. This is a novel way of studying the association between scalp EEG and the underlying cortical sources. Although this initial report describes very interesting results, a thorough detailed analysis and statistical evaluation of the methodology and results is required and is currently underway.

[1] The score values were re-scaled between 0 and 1, and the threshold values of 0.2 and 0.8 were heuristically determined to set the low and high scores values.

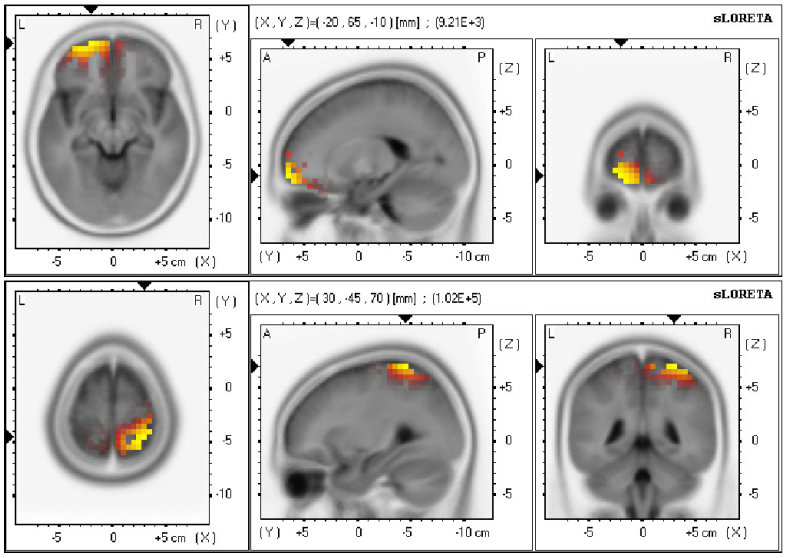

Fig. 2. *Top:* Averaged sLORETA corresponding to the low scores of the alpha atom. *Bottom:* Averaged sLORETA corresponding to the high scores of the alpha atom.

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