Using Dynamic Bayesian Networks for modeling EEG topographic sequences.

Kostas Michalopoulos-*Student Member, IEEE-EMBS,* and Nikolaos Bourbakis-*IEEE Fellow*

Abstract— **In this work we present a methodology for modeling the trajectory of EEG topography over time, using Dynamic Bayesian Networks (DBNs). Based on the microstate model we are using DBNs to model the evolution of the EEG topography. Analysis of the microstate model is being usually limited in the wide band signal or an isolated band. We are using Coupled Hidden Markov Models (CHMM) and a two level influence model in order to model the temporal evolution and the coupling of the topography states in three bands, delta, theta and alpha. We are applying this methodology for the classification of target and non-target single trial from a visual detection task. The results indicate that taking under consideration the interaction among the different bands improves the classification of single trials.**

I. Introduction

Different methods and techniques have been developed in order to extract features from electroencephalography (EEG) that are capable to characterize pathologies or discriminate different functional states. For the first case, we are interested in the extraction of features that characterize the different groups and are able to distinguish between normal and abnormal EEG. For the latter case we are more interested in the identification of features that characterize the brain response during a certain task. The EEG brain response specific to the given stimulus or event, is known as Event Related Potential (ERP). Approaches that try to extract features from Event related recordings have many applications for the development of brain computer interfaces and a lot of effort has been devoted towards this direction [1].

A lot of studies have focused in the analysis of time and frequency characteristics of the EEG signals. This approach usually entails the selection of a single channel and extraction of signal features on this particular electrode [2]. The selection of electrodes of interest is usually based on the experimental setup. Selecting the most informative single electrode or set of electrodes is not a trivial problem and many parameters have to be taken under consideration. A limitation of the single channel analysis approach is that due to volume conduction, the recorded electrical activity is the result of the summation of multiple sources activated in coordination [3]. Limiting the analysis on a single electrode misses information that is collected in other sites and disregards the fact that different aspects of the underlying brain activity are manifested in multiple locations. Multivariate techniques as Principal Component Analysis (PCA) and Independent Component Analysis (ICA) have been employed in an effort to alleviate this problem [3], [4]. Different methodologies have been used in order to extract features able to discriminate the brain responses to different tasks. Such features include the power of the different bands, auto-regressive parameters and information theoretical measures as Mutual Information and entropy [1]. Time-frequency methods have also been used for studying the temporal behavior of frequency specific features.

In contrast to the analysis that is focused on the temporal features of the multichannel EEG signal, the microstate model considers the spatial distribution of the electric field in the scalp also known as topographic map. It has been observed in [5] that certain topographic maps remain stable for a certain period of time before changing abruptly to a new configuration. These time segments can be interpreted as functional states of the brain that reflect atoms of information processing. Under this point of view, a change from one stable microstate to another indicates a change in the functional state of the brain [5]. Since the inverse problem is ill-conditioned, we have to keep in mind that the relationship between the observed topography and the generating sources is not a one to one mapping. Different active sources may result in the same observed topography. Nevertheless, it is reasonable to assume that a change in the topography reflects a change in the underlying generators. Such identified microstates have been considered as the atomic elements of higher cognition [6].

Microstate analysis usually considers the wideband EEG signal or is restricted to a single band of interest. The main assumption is that the underlying microstates remain the same throughout the different bands and subsequently the different bands activate in a synchronous and coherent manner [6],[7]. Features regarding the occurrence and duration of the identified microstates have been used for discriminating different pathologies. Recently, a classification method using HMMs was used for the classification of tasks in Electrocorticography data with promising results [8].

Regarding the band specific evolution of the topographic maps, results from the analysis of temporal features of the EEG and especially from the application of ICA, indicate that activity attributed to a certain band arises in certain electrodes in conjunction or as a response to other band activations in different locations [4],[9]. The ensemble of these activations constitutes an interacting network that characterizes the functional processing that takes place. In this paper we use DBNs to model the interaction of the different bands in terms of the temporal evolution of their topographies using DBNs [10] that generalize the concept of Hidden Markov Models and can model the interaction of multiple variables.

K.Michalopoulos is with the Assistive Research Technologies Center, Dayton, OH 45435 USA (e-mail: michalopoulos.2@wright.edu);
N. Bourbakis is with the Assistive Research Technologies Center, Dayton, OH 45435 USA, (e-mail: nikolaos.bourbakis@wright.edu).

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In this work we use the spatio-temporal features of the EEG as defined by the microstate model for the classification of single trials between tasks. To our knowledge little effort has been devoted regarding the use of the microstate model towards the classification of single trial responses. We evaluate this approach in a classification scenario where we try to distinguish among target and non-target trials, using the modeled temporal evolution of the topography map in the single trial level. Using different DBNs we are going to study the effect of the coupling between the modeled bands.

II. METHODS

A. Modeling of the EEG topography.

The approaches used for the identification of the dominant microstates are based on clustering techniques and variants of k-means and hierarchical agglomerative algorithm have been developed [11]. Different distance measures have been employed in order to calculate the similarity or dissimilarity between, two maps. Most of them treat the measurements of the channels at each time-point as a vector and well known vector distances are applied [11].

The main problem with the application of the microstate approach in the single trial level is that the single-trial recordings contain many more active sources than the average ERP. The signal to noise ratio on the single trial data is also very low, constituting the single trial analysis a difficult task in general.

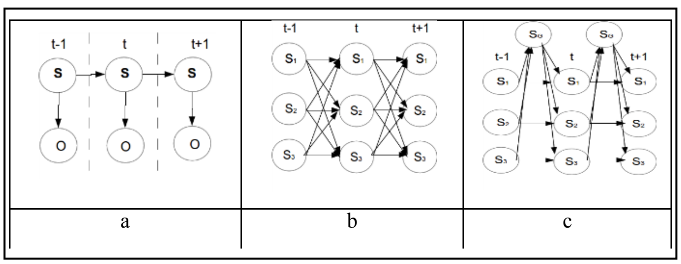


Figure 1. Graphical representation for the HMM(a), CHMM(b) and the two level influence model.(c) In models (b) and (c) the observed nodes arenot shown for simplicity.

In our case, we are using the technique described in [12]. We are taking under consideration the spatial relationship between the electrodes and we are working in the topographic image in order to find similarities between the maps. Each topographic map is normalized to unit variance among electrodes. We are using the marked watershed segmentation algorithm [13] in order to identify the dominant peaks of the topography and reduce the effect of noise in the measurements. The Local Global graph (LG graph) structure [14] is used as descriptor of the topography and the corresponding measures of similarity between LG graphs are used as described in [12].

The Local Global Graph (LG graph) is a method for modeling the structural information in images without sacrificing the local characteristics of the individual objects [14]. It is an attributed graph which allows holding local information in each node. The relationships between the nodes represent the geometrical relationship between regions of the image. To further simplify the representation, a node can be arbitrarily chosen and only connections to this node can be taken under consideration. This way we can fully characterize the geometrical relations between nodes by keeping only the relations to a common reference. Using this approach we are able to effectively compare two topographies and track the evolution of the EEG topography in time.

B. Spatio-Temporal modeling of the topography

The next step is to model the temporal evolution of the topography in the scalp. The clustering approach [11] has been used in order to represent the multichannel signal using a set of representative topographies that explain a sufficient amount of the data variance. The clustering approach disregards the temporal dependencies between adjacent topographies and considers that the samples are identically and independently distributed.

In our case we are considering the EEG signals as time series of topographies with temporal dependencies. We are using Dynamic Bayesian Networks (DBNs) [10] in order to model the temporal evolution of the EEG topography. Under this formulation, the modeled stable microstates are represented by hidden states in the Bayesian Network and form a Markov chain while the different topographies represent the observations. A Hidden Markov Model (HMM) can be considered a simple DBN and we can observe it in Figure 1a.

The assumption that all the bands display the same topography is seriously challenged by findings based on other studies [4],[9]. In our case we want to take under consideration the relationships between the different bands and use this information for better modeling of the data. For this reason we apply three different models to evaluate the interaction between the bands and their effect on the classification result.

Coupled Hidden Markov Models (CHMMs) [10] have been used in order to evaluate the coupling and dependencies between Markov chains. In our case we are considering each band a different Markov Chain and model the ensemble of the bands using CHMM. The graphical model of the CHMM can be seen in Figure 1b.

Removing the coupling between the chains results in a Parallel Hidden Markov model (PHMM) [15], where each chain follows its own dynamics independently. Using the PHMM we want to assess the importance of the interaction between the bands. The idea is that if the classification results of the PHMM are comparable to those of the CHMM then we cannot justify the extra computational complexity introduced by the CHMM model.

A different model that can represent the influence between Markov Chains was proposed in [17]. Under this model, there exists an extra node, which represents the global state of the system and depends on the states of the individual chains. The next state of each chain depends on the current state and the global system state. The graphical representation of this model can be seen in Figure 1c and is adapted from [17]. Under this model we have the individual chains of the different bands and in contrast to the CHMM the influence of each node to the other is indirectly modeled through the global node. A hidden switching node Q (not shown) is used to simplify the model and represents the individual influence of each band to the global state.

Overall for all models, we consider that each band is characterized by a Markov chain with hidden states. The observed topographies are conditionally independent given the hidden state. We assume that the number of hidden states are discrete and the same for each band. We are also considering that the observations are discrete. This choice allows for a non-parametric modeling of the conditional distribution of the observations on the one hand and on the other it is easier to work with the LG graph modeling. All the models were evaluated using the Bayes Net Toolbox for Matlab. In the next section we describe the steps used for discretization of the dataset and the construction of the resulting codebook.

C. *Discretization and codebook generation*

We apply the single-link hierarchical agglomerative algorithm in the data using the LG graph distance defined before. The single link algorithm provides compact clusters and has been used for vector quantization successfully before [17]. We are using a distance threshold depending on the fidelity of the quantization procedure and the desired number of clusters. We apply this procedure for each band separately. At a second level we are using the same strategy on the centrotypes of the clusters in order to merge similar topographies among bands together. Using the same codebook for all bands we encode the single trials by selecting the symbol (LG graph) that presents the minimum distance from the original topography. In this study we ignore the effect of the discretization error and we assume that it equally affects the training and test procedure of the classification.

III. Experiments

A. *Data Description and preprocessing*

The dataset used was provided by Clinical Neurophysiology and Neuroimaging Unit, University Hospitals of Geneva. We used all trials from a detection task in our analysis. We used only the period 1000ms after the stimulus where we expect the main response.

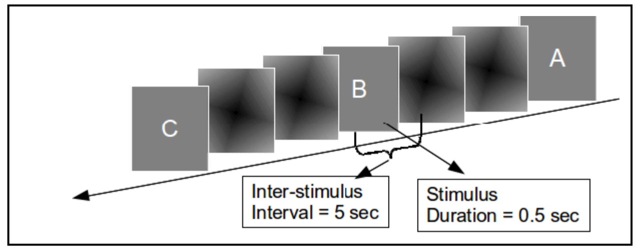
Subjects were seated and watched a computer screen. We used the trials from a detection task, where the subjects were asked to press a button with their right index finger as soon as a target appeared [18]. In the detection task background patches and patches containing letters were sequentially displayed in the screen. The later were considered as targets and required motor response from the subject. When background patches without letter were displayed no motor action was required. EEG data were recorded using 20 surface electrodes, according to the $10-20$ international system. The stimulus duration was 0.5 sec and the inter-stimulus interval was 5 sec. In total for each subject we have 20 target trials and 69 non target trials.

The data were examined for artifacts and only artifact-free trials were used. We used 8 subjects in the current study. The data were band-pass filtered in the range of delta(0.5 to 3Hz), theta(3 to 8Hz) and alpha band(8 to 13Hz) using a linear Finite Impulse response filter. For the classification procedure only a window of one second after the stimulus was used, where the main response component is expected [18].

B. *Results*

We treated each subject separately and for each, a separate codebook was constructed. For the construction of the codebook we considered twenty clusters, as many as the number of electrodes. The error introduced by the quantization procedure is going to be transferred and affect the classification step. At this point though, we are not interested in the quantization procedure itself and since we used all the train and test trials for the codebook construction we assume that the quantization error is a common factor for both training and testing.

Figure 2. Illustration of the experiment used for evaluuation of the three models. The target trials are displayed as boxes with letters.



An important part of the procedure is the model selection. We tried different numbers of parameters for each model. For all models we assumed that all the chains have the same number of states and for the influence model we assumed that the global node also has the same number of states as the individual chains. As the number of hidden states increased so did the classification accuracy of the model. We tried different models ranging from four to ten hidden states but the difference in the classification result was not significant when using more than six hidden states. For the influence model the number of hidden states of the individual chains does not play an important role in the classification or the behavior of the model as reported in [16]. We report the results from using six states for all hidden nodes.

We used a repeated random sub-sampling validation procedure in order to evaluate the performance of each model. Each model was trained using a train set of 10 target and 10 non-target trials selected from the dataset without replacement. The remaining 10 target trials and 10 random non-target trials were used for the test set. The train dataset and the test dataset were shuffled 10 times producing different sets and the results were averaged over all repetitions. The average results of this procedure are reported in Table I. The measures of performance are defined as:

$$\text{Precision} = tp/(tp+fp) \quad (1)$$

$$\text{Recall} = tp/(tp+fn) \quad (2)$$

$$\text{Accuracy} = (tp+tn)/(tp+tn+fp+fn) \quad (3)$$

In equations (1) to (3) by tp, tn, fp, fn we denote the number of true positive, the number of true negative, the number of false positive and the number of false negative predictions respectively. We can see that the PHMM model clearly has the worst performance out of the other two models. The CHMM model provides the highest accuracy over all models. This can be partly attributed to the fact that it is the most complex allowing direct interactions among bands. On the other hand the two-level influence model has fewer parameters to be computed and therefore is more computationally tractable but presents reduced accuracy compared to CHMM.

In order to evaluate whether the reduced performance of the PHMM model can be attributed to the lack of coupling between the bands or the model selection, we run multiple trials using models of different orders, up to ten hidden states.. In any case, the performance of the model remained lower than the CHMM and influence model. This result indicates that interactions between the different bands play an important role in the classification result and contribute to the increased performance of the two models that take them under consideration

TABLE I. MEAN RESULTS OVER SUBJECTS

	Classification results		
	Precision	***Recall***	***Accuracy***
PHMM	0.833	0.75	0.790
CHMM	0.901	0.949	0.925
Influence Model	0.88	0.80	0.85

IV. CONCLUSION

We presented a study for the classification of target and non-target single trials from a visual experiment. We modeled the evolution of the EEG topography using dynamic Bayesian nets in an effort to evaluate it as a feature capable to discriminate among tasks. Based on the concept of microstates we are using the hidden states of the Bayesian network to represent the temporal evolution of the EEG topography. We acquired good classification results although we took under consideration only the spatial configuration of the electric field in the scalp. Since we used only the normalized maps our analysis did not account for differences in the amplitude of the topographic response.

We are extending the microstate notion by modeling the interaction of the states among three bands. Using two DBNs capable to represent the interactions between Markov chains, the CHMMs and a two level influence model, we were able to capture the dependencies and interactions between the topographic activations in different bands. This aspect of the microstate model is often neglected. The results indicate that using this information allowed to capture the dynamics among the bands and improved the classification results. The models that capture the coupling between the different bands provide more information and better results that the PHMM which ignores any interaction between the chains.

In future work we intend to incorporate more features in our analysis, taking advantage of the flexibility provided by the DBNs. An interesting extension is to explore the relation between topographic and time-frequency features using DBNs. Using this methodology we can explore the dynamic interaction between bands and derive useful features that can be used for the discrimination of different pathologies and can also be used for Brain Computer Interface applications.

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