A Two-step Subspace Approach for Automatic Detection of CAP Phases in Multichannel Ambulatory Sleep EEG

Ammar Hussain Khan[1], Ibrahim Onaran[2], Nuri Firat Ince[1,2], Mostafa Kaveh[1] , Tacjana Friday[3], Mike Howell[3], Thomas Henry[3] and Zhiyi Sha[3]

[1]*Department of Electrical and Computer Engineering, University of Minnesota, 200 Union Street SE, Minneapolis, U.S.A.*
[2]*Department of Neurosurgery, University of Minnesota, 420 Delaware Street SE, Minneapolis, U.S.A.*
[3]*Department of Neurology, University of Minnesota, 420 Delaware Street SE, Minneapolis, U.S.A.*

Keywords: Cyclic Alternating Pattern, Ambulatory EEG, Principal Component Analysis, Spatial PCA, Classification.

Abstract: Cyclic Alternating Pattern (CAP) Occurs during Non-Rapid Eye Movement (NREM) Sleep and Is Exploited as a Neuro-Marker of Various Sleep Disorders. the CAP Is Build up from so Called a and B Phases Which Correspond to Widespread Synchronous and Regular Background Activities of EEG Respectively. Currently, These Phases Are Detected by Medical Experts through Visual Inspection, Thereby Limiting Their Potential to Be Used as a Gauge for Sleep Quality. This Paper Aims to Contribute to the Current Effort towards Automatic Detection of CAP Phases, so That Its Potential Can Be Improved in the Assessment of Sleep Quality. unlike Previous Research Where a Predefined Bipolar (and/or Monopolar) Channel Was Used for Automatic Detection, This Paper Explores the Use of a Two-Step Principal Component Analysis (PCA) in Spatial and Feature Domains to Extract Features from All 21 Recording Channels of Ambulatory EEG. Linear Discriminant Analysis (LDA) Was Used on the Extracted Features to Discriminate Phase a and B. over a Five Subject Database, Our Algorithm Reached an Average Classification Accuracy over 86%, Whereas the Baseline Approach Resulted in an 80.3% Success Rate. These Results Indicate That the Two Step PCA Procedure Can Be Used Effectively to Extract Features from Ambulatory EEG towards Detection of CAP.

1 INTRODUCTION

Physiologically sleep is divided into two broad categories: rapid eye movement (REM) and non-rapid eye movement (NREM). NREM sleep itself consists of sleep stages 1-3, parts of which contribute to the cyclic alternating pattern (CAP) (Terzano et al., 1985). As suggested by the name, CAP is a periodic phenomenon, which can be observed noninvasively in the electroencephalogram (EEG) signal. A particular CAP cycle is composed of phases A and B, where phase A is characterized by transient electro-cortical events as opposed to phase B, which is a return to the background (Terzano et al., 1985). Both phases A and B can last between 2 and 60 seconds and are called the microstructures of NREM sleep (Mariani et al., 2011).

Research on CAP in the past two decades has shown its potential as a marker for sleep instability. CAP has also been associated with several sleep pathologies such as sleep disordered breathing and periodic limb movement disorder (Terzano and Parrino, 1993). Increased amounts of CAP are normally found in cases with obstructive sleep apnea syndrome (Halász et al., 2004). In several studies, CAP A phase has been understood as a kind of gate through which certain pathological events occur more easily. This phenomenon has exhibited itself in sleep disturbances such as sleep bruxism and epilepsy (Kato et al., 2003); (Eisensehr et al., 2001); (Halász et al., 2002). In addition, CAP rate (the ratio between NREM CAP sleep and total NREM sleep) and the distributions of phase A during the CAP sequences can be used to characterize such sleep pathologies (Mariani et al., 2011).

Currently, the phases of CAP are detected by medical experts by visual inspection, which is a cumbersome and subjective procedure. In the past few years, there has been an increasing interest in the automatic detection of CAP in EEG. Largo et al. (2005) utilized a wavelet approach in combination

Khan A., Onaran I., Firat Ince N., Kaveh M., Friday T., Howell M., Henry T. and Sha Z..
A Two-step Subspace Approach for Automatic Detection of CAP Phases in Multichannel Ambulatory Sleep EEG.
DOI: 10.5220/0004247803420346
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2013), pages 342-346
ISBN: 978-989-8565-36-5

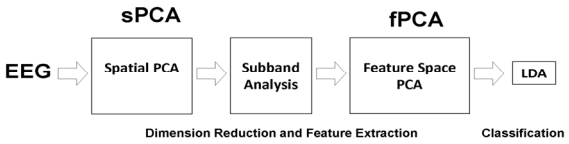

Figure 1: The schematic diagram of the two-step feature extraction and classification system.

with a genetic algorithm to detect CAP. Recently, machine learning approaches such as the use of neural networks and support vector machines have also been explored as methods for automatic CAP detection (Mariani et al., 2011); (Mariani et al., 2010). The subband power of EEG in delta (0-4Hz), theta (4-8Hz), alpha (8-12Hz) and beta (13-30Hz) are widely used as input features to classifiers. In these studies generally, a pre-selected bipolar electrode pair was used for feature extraction.

To our knowledge none of the previously-proposed methods have resulted in high enough accuracy such that they can be used in clinical practice. This paper contributes to the state of the art in CAP detection by developing such an automated method by employing a different feature extraction strategy using the standard tools of statistical signal processing. Unlike the previous attempts where a preselected bipolar (and/or monopolar) channel was used for automatic detection, the approach described in this paper uses a two-step Principal Component Analysis (PCA) executed in spatial and feature domains to extract a small feature set from multichannel ambulatory EEG recordings. A schematic diagram representing our approach is given in Figure 1. In the rest of the paper, we first describe the ambulatory EEG dataset used for performance evaluation. Then we explain our feature extraction and classification techniques. Finally, we provide classification results and compare our algorithm to a baseline technique utilizing predefined channels.

2 METHODS AND MATERIALS

2.1 Data Processing and Monitoring

Continuous ambulatory EEG recordings of five adult subjects (3 females and 2 males) with suspected seizure disorder were recorded at their homes. This was different from previous research, where the EEG recordings were made in laboratories. Using a home setting is beneficial as it might eliminate or reduce any subconscious changes in the sleep pattern that might occur as a result of a lab based sleep setting. The subjects had no known history of sleep disorders. Their age ranged from 19 to 41. The recordings were obtained with a portable data acquisition unit (XLTEK Trex, Natus Medical CA). EEG was sampled at 200 Hz from 21 channels that were in accordance with the 10-20 system. The recordings were obtained by the neurology department at the University of Minnesota and approval was obtained from the University of Minnesota institutional review board to analyse the data offline. In order to define a ground truth, an expert visually scored the continuous ambulatory EEG into the following events:

i) macrostructure: sleep stages 1-4, wake, REM sleep,
ii) arousal,
iii) microstructure: A and B phases.

A representative annotated multichannel EEG data composed of A and B phases is presented in Figure 2. The data was converted from XLTEK to Matlab format for further analysis by using in-house developed software tools.

2.2 Spatial PCA (sPCA)

Our preliminary observations in the collected ambulatory EEG data (as depicted in Figure 2) indicated that the phase A is characterized by transient widespread synchronous electro-cortical events. These events are followed by background activity (phase B). With this motivation, rather than using a predefined channel set, we used spatial principal component analysis (sPCA) to transform the full multichannel EEG into linear projections of the data on a set of virtual orthogonal channels represented by the spatial eigenvectors. Each eigenvector is a weighted linear combination of the EEG recording channels. The orthogonal principal components are tuned to account for the spatial variance in the data with minimum number of elements. This property of PCA makes it possible to

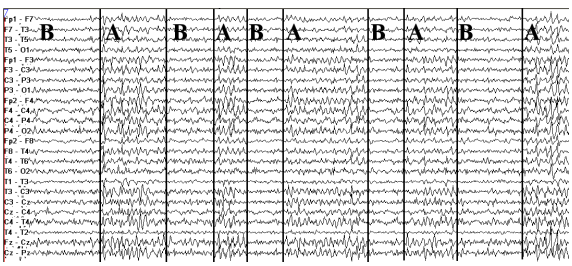

Figure 2: The raw EEG data and the CAP annotations as seen on the XLTeK recording system.

represent the multi-channel EEG data with a small set of virtual channels, and, thereby serves as a dimension reduction and SNR improvement step. The sPCA was computed by running an eigenvalue decomposition on the spatial covariance matrix with a dimension of 21x21. The cumulative energy spectrum of the eigenvalues of the sPCA is given in Figure 3-A. We observe that only five components were able to account for the 95% of the total variance in the data. Consequently, we elected to use the first five components to project the multichannel EEG data into virtual channels. Thus performing the sPCA reduced the initial dimensionality from 21 to 5.

In order to give a flavour about the distribution of spatial projections, the top five spatial eigenvectors are visualized on 2D topological head maps in Figure 3-B.

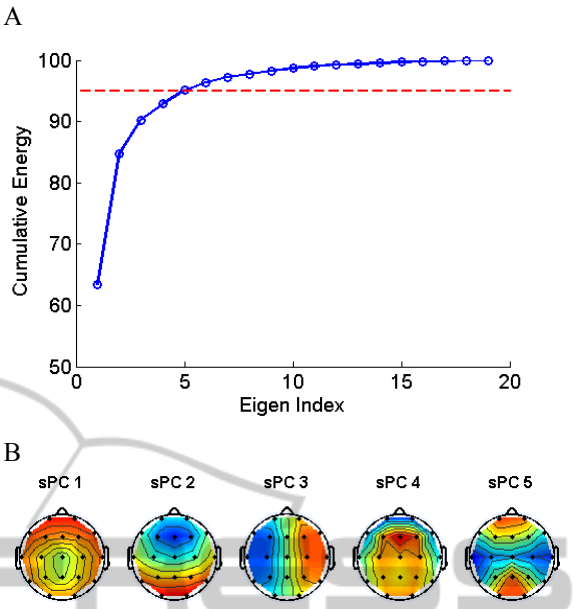

Figure 3: A) sPCA spectrum. The red line indicates that the at least 95% of spatial PCA spectrum is preserved by the coefficients below the line. B) 2D topological head maps of the sPCA components computed from all subjects.

2.3 Subband Features

After projecting the 21 channel EEG into the virtual channels, we computed the power in the following five frequency bands as features:

- Delta Low (0-2Hz)
- Delta High (2-4Hz)
- Theta (4-8 Hz)
- Alpha (8-13Hz)
- Beta (13-30 Hz)

To find the power in each of these bands, a Welch periodogram (Hayes, 2009) was computed by using a Hamming window of size 200 samples with an overlap of 50 samples where the FFT was computed at 512 points.

After computing the five subband powers for each of the five virtual channel, a feature vector of size 25 was obtained for use in classification

A straightforward strategy would be to feed the above 25-dimensional feature vector into a classifier for final decision. However, high dimension is generally associated with poor generalization capability in the classifier. For this reason, we implemented another dimension reduction step via PCA. In this approach, a subband matrix was formed with a structure of Nx25 where N represents the total number of A and B phase instances. Then the data was converted to log scale to suppress the skewness of the distribution and the effect of outliers and normalized. We executed another PCA in this feature space (fPCA) and examined the Eigen spectrum as in the previous sPCA step. The cumulative energy spectrum related to fPCA is given in Figure 4. It is observed that only two principal components accounted for more than 95% of the variance in the feature space. Consequently, we selected the top two vectors for final feature extraction.

In order to give an idea about the discriminatory power of these components we calculated the receiver operating characteristic curve (ROC) for each feature. The ROC curves for the top two components are given in Figure 5. A scatter plot representing the distribution of A and B instances of all subjects in this 2D space is given in Figure 6. It is observed that these two features provided noticeable discrimination between phase A and phase B.

2.4 LDA Classifier

For CAP detection, classification entailed using part of the provided data to form a ‘classifier’ that would distinguish between phase A and phase B. Then using the remaining data, the performance of the classifier was tested to determine the potential for automatic detection of CAP. We used a leave-one-subject-out strategy to train and test the LDA classifier.

Classification was chosen as one of the methods because it works as a ‘supervised’ learning technique; that is for any given instance, the class or category to which it belongs is known apriori.

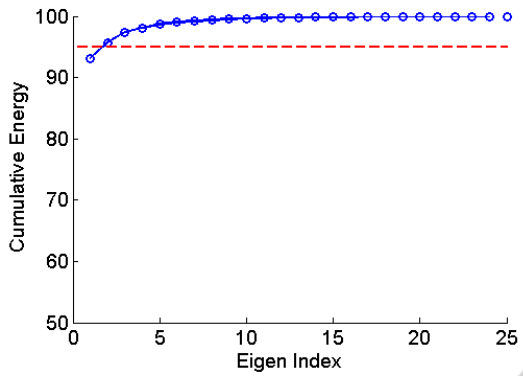

Figure 4: The spectral PCA spectrum (fPCA). The red line indicates 95% of the cumulative energy preserved in the PCA coefficients.

Hence, for any given inputs the desired output is well defined. Along these lines, previous research on the topic of CAP detection has tried different machine learning algorithms including neural networks, genetic algorithms and support vector machines (SVM). In this study, an LDA, which is a parameter free classifier, was used.

In order to compare the efficacy of our approach we compared it to a baseline technique, where predefined bipolar and monopolar channels are used for feature extraction. In this study, we used F4-C4 bipolar and C4 monopolar electrodes as in (Mariani et al., 2011). The same subband features were extracted and fed to an LDA classifier to obtain a fair comparison.

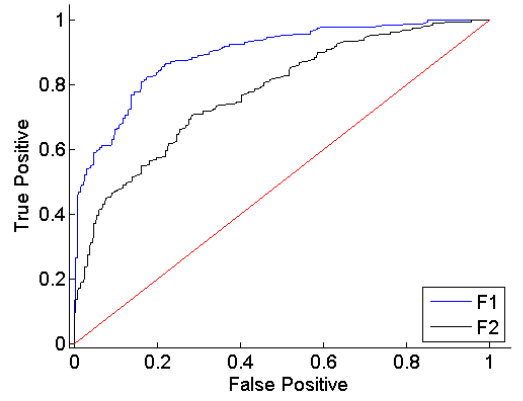

Figure 5: ROC curve of the first two components (F1 and F2) of the fPCA.

3 RESULTS

Table 1 shows the classification results obtained from our two-step PCA method and the baseline approach. Over a 5-subject database, our method provided 86.8% classification accuracy. The baseline approach was able to reach 80.3% classification accuracy on the same database. We note that our approach not only provided significantly better results ($p=0.006$, paired t-test) but also outperformed the baseline technique in each subject.

4 CONCLUSIONS

In previous research on CAP detection, the EEG signal was processed from the difference between two predefined channels (varying depending on particular research) from the 10-20 EEG system. One disadvantage of using the difference of a particular pair of channels is that these channels actually might not have the most significant contribution to the different phase subtypes. By using a particular pair, there is hence the chance that the channels with the most vivid distinctions between the different phases are overlooked. In this study, by taking a completely different approach from previous research we performed a two-step PCA to account for the information in all channels while removing redundancies, and reducing the influence of noise and other non-informative signal components.

Performing the sPCA essentially yielded in ‘virtual channels’. These channels were then used to form topological head maps to observe the distribution of spatial projection weights. Given that each sPC is linear combination of the 21 channels, the topological head maps for each sPC demonstrated how much a particular area was contributing to CAP.

Table 1: The Classification Results of Spatial & Feature Space PCA and fixed channel method using C4-F4 & C4 electrodes.

Subject	sPCA & fPCA	C4-F4 + C4
1	88.5	81.5
2	84.0	74.8
3	87.2	76.9
4	87.9	84.6
5	86.6	83.6
Avg.	**86.8**	**80.3**

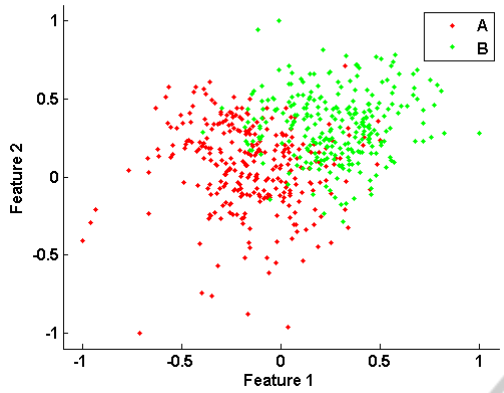

Figure 6: The scatter plot of the first two fPCA features for all subjects.

After performing another PCA on the feature space composed of subband powers of virtual channels, we utilized an LDA classifier for final decision. By using this technique, we demonstrated that automatic detection of CAP phases such as A (activity) and phase B (background) could be achieved with an average accuracy of 86.8% by using only two effective features.

It should be noted that the current classification results were obtained from features extracted in manually segmented EEG. However, in a fully automated detection system, the borders of A and B phases should be detected as well. Therefore, additional research is needed to extend this algorithm to continuous EEG recordings.

REFERENCES

Eisensehr, I., Parrino, L., Noachtar, S., Smerieri, A., and Terzano, M. (2001). Sleep in Lennox-Gastaut syndrome: the role of the cyclic alternating pattern (CAP) in the gate control of clinical seizures and generalized polyspikes. *Epilepsy Research*, 46(3):241 — 250.

Halász, P., Terzano, M., and Parrino, L. (2002). Spike-wave discharge and the microstructure of sleep-wake continuum in idiopathic generalised epilepsy. *Neurophysiologie Clinique/Clinical Neurophysiology*, 32(1):38 — 53.

Halász, P., Terzano, M., Parrino, L., and Bódizs, R. (2004). The nature of arousal in sleep. *Journal of Sleep Research*, 13(1):1—23.

Hayes, M. H. (2009). *Statistical digital signal processing and modeling*.

Kato, T., Montplaisir, J., Guitard, F., Sessle, B., Lund, J., *and* Lavigne, G. (2003). Evidence that Experimentally Induced Sleep Bruxism is a Consequence of Transient Arousal. *Journal of Dental Research*, 82(4):284—288.

Largo, R., Munteanu, C., and Rosa, A. (2005). CAP *event* detection by wavelets and GA tuning. In *Intelligent Signal Processing, 2005 IEEE International Workshop on*, pages 44 — 48.

Mariani, S., Bianchi, A., Manfredini, E., Rosso, V., Mendez, M., Parrino, L., Matteucci, M., Grassi, A., Cerutti, S., and Terzano, M. (2010). Automatic detection of a phases of the cyclic alternating pattern during sleep. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, pages 5085 —5088.

Mariani, S., Grassi, A., Mendez, M., Parrino, L., Terzano, M., and Bianchi, A. (2011). Automatic *detection* of CAP on central and fronto-central EEG leads via support vector machines. In *Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE*, pages 1491 — 1494.

Terzano, M. G., Mancia, D., Salati, M. R., Costani, G., and et al (1985). The cyclic alternating pattern as a physiologic component of normal NREM sleep. *Sleep: Journal of Sleep Research & Sleep Medicine*, 8(2):137—145. ID: 1989-28667-001.

Terzano, M. G. and Parrino, L. (1993). Clinical *applications* of cyclic alternating pattern. *Physiology & Behavior*, no. 54, pp. 807-813.