Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Frequency Domain Analysis of Sleep EEG for Visualization and Automated State Detection

Ennio A. Vivaldi, *Member, IEEE* and Alejandro Bassi

***Abstract*—Conventional analysis of EEG signals for sleep scoring is based on the time domain assessment of wave patterns. Human experts carry out this task relying on the direct visualization of EEG epochs. Techniques that enhance an intuitive visualization may encourage a wider use of more abstract descriptors, such as frequency domain features. This paper presents a feature extraction method for EEG signals based on FFT and principal component analysis. The result of the method is a characterization of EEG epochs with only two variables. Density plots of this 2D projection show compact clusters that correspond to sleep behavioral states. The distance to the centroid of a cluster is a reliable scoring criterion which is both easy to visualize and easy to automate. The techniques presented here have been shown to work reliably for both human and rat sleep studies.**

I. Introduction

DATA analysis of sleep recordings is required both for clinical evaluation and for human and animal research. A fundamental concept in sleep physiology asserts that there are distinct and discrete modes in which the brain can function, modes that are referred to as behavioral states: wakefulness (W), REM sleep (so named because of the presence of rapid eye movements) and NREM sleep. The standard classification of sleep is based on the recording of three signals: EEG, EMG and EOG. Although the latter two are useful in the diagnosis of REM sleep and W, it is undoubtedly the EEG signal the one that has deserved more attention not only in sleep state definitions, such as the subdivision of NREM into four stages according to EEG elements, but also in hypothesizing about the neural basis of the restorative and cognitive functions of sleep. The original sleep classification system of Rechtschaffen & Kales (R&K), still a widely accepted standard, was based on visual recognition and manual measurements of chart recordings [1]. A long history has afterward ensued that aims at automating sleep analysis from computer-based recordings. These projects have aimed either at imitating as close as possible the scoring paradigm of R&K or at offering alternative, unprejudiced paradigms [2]. Automated sleep analysis is necessary both for the feasibility of conducting long-term sleep recordings and for obtaining information beyond visual pattern recognition. Time and frequency domain analysis have been extensively explored in sleep research [3], [4].

No standardized scoring method based on frequency domain signal processing techniques has emerged that can be compared in widespread acceptance to the rules for visual sleep scoring provided R&K. It should be pointed out that a major feature of automatic scoring systems built according to R&K time domain rules is that they allow for visual validation by human experts. Intuitive visualization is a requirement that must also be satisfied when using frequency domain techniques.

The method presented in this paper is aimed at on-line automatic sleep scoring to support sleep deprivation experiments. Besides being capable of separating adequately the different behavioral states to be recognized, which is tantamount to a good visualization, a practical requirement for such a system is to facilitate the adaptation of the scoring criteria to each experimental subject. The frequency domain approach proposed in this paper provides a uniform feature extraction that does not need to be tailored to a particular case. Moreover, the extracted features are statistically good behaved so as to adapt the scoring criteria using a straightforward automatic procedure. In spite of not relying on the same EEG cues than R&K, the behavioral state visualization provides an intuitive feedback to validate the system, and it defines an alternative, perhaps more abstract, characterization of behavioral states.

II. Methods

Well established pattern recognition techniques such as FFT, principal component analysis (PCA) and nearest centroid classification were preferred [5]. In rat studies, the sleep deprivation paradigms were based on the on-line scoring method explained below.

A. Data acquisition and processing of human EEG

1) Signal Acquisition. The normal full-night polysomnographic variables of healthy subjects were recorded at 100 Hz using Alice 3, a standard clinical system.

2) Channel Selection. The EEG contains several channels that correspond to signals obtained from different electrode locations. The results presented in this paper were achieved using only one channel.

Manuscript submitted April 24, 2006. This work was supported by grant FONDECYT Chile 1030141.

A. Bassi is with the Departamento de Ciencias de la Computación, Universidad de Chile, Santiago (phone: 56-2-9784365; fax: 56-2-6895531; e-mail: abassi@ dcc.uchile.cl).

E. A. Vivaldi is with the Laboratorio de Sueño y Cronobiología, Facultad de Medicina, Universidad de Chile (e-mail: evivaldi@med.uchile.cl).

3) Short Term Fourier Analysis. The signal is divided into a sequence of Hamming windowed segments of 500 samples (5 seconds) with 50% overlapping. A spectrogram consisting of the power spectrum of each segment is created for the whole signal. The first 100 spectral components are selected (ranging up to 40 Hz, but discarding 0 Hz). If more than one channel is used, one spectrogram is created for each channel and afterwards they are all stacked.

4) Spectrogram Normalization. EEG power spectrum components have very skewed distributions. Log scaled components show better statistical properties. As a consequence, the power spectrogram is first scaled using a log transformation. Each component is then normalized to a zero mean. Finally, the spectrogram is time smoothed using a Gaussian convolution. This last step reduces the variance of the spectral characteristics of the underlying behavioral states because the EEG is locally stationary (see Fig. 3) at least at the detail level required for a broad class scoring. If the analysis is to be carried out on-line, a causal exponential smoothing filter is used instead.

5) Dimension Reduction. The total number of spectral components is unwieldy, but they are often strongly correlated. Furthermore, since the intra-class variance has been smoothed out, the remaining variance explains mainly the inter-class separation. A principal component analysis PCA is then used to select the maximal variance projection axes that present the maximal separation between the existing behavioral states. According to our empirical evidence, three projection axes are sufficient. The second and third principal components are combined to produce a 2D projection.

B. Data acquisition and processing in Rat studies

1) Signal Acquisition. Data were recorded continuously at 250 Hz using a computer based system. Both undisturbed spontaneous sequences of wake, NREM and REM segments and recordings during sleep deprivation paradigms were considered.

2) Channel Selection. Four channels were available: three EEG channels and one EMG channel. The EMG channel is needed to separate W from REM.

3) Short Term Fourier Analysis. The signals were divided into a sequence of Hamming windowed segments of 500 samples (2 seconds) with 75% overlapping. A spectrogram consisting of the power spectrum of each segment is created for the whole signal. The first 40 spectral components of EEG channels are selected (ranging up to 20 Hz, but discarding 0 Hz). The higher components of the EMG (over 100 Hz) are selected because they are less prone to interference.

4) Activity Feature Extraction. Instead of using the full spectrum, the three standard spectral bands employed in rat sleep analysis were determined: delta, theta, sigma that, respectively, correspond to approximately the 1-4, 4-8 and 12-16 Hz ranges,. The activity of each band was calculated by integration of the corresponding frequency ranges after selecting a source channel. The best source channel could be different for different bands. The EMG activity was also calculated by integration. Finally, a log transformation was applied to improve the statistical soundness of the variables.

5) Dimension Reduction. The four original variables were combined to generate two synthetic variables for projection on a 2D plane. A PCA analysis could be used for this task.

6) Clustering. The 2D projection of the activities would normally configure three clusters that could be represented by their centroids. The distances to those centroids were used as scoring criteria.

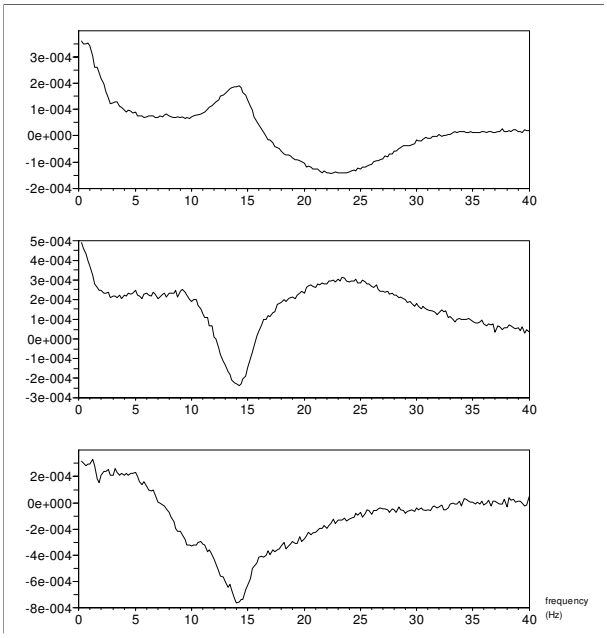

Fig. 1. From top to bottom: The first three principal eigenvectors obtained from the log scaled power spectrogram of a full night human sleep EEG.

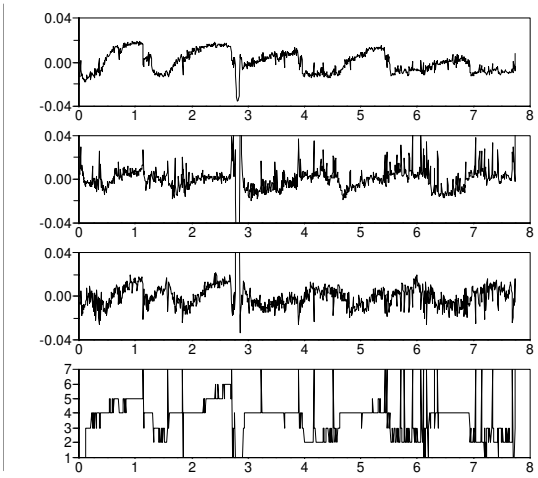

Fig. 2. From top to bottom: The first three principal components of log scaled power spectrum of 30-s epochs from a full night human sleep EEG and the corresponding sleep stage scorings (1: unscored; 2: REM; 3 to 6: NREM Stages 1 to 4; 7: movement time).

III. RESULTS

To illustrate the frequency analysis method, results will be presented from the EEG of one night of human sleep and from 34 hours of rat sleep-wake cycle recording, one baseline day followed by 10 hours of sleep perturbation.

A. *Human sleep EEG studies*

Fig. 1 displays the principal projection axes for the human data. The most prominent peaks match the frequency ranges traditionally referenced in human EEG analysis as delta and sigma bands.

Fig. 2 displays the time course of the three principal components plus a fourth panel indicating the 30-second epochs manual scoring. A correspondence between the first component and the depth of NREM sleep is evidenced. A gradual increase in this component as NREM sleep deepens can be observed.

Fig. 3 shows the clusters in the density plots of 2D projections. These density plots are built by a spatial smoothing of a scatter plot of the first and second (upper plots) and first and third (lower plots) principal components. The left side graphs are constructed with 5-second epochs as opposed to the 30-second epochs of the right side graphs. The comparison highlights the usefulness of time smoothing to separate the behavioral state clusters, as explained in the methods section.

Fig. 4 displays as a density plot the combination of the two right side graphs of Fig. 3. Fig. 5 is the related scatter plot that codes the behavioral scoring by the human expert. The correspondence between the clusters and the state and stages is made evident. The upper left cluster corresponds to REM sleep, the upper right cluster to stages 3 and 4 of NREM sleep and the lower to stages 1 and 2. Note the tendency of the expert to classify as stages 1 and 2 epochs that are more distant from its cluster centroid.

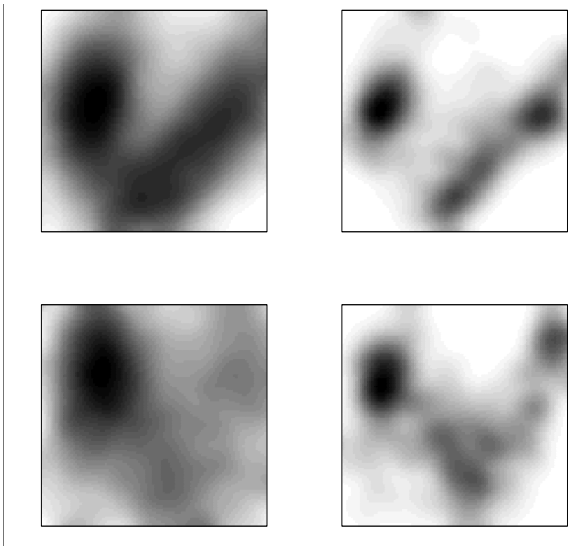

Fig. 3. Top: Density plots of 2D projections of first (abscissa) and second (ordinate) principal components. Bottom: Density plots of 2D projections of first (abscissa) and third (ordinate) principal components. Left: 5-second epochs. Right: 30-second epochs.

B. *Rat sleep studies*

Fig. 6 displays the clusters corresponding to wake (bottom left), REM (bottom right) and NREM (upper) from 24 hours of a rat baseline sleep recording. When sleep is disturbed by deprivation, as is the case in Fig. 7, the REM sleep cluster disappears and the NREM cluster migrates toward wakefulness.

State diagnosis for a given epoch is achieved by assessing the distances to each of the three centroids. These three distances have been previously normalized so that their sum equals 1. Fig. 8 illustrates the normalized distance to each state centroid for every 5-second epoch. An epoch is assigned to a given state when its ordinate descends under

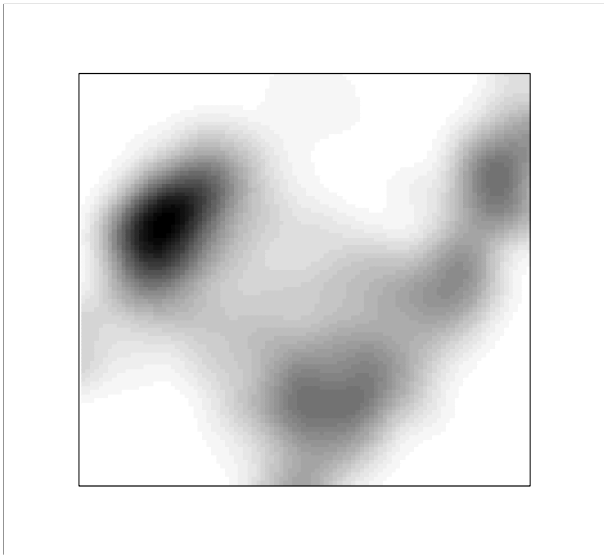

Fig. 4. Density plot of 2D projection of first principal component (abscissa) versus mean of second and third components (ordinate).

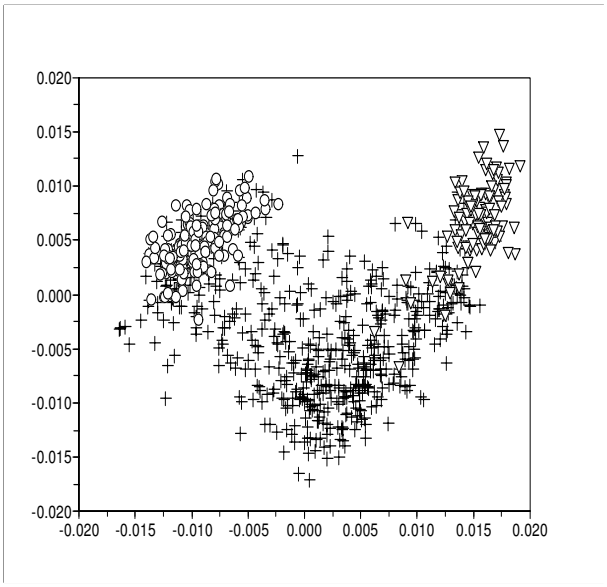

Fig. 5. Behavioral states and the 2D scatter plot of first principal component (abscissa) versus mean of second and third components (ordinate). Circles represent REM epochs, triangles stages 3 and 4 of NREM and crosses stages 1 and 2 of NREM.

the 0.2 threshold level for the case of wake and NREM sleep, or under the 0.15 threshold for the case of REM sleep. These levels were empirically chosen, because they provide a reasonable certainty of state diagnosis. When no ordinate reached the threshold, the previous epoch state was maintained. This algorithm works sufficiently rapidly to allow on-line state detection. In fact, the deprivation experiment whose data are shown in Fig. 7 was implemented by linking the state detection algorithm working on-line to an output that would activate a servomotor based mechanism that would shake the animal cage.

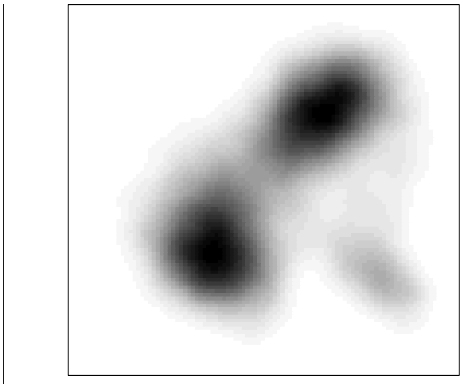

Fig. 6. 2D density plot of synthetic variables extracted from EEG and EMG 5-second epochs throughout a 24-hour baseline rat recording.

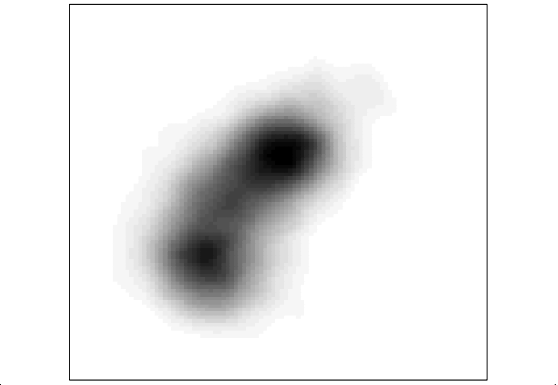

Fig. 7. 2D density plot of synthetic variables extracted from EEG and EMG 5-second epochs throughout a 10 hours sleep deprivation protocol in a rat.

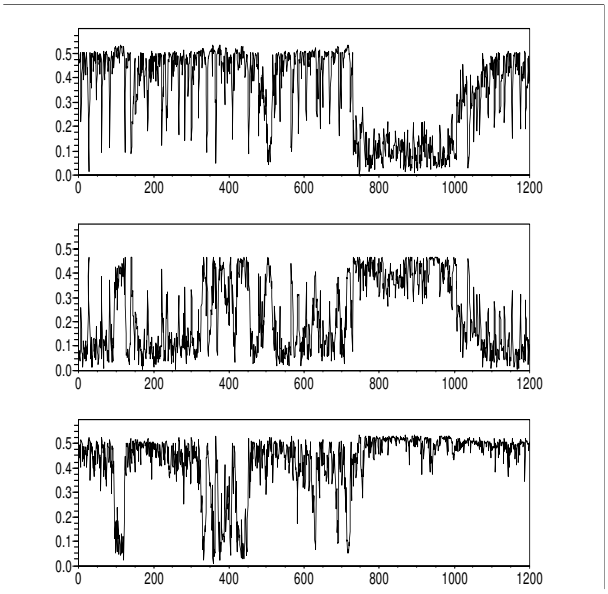

Fig. 8. Distance to the W, NREM and REM centroids (top to bottom panels) throughout 100 minutes of recording (1200 5-second epochs).

IV. Conclusion

A technique is presented aimed at visualizing the relevant EEG data for sleep studies in humans and animals. The graphical representations emphasize two key issues in sleep studies: the data clusters that represent the configurations that characterize each behavioral state and the dynamics of the transitions between them. The method involves a state assignation procedure that is sufficiently rapid and efficient to be employed for on-line state diagnosis. The system has been successfully applied to automate total or REM specific sleep deprivation paradigms.

References

[1] A. Rechtschaffen and A. Kales, *A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects*. US Department of Health, Education, and Welfare Public Health Service - NIH/NIND, 1968.

[2] P. Anderer, G. Gruber, S. Parapatics, M. Woertz, T. Miazhynskaia, G. Klosch, B. Saletu, J. Zeitlhofer, M. J. Barbanoj, H. Danker-Hopfe, S. L. Himanen, B. Kemp, T. Penzel, M. Grozinger, D. Kunz, P. Rappelsberger, A. Schlogl, G. Dorffner. *An E-health solution for automatic sleep classification according to Rechtschaffen and Kales: validation study of the Somnolyzer 24 x 7 utilizing the Siesta database.* Neuropsychobiology, vol. 51, no. 3, pp. 115-133, May 2005.

[3] B. A. Geering, P. Achermann, F. Eggimann, A. A. Borbely. *Period-amplitude analysis and power spectral analysis: a comparison based on all-night sleep EEG recordings.* J Sleep Res., vol. 2, no. 3, pp. 121-129, Sep 1993.

[4] C. Robert, C. Guilpin, A. Limoge. Automated sleep staging systems in rats. J Neurosci Methods, vol. 2, no. 88, pp. 111-122, May 1999.

[5] S. Theodoridis, and K. Koutroumbas, "Pattern Recognition", *Academic Press*, 1999.