Non-linear Analysis of Polysomnographic Data in Children

Traditional linear analysis of sleep data utilizing the visual scoring methods for sleep stages (Rechtschaffen and Kales) often fail to characterize problems of excessive daytime somnolence and sleep fragmentation. Polysmnographic variables [electroencephalogram (EEG), eye movement (EOG), electromyogram (EMG), respiratory effort measured via inductance pleysmography, Air flow and Electrocardiogram] as recorded via digital polysomnography represent a group of interrelated time series. These physiologic signals are utilized to characterize changes in sleep stage and pathologic events. In this paper we demonstrate the use of nonlinear time series analysis to characterize sleep state. Standard 30 second epochs scored via Rechtschaffen and Kales criteria are subjected to nonlinear analysis. The Epochs are chosen to reflect typical stages of REM and NREM sleep and waking state. Sampling rate was 128 hz. per channel. EEG (C3, C_4, O_2 and C_z electrodes), chin EMG, EOG, chest and abdominal respiratory effort and end tidal CO_2 were recorded.

These recordings are characterized using variables based on techniques from non-linear time series analysis. The estimation of these values is based on attractor reconstruction. The state of the system that generates our time series can be represented by a projection of all variables in a multi-dimensional state space. A collection of points in the state space, representing the dynamics of the system, is called the attractor. Takens (1981) proved that the dynamic state of a system can be reconstructed from the time series by using time delay coordinates. With this technique a time series x(1), x(2), x(3), ..x(N) is converted into a set of vectors with m elements

$$X_i = (x_i , x_{i+k} , x_{i+2k} , ..., x_{i+(m-1)k})^T$$

k is the delay in number of samples and T is the epoch of the time series embedded in the vector. Starting from the vectors in the state space, different variables can be extracted to characterize the underlying system. We applied different estimations of correlation dimension and order-2 Kolmogorov entropy.

The correlation dimension is based on the correlation integral:

$$C(s) = \{1/N.(N-1)\} \Sigma \Theta(s - | X_i - X_j |) \qquad (1)$$

With Q – Heaviside function. The integral counts the number of pairs of points (X_i, X_j) whose distance is smaller than s. The term $| X_i - X_j |$ denotes the distance between the points in state space. The distance between point in

space may be evaluated with the Euclidian norm or the maximum norm, the results obtained with both techniques are generally equivalent; using the maximum norm is computationally advantageous (Schouten et al 1994a, 1994b). Evaluation of time series using this approach was used by Schouten et al (1994b) to estimate correlation dimension of noisy attractors. If N → infinity and s → 0 in equation (1), C(s) scales according to a power law $C(s) \sim s^D$, with D – correlation dimension of the attractor. Both a least-square method, and a maximum-likelihood estimator for D are developed by Schouten et al (1994b).

Based on the same type of embedding shown in (2), Schouten et al (1994a) developed a maximum-likelihood estimator for the order-2 Kolmogorov entropy. (Takens, 1983; Grassberger and Procaccia, 1983). Entropy is estimated by examination of two initially close orbits on an attractor, and measuring the time required for the orbits to diverge beyond a set distance. In this study we applied the algorithms for estimation of correlation dimension and entropy as implemented in a menu driven software package (Schouten and van den Bleek, 1993).

We found that sleep state is associated with changes in Kolmogorov entropy. Delta sleep and stage 2 of NREM sleep demonstrate lowest Kolmogorov entropy, Rem Sleep intermediate Kolmogorov entropy and the waking state the highest Kolmogorov entropy. Examples of epochs from one subject are displayed in figure 1. Entropy values for each state are reproducible across physiologic parameters as shown in two epoch from the same subject during stage 2 sleep, delta sleep and REM sleep in figure 2.

The finding of reproducible Kolmogorov entropy in typical epochs of normal sleep across multiple physiologic time series is the first step in our plan to utilize non-linear techniques to study pathological events during sleep. Further characterization of sleep state through the use of non-linear time series analysis may lead to improved detection and possible prediction of the changes associated with sleep disorders including restless leg syndrome, central and obstructive sleep apnea, and disorders producing hypersomnolence not presently possible with traditional linear analysis.

References

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