Non-linear Analysis of Polysomnographic Data in Children

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Abstract

We describe the nonlinear characteristics of sleep stages in three children ages 6-7 years. We found Kolmogorov entropy to be a robust measure across multiple physiologic time series recorded in the polysomnogram. Entropy was reproducible within subjects and had similar relationships across subjects.

Introduction

Traditional analysis of polysomnographic recordings of sleep, utilizing the visual scoring methods for sleep stages of Rechtschaffen and Kales[1] often fail to characterize problems of excessive daytime somnolence and sleep fragmentation. This lack of sensitivity for these clinical problems prompts to search for new methods of analysis of sleep data. polysomnographic variables [electroencephalogram (EEG), eye movement (EOG), electromyogram (EMG), respiratory effort, airflow 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 illustrate use of nonlinear time series analysis to characterize sleep state in children.

Methods

Overnight polysomnography was obtained 3 children referred for sleep studies at the University of Chicago. These studies were read as normal as part of the clinical interpretation. IRB approval for off line analysis of EEG data was obtained. Standard 30-second epochs scored via Rechtschaffen and Kales[1] criteria, are subjected to nonlinear analysis. The epochs are chosen to reflect typical stages of REM, Non-REM 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.

The recordings were 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[2] in1981 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

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

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 Θ – 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 equivalent; using the maximum norm is computationally advantageous [3, 4]. Evaluation of time series using this approach was used by Schouten et al [4] 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 [4].

Based on the same type of embedding shown in (2), Schouten et al [3] developed a maximum-likelihood estimator for the order-2 Kolmogorov entropy[5]. 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[6]

Results

Sleep state is associated with changes in Kolmogorov entropy. Delta sleep and stage 2 of Non-REM sleep demonstrate lowest Kolmogorov entropy, REM sleep intermediate Kolmogorov entropy and the waking state the highest Kolmogorov entropy. Examples of epochs from subject 1 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 Non-REM sleep, REM sleep, and wake in figure 2 a-c.

Discussion

Kolmogorov entropy estimates appear to be reproducible within subjects and different across sleep and waking states in children. A number of authors have utilized non-linear measures to characterize sleep stages in adults. Koybayashi et al [7] found a decrease in the correlation dimension across Non-REM sleep stages. Pereda et al [8] found stability of the correlation dimension with embedding dimensions greater than 15. Their data suggest nonlinear properties for Non-REM sleep. Bock and Gough [9] found correlation dimension superior to Lyapunov exponent in analysis of sleep apnea. Fell et al [10] used multiple non-linear measures to characterize ECG and EEG across sleep stages in adults. They found similar entropy changes across state for ECG and EEG as we did for EEG in our children. Use of traditional visual inspection and linear analysis techniques have provided an excellent means to characterize many events normal and pathological events during sleep. Clinical syndromes including restless leg syndrome, periodic leg movement disorder, central sleep apnea, obstructive sleep apnea, fibromyalgia and seizure disorders are easily identified by these methods. However, these techniques fail to characterize are changes in sleep that produce hypersomnolesence. For example, patients with periodic leg movement disorder with similar numbers of limb movements will have radically different levels of excessive daytime sleepiness.

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. Studies are currently underway to expand these findings and apply this method to nocturnal arousals.

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.

Acknowledgement

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Figure legends

Figure 1. Entropy (Ks) from patient 1 from two epochs recorded at the C3 electrode during different sleep stages.

Figure 2. Entropy (Ks) from Subjects 1-3 recorded during sleep stages across multiple scalp EEG and physiologic parameters.

References

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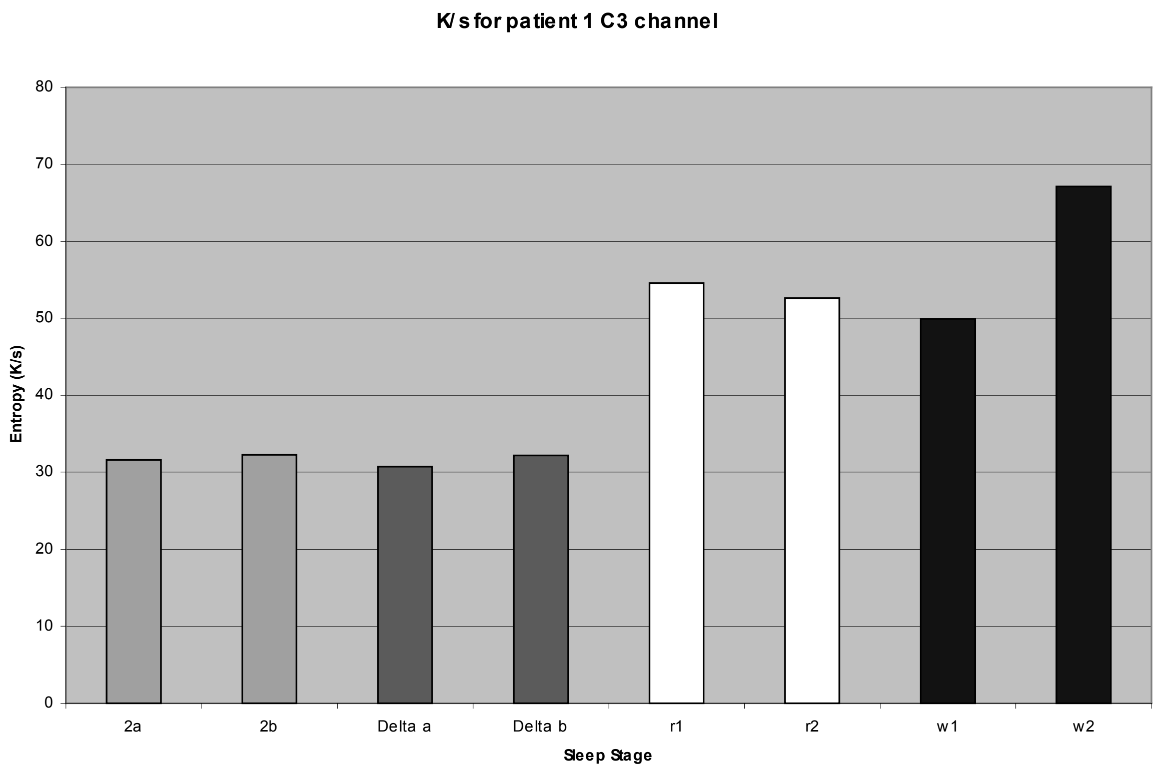
Figure 1



K/s for patient 1 C3 channel
80
70
60
50
40
30
20
10
0
Entropy (K/s)
2a
2b
Delta a
Delta b
r1
r2
w1
w2
Sleep Stage

figure 2a

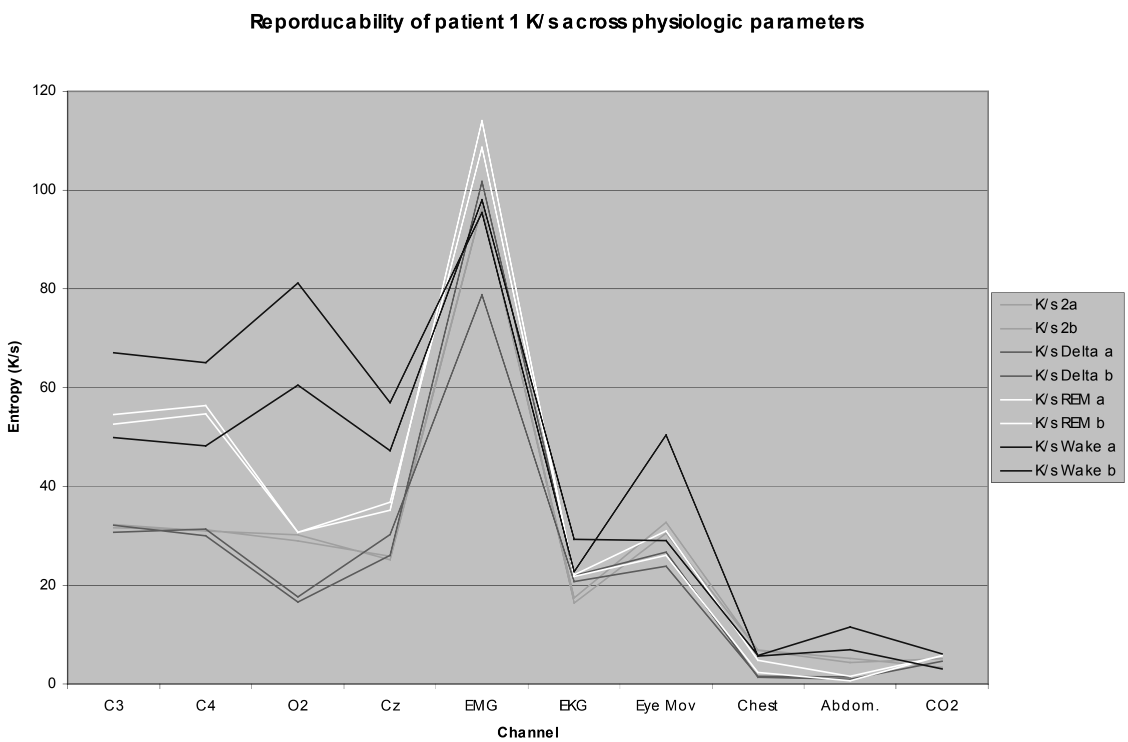

Reporducability of patient 1 K/s across physiologic parameters
120
100
80
60
40
20
0
Entropy (K/s)
C3
C4
O2
Cz
EMG
EKG
Eye Mov
Chest
Abdom.
CO2
Channel
K/s 2a
K/s 2b
K/s Delta a
K/s Delta b
K/s REM a
K/s REM b
K/s Wake a
K/s Wake b

figure 2b

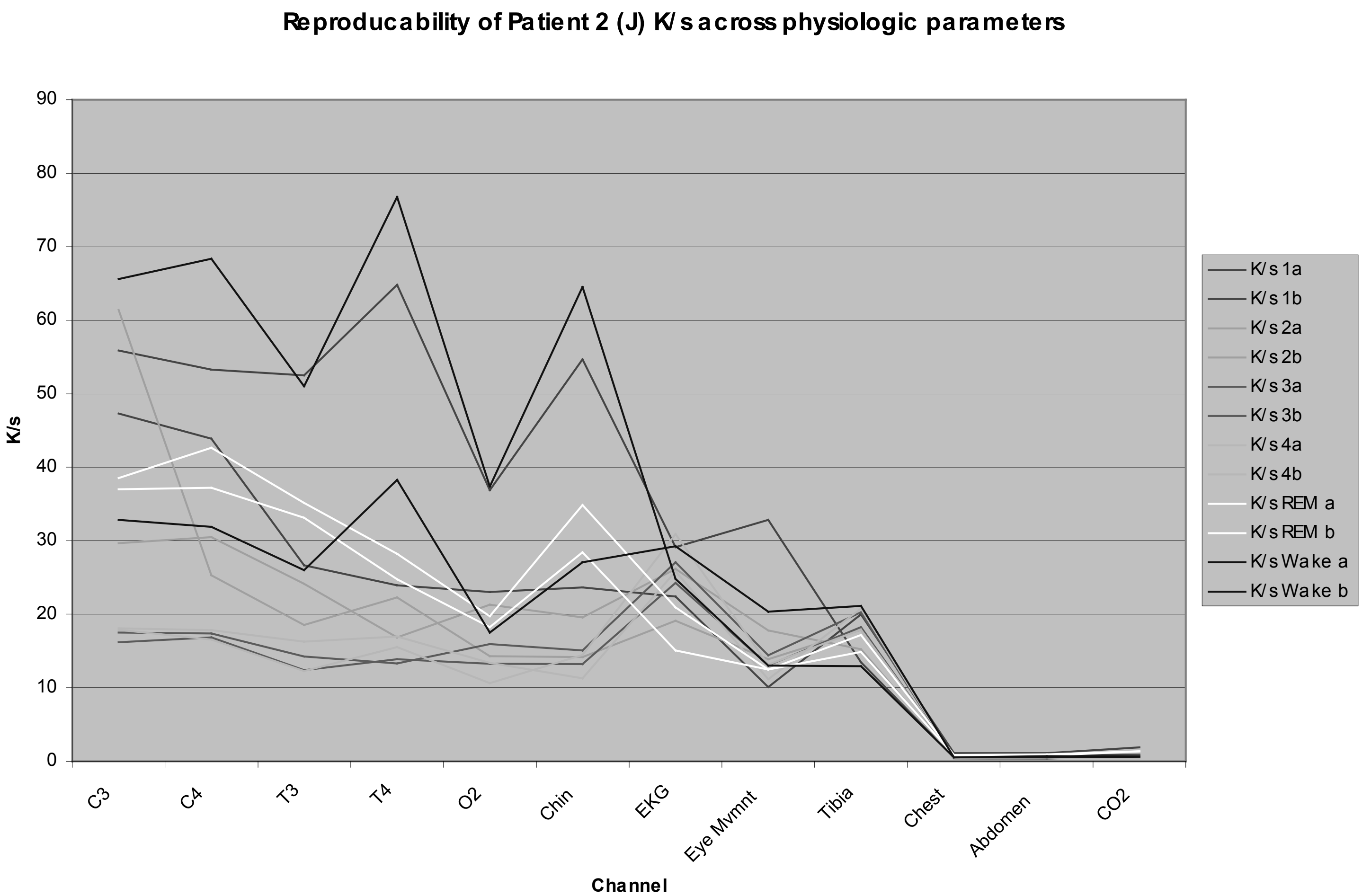
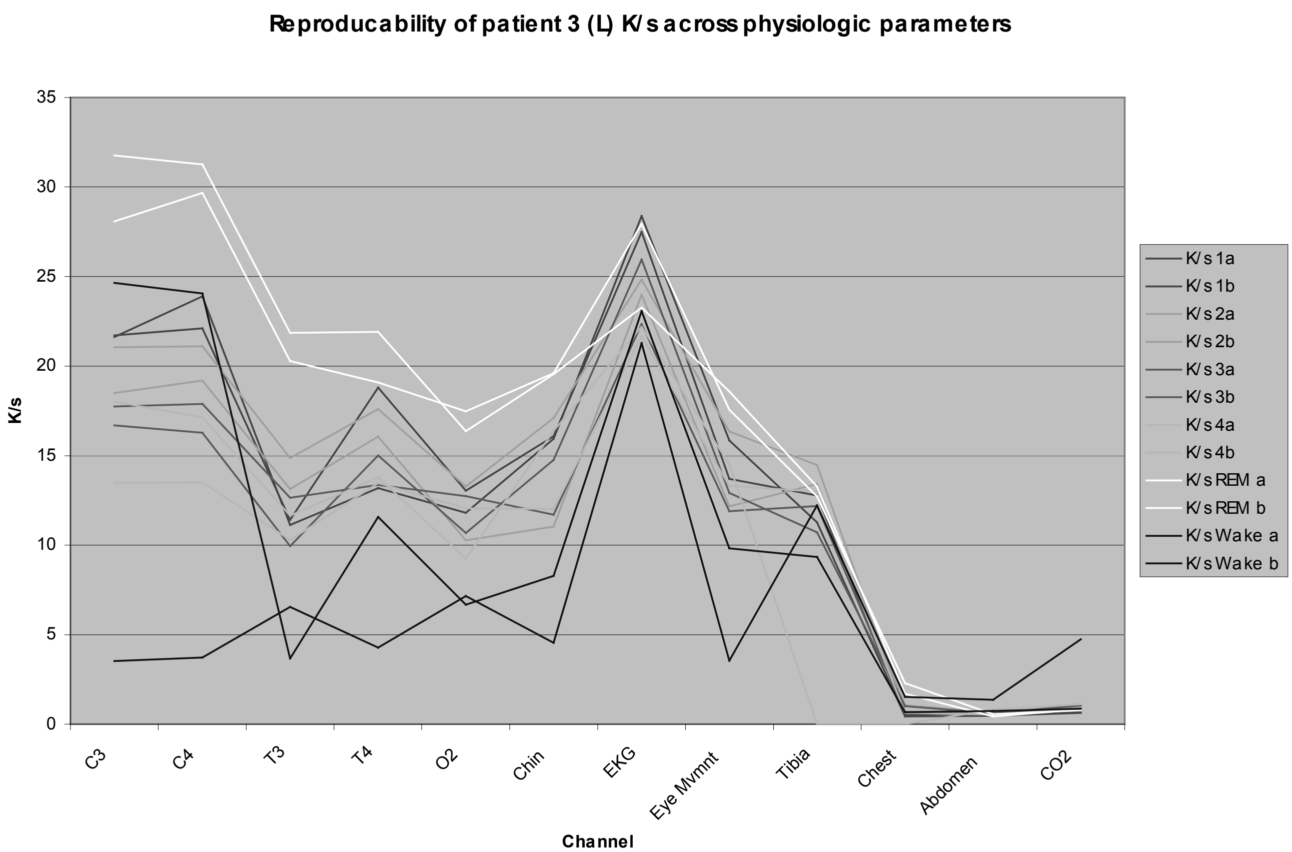

Reproducability of Patient 2 (J) K/s across physiologic parameters
90
80
70
60
50
40
30
20
10
0
K/s
C3
C4
T3
T4
O2
Chin
EKG
Eye Mvmnt
Tibia
Chest
Abdomen
CO2
Channel
K/s 1a
K/s 1b
K/s 2a
K/s 2b
K/s 3a
K/s 3b
K/s 4a
K/s 4b
K/s REM a
K/s REM b
K/s Wake a
K/s Wake b

figure 2c


Reproducability of patient 3 (L) K/s across physiologic parameters
35
30
25
20
15
10
5
0
K/s
C3
C4
T3
T4
O2
Chin
EKG
Eye Mvmnt
Tibia
Chest
Abdomen
CO2
Channel
K/s 1a
K/s 1b
K/s 2a
K/s 2b
K/s 3a
K/s 3b
K/s 4a
K/s 4b
K/s REM a
K/s REM b
K/s Wake a
K/s Wake b