Classification of Sleep States Based on Brain Electro-physiology Assessed Using Recurrence Analysis of Single-Channel EEG

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Abstract

Analysis of brain recurrence (ABR) is a method for quantifying non-randomness (law-governed complexity) in the EEG. Epochs of sleep EEG represented by four ABR variables were found to be separable into 3–12 statistically distinct clusters. The most physiologically realistic models consisted of 4–6 clusters. The choice of four clusters corresponded generally with syntactic sleep staging.

Introduction

ABR quantifies the pattern (not the amplitude) of the EEG (1–3), characterizes sleep depth and phasic events (4), and detects functional changes associated with neurological disorders (5,6).

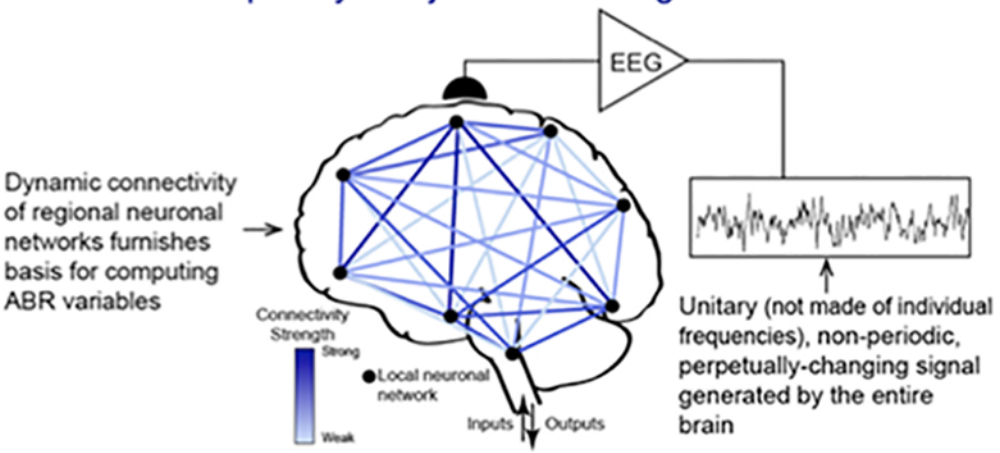
In conjunction with conventional sleep staging, ABR facilitated detection of REM (7), REM sleep disorder (8), OSA (9), and depression (10).

The objective was to show that ABR permitted objective classification of the functional states of brain electrical that occurred during sleep.

Statistical staging of functional brain states during sleep has the potential to replace syntactical staging of sleep states for the purpose of assisting in diagnoses of specific clinical disorders.

Analysis of Brain Recurrence

Complexity Conjecture for Origin of EEG



Definition of ABR Variables

(Not your Father's variables)

Physiological Basis	ABR Variable	Symbol
Complexity of law-governed activity	Recurrence	r
	Determinism	d
Rate of change in complexity	Recurrence	$\dot{r}$ (dr/dt)
	Determinism	$\dot{d}$ (dd/dt)

Recurrence and determinism are quantitative measures of the complexity of the EEG (higher values indicate less complexity); r, d, $\dot{r}$, and $\dot{d}$ are invariant to changes in the amplitude of the EEG. The variables were computed second by second and averaged over 30-second epochs. All values were normalized by the means of their respective time series, thereby permitting the values to be expressed in comparable units (percent) and compared across subjects.

Data Analysis

Sleep EEG
divided into consecutive 30-sec epochs

→

ABR Processing
Each second of EEG embedded in phase space. One value of $r, d, \dot{r}, \dot{d}$ calculated second by second

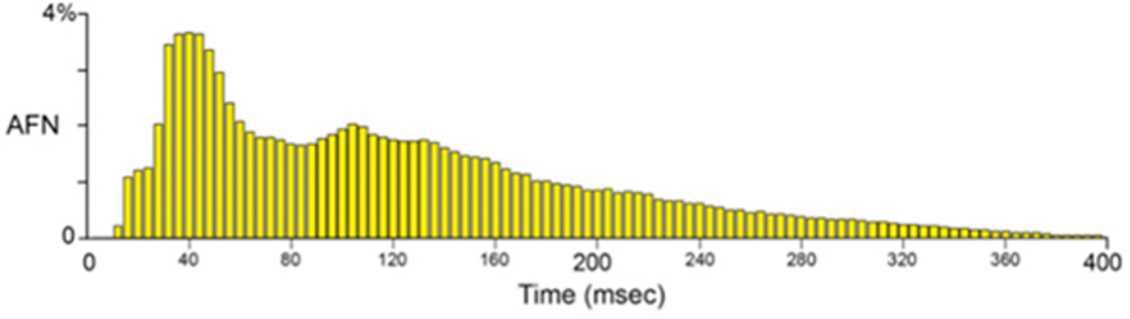
Feature Extraction
Values averaged epoch by epoch to produce 4-component vectors $(\bar{r}, \bar{d}, \bar{\dot{r}}, \bar{\dot{d}})$

→

Cluster Analysis (11)
The natural groupings of vectors determined statistically

Results

Fundamental Structure of the EEG During Sleep



The first zero of the autocorrelation function(*) was determined second-by-second in PSG EEGs (C3, 500 Hz, N=10, ~28,000 values/subject). The histogram shows the average fractional number (AFN) of the seconds in the EEG whose autocorrelation function became zero within the indicated 4-ms bins.

*A standard statistical measure of how long is required for the EEG in a given second to become linearly independent of the EEG in the next second.

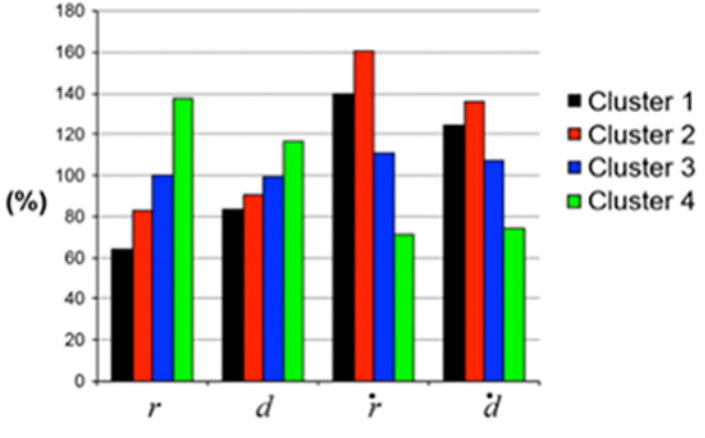
The histogram documents that the statistical properties of the EEG during sleep change drastically from second to second (statistical "nonstationarity").

Identification of ABR Sleep Brain States

Based on the dynamical activity in the EEG as characterized by ABR (r, d, $\dot{r}$, $\dot{d}$), cluster analysis performed individually on the 149 subjects (~1000 4-component vectors that each corresponded to a 30-sec epoch of sleep) identified 3–12 statistically distinct clusters in each subject, depending on the *a priori* choice of cluster number.

- The most physiologically realistic cluster models of brain activity consisted of 4–6 clusters.
- The choice of four clusters corresponded generally with syntactic sleep staging, and was examined in detail:
  - One cluster consisted of vectors with the lowest average r (Cluster 1);
  - One cluster consisted of vectors had the highest average r (Cluster 4);
  - Clusters 2 and 3 corresponded respectively to the higher and lower average values of $\dot{r}$:

Four-Cluster Characterization of Brain-States During Sleep

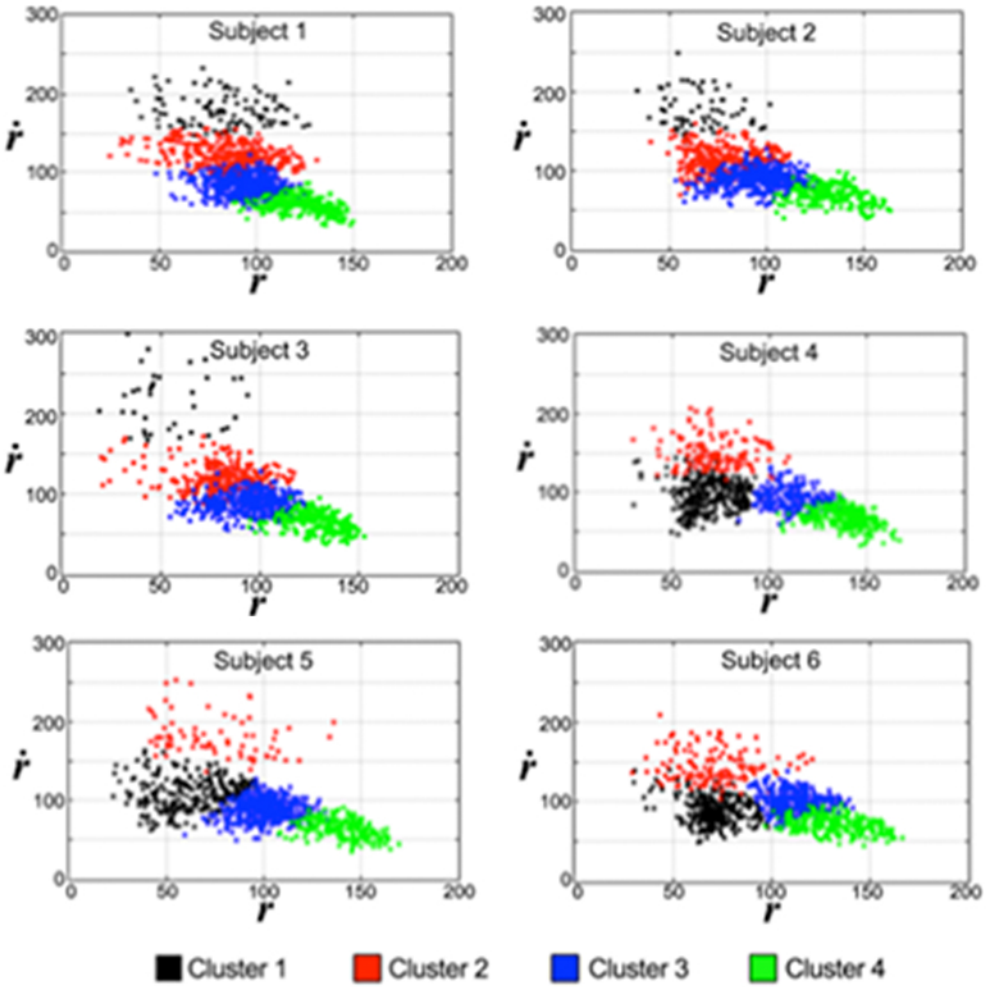


Distinct Clusters of 155,089 sleep epochs as determined by ABR (N=149 normal subjects). Each epoch was statistically assigned to one of four clusters based on its values for r, d, $\dot{r}$, and $\dot{d}$ The illustrated means were calculated by averaging over each subject and then over all subjects. The SE were too small to be resolved at the scale shown.

The graph shows that, on average, recurrence and determinism increased continuously with cluster number; the rates of change of both variables increased in Cluster 2 compared with Cluster 1, and then decreased thereafter.

Four-Cluster Results in Typical Subjects

Two-Dimensional Projections from Four Dimensions Showing Locations of the Four Clusters and their Constituent Epochs



Representative 3-dimensional scatterplots of clusters from six subjects.

The graphs show that the epochs in Clusters 3 and 4 were located consistently relative to one another and to position in the vector space. The locations of the other Clusters were more variable and subject-dependent.

Relation to Conventional Staging

We expected the statistical classification of brain states using ABR to partially agree with the syntactic classification of sleep states using R&K or ASSM rules because for some states the rules for labeling epochs are partially based on the EEG.

As expected, brain-state classification using ABR corresponded generally but was not identical to R&K staging by SHHS investigators.

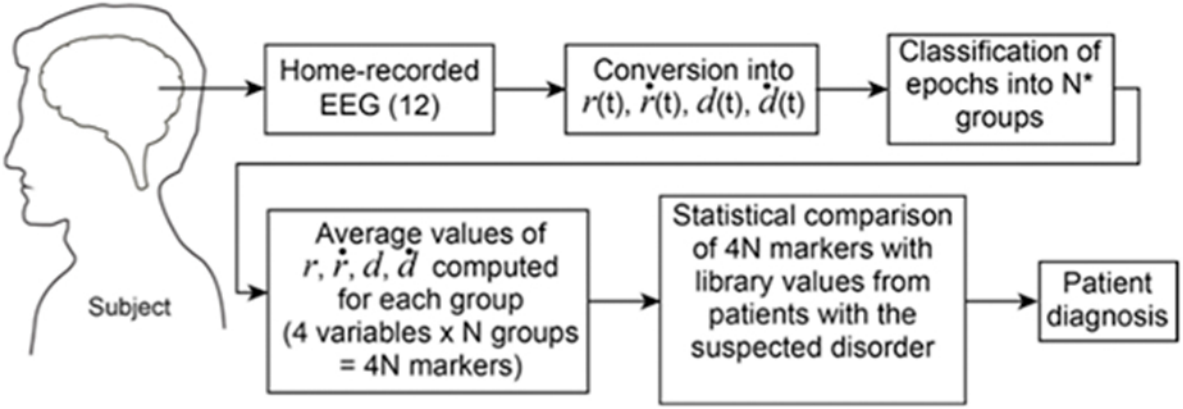
C1				C2				C3				C4			
WASO	REM	N1/N2	N3/N4	WASO	REM	N1/N2	N3/N4	WASO	REM	N1/N2	N3/N4	WASO	REM	N1/N2	N3/N4
68	16	16	0	57	19	23	1	18	21	58	3	3	4	48	45

Observed Relationship Between Statistical and Syntactic Classification Systems: R&K results as a function of ABR results, expressed as a percent.

Discussion

- The functional complexity of the brain as manifested in the EEG can be quantified objectively.
- 30-sec EEG epochs during sleep fall naturally into 3–12 groups, depending on the criteria chosen for cluster identification.
- The utility of ABR classification remains to be established.
- Clinical diagnosis is an area of potential application (7–10).

Potential Application of Sleep-Brain-State Classification to Clinical Diagnosis



*N is the empirically determined number of groups that results in optimal diagnostic accuracy.

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12. Any FDA-cleared device. General Sleep, Cleveland, OH. Camntech, Boerne, TX, as examples.

Abbreviations

ABR	Analysis of brain recurrence	EEG	Electroencephalogram
AFN	Average fractional number	NSRR	National Sleep Research Resource (https://sleepdata.org)
r	ABR variable "recurrence"		
d	ABR variable "determinism"	OSA	Obstructive sleep apnea
$\dot{r}$	Rate of change in r	PSG	Polysomnogram
$\dot{d}$	Rate of change in d	SE	Standard Error
BMI	Body mass index	SHHS	Sleep Heart Health Study
CA	Cluster analysis		