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Nonlinear Dynamics Analysis of Heart Rate Variability Signals to Detect Sleep Disordered Breathing in Children

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Abstract—**This paper reports a preliminary investigation to evaluate the significance of various nonlinear dynamics approaches to analyze the heart rate variability (HRV) signal in children with sleep disordered breathing (SDB). Data collected from children in the age group of 1-17 years diagnosed with sleep apnea were used in this study. Both short term (5 minutes) and long term data from a full night polysomnography (7-9 hours) were analyzed. For short term data, the presence of nonstationarity in the derived HRV signal was determined by calculating the local Hurst exponent. Poincaré plots and approximate entropy (ApEn) were then used to show the presence of correlation in the data. For long term data, the derived HRV signal was first separated into corresponding sleep stages with the aid of the recorded sleep hypnogram values at 30 seconds epochs. The scaling exponents using detrended fluctuation analysis (DFA) and the ApEn were then calculated for each sleep stage.**

Data from two sample subjects recorded for different sleep stages and breathing patterns were considered for short term analysis. Data from 7 sample subjects (after sleep staging) were considered for long term analysis. The accuracy rate of ApEn was about 72% for both long term and short term data sets. The accuracy rate of Alpha (α) derived from DFA for long term correlations was 57%. Further work is necessary to improve on the accuracies of these useful nonlinear dynamic measures and determine their sensitivity and specificity to detect SDB in children.

I. INTRODUCTION

A variety of respiration abnormalities that could occur during sleep are called sleep disordered breathing (SDB). Obstructive sleep apnea syndrome (OSAS) is the most common type of SDB. In OSAS, sleep is interrupted by repetitive pauses in breathing due to the collapse and/or blockage of the upper airway with a concurrent reduction in blood oxygen saturation (SaO_2), causing an arousal from sleep to breathe. This is called an *apnea or apneic event*. A person suffering from OSA will have a large number of apnea events during a full night sleep [1].

In children as in adults OSAS is also characterized by upper airway obstruction that occurs during sleep. Apnea and hypopnea events are complete or partial blockage of the airway during sleep, respectively. These lead to a fall in SaO2. Apnea and Hypopnea index (AHI) denotes the average number of apnea or hypopnea events that occur per hour during sleep. An AHI of less than 5 per hour is considered to be normal in adults. However, in children the number of events that occur per hour is less than that in adults. So, the standard criterion does not hold for children. Sleep labs consider 1 event per hour as abnormal for children. An apnea/hypopnea event is taken into consideration if it lasts for more than 10 seconds irrespective of subject's age. Consequently in children, if the event lasts for 2 or more breaths or less than 10 seconds, it is considered as an apnea/hypopnea event [2].

During sleep or rest, there is an increase in parasympathetic and an opposing decrease in sympathetic activities of the nervous system. During apneic events there is a drop in SaO2. This fall in oxygen level leads to an increase in the heart rate. Studies have shown that there is an increase in sympathetic activity during OSAS [3].

Different research groups around the world have performed extensive research using various analytical tools to detect OSA in adults. However, there is no substantial research in detection of pediatric OSA condition using nonlinear dynamic methods. In this study we used data collected from children to show whether nonlinear dynamic methods deployed for analysis of adult data are equally applicable to analyze pediatric data.

Nocturnal polysomonography (NPSG) is considered as a gold standard for detecting sleep apnea. However, nocturnal polysomnography tests are expensive (costing $2000 – $4000) and the number of sensors and wires attached to the body makes it extremely uncomfortable to have a good night's sleep. The easily accessible and relatively inexpensive electrocardiogram (ECG) signal was used to extract suitable nonlinear dynamic measures of HRV signal to detect sleep apnea in children.

It is well established that all physiological signals are nonlinear and nonstationary in nature. This nonstationarity in the signals can be detected using fractal theory.

The objective of this paper was to extract various nonlinear dynamic measures from both short term and long term HRV signals to explore whether these measures could prove useful and provide fairly accurate indices to detect SDB, specifically OSA from ECG signals in children.

II. MATERIALS AND METHODS

A. Polysomnography Data

Prerecorded data collected from children undergoing NPSG in the Adelaide's Women's and Children's Hospital (Sleep Disorder Unit) for suspicion of SDB. We used data from 2 subjects for short term and 7 subjects for long term analysis. ECG data were sampled at 500 Hz and digitized with a resolution of 16 bits/sample. For short term analysis, data used were 2-5 minutes in duration. The sleep data for long term analysis were from 7-9 hours in length (corresponding to a normal average sleep time for a child).

ECG data were resampled at 360 Hz for extraction of the HRV using an enhanced Hilbert transform method [4].

It has been speculated that analysis of HRV signal based on nonlinear dynamics methods might supply valuable information for physiological interpretation of this signal [5, 6]. In our work, we deployed approximate entropy, Poincaré plots and fractal exponents using singularity spectra to detect short term correlations. Approximate entropy, DFA and Poincaré plots were used to detect long term correlations in the data.

B. Approximate Entropy

Approximate Entropy (ApEn) is a "regularity statistic" used to compute the unpredictability of fluctuations in the heart rate time series [5]. The presence of repetitive fluctuation patterns in a time series makes it more predictable than a time series in which repetitive patterns are absent. ApEn shows the likelihood that a repetitive pattern is not followed by other repetitive patterns. A time series that has higher ApEn value is less predictable than one with a lesser ApEn which contains more number of repetitive patterns. ApEn was calculated as a robust quantitative descriptor of the degree of regularity of HRV signals [5].

C. Poincaré Plots

Poincaré plots are effective visualization tools for HRV signal analysis as they display the nonlinear aspects of the signal. In a Poincaré plot, the value of each interval is plotted against its successive interval. The results are quantified by using the ellipse fitting technique. Statistically the Poincaré plot displays the correlation between its successive intervals in a graphical manner. In nonlinear dynamics, it is the 2D reconstruction of the RR interval phase space, which is a projection of the reconstructed attractor that displays the dynamics of the heart rate variations [6]. The points appear as an elongated cloud of points. The points that are perpendicular to the line of identity are said to indicate short-term variability of the HRV signal. Given by,

$$SD_1^2 = \phi_{RR}(0) - \phi_{RR}(1) \qquad (1)$$

where, ϕ_{RR} is the auto-covariance function of the RR intervals and SD_1 is the standard deviation along the axis perpendicular to the dispersion of the points. The long-term variability is the dispersion of points parallel to the line of identity, given by

$$SD_2^2 = \phi_{RR}(0) + \phi_{RR}(1) \qquad (2)$$

SD_2 is the standard deviation along the axis parallel to the dispersion of the points in the Poincaré section. This approximation of the auto-covariance function is done assuming that the RR intervals are stationary in nature. The assumed axis for the Poincaré cloud is rotated by $\pi/4$ radians [6].

D. Detrended Fluctuation Analysis

Detrended Fluctuation Analysis (DFA) is used to detect long-term correlations in a seemingly non-stationary data. This method is a modified root-mean-square analysis of random walk, which quantifies the presence or absence of fractal correlation properties and has been validated for time series [7]. DFA provides the long-range correlations in a time series. The details of DFA calculations are described elsewhere [8].

E. Singularity Spectra Using Wavelet Transform

Physiological signals especially HRV are multi-fractal signals that require a larger number of indices to characterize their scaling properties. The sharp signal transitions create large amplitude wavelet coefficients. Singularities are detected by following the local maxima across various time scales [9]. The singularities of a multi-fractal signal vary constantly and the distribution of these singularities is important for analyzing the signal. The modulus maxima method can be used to calculate the singularity spectra to check the multi-fractal scaling of the physiological data [10]. To calculate the singularity spectrum D(α), the wavelet transform of the signal *Wf(u,s)* has a sequence of modulus maxima that converge towards v at fine scales. The calculation can be summarized as follows:

1. Compute the continuous wavelet transform *Wf(u,s)* and its local modulus maxima and chain the transform at each scale.
2. Compute the partition function *Z(q,s)* that measures the sum at a power *q* of all these wavelet modulus maxima. This partition function eliminates all maxima lines that do not propagate to the finest scales in the calculation of *Z(q,s)*.

$$Z(q,s) = \sum |Wf(u,s)|^q \qquad (3)$$

3. The scaling exponent $\tau(q)$ measures the asymptotic decay of *Z(q,s)* at fine scales *s*, it is computed with a linear regression of $\log_2 Z(q,s)$ as a function of $\log_2 s$:

$$\log_2 Z(q,s) \approx \tau(q)\log_2 s + C(q) \qquad (4)$$

4. The singularity spectrum is calculated by computing the Legendre Transform of $\tau(q)$ given by,

$$D(\alpha) = \min_{q \in \Re} (q(\alpha + 1/2) - \tau(q)) \qquad (5)$$

D(α) is plotted to obtain a convex spectrum [9]. The local Hurst exponent that is calculated from the convex singularity spectrum indicates the long range dependency embedded in a time series. For a healthy human heart, the Hurst exponent lies in the range of -0.1 to 0.5. For unhealthy human heart, there is a significant loss of the multi-fractal complexity by displaying a smaller range of h [11]. The Hurst exponent determined in this case was the point where q crosses zero. In the singularity spectra, *q=0* where D (α) is the maximum [9]. The singularities were determined using the WaveLab Software [12].

F. Integrated HRV Signal Analysis Environment

An integrated signal processing environment comprised of time-domain, frequency-domain, and nonlinear dynamic methods discussed above was developed to analyze the heart rate variability (HRV) signal. The signal processing algorithms and graphical user interface (GUI) were developed in Matlab 6.5 and LabVIEW 7.0, respectively. This environment enables the user to browse and select the desired length of ECG signal to be analyzed and perform various analyses by click of a button. The front panel of the

environment displays all the graphs and numerical parameters obtained and the user is presented with a report with the summary of all the analyses which can be saved or printed for future reference. Fig. 1 shows this GUI.

In designing the components of the GUI, we carefully considered their functional use and observed principles of consistency based on end-user feedback. This GUI makes the end-user feel competent [14]. Complex signal processing tasks are easy to perform and visualize for the sleep specialist. The GUI is easy to read due to it highly visible clarity. The GUI is efficient and simple to use, easy to remember, and errors are easy to recover from the software environment. The GUI is esthetically pleasing. It demonstrates high quality and clear graphics due to attention to detail and emphasis on salient features.

III. RESULTS AND DISCUSSION

The HRV signal analyses were carried out on the two different lengths of data: Short term data, 5 minutes in duration and long term data, a complete sleep cycle (ranging from 7-9 hours). The short term data were acquired from two children aged 10 years and 11 months, and 3 years and 8 months. Approximate entropy and singularity spectra were determined to detect multi-fractals in the data. Poincaré sections and continuous wavelet transforms were used as a visual display tool to show any non-stationarities in the given datasets.

The long term data were complete nocturnal sleep data with the corresponding sleep hypnograms from seven children with demographics shown in Table 1.

TABLE I
DEMOGRAPHIC INFORMATION ON SAMPLE SUBJECTS.

HRV File	*Sex*	*Age*	*BMI*	*Weight Status*
HRV002	M	1 year	19.3	Normal
HRV003	M	1yr 8 mo	17.6	Underweight
HRV004	F	6 yrs 1 mo	17.7	Underweight
HRV005	F	17 yrs 3 mo	32.3	Obese
HRV007	M	7 years 4 mo	16	Underweight
HRV008	F	8 years 5 mo	26.3	Overweight
HRV009	M	15 years 6mo	43.1	Obese

The data were segmented according to the sleep hypnogram graph that consisted of 30 second epochs of the sleep stages. The sleep stages in the hypnogram were NREM Sleep Stages '1' and '2' (light sleep), '3' and '4' (deep sleep), REM Sleep Stage and Wake Stage. The Sleep Stages were divided into 4 stages instead of 6, namely Light Sleep, Deep Sleep, REM Sleep and Wake Stage. DFA was used to perform scaling analysis. The value Alpha (α) was also determined from DFA.

For short term and long term data, Poincaré plots were used to show the correlations of the RR intervals. The ellipse fitting technique was used for short term data and not for long term data, as the ellipse could not fit larger data points efficiently. The ellipse fitted to short term data shows short term and long term variations in the HRV. A broader ellipse shows short term variation and a longer ellipse shows long term variation in the HRV data. Poincré plots also proved very helpful in visualizing the presence of any artifacts in the data.

A. Short Term Data

Short term correlations were calculated from HRV data 5 minutes in duration. Two data sets were considered with apnea events. The singularity spectrum was obtained from sample data segmented with respect to presence or absence of apnea events that occurred during REM and NREM sleep stages. The data fort the male child (age 3 years and 8 months) were used for Figs. 2 and 3. The ApEn and the Hurst exponents for different sleep states are shown in Table 2. The sleep stage with apnea events has a comparatively lower ApEn and local Hurst Exponent.

TABLE 2
THE APEN AND THE HURST EXPONENST OF DIFFERENT SLEEP STATGES.

Sleep Stage	*ApEn*	*Hurst Exponent*
NREM Sleep	1.2613	0.4254
REM Sleep	1.2787	0.4390
REM Sleep with Apnea events	0.8779	0.2220

The specificity, sensitivity and accuracy of the ApEn were calculated for the two sample data sets. The sensitivity was calculated to be 67%, specificity was calculated as 78% and the accuracy for ApEn for short term correlations was 73%.

In Fig. 3, both the ApEn and Hurst Exponents show the presence of apnea events of 10 or higher. Using the Wavelet Transform Modulus Maxima Method (WTMM) shows the loss of multifractal scaling. The Hurst Exponent calculated from the singularity spectrum using WTMM shows a low value [Table 1]. The small value of the Hurst Exponent and the narrow singularity spectrum signify a loss or degradation in the correlation of the signal. This breakdown or loss in fractal dynamics is due to uncorrelated randomness in the signal [10].

B. Long Term Data

The demographics of subjects used for long term correlation calculations are given in Table 1. The full overnight ECG data were analyzed for these subjects. The corresponding sleep hypnograms were recorded at epochs of size 30 seconds. The sleep hypnogram divides the sleep record into REM, NREM and Wake stages. The NREM stages are 1, 2, 3 and 4. The sleep hypnogram was slightly modified to differentiate it as light (NREM stages 1, 2), deep (NREM stages 3, 4), REM and Wake stages. Assigning different amplitudes for each stage plotted the modified hypnogram. See Fig.4.

DFA was performed for each sleep stage and the value of α was calculated for each stage for all the available data sets. The Hurst Exponent is related to α by $\alpha = 1 + h$. The Apnea/Hypopnea index (AHI) was calculated for all the sample data sets for specific sleep stages. The total number of apnea and hypopnea events that occurred during each sleep stage was recorded and divided by the length of each

sleep stage calculated in hours [13]. The subjects were considered to have apnea if the AHI was greater than 3.0.

The Alpha indicator for a high AHI was considered to be anything less than 1.0. For all values of Alpha greater than 1, the time series is said to be smooth [10]. The ApEn indicator was calculated based on the data length, the overall mean and standard deviation. The higher ApEn in a time series reflects a lesser predictability than a lower ApEn. All ApEn values greater than 0.9 corresponded to a high AHI value.

The accuracy for the Alpha exponent was calculated to be 57%. The sensitivity was 67% and specificity was calculated to be 47%. Two of the HRVs that were used to calculate the specificity and the sensitivity had more than 90% negatives as compared to other sample data sets, dropping the overall accuracy of the Alpha exponents. The low specificity shows that the signal has a very high number of false negatives.

The accuracy of the ApEn values determined from the long term sample data sets was 73%. The sensitivity was calculated to be 89%. However, the specificity was a low 57%.

V. CONCLUSIONS

The analysis of the HRV signal using nonlinear dynamic measures obtained from the pediatric data set is comparable to results published for adults. This indicates the fairly high accuracy rates for ApEn and also the small local Hurst exponent values for short term data sets. The smaller apnea events and the higher heart rates in children were successfully detected by using the ApEn. The Hurst exponent and the DFA resulted in an accuracy of 57%. The low specificity value for all calculated parameters is an issue that requires further investigation in pediatric sleep research.

Non-linear dynamics analyses were carried out on short term and long term data lengths to evaluate the significance of short term and term correlations on the data. The DFA showed an accuracy of 57%, it did not fair as well as the ApEn that provided an accuracy rate of 73%. Even though DFA showed a low accuracy rate, it is a very powerful tool to detect non-stationarites in the signal. The reason for the low accuracy rate of DFA compared to ApEn is due to the segmentation of the sleep data from the corresponding sleep hypnogram. The method used in this case was basic thresholding to eliminate any artifacts from appending the sleep stages from its corresponding hypnogram. A more robust method is required to segment the NPSG data for sleep stages. This method should be able to remove sleep stages that occurred for a short interval of time and eliminate the artifacts that are created from appending various sleep stages. These factors could help improve the accuracy of the DFA analysis.

More in-depth methods in using the powerful wavelet transforms for detecting multifractals in the signal need to be explored. Initial results as shown in Fig. 3 prove to be promising and the calculated Hurst exponents have given us some insight into the presence of apnea events in the data.

The shift of α_{max} for the data set with apnea events compared to that with normal breathing could be used as an indicator of the presence of apnea for a given number of apnea events in the sample data set. More detailed analyses need to be performed to address following issues: 1). The ideal length of the data (both short term and long term) to be analyzed; 2). The length of the scales for different data lengths; 3) The type of analyzing wavelets to be used and; 4) Other parameters that could be derived to detect any breakdown in the multifractality of the data.

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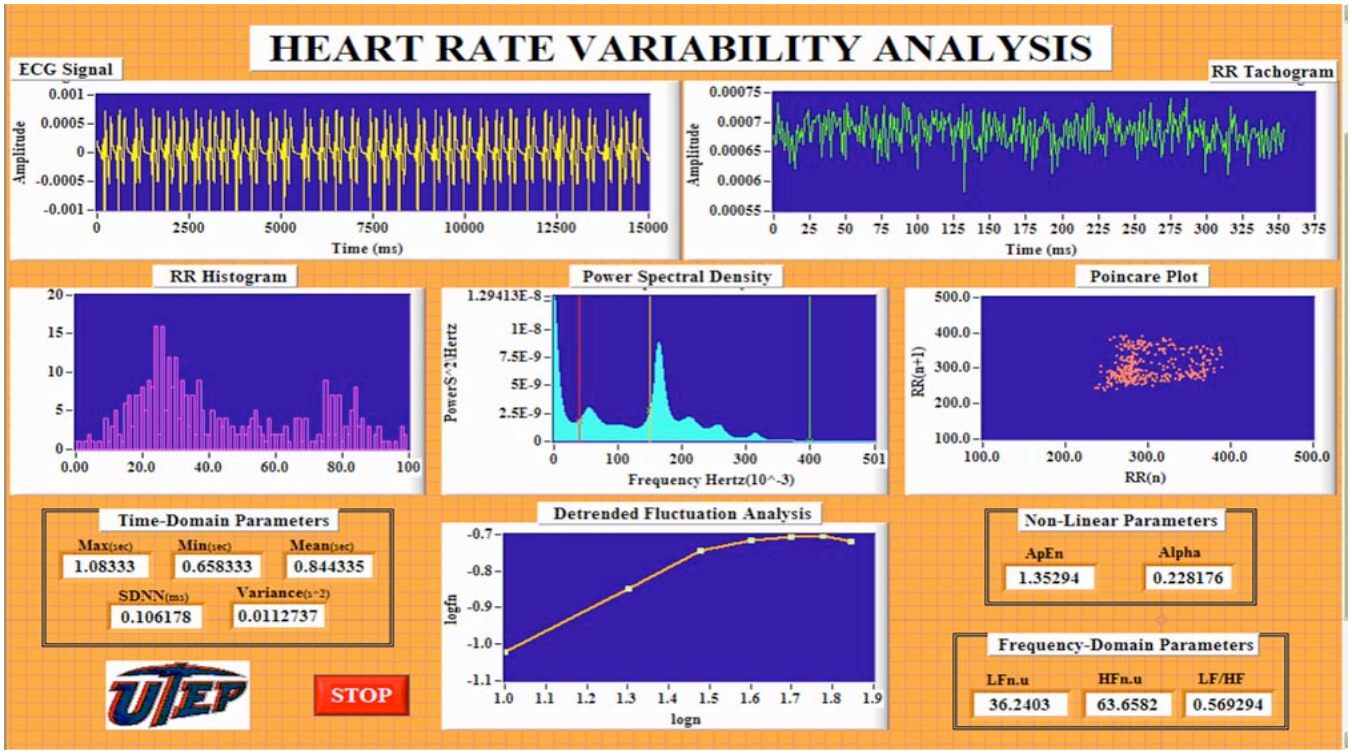

Fig. 1. Analysis of a child's HRV data with normal breathing during non-rapid eye movement NREM stage 4 sleep.

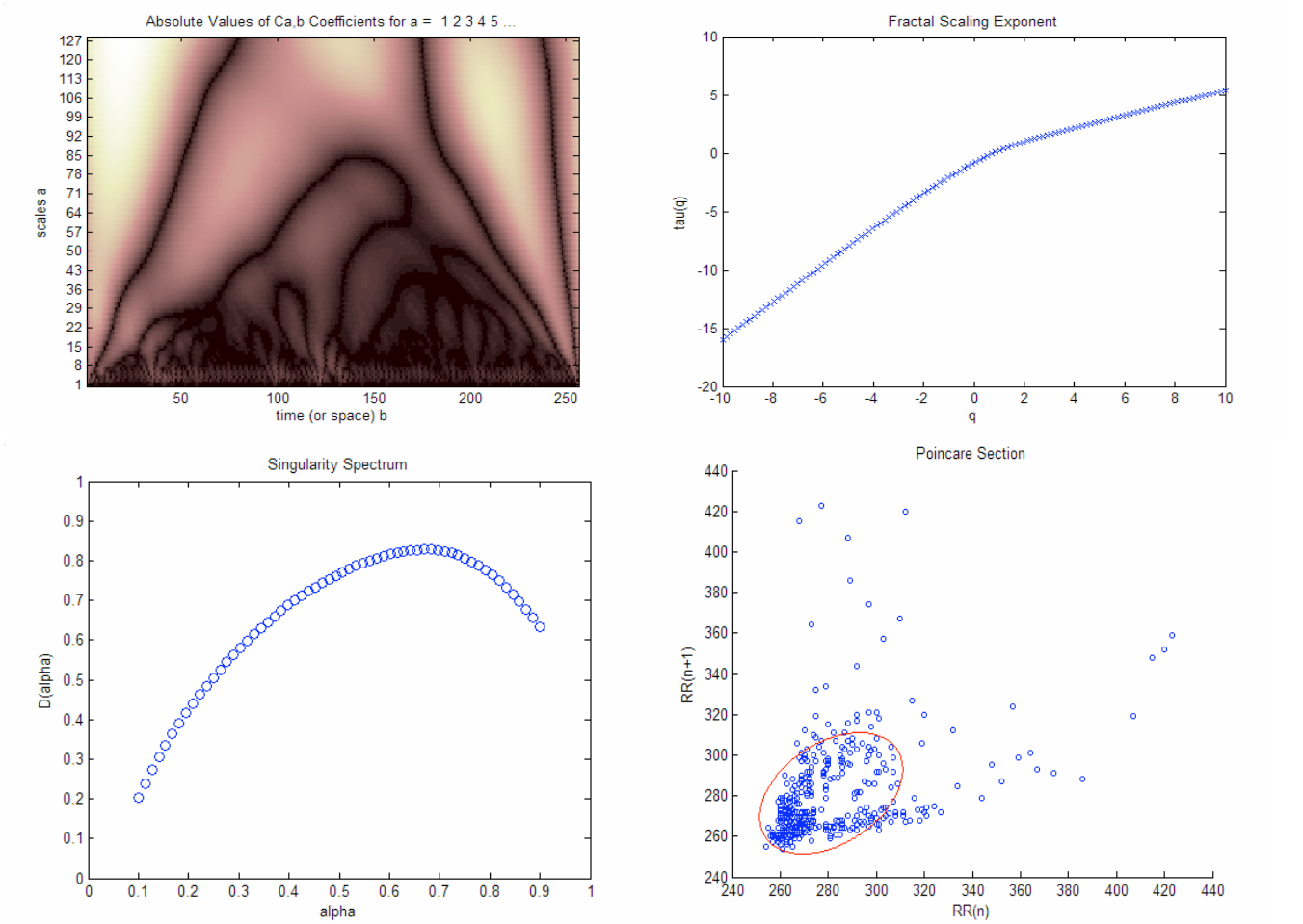

Fig.2. Continous wavelet transform, fractal scaling exponent, singularity spectra and Poincaré section for a sample data set with length 5 minutes (3 years and 8 month old male child).

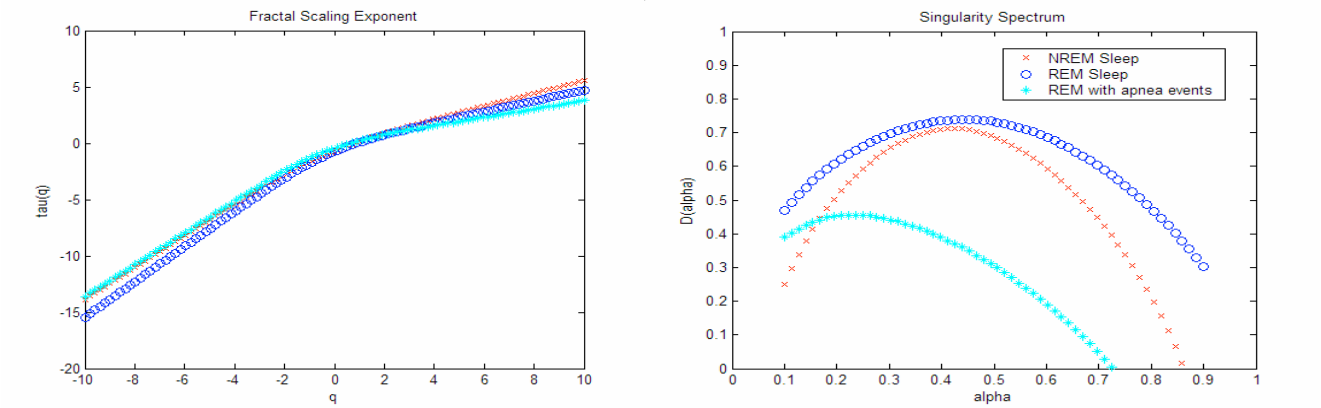

Fig. 3: The fractal scalar exponent and the singularity spectra plotted for REM, NREM and REM with apnea events. The normal sleep stages give a broad spectrum whereas the stages where there is apnea, the spectrum gives a much narrower range for the values of the Hurst exponents.

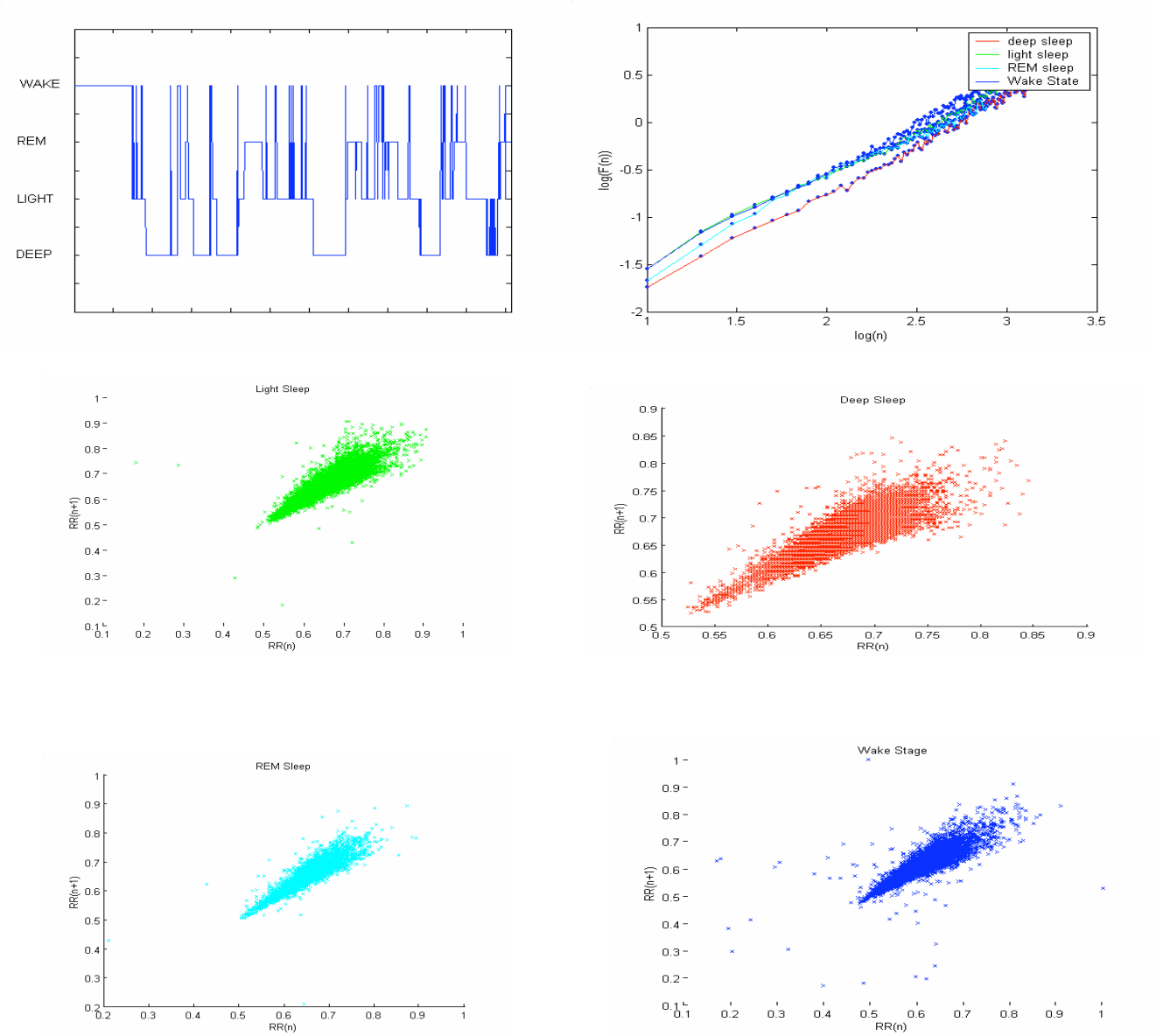

Fig. 4: Sleep Hypnogram, DFA and Poincaré sections for sample long term data collected from a female child, 6 yrs and 1 month old, during overnight sleep.