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



# Dynamic Data Analysis in Obstructive Sleep Apnea

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***Abstract*—Obstructive Sleep Apnea (OSA) is a serious disease caused by the collapse of upper airways during sleep. The present method of measuring the severity of OSA is the Apnea Hypopnea Index (AHI). The AHI is defined as the average number of Obstructive events (Apnea and Hypopnea, OAH-events) during the total sleep period. The number of occurrence of OAH events during each hour of sleep is a random variable with an unknown probability density function. Thus the measure AHI alone is insufficient to describe its true nature. We propose a new measure *Dynamic Apnea Hypopnea Index Time Series* (DAHI), which captures the temporal density of Apnea event over shorter time intervals, and use its higher moments to obtain a dynamic characterization of OSA.**

## I. INTRODUCTION

OBSTRUCTIVE Sleep Apnea (OSA) is a serious sleep disorder caused by repeated collapse of upper airways during sleep leading to cessation of breathing (Apnea), resulting in oxygen de-saturation and frequent arousals. Although by itself is not life-threatening, OSA could lead to many serious health complications such as reduction in cognitive function, cardiovascular diseases, stroke, decreased quality of life, fatigue and increased vulnerability to accidents [1-3].

About 24% of men and 9% of women in the US population of aged between 30-60 years may fall within the Medicare guidelines [1] for receiving treatment, whereas 2-4% of the total population displays full symptomatic forms of the disease [1].

One major criterion [AASM Taskforce] for OSA detection is the overnight monitoring for obstructed breathing events during a test called Polysomnography (PSG) which requires a full-night sleep session in the hospital. The severity of OSA is measured using a measure called the Apnea Hypopnea Index (AHI). The AHI is defined as the number of OAH events averaged over the total overnight sleep duration [3].

Even though the AHI is used as the de-facto "gold standard" of measurement [4], it, unfortunately, does not enjoy widespread credibility among sleep researchers or clinicians. Studies have found that AHI does not correlate well with sleepiness and fatigue, [5, 6] which are two major symptoms of OSA.

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OAH events do not occur uniformly spread throughout the sleep period, as implicitly assumed in the usage of AHI index. In contrast, the distribution of events is a complicated phenomenon, which shows various characteristics such as clustering and peaking. A patient may experience an extremely high number of OAH events spread over a combined duration of, say, two hours and then remain relatively unremarkable for the rest of the time. The AHI index, which averages the number of events over the *total sleep period*, will be low in such a case. Thus the subject is likely to be classified as 'normal', even if he is fully symptomatic and suffers severely from the disease. This paper is concerned about such situations, and addresses the insufficiency of AHI index in the PSG-based diagnosis of OSA.

We propose a new concept, the *Dynamic Apnea Hyponea Index Time Series (DAHI)*, which represents the number density $\{d_i \mid, i = 1,2, ..\}$ of OAH events over shorter time intervals, T (where T<< 8 hours). The quantities $d_i$ can be considered as drawn from a discrete random variable with an unknown probability density function $f(d_i)$. Thus, the traditional AHI index closely corresponds to the *mean* value of the $d_i$ distribution.

As well known from probability theory the mean value (the *first moment of* $f(d_i)$) alone is not sufficient to adequately describe an arbitrary probability density function. In particular, the *Theory of Moments* [7] in Probability states that an arbitrary density function requires *moments* of all orders, for a complete description. In this paper, we exploit this environment and propose to estimate higher moments ($2^{nd}$ moment and higher) of $f(d_i)$ based on the DAHI time series $\{d_i \mid, i = 1,2, ..\}$. Our particular interest is in the second, third and fourth central moments which are closely related to the variance, skewness and the kurtosis, some of the common measures used to describe data.

The variance provides us information on the spread of $d_i$ about its mean value, and the skewness carries information on the symmetry about the mean. Kurtosis is a measure related to the 'peakedness', and will convey information on the 'clustering' of OAH events along the time axis.

The "histogram" is the graphical summery of the distribution of the data. Histogram could be used to graphically show the following features; a) the centre (mean) of the data, b) the spread (variance) of the data, c) symmetry (skewness) of the data, d) peakedness (kurtosis) of the data and e) presence of isolated (outliers) values of data.

With DAHI and its moments and the histogram, it is possible to obtain a dynamic picture of the patient's suffering. The DAHI and the indexes generated from

moments will aid in comprehensive description of the OSA, to facilitate better remedial action.

## II. METHOD

The method proposed in this paper depends on having full access to routine PSG results. The information available to us include the (i) start and end times of the overall PSG test, (ii) start and end times of OAH events and the event classifications into apnea/hypopnea, and (iii) sleep and wake status of the patient during the PSG test.

In order to estimate the DAHI we first divide the sleep time into epochs $E_i$, i =1,2,…..L/T, each of length T seconds. The value L is equal to total duration of PSG.

The DAHI ($d_i$) of each $E_i$ is derived as follows;

$$d_i = \frac{(\sum OAH\ events\ in\ E_i) \times 3600}{(T_i - T_{ai})} \quad (1)$$

where $T_{ai}$ is the awake duration (if any) in the epoch $E_i$.

We calculate $\eta_T$ and $\sigma_T$ using the formulae

$$\eta_T = \frac{\sum d_i}{N} \quad \text{and} \quad \sigma_T^2 = \frac{\sum (d_i - \eta_T)^2}{N-1} \quad \text{where } N = \text{L/ T.}$$

We calculate the skewness and the kurtosis using formulae

$$skewness = \frac{\sum_{i=1}^{N} (d_i - \eta_T)^3}{(N-1)\sigma^3} \text{ and } kurtosis = \frac{\sum_{i=1}^{N} (d_i - \eta_T)^4}{(N-1)\sigma^4}.$$

Once we have the mean, variance, skewness and the kurtosis we could characterize the distribution of $d_i$. The standard deviation $\sigma_T$, the measure of deviation of $d_i$ from the mean $\eta_T$ will describe the degree of change in the occurrence of OAH events among the time epochs $E_i$. Larger the $\sigma_T$ less accurate is the AHI in describing the severity of the occurrence of OAH events. The skewness, the measure of asymmetry of data ($d_i$) around the sample mean $\eta_T$. The kurtosis, the peakedness of the distribution, will describe whether there are few instances of very highly concentrated events of OAH with relatively low concentration of OAH events during rest of the time.

The estimation of variance, skewness and kurtosis will make it possible to provide a better description of the OAH event occurrence. Use of AHI based on the single parameter mean, to characterize the occurrence of OAH events is only a partial representation of the nature of the sleep disorder.

## III. RESULTS AND DISCUSSION

We analysed PSG results from 10 patients (5 Male and 5 Female) obtained during routine PSG tests conducted at the Princess Alexandria hospital, in Brisbane. The data consists of full PSG data, as obtained from a *Compumedics*® sleep acquisition system. They are accompanied by an edited annotation file with an event-by-event description of features such as Apneas (obstructive, hypopnea, central, mixed) and sleep stages. The average AHI values of the ten patients were in the range 4.1-94.4. The table I gives a general description of the patient sample used in our analysis.

Table I. Patient General Information.

| Patient No | Age | Gender | BMI | AHI |
|---|---|---|---|---|
| 1 | 63 | F | 20.6 | 4.1 |
| 2 | 52 | F | 21.6 | 5.1 |
| 3 | 44 | F | 38.1 | 13.8 |
| 4 | 50 | M | 42.2 | 19.5 |
| 5 | 62 | M | 28.1 | 32.8 |
| 6 | 53 | M | 32.2 | 30.4 |
| 7 | 71 | F | 29.7 | 33.6 |
| 8 | 46 | F | 25.1 | 35.8 |
| 9 | 74 | M | 29.1 | 75.4 |
| 10 | 27 | M | 45.5 | 94.4 |

Table II shows AHI and $\eta_T \pm \sigma_T$ derived from PSG data of the ten patients analysed in 15, 30 and 60 minutes (γ = 900, 1800, 3600) epochs. The value of $\sigma_T$ increases with the severity of OSA but as the T increases i.e. the size of the epoch increases $\sigma_T$ decreases and become zero when T is equal to the total sleep time. This shows that when the OAH events are averaged over larger durations the information on the distribution of OAH event occurrence is lost gradually.

Table II. AHI and $\eta_T \pm \sigma_T$ for T = 900, 1800, 3600

| Patient No | $\eta_{900} \pm \sigma_{900}$ | $\eta_{1800} \pm \sigma_{1800}$ | $\eta_{3600} \pm \sigma_{3600}$ |
|---|---|---|---|
| 1 | 4.1 ± 7.4 | 3.8 ± 6.9 | 3.8 ± 5.0 |
| 2 | 4.9 ± 9.2 | 4.9 ± 8.1 | 4.8 ± 5.6 |
| 3 | 13.2 ± 11.4 | 13.0 ± 9.5 | 13.1 ± 6.6 |
| 4 | 17.1 ± 17.3 | 18.6 ± 14.1 | 16.7 ± 11.8 |
| 5 | 31.7 ± 28.0 | 29.34 ± 26.4 | 29.19 ± 17.3 |
| 6 | 31.3 ± 23.8 | 27.3 ± 21.6 | 30.3 ± 19.2 |
| 7 | 33.9 ± 36.4 | 30.2 ± 29.2 | 32.1 ± 26.3 |
| 8 | 39.3 ± 39.4 | 28.4 ± 32.7 | 32.4 ± 26.9 |
| 9 | 80.1 ± 115.8 | 52.1 ± 45.1 | 68.7 ± 44.3 |
| 10 | 95.4 ± 64.6 | 76.9 ± 51.3 | 82.8 ± 44.2 |

Figs. 1, 2 and 3 shows the sleep distribution and the DAHI for 900, 1800 and 3600 second epochs for patients 2, 4, 7 and 10. The vertical bars represent the epochs with green (darker colour) representing the sleep time and yellow (lighter colour), the wake time within the epoch. The scatter

plot represents the DAHI ($d_i$) in each epoch. The read solid line marks the average DAHI ($\eta_T$) and the blue line represents the average plus standard deviation ($\eta_T + \sigma_T$).

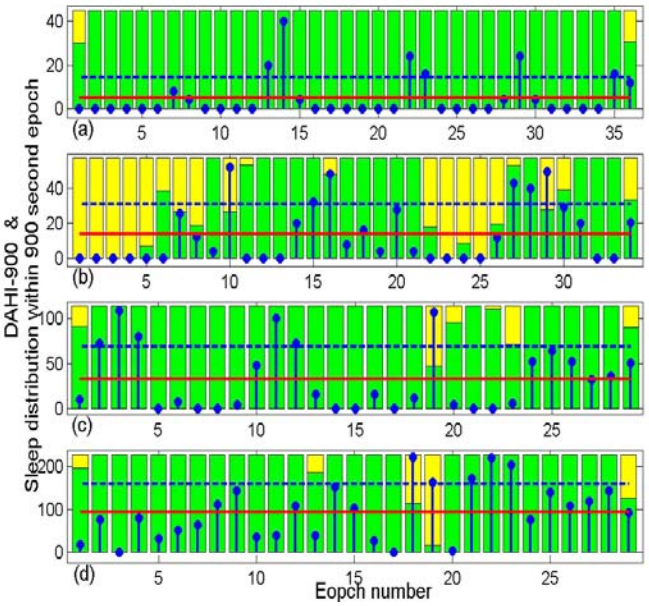


Fig. 1 DAHI_900 and sleep distribution within each 900s epoch vs the Epoch number for (a) Patient no 2 (b) Patient no 4 (c) Patient no 7 (d) Patient no 10. $\eta_T$ and $\eta_T + \sigma_T$ are marked using solid and dashed lines respectively.

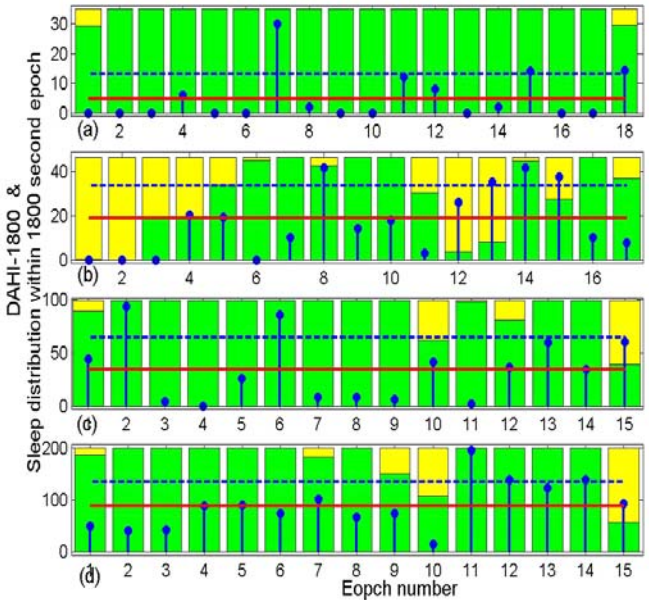


Fig. 2 DAHI_1800 and sleep distribution within each 1800s epoch vs the Epoch number for (a) Patient no 2 (b) Patient no 4 (c) Patient no 7 (d) Patient no 10. $\eta_T$ and $\eta_T + \sigma_T$ are marked using solid and dashed lines respectively.

Fig. 1(a) indicates how a patient with $\eta_T = 4.8$ had suffered from several short periods of severe AHI attacks lasting for approximately one to two epochs. As per Fig.1(a) during such attacks DAHI has reached values as high as 40. If only AHI value is used to diagnose, this patient will be categorized as suffering from mild OSA or a normal person. With DAHI it is evident that the patient needs medical attention despite the low AHI.

The clustered nature of OAH attacks are again demonstrated in fig. 1(b) & (c) with added information on the severity of suffering. In the case of patient no 10 shown in fig.1(d) is an example of OAH events spreading almost over the entire night.

Figs. 2 and 3 show how information such as the severe OAH event densities and pattern of their occurrence are gradually being lost as the epoch duration is increased. As the epoch duration increases the standard deviation decreases showing lesser variation on the OAH occurrence distribution giving rise to reduced information of the patient's suffering.

Figure 4 shows the histograms for two patients show that the distribution of DAHI is arbitrary. This can be confirmed by the higher moments of DAHI given in Table III.

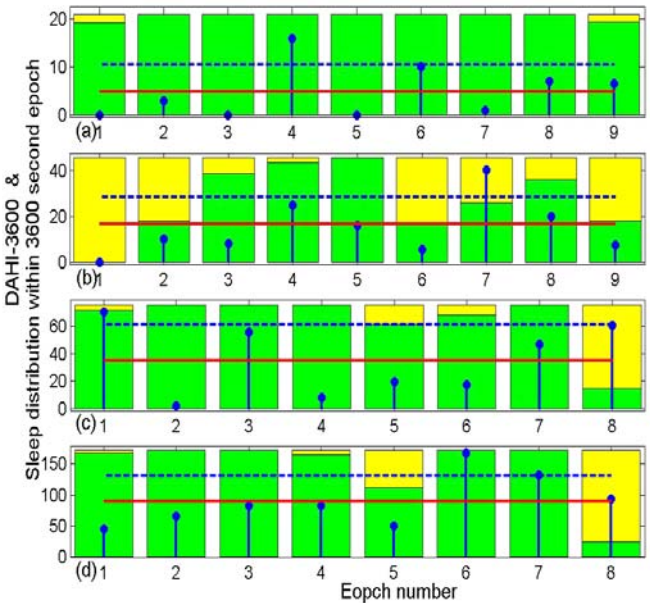


Fig. 3 DAHI_3600 and sleep distribution within each 3600s epoch vs the Epoch number for (a) Patient no 2 (b) Patient no 4 (c) Patient no 7 (d) Patient no 10. $\eta_\gamma$ and $\eta_\gamma + \sigma_\gamma$ are marked using solid and dashed lines respectively.

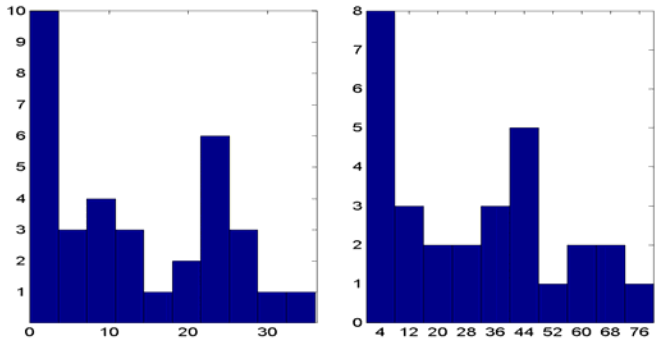

Fig.4 Histograms of DAHI for two patients showing the nature of the distribution

The Table III shows the first four moments of $D_{900}$ the standard deviation $\sigma_{900}$, Skewness and the Kurtosis. From table 3 we can see that patients No 1 & 2 have almost equal mean ($=\eta_{900}$) values. They also have similar values for all parameters estimated and tabulated in table III. The high Kurtosis indicate the clustered nature of the DAHI in both these patients as evident in the DAHI plot for patient no 2 in fig. 1(a). This means that patient suffers relatively high number of OAH events only on few isolated instances and rest of the time the patient either suffers from no or very small number of OAH events. The higher $\sigma_{900}$ of patient 2 indicates that greater variation of DAHI in this patient compared to patient no 1. The relatively high skewness in DAHI of patients 1& 2 indicate that they have asymmetric distributions of the DAHI value.

Table III. Moments of $D_{900}$

| Patient | mean | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|
| 1 | 4.14 | 7.42 | 2.23 | 7.79 |
| 2 | 4.88 | 9.24 | 2.15 | 7.20 |
| 3 | 13.23 | 11.37 | 0.26 | 1.64 |
| 4 | 17.15 | 17.27 | 0.65 | 2.10 |
| 5 | 31.73 | 28.02 | 0.37 | 2.11 |
| 6 | 31.31 | 23.84 | 0.28 | 1.90 |
| 7 | 33.85 | 36.36 | 0.80 | 2.36 |
| 8 | 39.25 | 39.43 | 0.47 | 1.71 |
| 9 | 80.11 | 115.78 | 3.21 | 14.30 |
| 10 | 95.43 | 64.63 | 0.31 | 2.11 |

The patients no 5 & 6 too have similar mean values but have are considerably large difference in $\sigma_{900}$. They both have skewness close to 0 indicates that they have symmetric distributions around the mean value indicating smooth increase and decrease in occurrence of OAH events. Though the kurtosis values are not high, they being close to 3 (2.11 and 1.9) indicates that the two patients exhibit near normal OAH distributions.

The patient no 9 displays very high $\sigma_{900}$ indicating much variance from the mean value. This patient has a DAHI distribution which is asymmetric and high peaked.

## IV. Conclution

The single Index AHI has limited ability to describe the distribution of OAH event occurrence. The DAHI can provide a dynamic picture of the OAH occurrence with better description of OSA events. The Indices such as Skewness and Kurtosis describes the spread and cluster and they could be used to identify patients having similar AHI values but different patterns of OAH event densities.


## Acknowledgement

The author wish to thank Dr. Craig Hukins, Ms. Lyn Fraser and Kevin Hanssen, Princess Alexandra Hospital, Australia for access to routine PSG data. This work was partly sponsored by a University of Queensland Early Career Researcher Grant (#2003001515) to the second author.


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