In early 90’s the National Center on Sleep Disorders served to have pauses in their breathing during sleep at least eight percent of responders experienced or have been observed to institute a standard system for visually scoring stages of sleep [4]. This standard was rapidly implemented after its publication.

Studies have shown that sleep-related problems affect more than 50 to 70 million Americans [1]. Furthermore, in 2005, the National Sleep Foundation (NSF) carried out an annual sleep poll that included a representative sample of US adult population [2]. The NSF study concluded that of the 1,506 respondents, 26% met the Berlin questionnaire criteria, indicating a high risk of OSA, and the risk of OSA increased with age up to 64 years. In addition, it was found that as many as one in four American adults could benefit from the early detection of OSA. Other epidemiologic data suggest that 18 million American adults have sleep apnea. During childhood there is a prevalence of two or three percent. The same study found that eight percent of responders experienced or have been observed to have pauses in their breathing during sleep at least three nights per week.

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The plan also highlights that quantification of breathing abnormalities during sleep, such as sleep apnea, represents a challenge that must be addressed. The NCRS issues essential directives on sleep-wake stage research topics, allowing the medical community by means of new and sophisticated computer-based signal processing methodologies (both linear and non linear approaches), to timely diagnose and treat patients during an early stage of the disorder. It also indicates that these new methods must enable the design of portable ambulatory systems to measure sleep and other physiologic variables at home providing high accuracy measurements. One of the major limitations in diagnosing Sleep Breathing Disorders (SBD) is the need for relatively complex procedures as well as bulky and costly equipment such as a polysomnograph.

In this paper we present a compendium of features extracted from EEG and HRV signals acquired from patients suffering from sleep apnea. These features could then be fed into a classifier system such as an artificial neural network (ANN) or a neuro-fuzzy system for further classification.

1.1 Sleep
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The main objective of this work is to explore possible relationships among sleep stages and apneic events and improve on the accuracy of algorithms for sleep classification and apnea detection. Electroencephalogram (EEG) and Heart Rate Variability (HRV) will be assessed using advanced signal processing approaches such as Detrend Fluctuation Analysis (DFA). In this paper, we present a compendium of features extracted from EEG and Heart Rate Variability (HRV) data acquired from twenty five patients (21 males and 4 females) suffering from sleep apnea (age: 50 ± 10 years, range 28-68 years undergoing polysomnography). Polysomnographic data were available online from the Physionet database. Results show that trends detected by these features could distinguish between different sleep stages at a very significant level (p<0.01). These features could prove helpful in computer-aided detection of sleep apnea.

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lication in 1968 under the auspices of the UCLA Brain Information Service as ‘A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects’. The R&K acronym was named after Alan Rechtschaffen and Anthony Kales, editors and co-chairpersons of the Committee. The proposal to standardize recording techniques and scoring criteria was planned to increase the comparability of results reported by different investigators. This method of scoring implies a visual screening on polysomnogram recordings, yielding an epoch-by-epoch approach. The standard time period of observation is 30 seconds for any tracing (e.g. EEG). The epoch-by-epoch approach does not imply that each epoch is considered in isolation. There are many cases where the stage assigned to a particular epoch depends in part on the polygraphic features of preceding and succeeding epochs.

Epoch classification depends mainly on EEG, EOG and EMG signals. Thus, the gold standard for sleep stage classification defines two groups of stages for sleep depth determination. First, Non-Rapid Eye Movement Stage (N-REM), which is subdivided in four stages. Secondly, Rapid Eye Movement Stage (REM), which has high ocular activity presence in the EOG recordings.

1.2 Sleep apnea
Sleep apnea is defined as cessation of breathing for 20 seconds or longer (or for a shorter period of time if accompanied by bradycardia, cyanosis, or pallor). Basically, apnea can be subdivided into three different categories. Obstructive Sleep Apnea (OSA) is due to complete closure (collapse) of the throat. This is most likely to happen during sleep because that is when the soft tissue at the back of the throat is most relaxed. Nine out of ten patients with sleep apnea have this type of apnea. This type of sleep apnea is also present in children.

OSA, which is the most common form of apnea, occurs when mechanical or structural abnormalities in the upper airway cause interruptions to breathing during sleep. When the throat muscles collapse, the muscles of the diaphragm struggle harder and harder against the blocked passage, without success. At this time, carbon dioxide builds up in the bloodstream and after a minute or more, the brain is screaming out for oxygen, then the subject suddenly struggles to wake up and the tongue and throat muscles tighten, allowing oxygen to flow into the lungs. In the worst case scenario, the apnea event lasts between 10 to 60 seconds. Instead of being alarmed and staying awake, the victim immediately goes back to sleep again. This cycle is repeated several times during one night [5]. As a consequence of the quality of sleep being compromised by the apnea events, the sleep debt increases. This makes the subject to suffer from the most common apnea related symptoms such as extreme fatigue, high blood pressure, drowsiness, etc. In worse cases it can lead to fatal heart attacks and strokes.

Central Sleep Apnea (CSA) is associated with problems in the central nervous system. In CSA, part of the brain that controls breathing does not start or maintain the breathing process properly. Therefore, the muscles used in breathing do not get the activation signal from the brain. Either the brain does not send the signal, or the signal gets interrupted. It is the least common form of apnea and often has a neurological cause. Mixed sleep apnea is a combination of central and obstructive sleep apnea.

2. Methods
2.1 Data
Data were available on the Physionet website for downloading in EDF format. Subjects were randomly selected over a 6-month period from patients referred to the Sleep Disorders Clinic at St Vincent's University Hospital, Dublin, for possible diagnosis of obstructive sleep apnea, central sleep apnea or primary snoring [6]. The 10-20 standard electrode placement system was used for EEG recordings. Polysomnograms were obtained using the Jaeger-Toennies system. A sample rate of 128 Hz was used for EEG and ECG (modified lead V2) tracings.

2.2 EEG Features
Relative Percent Spectral Energy Band
As described before, EEG rhythms and sleep stages are strongly related. The spectral energy band is the energy contained in a well-defined range of frequencies, and the ratio between the total power content (100 percent of the energy) and a spectral energy band (the amount of energy that belongs to this range) is defined as the relative percent energy band (RPEB) [7].

For this analysis, the total power content (TPC) or $P(f)$ was computed (from 0.5 to 45 Hz). Then, $P(f)$ was divided into seven different energy bands (see Table 1), and the respective power energy bands (PEB) were calculated. The relative percent spectral energy band (RPEB) was then expressed as:

$$RPEB = \frac{PEB}{TPC} \times 100$$

Table 1: Spectral Energy Bands.

<table>
<thead>
<tr>
<th>Band energy</th>
<th>Bandwidth (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta 1 ($\delta_1$)</td>
<td>0.5-2.5</td>
</tr>
<tr>
<td>Delta 2 ($\delta_2$)</td>
<td>2.5-4</td>
</tr>
<tr>
<td>Theta 1 ($\theta_1$)</td>
<td>4-6</td>
</tr>
<tr>
<td>Theta 2 ($\theta_2$)</td>
<td>6-8</td>
</tr>
<tr>
<td>Alpha ($\alpha$)</td>
<td>8-12</td>
</tr>
<tr>
<td>Beta 1 ($\beta_1$)</td>
<td>12-20</td>
</tr>
<tr>
<td>Beta 2 ($\beta_2$)</td>
<td>20-45</td>
</tr>
</tbody>
</table>
**Hjorth Parameters**

Hjorth formulated three parameters capable of characterizing any signal and its derivatives in the frequency and time domains. The Hjorth parameters are called normalized slope descriptors because they can be defined as first and second derivatives. They are named: Activity (a measure of the mean power), Mobility (an estimate of the mean frequency) and Complexity (an estimate of the frequency spread or bandwidth) [7].

Their computation in discrete time involves the variance ($\sigma_0^2$) of $x[n]$ (the segment of the EEG signal to be analyzed) as well as the variance of the first and second derivatives of $x[n]$ ($\sigma_1$ and $\sigma_2$, respectively). These measures are described by the following formulas:

- **Activity**
  \[
  \text{Activity} = \sigma_0^2 \tag{2}
  \]

- **Mobility**
  \[
  \text{Mobility} = \frac{\sigma_1}{\sigma_0} \tag{3}
  \]

- **Complexity**
  \[
  \text{Complexity} = \sqrt{\frac{\sigma_2^2}{\sigma_1} - \frac{\sigma_1^2}{\sigma_0^2}} \tag{4}
  \]

Given that Hjorth parameters are based on variances, the computational cost is affordable compared to other methods.

**Harmonic Hjorth Parameters**

The harmonic Hjorth parameters [7,8], which are the frequency-domain versions of the Hjorth parameters are: the center frequency ($f_c$), the bandwidth ($f_o$), and the value at the central frequency ($P(f_c)$). Their calculation requires power spectrum estimation $P(f)$ of the epoch and they are defined as follows:

- **$f_c$**
  \[
  f_c = \int_{f_{\text{low}}}^{f_{\text{up}}} P(f) \, df / \int_{f_{\text{low}}}^{f_{\text{up}}} P(f) \, df \tag{5}
  \]

- **$f_o$**
  \[
  f_o = \sqrt{\int_{f_{\text{low}}}^{f_{\text{up}}} (f - f_c)^2 P(f) \, df / \int_{f_{\text{low}}}^{f_{\text{up}}} P(f) \, df} \tag{6}
  \]

- **$P_{f_c}$**
  \[
  P_{f_c} = P(f_c) \tag{7}
  \]

**Itakura Distance**

Itakura distance is used widely in speech processing applications to measure the distance between 2 AR processes [9, 10]. Here the Itakura distance was used to measure the similarity of a baseline EEG epoch (Awake, Stage1, Stage2, Stage3, Stage4, REM) with the rest of the epochs in the EEG vector. If we let the baseline epoch $x[n]$ be an AR process given by $a_x = [1 -a_1 -a_2 \ldots -a_p]$ and the segment $y[n]$ to be compared to it given by $a_y = [1 -a_1 -a_2 \ldots -a_p]$, then the minimum squared error (MSE) for the baseline process is:

\[
\text{MSE}_{x,x} = a_x^T R_x(p) a_x \tag{8}
\]

where the $R_x(p)$ is the autocorrelation matrix for the baseline epoch of size $p+1$:

\[
R_x(p) = \begin{bmatrix}
  r_x(0) & r_x(1) & \ldots & r_x(p) \\
  r_x(1) & r_x(0) & \ldots & \ldots \\
  \ldots & \ldots & \ldots & \ldots \\
  r_x(p) & \ldots & \ldots & r_x(0)
\end{bmatrix} \tag{9}
\]

Similarly the MSE of the other processes passing through the baseline model will be:

\[
\text{MSE}_{x,y} = a_y^T R_x(p) a_y \tag{10}
\]

The Itakura distance of the baseline to the other epochs is defined as:

\[
d_{I,x,y} = \log \left( \frac{\text{MSE}_{x,y}}{\text{MSE}_{x,x}} \right) = \log \left( \frac{a_y^T R_x(p) a_y}{a_x^T R_x(p) a_x} \right) \tag{11}
\]

The closer to $a_x$ the parameter set $a_y$ is, the smaller the MSE$_{x,y}$, since $a_y$ is obtained to produce the minimum squared error. A distance closer to zero indicates a ratio closer to one, thus a closer match between the baseline $x[n]$ and segment $y[n]$. Furthermore, an analysis of how well $y[n]$ is modeled via the AR parameters of $x[n]$ can be done, thus the new Itakura distance is:

\[
d_{I,x,y} = \log \left( \frac{\text{MSE}_{y,x}}{\text{MSE}_{y,y}} \right) = \log \left( \frac{a_y^T R_y(p) a_x}{a_y^T R_y(p) a_y} \right) \tag{12}
\]

Combining $d_{I,x}$ and $d_{I,y}$, we obtain the symmetric Itakura distance as:

\[
d_I(x,y) = 0.5 \left( d_{I,x,y} + d_{I,y,x} \right) \tag{13}
\]

The Awake stage segment is set as the baseline and it is compared with the subsequent epochs. Itakura distance obtained with different AR model orders reveals that regardless of the model order “p”, it changes significantly when brain activity changes [11].

**Detrended Fluctuation Analysis (DFA)**

This method has been devised to detrend variability in a sequence of events [12]. The DFA computation involved the calculation of the summed series:

\[
y(k) = \sum_{t=1}^{k} \{X(t) - E[X]\} \tag{14}
\]

where $y(k)$ is the $k$th value of the summed series, $X(t)$ represents the sequence (epoch to be evaluated) at time $t$, and $E[X]$ denotes the average of the entire time series $[X(t)]$. The summed series was divided into sub sequences of length $m$ and a least squares fit was performed on each of the data segments, providing the detrends for the individual segments. De-
trending was carried out by subtracting the local trend \( y_m(k) \) in each segment.

Finally, the root-mean-square fluctuation of the resulting series was then:

\[
F(\ m) = \left\{ \frac{1}{L} \sum \left[ y(k) - y_m(k) \right]^2 \right\}^{1/2}
\]

A linear relationship on a log-log plot indicates the presence of power law (fractal) scaling. Under such conditions, the fluctuations can be characterized by a scaling exponent \( \alpha \), the slope of the line relating \( \log F(m) \) to \( \log m \).

### 2.3 Heart Rate Variability (HRV) Signal Features

#### Time-domain Features of HRV Signals

Time-domain analysis of the derived HRV signal was performed as detailed in [13]. We calculated Max RR, Min RR, Mean RR, SDNN (standard deviation of R to R intervals) and Variance.

#### Frequency-domain Parameters of HRV Signals

The PSD of HRV signals were computed using the autoregressive (AR) spectral estimation method as detailed in [8]. Then VLF, LF, HF, LF norm, HF norm, LF/HF ratio were extracted.

#### Approximate Entropy (ApEn)

It is a nonlinear dynamics parameter of HRV Signals. ApEn is a “regularity statistic” method that quantifies the unpredictability of fluctuations in a HRV time series [9].

### 3. Results

Statistical measures were computed to show the tendencies for each stage (mean, standard deviation, maximum value and minimum value). These tendencies are summarized in box-plots (Figures 1-18) the middle line represents the mean value of the feature for all 25 patients.

The relationships among sleep stages and brain rhythms (or in this case, RPEB’s) are presented in Figures 1 - 7. RPEB Delta 1 statistics supports that Stage4 has delta rhythms as its major content (as established by RK rules) and RPEB theta 1 and theta 2 are higher in Stage1 as expected (Figures 3 and 4). Beta waves, the fastest rhythm, are strongly present in Awake stage (Figures 6 and 7).

Furthermore, Stage4 presents the largest activity and mobility than any other sleep stage (Figures 8 and 9). Perhaps, it has the lowest complexity in the signal, making the Awake stage the one with the largest complexity mean value (Figure 10). Central frequency also provides a true tendency. Awake Stage presents the highest value and, Stage4 the lowest one (Figure 11).

The bandwidth feature extraction algorithm showed that the rhythms present in Awake Stage are wider in frequency range than those in NREM and REM stages (Figure 12).

The value at the central frequency illustrate how this measurement of the power spectrum is higher for Awake stage. (Figure 13). Itakura distance shows that the distance between baseline (an Awake segment) and Awake stage is the smallest, and it becomes larger for deeper sleep stages (Figure 14). DFA shows the tendencies found in sleep stages. Stage4 has the lowest \( \alpha \) mean value, in contrast to the Awake stage, which is the one with the largest scaling exponent \( \alpha \). (Figure 15).

It is important to note that the REM statistics are always overlapping with at least one other stage statistics (as described in the introduction, in REM stage the brain activity is similar to Stage1 brain activity. This justifies the similarity of the statistics for both stages).

### 4. Conclusions

The analysis of the polysomnographic data and extraction of sensitive measures from it is a challenging task due to the complexities and variability of the acquired physiological signals. The results demonstrate that the extracted features provide promising possibilities to distinguish between different sleep stages: Awake, N-REM and REM stages. It is also evident that REM is quite difficult to separate from other sleep stages due to its spectral overlap with those of the other stages. The EOG signal or fuzzy classification scheme may provide a more discerning signal or method for the detection of REM activity. Therefore, detection of the REM stage from EEG signal analysis remains a challenging research topic that warrants further investigation. Itakura distance appears to be a good quality indicator to segregate the Awake stage from N-REM and REM stages. The main disadvantage is that a baseline is required to measure the distance among other epochs and therefore, baselines must be previously scored.

The overall results demonstrate that the extracted EEG features provide promising possibilities to distinguish between different sleep stages: Awake, N-REM and REM stages at a very significant level (p<0.01).

### 5. References


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Figure 9. Mobility ($p<0.01$)

Figure 10. Complexity ($p<0.01$)

Figure 11. Central Frequency ($p<0.01$)

Figure 12. Bandwidth Frequency ($p<0.01$)

Figure 13. Value at the Central Frequency ($p<0.01$)

Figure 14. Itakura Distance ($p<0.01$)

Figure 15. DFA-alpha ($p<0.01$)

Figure 16. HRV - LF ($p>0.01$)

Figure 17. HRV - ApEn ($p>0.01$)

Figure 18. HRV – RR Standard Deviation ($p>0.01$)