Sleep apnea related micro-arousal detection with EEG analysis

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ABSTRACT

Arousals are regarded as one of the most influential causes of daytime sleepiness and are frequent occurrences in patients with breathing disorders during sleep. These arousals can result from external stimuli or from an internal stimulus, interpreted as having a sleep protective role. This study will focus on automatic detection of arousals, especially those caused by sleep-related breathing disorders (apnea, hypopnea), based on all-night measurements of several subjects classified as having upper airway resistance syndrome (UARS). The detection algorithm follows the scoring rules defined by the American Sleep Disorder Association (ASDA) and the detection algorithm is based on frequency analysis of about 8 hours of sleep on a single EEG channel, and using other available channels to validate the results. We concluded that the automatic detector has a detection rate of about 70% which is comparable to reported visual analysis inter scorer agreement rates.

INTRODUCTION

The high frequency components of the EEG signal are closely related to the level of consciousness of the subject. As the activity increases, the dominating frequency shifts to higher frequencies and lower amplitude. We will focus on alpha (α, 8-12Hz), beta (β, 16-20Hz) and also on lower frequency rhythms delta (δ, 0.1-4Hz) and theta (θ, 4-8Hz) during sleep.

The detection of breathing events during sleep with only one EEG sensor becomes extremely difficult, given that many of them occur through REM sleep, where the EEG recording has a lot of high frequency noise.

The presence of non respiratory event-related arousals, presents a problem for automatic detection of apneas and hypopnoea, thus we will proceed to their study in order to find criterion for their differentiation.

METHODOLOGY

We had access to all-night measurements of several subjects classified as having upper airway resistance syndrome (UARS) with recordings of sensors such as: electroencephalographic sensor (EEG) (128Hz), electrocardiogram (EKG) (256Hz), airflow (16Hz), chest (16Hz), abdomen (16Hz), PAT (128Hz), PES (16Hz), cannula (16Hz).

The EEG channel C3-A2, according to the 10-20 international system is used for analysis.

The EKG recording wasn’t used in our study, although it could be useful to observe a decrease of the heart rate during sleep apnea. The airflow sensor measures the nasal airflow (16Hz) through temperature changes. Thus we observed a small decreasing variation of the mean value measured by the airflow sensor during sleep apnea. Both chest and abdomen sensors measure the contractions and dilations of the thorax, thus showing how the subject is breathing. The PAT (Periphery Arterial Tonus) sensor is applied on one of the subject’s finger and was used to measure the mean propagation speed of the heart pulse through the blood vessels.

The PES sensor measures the esophageic pressure, while the cannula recording is useful to perceive breathing efforts from the subject and it is given by a balloon pressure sensor located on the nose cannula. When analysing the subjects breathing, we should remember that it can partially occur through the lower airway, thus being important to consider chest and abdomen sensors, in order to avoid detecting false upper airway breathing efforts.

CLASSIFICATION CRITERIA

Since we were interested in the classification of breathing-related arousals, a set of scoring rules was necessary. We used the scoring rules published in 1992 by the ASDA (American Sleep Disorder Association), which state that an arousal is a noticeable change in EEG by the abrupt shift to higher dominant frequencies which can
include alpha, theta and other frequencies above 16Hz under certain conditions. In REM sleep, these conditions need the confirmation of EMG activity. Since we don’t have an REM detector, we compiled the applied scoring rules as follows:

- It’s necessary to be in sleep state for at least 10 seconds to classify an arousal. So a minimum interval of 10 seconds is required to classify a new arousal.
- The dominant frequency shift should be noticeable for at least 3 seconds.
- No distinction made between REM or NREM arousals.

**EEG ANALYSIS**

The EEG recordings are commonly contaminated with artifacts such as: eye movements, eye blinks, cardiac signals and muscle noise, which lead to serious problems on the EEG interpretation and analysis. Many methods have been proposed to remove artifacts from EEG recordings, like Independent Component Analysis (various EEG channels) using EMG recordings and the scoring rules defined in [2]. Another way of doing this, is based on the rejection of EEG segments with unacceptable noise levels. The first method is based on the idea that the signal measured in each EEG sensor, which varies with its location on the scalp, is mainly influenced by the closer brain cells and results from a combination of all brain activity. As a result, if we have various sensors available, removing the noise from the closer brain cells in each recording would be a good way to eliminate artifacts. However, this solution isn’t completely effective because eye blinks and muscle noise have a greater amplitude than the signal in study. Other noise sources like eye movements or cardiac signals occur frequently enough to make this a hard job. The second method, based on the use of EMG and EEG together, has given the best results when applied to breathing-related micro-arousal detection. Since we only have access to a single EEG channel and no EMG records, these methods can’t be considered and EEG segments with excessive noise will have to be rejected thus some apnoeas won’t be detected.

In order to accelerate the search, we chose to run the entire EEG recording through consecutive 8 seconds samples. The sample length was based on the minimum interval of 10 seconds between two sleep apneas, thus with 8 second samples we’ll never lose the detection by having two apneas in the same sample interval, and we also obtain a simpler and faster algorithm. FFTs is applied to 2 second windows with Hamming windowing, in order to set a time evolution of the frequencies within the 8 seconds samples. Evolution of alpha activity is then analysed as we search for its maximum value. Next, we centre a 28 second window, which allows us to observe the evolution of the alpha activity maximum (called T0) before the sleep apnea and after the arousal. The next step will be to ensure low alpha activity within the first 10 seconds before the event. This way we ensure that there are no artifacts and that this could be a sleep apnoea of at least 10 seconds. Next, we’ll test if the sudden increase of alpha activity (must be at least 150% of the mean low activity level of alpha), is within the ASDA time limits, and if it is, it must return to low activity levels within the next seconds (otherwise the subject will be awake).

![Figure 2 - Apnea with arousal](image-url)
Based on the information collected from the training all-night measurements, we created a small statistical data-base to define the classifier’s parameters. Thus we studied several visually scored sleep apneas and assuming a normal distribution (see Figure 1) for the low activity level intervals of alpha and beta, we calculated mean and standard deviation for these frequency bands.

The goal of alpha low and alpha high separation was to achieve a more accurate detection, but that revealed to be useless after a comparison with a simpler classifier which only uses one alpha band and results in a faster algorithm, given that we’ll have less calculations (one time evolution calculation less) in each test cycle.

The graphics presented in Figure 2 show several sensor recordings (EEG signal, airflow, chest, abdomen and time evolution of alpha, beta, delta and theta band activity level) near the energy maximum of alpha band activity T0 (following the start of the micro-arousal) from the training all-night measurements of a visually detected sleep apnoea. Note also the beta band activity level maximum and low activity level of delta low and delta high, which characterizes a micro-arousal.

As each subject presents EEG signals with different characteristics - like mean activity value of alpha, beta, delta and theta bands - standardized parameters had to be used to filter low activity segments of alpha and beta. This way the analysis will only be effective with all-night measurements of adult subjects given that children, because of their smaller thorax and superior breathing rhythm (which means smaller micro-arousal and apnoea minimum duration), won’t allow us to apply the ASDA scoring rules as described in [2].

RESULTS

The automatic analysis of EEG frequency bands alpha and beta (following the ASDA scoring rules) over the entire all-night measurements revealed several examples of micro-arousal related events.

The implemented automatic detector classified successfully 8 out of 10 sleep apneas, (only 10 were considered after rejecting some REM segments as described above) with micro-arousals present in the training file, but also 143 micro-arousals related with other breathing events referred on Table 1, and 2 events with no noticeable micro-arousal (see results at Table 4). An example of these events is showed in Figure 3.

The automatic detector scored successfully 78% of the micro-arousals present on the training file without classification of each event.

<table>
<thead>
<tr>
<th></th>
<th>PES</th>
<th>PAT</th>
<th>AR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PES</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>PES</td>
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<td>PES</td>
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<td>AR</td>
</tr>
<tr>
<td>4</td>
<td>PES</td>
<td>-</td>
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<td>5</td>
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<td>AR</td>
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<tr>
<td>6</td>
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<td>PAT</td>
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</tr>
<tr>
<td>7</td>
<td>-</td>
<td>-</td>
<td>AR</td>
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</table>

Table 1 – Type of events

<table>
<thead>
<tr>
<th>Classification</th>
<th>Events Detected</th>
<th>Accuracy</th>
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</thead>
<tbody>
<tr>
<td>Apneas w/ arousal</td>
<td>22</td>
<td>26.2%</td>
</tr>
<tr>
<td>Apneas w/o arousal</td>
<td>62</td>
<td>73.8%</td>
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</tbody>
</table>

Table 2 – Sleep apnea related events

<table>
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<tr>
<th>Classification</th>
<th>Events Detected</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apneas w/ arousal</td>
<td>8</td>
<td>5.2%</td>
</tr>
<tr>
<td>Events w/ arousal</td>
<td>143</td>
<td>93.5%</td>
</tr>
<tr>
<td>Without arousal</td>
<td>2</td>
<td>1.3%</td>
</tr>
</tbody>
</table>

Table 3 – Successfully scored sleep apnea related micro-arousals within total scored micro-arousals

<table>
<thead>
<tr>
<th>Classification</th>
<th>Events Detected</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apneas w/ arousal</td>
<td>16</td>
<td>5.2%</td>
</tr>
<tr>
<td>Other events</td>
<td>288</td>
<td>94.1%</td>
</tr>
<tr>
<td>Without arousal</td>
<td>2</td>
<td>0.7%</td>
</tr>
</tbody>
</table>

Table 4 – Results using the training recording NPH.REC

The time evolution of alpha and beta frequencies during PES events is very similar to the observed during sleep apnea (see Figure 3), which presents a serious problem since we’re using a single EEG channel recording. The same problem affects the events listed on Table 1. This set of events was visually classified from the training file by an expert who scored events noticeable at PES, PAT and EEG channels. The interest on their study comes from the fact that 1, 3, 5 and 7 are micro-arousal related events.

We used the airflow channel to filter the interesting breathing events (such as sleep apneas), given that it allows an easy identification of the breathing blocks. Thus, we used a filter in series with the automatic detector, that is, we selected the events with stationary airflow for about 10 seconds of the sleep apnea from the total detected events. Within the 28 second window centred on T0, we derive the airflow signal in each point, and if it remains under 30% of the normal value for at least 10 seconds, the event is scored as sleep apnea. With this method we’ve eliminated 140 breathing events that weren’t apneas and 2 fragments which weren’t micro-arousals or sleep apneas.

Thus using the described automatic detector with the airflow based filter, the combined effectiveness will reach about 74% successful detections and 26% false alarms.

The results obtained with the test all-night measurements are presented in Table 5. In spite of the differences between the test and training recordings, the automatic detection resulted in similar percentages of false detections of micro-arousals.
CONCLUSION

Many times the scoring differs from expert to expert while analyzing the same data, in part because of the ambiguity when applying the selection criteria.

Also, it is difficult to express the selection criteria, used and perfected by experience, in a mathematical way, because even when using the proper tools, a rigorous refining of the classifiers is still necessary, as well as the fact that the classifiers must work with different subjects. The same algorithm can show very good or very bad results according to its restrictions.

In the diagnosis of sleep obstructed by apneas and hypopnoeas it is preferable to have a false alarm than a false detection, causing little restriction in the choice of barriers.

Analysing the events scored by the automatic detector, we found about 70% of micro-arousals related to apnea or hypopnoea and 30% of micro-arousals related with other events. Thus, we concluded that the automatic detector has a reasonable efficiency of about 70% which is acceptable compared with visual analysis of standard polysomnographic signals.

REFERENCE

1 Stanford University Sleep Disorders Clinic, Stanford, California.
2. Department of Psychology, Unioiversity of Melbourne, Australia.
“Upper Airway Resistance Syndrome: Central EEG Power and changes in breathing effort”


