Apnea episodes detection using sleep microstructure features in EEG C4 channel in polysomnography

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Abstract

An algorithm to detect sleep apnea events in EEG signals is developed. A-phases from the sleep microstructure are segmented and used to perform the discrimination. It has been shown that using the duration and the period between A-phases with an appropriate decision rule the model can achieve a specificity of 89% and a sensibility of 60%.

1. Motivation

Obstructive sleep apnea (OSA) with ICD code G47.33 is a frequent breathing affection in which the respiratory flow stops reducing below to 10% of normal levels for at least 10 seconds during sleep [1]. OSA is estimated to affect at least 2% to 4% of people with a rising tendency in the last ten years. It is more prevalent in men than women and the prevalence tends to increase with age. Some other OAS associated factors are obesity, smoking, alcohol, excessive daytime sleepiness, previous cardiovascular diseases, diabetes mellitus, etc [2].

OAS can cause oxygen desaturation, daytime sleepiness and fatigue, among others, leading to long-term complications that affect the quality of life of those undiagnosed and therefore untreated patients. In addition to lifestyle changes, treatments can be classified in the ones that try to reduce breathing interruptions like PAP therapies, nasal surgeries, etc. [3]; and the ones that try to increase the capability to stay asleep like opioid antagonists, Angiotensin-converting enzyme (ACE) inhibitors, etc.

The evaluation of the last group of treatments leads to the necessity of creating models that characterize the apnea event at EEG. Micro-awakening has been shown to be highly related to the physiology of sleep alterations, this phenomenon can be isolated or repetitive receiving the name of cyclic alternating pattern (CAP), this pattern can be affected due to different factors that alterate its periodicity potentially offering a quantitative measurement of the alterations during sleep [4].

The sleep can be divided between NCAP periods and CAP periods, at the same time, these CAP periods can be divided between A-phases that are related with these micro-awakenings and B-phases. Both facts converge in the interest in segmenting A-phases and evaluate its capacity to predict apnea episodes.

2. Objectives and study description

The creation of an algorithm that is able to segment and characterize A-phases from an EEG. Furthermore, it uses these features to predict apnea events in the EEG.

The algorithm is developed from a polysomnography (PSG) made for a study realized at Hospital Universitario de Mostoles on October 25, 2022. The subject is a woman who is between 50 and 60 years old and suffers from OSA.

The PSG were recorded with a 24-monopolar-channels EEG and 14 additional channels including nasal flow signal. It was recorded with a sampling rate of 256 Hz. The PSG were processed with a High-Pass filter of 0.15 Hz and a Low-Pass filter of 67 Hz.

Some annotations of the development of the study were given, including the opening and closing of the eyes at the beginning and when the time the subject woke up.

3. Methodology

Previous to the development of the algorithm, the apnea events are obtained from the nasal flow signal. It will allow the evaluation of the performance of the model.

In the algorithm, the A-phases will be segmented from the EEG recorded at channel C4. Then, the duration of the A-phases and they will be characterized by the duration and the time from the last phases. A simple model based on thresholding both characteristics is proposed.

3.1 Pre-processing

During the development, two signals will be used. The PSD of those signals is computed to evaluate if there is some noise. Nasal flow does not show any noise, however, EEG C4 shows some noise at 50 Hz caused by the power supply.

So, a notch filter is applied at 50 HZ. It is configured as a FIR filter with a windowed time-domain designed method using a Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation.

The signals are chopped from the beginning to time 123.3 seconds to avoid the time the subject falls asleep and from 28883 to the end of the records since it is given the annotation of the end of the studio.

3.2 Apnea detection in air flow signal

Applying the clinical criteria to the nasal flow signal, it is desired to know where the breath is below 10% of the baseline value for at least 10 seconds. For this purpose, the root-mean-square (RMS) with a window of ten seconds [5].

$$RMS = \frac{1}{2561}\sqrt{\sum_{i=0}^{2561} x[i]^2} \approx \frac{\sum_{i=0}^{2561} |x[i]|}{2561}$$

A new signal is obtained computing the RMS from the five seconds from the beginning of the signal and five seconds before the ending as no padding is used. The baseline estimation of the signal is obtained by computing the median to avoid the apnea interference that would be caused by estimating the baseline with the mean. Then, the apnea events are calculated as:

$$RMS < Baseline * 0.1$$

At this the true values mean that an apnea event has started five seconds before the first true value and ends five seconds after the last True values. To compute these values the signal is interpreted as an integer signal and then differentiated, being the ones initial event signals five seconds shifted to the right and the negative ones end event signals five seconds shifted to the left.

3.3 A-phases segmentation

In parallel, the evaluation of the sleep microstructure starts with the segmentation of the A-phases. Different methods had been proposed to archive the CAP features. We use a method proposed by Barcaro et al [4]. that allows the quantitative description of sleep microstructure through the A-phases segmentation.

The method relies on the computation of some frequency descriptors. So as a first step the spectrogram of the EEG signal is computed. The parameters of the spectrogram are a window of 128 segments with an overlapping of 124 segments leading to a loss of resolution from 256 segments per second to 64 segments per second.

Then, two mean amplitudes in the frequency band of 1-4Hz are computed, one over a time of two seconds that is closely related to the sleep microstructure and a second one over a time of 64 seconds that is closely related to the sleep macrostructure. Then the descriptor is computed as:

$$\mu_\delta(t) = \frac{C_{\delta,2}(t) - C_{\delta,64}(t)}{C_{\delta,64}}$$

From this descriptor, A-phases can be segmented by applying two threshold $\mu(t) \succ 0$ is used to obtain the length of the A-phases and $\mu(t) \succ 1$ is used to classify the A-phases.

To perform the segmentation the first signal is processed in a similar way than 3.2 but taking into account that the time shift is greater since a window of 64 seconds is being used. A second step is added to avoid classifying false A-phases, only keeping those one that at some point reaches one. So, they are evaluated at the second threshold and they are kept if the sum of the segmented period in the second threshold signal is greater than one.

3.4 Feature extraction and model set up

Those A-phases can be characterized by the duration and the time between phases. For that purpose the duration is calculated as the sample the phase end minus the sample the phase start. The time between phases is calculated as the time the phase starts minus the time the last phase ends. In the case of the first phase the last phase end is considered the zero. Then, the duration and the time between phases are divided by 64 to return the feature to seconds. In the case of the time between phases the first derivative is also considered.

The A-phases characterized show information about what is happening with microstructure. Since abrupt rupture of the sleep microstructure are connected with alteration during sleep phases much shorter than normal and with a reduction of interphase larger than normal are found.

The model proposed, set A-phases with a duration shorter than one second and with a change of interphase given by the first derivative of the interphase lower than 200.

4. Results

4.1 Air flow signal apneas results

The nasal air flow signal shows that the patient has suffered six apnea events during the study and hypopneas are not calculated as they are not under consideration.

Since preprocessing with a moving average filter has not been done with the nasal air flow signal, coherence post processing is needed as an event can be split in more than one by small abrupt increase of the RMS signal. Initial results show nine events but two of them were split events.

Apnea	Start	End	Duration
Apnea 1	531351	539931	134s
Apnea 2	572719	580753	125.5s
Apnea 3	1378536	1386588	125.84s
Apnrea 4	1602563	1610667	126.62s
Apnea 5	1712368	1720589	128.45s
Apnrea 6	1740419	1751159	167.81s

Tabla 1. *Table with the apnea events, with its starts, its ends and its durations. The starts and the ends are referenced with the number of samples that will correspond to the signal with resolution of 64 samples per signal and starting 32 seconds after the signal slice for the study. The duration is in seconds.*

As can be seen in Table 1 the apnea events last between 125 seconds and 168 seconds. Four of them last less than 130 seconds. Regarding the post processing one was interpreted as two and another one as three.

4.2 A-phases results

After computing the descriptor, there were 3358 candidate segments of which 169 resulted in an A-phase. The mean duration of the A-phases was 2.55 seconds with a standard deviation of 1.88 seconds. The mean duration of the period between phases was 165.9 seconds with a standard deviation of 220.7 seconds.

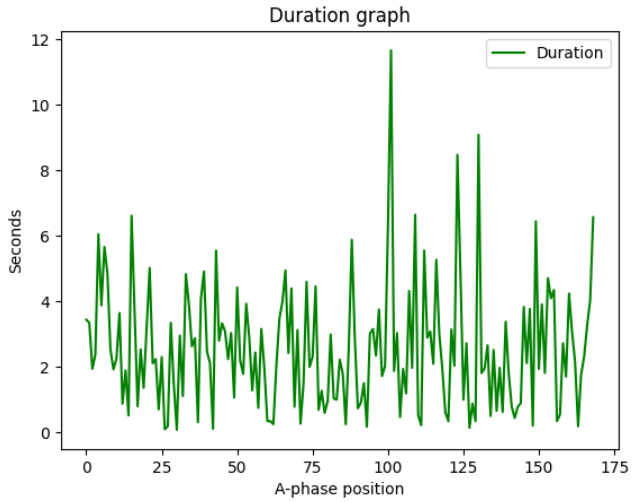

Figura 1. *A-phases duration*

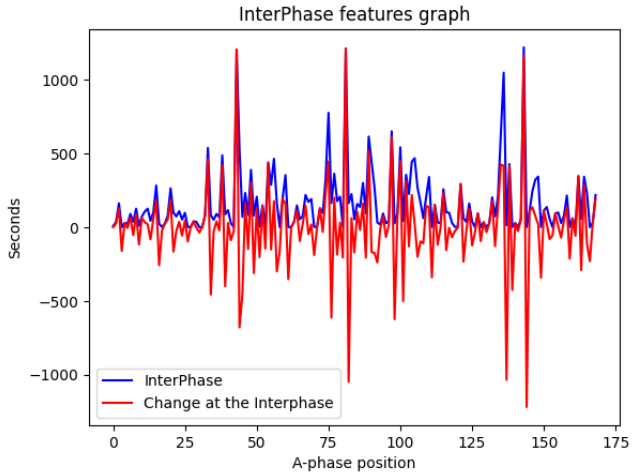

Figura 2. *Inter-phases and change*

From figure 1, it is seen that short duration A-phases, subject of interest at this work, are well characterized by a short duration while interphase duration is better discriminated by abrupt reduction in the change of the interphase.

4.3 Model evaluation

In order to evaluate the model it is necessary at first instance to determine which A-phases can be considered candidates to be predictive of an apnea. The criteria established is that an A-phase can predict an apnea if it appears during the apnea or if it is one of the two phases that goes right after the end of the apnea.

Defining the specificity as the probability of an A-phase that does not correspond to an apnea showing in the model that an apnea event is not associated. 109 phases results in no apnea detection of which 98 does not match with any apnea leading to an specificity of 0.89.

Defining the sensibility as the probability of an A-phase that does correspond to an apnea showing in the model that an apnea event is associated. 5 phases results in apnea detection of which 3 match with any apnea leading to an sensibility of 0.6.

A-phase	Duration	InterPhase derivative	Truth
57	0.750000	-300	0.0
61	0.343750	-352	1.0
111	0.218750	-340	0.0
144	0.890625	-1220	4.0
163	0.187500	-291	6.0

Tabla 2. *Table with the A-phases that were classified as apnea events markers with the duration, the Interphase derivative and the truth (0 mean no apnea related).*

The sensibility shows that the A-phase segmentation and the decision model are a robust criteria for discriminating Apnea effects in the EEG. At the specificity, it is observed that there are few phases that follow the same microstructure break. That agrees with the literature since sleep microstructure can be altered by other awakening events and other sleep disorders.

Therefore, further research is needed to discriminate between these awakening events and other sleep disorders. Also, it is needed to go deep in the criteria to establish and generalize the decision model.

4. Conclusions

At this work, it has been shown the feasibility of using the A-phase segmentation method proposed by Barcaro et al [4]. to detect Apnea events in EEG signals.

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