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A Novel Method to Assist the Detection of the Cyclic Alternating Pattern (CAP)

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Abstract—**This study proposes a novel method to assist the detection of the components that build up the Cyclic Alternating Pattern (CAP). CAP is a sleep phenomenon formed by consecutive sequences of activations (A1, A2, A3) and non-activations during nonREM sleep. The main importance of CAP evaluation is the possibility of defining the sleep process more accurately. Ten recordings from healthy and good sleepers were included in this study. The method is based on inferential statistics to define the initial and ending points of the CAP components based only on an initialization point given by the expert. The results show concordance up to 95% for A1, 85% for A2 and 60% for A3, together with an overestimation of 1.5 s in A1, 1.3 s in A2 and 0 s in A3. The total CAP rate presents a total underestimation of 7 min. Those results suggest that the method is able to accurately detect the initial and ending points of the activations, and may be helpful for the physicians by reducing the time dedicated to the manual inspection task.**

I. Introduction

During the analysis of the electroencephalography records (EEG) in sleep, the physicians have observed some patterns in the EEG that are superimposed to the natural oscillations of the sleep stages [1]. These patterns present characteristics of repetition and frequency that are related to the sleep stage, sleep cycle and sleep condition. These features have been broadly studied in normal and pathologic conditions allowing for a deeper understanding of the sleep process [2-3]. This phenomenon is called Cyclic Alternating Pattern (CAP), since the patterns appear quasi-periodically during sleep.

The superimposed patterns are named Phases A and are subdivided into three subtypes based on the characteristics of the oscillations present in the Phase A:

a) A1, composed by strong delta waves (0.5 Hz - 4 Hz).

b) A2 with rapid EEG oscillations with 20 % - 50 % of the total activation time.

c) A3 also with rapid activities, especially beta (16 Hz - 30 Hz), with more than 50% of the total activation time.

The shortest instance of the CAP is a CAP sequence. A CAP sequence is defined by three or more consecutive Phases A, separated by segments of background activity, that follow a specific rule based on their temporal relation and duration. The separation between two Phases A must be shorter than 60 s and longer than 2 s and at least 3 Phases A have to obey this rule to define a CAP sequence [1]. Finally from the CAP sequences a clinical index is defined which is called CAP rate. This index is computed by summing up the total duration of CAP sequences and dividing it by the total NREM sleep time. The CAP rate is low during normal sleep and high in pathological conditions.

As mentioned previously, the Phases A must be found in order to compute the CAP rate. However, this task is hard and tedious, and the training process is long before a physician is expert enough to score a recording. After locating the Phases A, the second step is to identify the transition points between the Phases A and the background activity, in order to determine the duration of each activation. Generally, this process is even more difficult than identifying the Phases A, since sometimes the transitions are not clear. Furthermore, after some time of scoring, the expert may be tired and lose concentration, and as a consequence, some of the borders may be incorrectly located. These problems make CAP analysis a hard task, which is prone to errors and subjectivity. In addition, as commented in the definition of the Phases A, they present segments with specific oscillations but the distribution of these segments could be random. Thus, the automatic detection of the borders becomes a challenge.

To solve this problem, some studies have analyzed the Phases A by obtaining indices such as power, complexity and spectral components. Most studies have used these indices to develop algorithms for automatic CAP detection [4-9]. Automatic methods achieved interesting results, but most of these studies fail in correctly locating the borders of the Phases A. Thus, a mathematical approach to automatically find the Phase A borders may be very useful to assist the physicians and the automatic methods in this hard task and reduce the subjectivity.

The aim of the present study is to propose a novel method, based on statistical inference, to assist in the visual CAP scoring.

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II. Materials and Methods

A. Polysomnographic Data and Annotations

The study was carried out on 10 healthy adult subjects, 4 males and 6 females, of age between 25 and 45 years (mean 32.7 yrs). The sleep polysomnographic recordings (PSG), one per subject, were provided by the Parma University Sleep Disorders Center. Sleep analysis was carried out after one adaptation night to the sleep lab for screening purposes and adjustment.

- *Sleep structure annotation description.* Hypnogram and CAP scoring were performed by sleep experts, following standard approaches. The macrostructure was defined according to conventional R&K rules, leading to a characterization of sleep stages every 30 s, while CAP scoring was based on published guidelines [1].
- *EEG data preprocessing*. A single unipolar EEG derivation per subject was used for this analysis, either C3-A2 or C4-A1. The signal was sampled at 100 Hz, and bandpass-filtered at 0.3-40 Hz.

B. Method for border detection

The automatic detection of the borders of a Phase A needs an initialization point (P) inside the Phase A. The process to define the right border is as follows:

I. From a given point P inside a Phase A, a vector $\boldsymbol{x}$ (of length n) centered around P is defined.
II. A new vector $\boldsymbol{y}$ (of length n) to the right of $\boldsymbol{x}$ is defined with an initial percentage σ of overlapping with $\boldsymbol{x}$.
III. A statistical test for equal variance is computed between $\boldsymbol{x}$ and $\boldsymbol{y}$. The null hypothesis H_0 assumes that the standard deviation is equal for both vectors $\boldsymbol{x}$ and $\boldsymbol{y}$. Note that this test will be biased, depending on the overlapping ratio σ.
IV. If H_0 is accepted, thus:
  a. Replace $\boldsymbol{x}$ with $\boldsymbol{y}$.
  b. Let $\sigma = \tau*\sigma$, where τ is between 0 and 1. The factor τ reduces the amount of overlapping between $\boldsymbol{x}$ and $\boldsymbol{y}$, and the bias of the statistical test.
  c. Obtain a new vector $\boldsymbol{y}$ to the right of $\boldsymbol{x}$ with an overlapping percentage given by σ.
  d. Return to step III
V. If H_0 is rejected, then:
  a. Border position is found
  b. End

A similar procedure can be performed to find the left border.

The rationale for allowing a certain overlap between vectors $\boldsymbol{x}$ and $\boldsymbol{y}$, and thus biasing the variance test, is that we want the test to be less strict around the initial point P, and become more strict as it becomes closer to the border.

Fig. 1 shows the procedure graphically. Empty arrows show the initial and ending points defined by the expert while filled arrows represent the borders found by the assisted method.

C. Evaluation process.

To evaluate the performance of the algorithm, the Phases A were divided by type and additionally A1 according to the sleep stage. Table I shows the number of activations that belong to each type.

TABLE I.
NUMBER OF PHASES A GROUPED BY TYPE AND SLEEP STAGE

Stage S1 and S2			**Stage S3 y S4**
A1	*A2*	*A3*	*A1*
826	792	649	1678

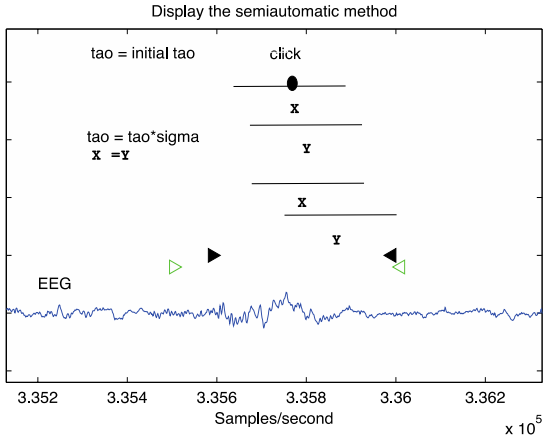

Fig 1. Procedure used to assist the Phase A detection. **x** represents the base data vector and **y** the vector to be compared. Empty arrows are initial and ending points defined by the expert while the filled arrows are the borders found by the assisted method. σ is the initial overlapping percentage between **x** and **y**, and **τ** is the overlapping reduction factor at each iteration.

The following procedure was applied for each Phase A:

I. We assume that the expert will give the initial point relatively close to the center of the Phase A. Thus, we give randomly an initial point in the center of the Phase A +/- 25 % of the total duration.
II. The borders are defined following the procedure described in section B.
III. For each Phase A, the performance of the method is measured with respect to the expert annotations based on two measures: overestimation and concordance.

- Concordance. Time that the computed Phase A duration overlaps with the expert annotation.
- Overestimation: The difference between the computed duration when this is higher than the expert annotation.

D. Parameter selection.

The parameters to be defined are n, σ and τ. The optimal values of the parameters are those that maximize the concordance and minimize the overestimation. Note that n must be carefully selected because: a) a small value of n

produces a fast rejection of H_0 thus an underestimation occurs and b) a large value of n produces a low rejection of H_0 leading to overestimation of the duration. The value of n was defined for A1-A2 (3 s) and A3 (7 s), based on the mode of the duration histogram found for each type of activation (see Fig. 2).

Thereafter, a brute-force search algorithm was applied to the whole dataset to find the values of the σ and τ parameters that optimize the performance measures. The best performance measures were σ = 90% and τ >= 0.5.

Two metrics were employed to assess the proposed approach:

- A detailed comparison of the detected segments via concordance and overestimation histograms
- A macroscopic comparison of the outcome, based on a well established CAP-based index [10], the CAP-rate, which represents the total CAP time in NREM.

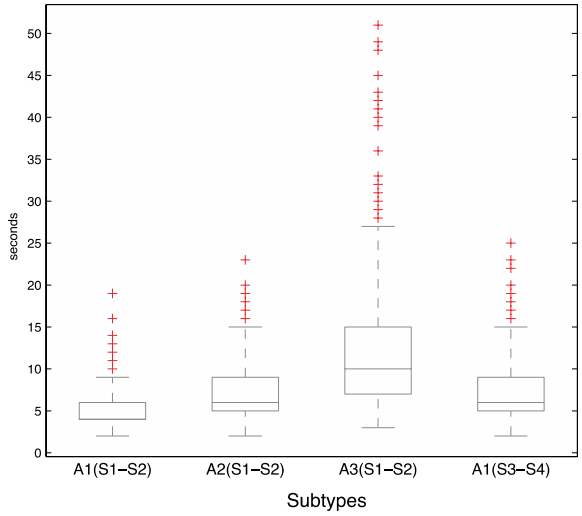

Fig 2. Box plot representation of the duration for each type of Phase A.

III. RESULTS

Figure 3 shows the histograms of the percentage of concordance and overestimation for the different types of Phases A. One can observe that the concordance is very high most for Phase A1 and A2, while generally the overestimation remains under the 3 seconds. However, this is not true for Phase A3. The histogram presents almost a flat distribution in the percentage of concordance even if the overestimation is generally very low.

Finally, Table II shows the CAP rate evaluated through the expert annotation and the assisted method. One can observe that the maximum error is around 7 min (subjects 2, 5) and the CAP rate computed by the assisted system is often lower (except for subject 3).

IV. DISCUSSION

This study proposes a novel method to detect the borders of the components that build up the Cyclic Alternating Pattern. This method is based on statistical inference and needs only one point of initialization inside each Phase A. Our main observations are: a) Statistical inference seems to be a fine tool to find the borders of the Phases A, b) The CAP rate evaluated trough the assisted system and the expert annotation are very close, this means that the proposed method could be useful to simplify the scorers work and c) Borders of Phases A1 seem to be well defined while borders for Phases A3 need further study, even if the results seem adequate.

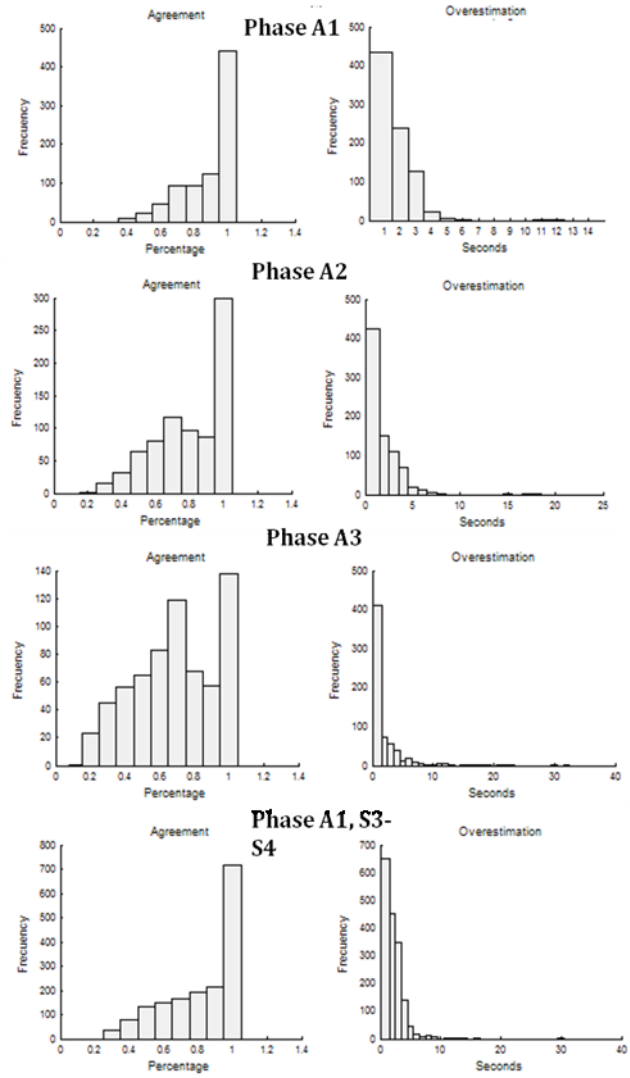

Fig 3. Histograms of the percentage of concordance and overestimation for the Phases A

TABLE II.
CAP RATE (HOUR:MINUTE).

Subjet	CAP Visual	CAP Assisted
0	3:33	3:27
1	3:39	3:36
2	3:07	3:00
3	2:27	2:33
4	1:48	1:43
5	1:23	1:16
6	2:20	2:17
7	2:48	2:45

8	2:40	2:36
9	2:06	2:00

In this study, a single statistical test (specifically a variance test) was used to detect the Phases A borders. Nevertheless, it is possible to combine this methodology with spectral, linear and nonlinear indices to obtain a more robust algorithm.

In general, the borders of the Phases A1 are well detected, while, for Phases A3 the performance was slightly poorer. The main reason is that Phase A3 is typically longer that A1 and A2. This affects directly the inference test, since the method underestimates the A3 duration. Another reason is due to the Phase A3 properties. As Phase A3 is long, it presents variations in the frequency content and complexity, this means, alternation between the EEG waves: Beta, Alpha, Theta and Delta, which produce changes in the statistical properties inside the Phase A. Thus, this generates errors since the statistical inference detects significant changes within the A3 activation.

The proposed method generates new perspectives to evaluate the CAP sleep. This method is intended to support to the physician in the hard task of detecting Phase A borders. It is easier to select only one point in the middle of each observed activation than to manually determine starting and ending point of thousand of activations that could be found in a single recording. In addition, this methodology could be part of the decision stage of an automatic system [9], allowing for a better detection of the borders.

V. Conclusion

Assisted detection of the Phases A borders can be performed by a simple algorithm based on statistical inference. This methodology could support the scorers by simplifying the CAP evaluation and reducing the time required to analyze a sleep recording. The borders of Phases A1 and A2 can be detected accurately, however, further research is needed to improve the results for Phases A3.

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