A Novel Method to Detect the A Phases of Cyclic Alternating Pattern (CAP) Using Similarity Index

Hamid Niknazar
Department of Biomedical Engineering
Science and Research Branch,
Islamic Azad University
Tehran, Iran
hd.niknazar@gmail.com

Saman Seifpour, Mohammad Mikaili, Ali Motie Nasrabadi
Department of Biomedical Engineering
Shahed University
Tehran, Iran

Anahita Khorrami Banaraki
Department of Cognitive Neuroscience
Institute for Cognitive Science Studies (ICSS)
Tehran, Iran

***Abstract*— The aim of this study is to implement an automatic system to detect the activation phases of Cyclic Alternating Pattern (CAP). CAP is a sleep phenomenon composed of consecutive sequences of activations and non-activations observed during the sleep time. Statistical Behavior of Local Extrema (SBLE) method is used for feature extraction and similarity index is used for decision making. SBLE is a symbolic technique that can characterize behavior of chaotic signals. The C4-A1 EEG lead of six healthy adult subjects was used. SBLE features are extracted from delta EEG band. By using this method and second by second comparison output of the system with sleep expert visual scoring, sensitivity of 75.83%, specificity of 81.30% and accuracy of 80.51% is achieved.**

Keywords*— cyclic alternating pattern; sleep; similarity index; EEG; symbolic technique, SBLE

I. INTRODUCTION

Based on eye movements, sleep is divided to REM (rapid eye movement) and NREM (Non-rapid eye movement) stages. According to electrophysiological findings with sleep EEG, NREM per se is divided to three sub-stages including N1 (sleepiness), N2 (light sleep) and N3 (deep or slow wave sleep). During NREM sleep, phasic EEG events, such as K-complexes, vertex waves, delta bursts, and short-lasting arousals show a peculiar time arrangement, indicated as 'cyclic alternating pattern' or CAP [1]. The cyclic Alternating Pattern is composed of two phases: brain activation phase called A phase and recovery or return to the background phase called B phase. Phase A of CAP is identified by transient events typically observed in non-REM sleep, which clearly stand out from the background rhythm, usually differing in frequency and/or amplitude (Fig 1.). Compared to B phases, A phases can be composed of slower, higher-voltage rhythms, faster lower voltage rhythms, or by mixed patterns including both [2]. The duration of the A and B phases must be greater than 2 seconds and less than 60 seconds. Using these rules, to start one CAP sequence, we must have at least three consecutive A phases, and the end of the sequence is in the beginning of a valid A phase [3]. The percentage of NREM occupied by CAP sequences defines the CAP rate. All the remaining NREM sleep, not occupied by CAP sequences is called non-CAP (NCAP) [1]. Based on the reciprocal proportion of high-voltage slow waves (EEG synchrony) and low amplitude fast rhythms (EEG desynchrony), phase A of CAP is divided into three subtypes: (i) A1, if EEG desynchrony occupies less than 20% of the entire phase A duration, (ii) A2, if 20–50% of phase A occupied by EEG desynchrony, and (iii) A3, if more than 50% of phase A occupied by EEG desynchrony [2]. Over the past decade there have been investigations aiming to describe the relationship between CAP (CAP sequences, CAP rate and CAP A subtypes), sleep disorders [3] [4] [5] and sleep related cognitive process [6] [7] [8].

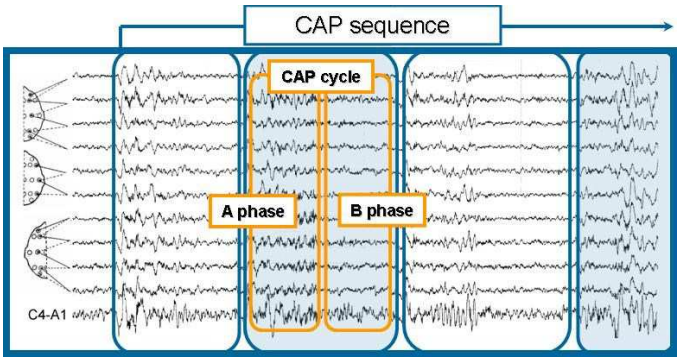

Fig 1. An example of cyclic alternating pattern (CAP) in sleep stage 2 [9]. A CAP cycle is defined as a phase A period followed by a phase B period lasting a minute or less. Two or more adjacent CAP cycles define a CAP sequence.

Unlike the macrostructural evaluation of sleep in particular visual inspection of sleep stages, the visual scoring of CAP events is a time-consuming and boring task, and as a consequence, after some time of scoring, the expert may be tired and lose concentration. Moreover, it has been estimated that the average inter-scorer agreement between the classifications of single EEG trace by two different clinician's ranges from 69% to 77% [10].

In recent years, several methods for automatic CAP detection have been proposed. Most of which rely on the extracting of features such as: power, complexity, Hjorth parameters and spectral parameters in different band and sub-band frequency from the EEG signal to compute descriptors on short and long time-windows. These features are given to various classifiers for classifying each window as belonging or not to a phase A of CAP [11] [12] [13] [14] [15].

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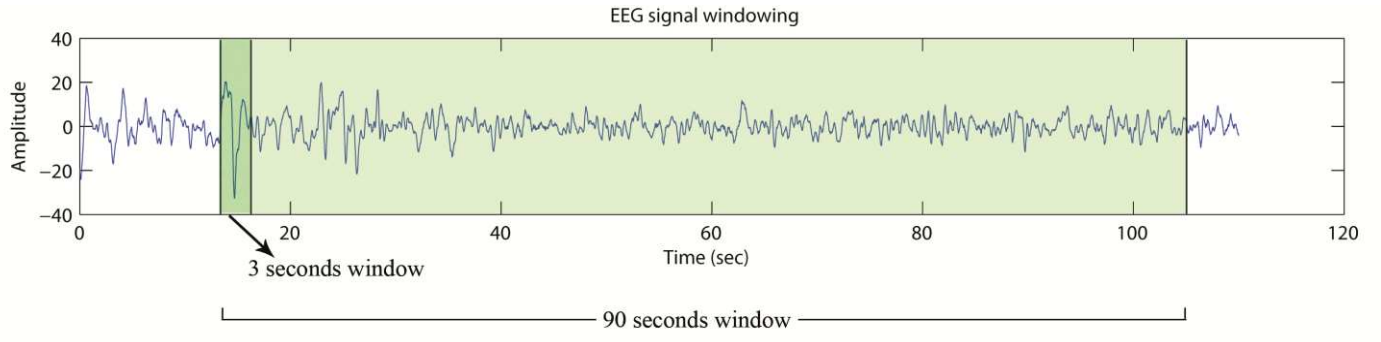

Fig 2. Two windows for nominating start time of CAP activation phase.

Based on some studies of the community of neurophysiology researchers, EEG signal is a multivariate time series stem from a highly nonlinear and multidimensional system when the brain activity is normal [16]. Chaotic signal processing techniques are based on wholeness approach (systemic approach) and they try to qualify any changes in signal or in source of signal. They aim at finding and presenting how signals or sources of signals behave through time. Symbolic method is one of the nonlinear techniques in the area of chaotic signal processing. Symbolic methods have been also used at several studies in the field of EEG signal processing [17] [18] [19]. These studies showed that symbolic methods have the ability to extract characteristics of EEG signal behavior.

In this study, we used a symbolic technique based on Statistical Behavior of Local Extrema (SBLE) [20] to detect CAP events.

II. MATERIALS AND METHODS

A. Polysomnographic Data

Polysomnographic data of six healthy adult subjects (four males and two females) was used in this study. The age of the subjects are ranged between 24 and 34 years (mean 29.3 years) and did not present any neurological disorders and were free of drugs affecting the central nervous system. The waveforms include at least 3 EEG channels (F3 or F4, C3 or C4 and O1 or O2, referred to A1 or A2), EOG (2 channels), EMG of the submentalis muscle, bilateral anterior tibial EMG, respiration signals and ECG. The scoring of the sleep macrostructure was carried out according to conventional R&K rules [21] in 30 s epochs, while the CAP was detected in agreement with Terzano's reference atlas of rules [2]. The signals and respective annotations employed for this study have been made available by the Sleep Center on the data repository [22], and they correspond to recordings n1–n16 of the CAP Sleep Database [9]. The monopolar EEG lead (C3-A2 or C4-A1) was employed alone for analysis. The signals were sampled at 100 Hz, and bandpass-filtered at 0.5-25 Hz. In some studies, it was shown that delta band (0.5 to 4 Hz) is the efficient band for CAP detection [11] [15]. So in this study we focused on delta band of EEG signal. A FIR filter with 50 coefficients and a hamming window was used for this purpose.

B. Method

Two time points must be labeled to detect CAP A, start time and end time. To nominate starting time of A phases, a threshold method is used. To accept the start time and to detect the end time of A phases, similarity of SBLE features are used.

In most cases CAP A start with high amplitude delta bursts or vertex sharp waves, so start times can be labeled by using a threshold on amplitude of EEG signal in three steps:

- Using 90 second windowing technique with 89 seconds of overlap (Fig 2.).
- Calculate the RMS of amplitude of each window on delta band EEG signal.

$$\mathrm{RMS}_q = \sqrt{\frac{\sum_i (x_q(i))^2}{\sum_i i}} \qquad (1)$$

Where $x_q(i)$ is the i-th sample of window q of signal.

- If $A_q > 1.5 * \mathrm{RMS}_q$ then start time of window q is nominated as start time of CAP and is named S_q [23].

$$A_q = \frac{\sum_j |x_q(j)|}{\sum_j j} \qquad j = \{j \mid j \in \text{first 3 seconds of winsow q}\} \qquad (2)$$

For each S_q, we define a growing window on delta band from 2 to 60 seconds by step one second on EEG signal with S_q start time. In each step, similarity of windowed signal and reference windows are measured. If this similarity was greater than a threshold, the signal windowed is considered as a CAP, otherwise S_q will be ignored. Similarities of windowed signals are measured based on SBLE method features.

B.1. Statistical behavior of local extrema (SBLE)

SBLE method [20] extracts some features from time series that can characterize behavior of signal in the time domain. This method consists of 6 steps:

Step1- finding local extrema of time series (Fig 3a.).

Step2- dividing amplitude of time series to M segments R1 to RM (Fig 3b.).

Step3- constructing string ST= $\{s_1, s_2, \ldots, s_n\}$ that contains position of local minimums and maximums in M segments (Fig 3c.).

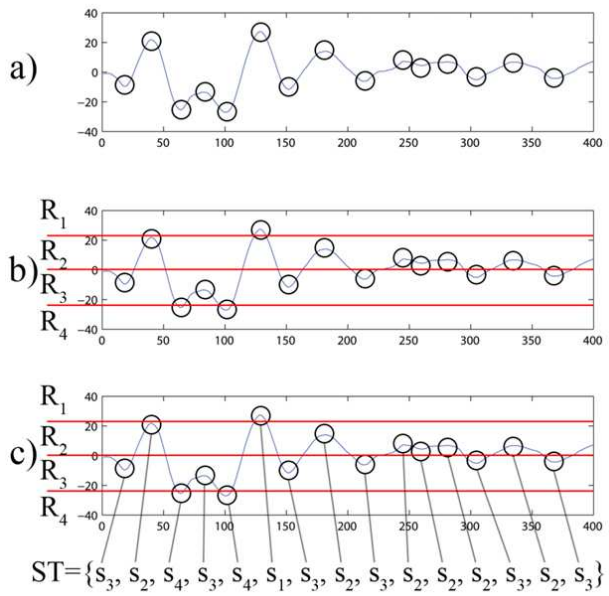

Fig 3. a) Finding local extrema of time series. b) Sample of dividing the amplitude to M=4 segments. c) Constructing string ST from position of local extrema in 4 segments.

Step 4- counting number of each 9 patterns:

- Increase pattern: existence of $s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-1} \in R_i$, $S_n \in R_j$ and i>j.
- Decrease pattern: existence of $s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-1} \in R_i$, $S_n \in R_j$ and i<j.
- U-turn1 pattern: existence of $s_{n-2}s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-2} \in R_i$, $s_{n-1} \in R_j$, $s_n \in R_k$ and i>j, j<k.
- U-turn2 pattern: existence of $s_{n-2}s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-2} \in R_i$, $s_{n-1} \in R_j$, $s_n \in R_k$ and i<j, j>k.
- Increase-Constant pattern: existence of $s_{n-2}s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-2} \in R_i$, $s_{n-1} \in R_j$, $s_n \in R_k$ and i>j, j=k.
- Decrease-Constant pattern: existence of $s_{n-2}s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-2} \in R_i$, $s_{n-1} \in R_j$, $s_n \in R_k$ and i<j, j=k.
- Constant-Increase pattern: existence of $s_{n-2}s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-2} \in R_i$, $s_{n-1} \in R_j$, $s_n \in R_k$ and i=j, j>k.
- Constant-Decrease pattern: existence of $s_{n-2}s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-2} \in R_i$, $s_{n-1} \in R_j$, $s_n \in R_k$ and i=j, j<k.
- Constant pattern: existence of $s_{n-2}s_{n-1}s_n$ sequence in string ST, where:
  - $s_{n-2} \in R_i$, $s_{n-1} \in R_j$, $s_n \in R_k$ and i=j, j=k.

Step 5- constructing features vector FV = $\{f_1, f_2, \ldots, f_{2M+9}\}$ that consist of:

1. Number of minima in each segment (M features)
2. Number of maxima in each segment (M features)
3. Number of increasing patterns
4. Number of decreasing patterns
5. Number of U-turn1 patterns
6. Number of U-turn2 patterns
7. Number of increasing-constant patterns
8. Number of decreasing-constant patterns
9. Number of constant-increasing patterns
10. Number of constant-decreasing patterns
11. Number of constant patterns

Step 6- Normalizing features vector using:

$$FV_{new} = \frac{FV}{\sum_{i=1}^{2M} f_i} \quad (3)$$

These 2M+9 features describe behavior of time series. Similarity of two time series can be obtained by cosine distance of features vectors:

$$\text{Similarity index} = \frac{\sum_{i=1}^{2M+9}(f_i f'_i)}{\sqrt{\sum_{i=1}^{2M+9}(f_i f_i) * \sum_{i=1}^{2M+9}(f'_i f'_i)}} \quad (4)$$

where f_i and f'_i are i-th feature of FV_{new} and FV'_{new} vectors.

B.1. Implementation of the method

For each growing signal window, features vector is extracted. Less than 2.5% percent of CAP A are selected randomly as reference windows and SBLE features vector are extracted from these windows. Similarity index between growing window and all reference windows is measured. If the average of 20 greater similarity indexes is greater than 0.95, that window is marked as CAP A.

III. RESULTS

By applying the proposed method, CAP A events are extracted from EEG signals. To evaluate our method, we have compared the starting and ending time of A phases detected by this method with the visual scoring of an sleep expert (Fig 4.). Then statistical analyses are done to calculate sensitivity, specificity and accuracy. Results are reported in table I.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (6)$$

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FP + FN} \quad (7)$$

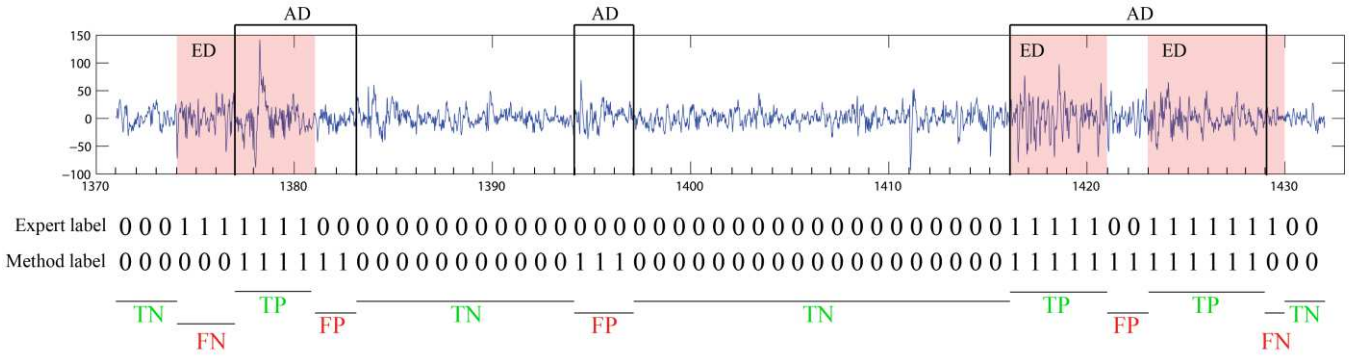

Fig 4. An example of the automatic system output for 60 second EEG signal in stage 2 of sleep. ED and AD labels belong to expert detection and automatic system detection respectively. Each "1" represents one second activation phase and "0" represents one second non-activation phase.

Where TP is true positive, TN is true negative, FP is false positive and FN is false negative.

TABLE I. STATISTICS OBTAINED FROM SIX SUBJECT BY PROPOSED METHOD.

Subject	Sensitivity%	Specificity%	Accuracy%
1	75.61	78.90	78.62
2	71.36	82.73	80.90
3	81.76	80.97	81.06
4	80.18	80.45	80.43
5	73.07	83.37	81.87
6	72.99	81.39	80.18
Mean	75.83	81.30	80.51

IV. DISCUSSION AND CONCLUSION

As mentioned earlier, CAP scoring is a hard and tedious task, and the training process is time consuming beside physician must be expert enough to score a recording. So, establishing a reliable automatic method for scoring CAPs is essential for its inclusion on regular clinical practice.

This work presents an automatic approach to classify sleep microstructure by using the symbolic method to extract SBLE features from the sleep EEG signal. Comparing results with other studies (Table II), shows that the proposed method has proper ability to extract activation phase of CAPs from EEG signals. In most of other studies, a classifier is used, that required training and validation data set which uses most of whole data. The proposed method uses less than 2.5% of data for decision making, although this set can be used for other datasets. This means, by increasing the dimensions of data we do not require more reference windows.

Using the classifiers in computation is time-consuming and increases the computational burden. While, first step of SBLE method, by removing non-extremum samples, convert a time series with high number of sample to a time series with very lowest number of sample. This sample reduction results in more efficient computation and response time of the system. Expert scoring rely on morphology of EEG signal and SBLE method features quantify this morphology statistically, so this method is near to expert knowledge.

In conclusion, the presented methodology, could assist the clinicians, sleep scorers and researchers to microstructure study of sleep by simplifying the CAP evaluation and reduce the time required for analysis.

TABLE II. COMPARING STATISTICS OBTAINED BY PROPOSED METHOD TO SOME OTHER STUDIES.

Researchers	Sensitivity%	Specificity%	Accuracy%
The proposed method	75.83	81.30	80.51
Mariani et. al [13]	73.82	85.93	84.05
Mariani et. al [15]	75.65	83.05	81.55
Mariani et. al [24]	71.70	70.56	70.74
	69.59	71.90	71.53

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