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Automatic Detection of CAP on central and fronto-central EEG leads via Support Vector Machines

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Abstract—**The aim of this study is to implement a high-accuracy automatic detector of the Cyclic Alternating Pattern (CAP) during sleep. EEG data from four healthy subjects were used. Both the C4-A1 and the F4-C4 leads were analyzed for this study. Seven features were extracted from each of the two leads and two separate studies were performed for each set of descriptors. For both sets, a Support Vector Machine was trained and tested on the data with the Leave One Out cross-validation method. The two final classifications obtained on the two sets were merged, by considering a CAP A phase scored only if it had been recognized both on the central and on the frontal lead. The length of the A phase was then determined by the result on the fronto-central lead. This method leads to encouraging results, with a classification sensitivity on the whole dataset equal to 73.82%, specificity equal to 85.93%, accuracy equal to 84,05% and Cohen's kappa equal to 0.50.**

I. INTRODUCTION

IN healthy conditions, the Cyclic Alternating Pattern (CAP) is a phenomenon occurring on the Electroencephalogram during non-REM sleep. It consists of a periodic activity in which a phase of brain activation, called phase A, and a phase of recovery or return to the background, called phase B, alternately appear. Phase A and B can both last between 2 and 60 seconds. Phases A have characteristics that may vary in amplitude and frequency of the signal: three different subtypes are recognized: A1, characterized by strong delta waves (0.5-4 Hz); A2, containing rapid activities that occur for 20-50% of the total activation time, and A3, characterized by rapid activities, especially beta (16-30 Hz), that occupy more than 50% of the total time [1].

Nowadays CAP is gaining increasing importance in clinics. In fact, although being a physiological phenomena, it is also a marker of sleep instability and can be correlated with several sleep pathologies. Increased amounts of CAP are a regular finding in obstructive sleep apnea syndrome (OSAS) [2] as a reaction of the sleeping brain to a repetitive breathing disturbance. Primary insomnia shows increased amounts of CAP, compared with healthy sleepers [3]. Furthermore, CAP A phase has been interpreted in several studies as a kind of gate through which pathologic events more easily occur. The gating effect has been demonstrated among several sleep disturbances such as Periodic Leg Movements (PLM) [4-6], sleep bruxism [7], and epilepsy [8-10]. The ratio between NREM CAP sleep and total NREM sleep (CAP-rate), and the different distribution of CAP A phases through the sleep stages can be measured in sleep centers to characterize such pathologies. These indexes can be considered as a valuable measure of sleep quality, however, the measure of CAP has not yet been introduced in regular clinical practice due to the time necessary for the neurologists for visually scoring CAP phases A on the whole night sleep recordings.

Some studies exist in literature that have developed automatic CAP classifiers, such as [11-14]. While all these methods achieve good results, none of them is yet applied to clinical practice since they either require some amount of clinician intervention or do not achieve a sufficient accuracy in the classification to allow for a reliable diagnosis.

According to Terzano [15], CAP is a global EEG phenomenon involving extensive cortical areas. Therefore, phases A should be visible in most of the EEG leads. Bipolar derivations such as Fp1-F3, F3-C3, C3-P3, P3-O1 or Fp2-F4, F4-C4, C4- P4, P4-O2 guarantee a favorable detection of the phenomenon. Monopolar EEG derivations (C3-A2 or C4-A1 and O1-A2 or O2-A1), eye movement channels and submentalis EMG, currently used for the conventional sleep staging scoring, are also essential for scoring CAP.

Many studies, e.g. [14], refer to a single EEG lead for the classification, the C3-A2 or the C4-A1 lead. However, classifications performed using only this lead show a large number of false positive A phases in the identification. In fact, many of the automatically recognized activations correspond to amplitude-frequency changes on the used central lead, but of regular EEG rhythms on the others. In Fig. 1 we report an example of visual CAP scoring over multiple leads. As shown in the picture, a CAP A phase is scored only if it is visible on all the leads (example on the right), while if the frequency-amplitude change is only present on the central lead (example on the left) it is not scored. Therefore, in this case, an automatic detector only trained and tested on the C4-A1 lead would classify a false positive.

In the light of this, the aim of our study is to create an automatic detector of phases A of CAP capable of achieving a higher accuracy and reliability in the classification.

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Since the fronto-central leads are also essential for the visual classification of CAP, here the F4-C4 lead was used together with the monopolar central lead to improve the classification accuracy. It was preferred over the frontal leads, since it is less prone to muscle or eye movement artifacts. An A phase was recognized only if it appeared on both the central and the fronto-central lead.

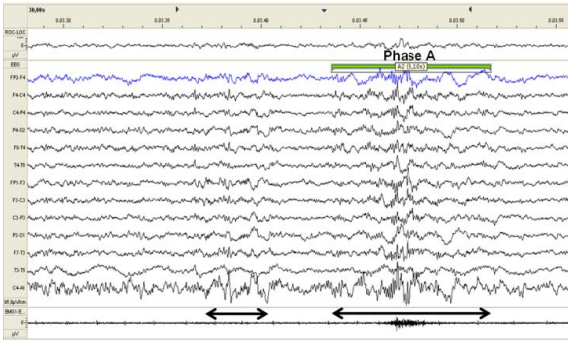

Fig. 1: Example of visual classification of CAP. The EEG activation on the left is not classified as an A phase because it only appears on the C4-A1 lead, while the one on the right is classified as an A phase because it is clearly visible on all the leads.

II. MATERIALS AND METHODS

A. Data acquisition

Four healthy adult subjects, two males and two females underwent a polysomnographic recording at the Sleep Center of the Department of Neurology of the Ospedale Maggiore di Parma. The age of the subjects ranged between 25 and 37 years. They did not present any neurological disorders and were free of drugs affecting the Central Nervous System. Among others, the C4-A1 and the F4-C4 leads were extracted. An expert neurologist visually scored the macrostructure of sleep, in terms of NREM, wake and REM distinction, and the microstructure, in terms of CAP A phases. Thus, the available data were, in total, 131,189 seconds of signal, 13,439 of which representative of CAP phases A and 117,750 representative of the background. The total number of examined phases A was 1746.

B. Extraction of the features

The portions of the recording relative to wake and REM were removed from the analysis. From the NREM sleep traces seven descriptors for each lead were extracted:

- *Five band descriptors*. The EEG signal was filtered with a low-pass anti-aliasing filter at 30 Hz. Then, it was separated in the following bands: Delta (from 0.5 Hz to 4 Hz), Theta (from 4 Hz to 8 Hz), Alpha (from 8 Hz to 12 Hz), Sigma (from 12 Hz to 15 Hz), and Beta (from 15 Hz to 30 Hz). A FIR filter with 30 coefficients and a Kaiser window was used for this purpose.

For each band, the resulting signal was squared and normalized between 0 and 1 (with respect to the maximum power in the band), and, for each of the five bands under study, a set of descriptors was implemented in the form:

$$d_b(t) = \frac{p_{bs}(t) - p_{bl}(t)}{p_{bl}(t)} \quad (1)$$

where p_{bs} and p_{bl} are the mean power in the considered band on a window of 2 and 64 seconds, respectively, centered on the second *t*.

- *Hjorth activity*. It was applied to the EEG signal filtered in the delta band. It was computed over overlapped 3-second windows, each centered on the second of interest. This descriptor captures the overall increase of the delta power occurring during the activations over a longer time span. It is calculated as the simple variance σ^2 of the signal segment.

- *Differential EEG variance*. The variance was computed from the raw EEG signal on 1-second windows. The variance difference between adjacent 1-second windows was calculated and the result normalized by its maximum value. This descriptor is expected to account for the abrupt frequency shifts occurring in correspondence with the activations.

The information content of these features has been assessed in [16], by means of ROC curves and statistical analyses, showing that they all contribute to the detection of CAP, the most informative being the delta descriptor, Hjorth activity and differential EEG variance. Fig. 2 shows an example of the trend of the extracted features for both the F4-C4 (left) and the C4-A1 (right) leads.

C. Pre-processing

The features were used as the training and testing set for the Support Vector Machines.

In order to homogenize the values of the descriptors around the activations, a moving window $f(x)$ was applied to all the features except the delta descriptor and the differential EEG variance, given by:

$$f(x_t) = max_{k\in[-r,+r]} x_{t+k} \quad (2)$$

where x_t is the center of the window, and r is equal to 2 for the band descriptors and to 1 for the activity.

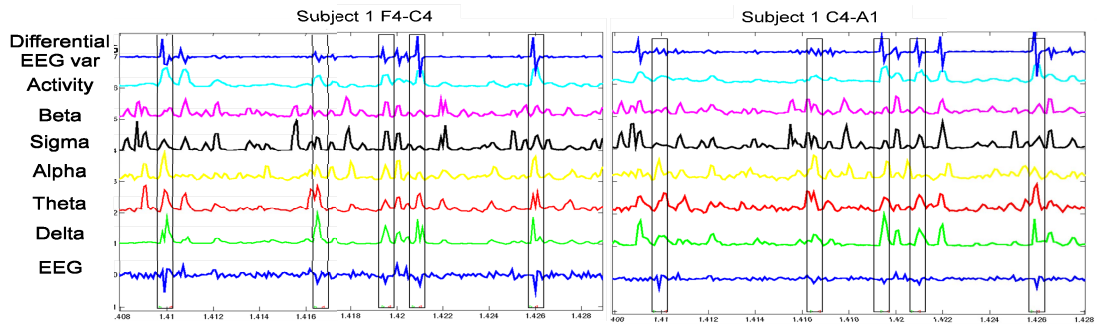

Fig. 2: Trend of the descriptors extracted from the F4-C4 (left) and the C4-A1 (right) leads in correspondence of the visually-scored phases A (boxes). It can be noticed how some of them, especially the delta, the beta and the differential EEG variance, show clear peaks in correspondence of the A phases.

For the differential variance of the EEG, the absolute value was computed.

The desired output data consisted of binary vectors of the same length of the features (one sample per second), where at each sample was assigned value 1 if belonging to a visually-scored activation, 0 if belonging to the background. Since it does exist more background than activation, there were more zeros than ones. Thus, in order to avoid biasing the classifier, a re-sampled training set was created that included an equal number of samples indicative of an A phase and of those indicative of the background. This was done simply by taking into account only a fraction of the samples corresponding to the background, uniformly distributed through the original descriptors.

D. Choice of the SVM parameters

Two separate studies were performed for the two sets of descriptors, and for each study, soft-margin Support Vector Machines with different kernels were trained. Both a Polynomial and a Gaussian kernel were used for the classification, and the Leave One Out (LOO) method was used to select the optimal kernel parameters (the Gaussian sigma for the Gaussian kernel and the polynomial order for the polynomial kernel) and the error penalty factor C.

The SVMs with each kernel and for each combination of parameters were trained over data from 3 subjects and then tested on the remaining subject. The results were then averaged over the subjects, and the best combination of the parameters was chosen by maximizing the Cohen's kappa coefficient in the classification:

$$\kappa = \frac{Pr(a) - Pr\,(e)}{1 - Pr\,(e)} \qquad (3)$$

where $Pr(a)$ is the relative observed agreement among raters (accuracy), and $Pr(e)$ is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category. For the polynomial kernel, the order varied between 1 and 6, while the C factor varied between 2^{-5} and 2^{15}; for the Gaussian kernel, the sigma varied between 2^{-13} and 2^{13} and the C factor varied between 2^{-13} and 2^{13}.

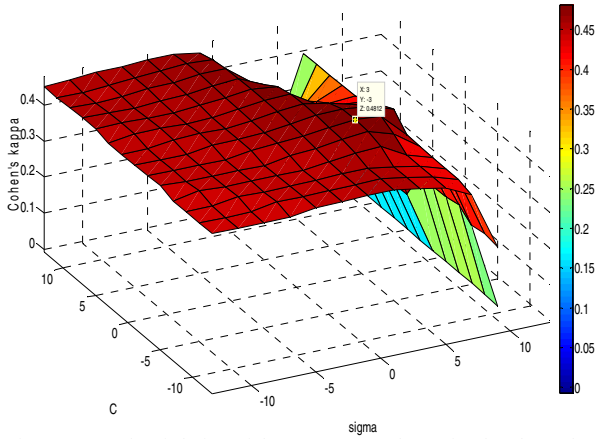

Fig. 3: Example of choice of the parameters: the optimal Cohen's kappa for the features extracted from the central lead is obtained with $C=2^{-3}$ and $\sigma=2^{3}$.

Fig. 3 reports an example of the Cohen's kappa values, averaged over seven subjects, while varying the values of the parameters.

The parameters providing the best results in terms of Cohen's kappa are reported in Table I: since the Gaussian kernel allows for slightly better results for both sets of features, it was chosen for this study.

TABLE I

PARAMETERS ALLOWING FOR THE BEST CLASSIFICATION RESULTS IN TERMS OF COHEN'S KAPPA (κ).

C4-A1 features					
Polynomial kernel			Gaussian kernel		
Order	C	κ	σ	C	κ
2	2^{5}	0.44	2^{3}	2^{-3}	0.46
F4-C4 features					
Polynomial kernel			Gaussian kernel		
Order	C	κ	σ	C	κ
2	7	0.47	2^{3}	2^{-3}	0.48

E. Training of the SVMs

SVMs with a Gaussian kernel and the chosen parameters were used to classify the data. Again, two different training and testing stages were used for the two sets of features, and the Leave One Out method was applied for the classification. This lead to two scoring vectors for each subject: one from the central and the other from the fronto-central features.

F. Application of logical principles

Based on the principle that an A phase is visually scored only if it appears on more than one lead, the resulting vectors for each subject were ANDed together. Then, the duration of each recognized phase A was corrected according to the F4-C4 classification. This choice is due to the fact that the F4-C4 lead allows for a better detection of the slow component of CAP, which characterizes most phases A (approximately 70%) in healthy subjects, with respect to the C4-A1. An example of this procedure is shown in Fig. 4.

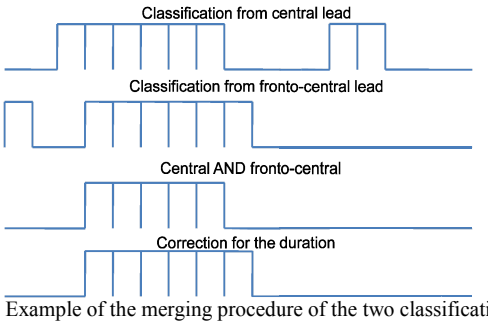

Fig. 4: Example of the merging procedure of the two classifications.

G. Post-processing

Finally, a post-processing was applied to the final classification vectors: since A and B phases cannot last less than 2 seconds, isolated one-second-lasting phases A and B were removed. That means, patterns 101 were converted into 111 and patterns 010 were turned into 000.

III. Results

The results of the classification are reported in Table II.

TABLE II

STATISTICS OF THE A PHASES AUTOMATIC SCORING COMPARED TO THE VISUAL SCORING.

Subject	Sens (%)	Spec (%)	Acc (%)	Cohen's kappa
1	68.45	88.32	85.58	0.48
2	77.20	82.59	82.00	0.39
3	72.80	88.88	85.43	0.59
4	79.55	82.86	82.36	0.48
Total	**73.82**	**85.93**	**84.05**	**0.50**

A graphic example of the results of the classification of a subject is reported in Fig. 5.

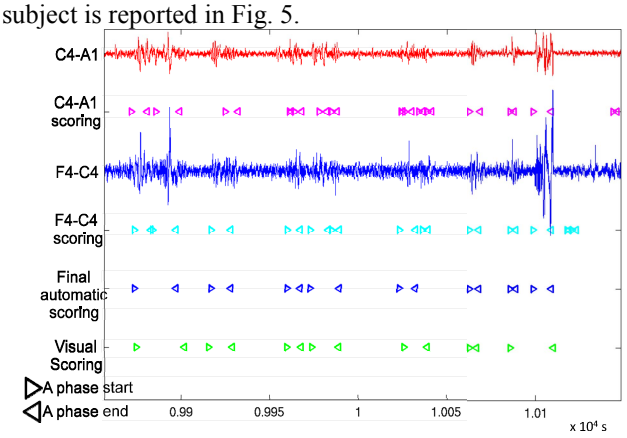

Fig. 5: Classification results: an example of the scoring of subject 1. Combining together the scorings performed on the C4-A1 and on the F4-C4 leads some false positives are eliminated.

IV. Discussion and Conclusions

CAP scoring is of crucial importance in sleep studies, since CAP indexes add information to the characterization of several sleep pathologies. Establishing a reliable automatic method for scoring CAP is fundamental for its inclusion on regular clinical practice, since this would overcome the difficulties due to visual scoring time-consume and to inter-scorer variability.

This study is related to only four subjects and this method is meant to be explored in more depth by testing it on a larger database. However, with respect to results obtained in previous works [14], here the application of two lead-EEG data allows for a higher accuracy and a good value for the Cohen's kappa is also obtained. With respect to other studies [11-13] also performing CAP A phase detection with good accuracies, our method has the advantage to perform a second - by - second scoring, instead on relying on a mere overlap criterion between automatic and visual scoring. The accuracy and Cohen's kappa values obtained with this method are comparable with the repeatability values between two different visual scorers, as reported by [17]. Support Vector Machines appear to be a reliable machine-learning method for the application to CAP scoring, and their performance is similar to that of Artificial Neural Networks [14] and Genetic Algorithms [13].

Further research has to be performed before the duration principles can be applied to the recognized phases A to score the actual CAP. In fact, even minor differences in length between automatically- and visually-scored phases A may bring to substantial changes in the scoring of a CAP sequence. In order to do so, instead of simply applying an AND rule, the SVMs could be trained on the two sets of features together, or different scoring methods accounting for temporal pattern recognition, such as Hidden Markov Models, could be applied.

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