Automatic Detection of a Phases for CAP Classification

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Abstract: The aim of this study is to develop an automatic detector of the cyclic alternating pattern by first detecting the activation phases (A phases) of this pattern, analysing the electroencephalogram during sleep, and then applying a finite state machine to implement the final classification. A public database was used to test the algorithms and a total of eleven features were analysed. Sequential feature selection was employed to select the most relevant features and a post processing procedure was used for further improvement of the classification. The classification of the A phases was produced using linear discriminant analysis and the average accuracy, sensitivity and specificity was, respectively, 75%, 78% and 74%. The cyclic alternating pattern detection accuracy was 75%. When comparing with the state of the art, the proposed method achieved the highest sensitivity but a lower accuracy since the fallowed approach was to keep the REM periods, contrary to the method that is used in the majority of the state of the art publications which leads to an increase in the overall performance. However, the approach of this work is more suitable for automatic system implementation since no alteration of the EEG data is needed.

1 INTRODUCTION

A variety of imaging techniques have been developed through time to analyse the human body, being frequently employed by modern medicine as auxiliary diagnosis elements. Electroencephalography is a member of the electrobiological measurements group, reading the electrical activity produced by the brain (created when neurons are activated) and the electroencephalogram (EEG) is one of the most used techniques in this field. EEG records the alternating electrical activity at the scalp surface using conductive media and metal electrodes (Schomer and Silva, 2010). The scalp electrodes distribution usually follows the 10-20 electrode placement standardization, presented in figure 1, and the EEG power spectrum, calculated by the Fourier transform, is typically categorized in four bands (Teplan, 2002), delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz).

The EEG is commonly used for sleep analysis. Two major states of sleep have been defined, the rapid eye movement (REM) and the non-REM (NREM). The NREM can be divided into four stages, from S1 to S4, increasing from stage to stage the slow-wave activity. An example of a normal hypnogram is presented in figure 2. In the most recent classification the third and fourth states are combined, being named N3, the second stage is N2 and the first N1. Cyclic patterns of NREM stages and REM define the sleep macrostructure. However, the microstructure is characterised by transitional states such as the cyclic alternating pattern (CAP), characterized by a cycle of activation (A phase) and quiescent (B phase) phases as represented in figure 3. This pattern is not defined in the REM sleep. Each phase has a minimum duration of 2 seconds, being 60 seconds the maximum (Chokroverty, 2009).

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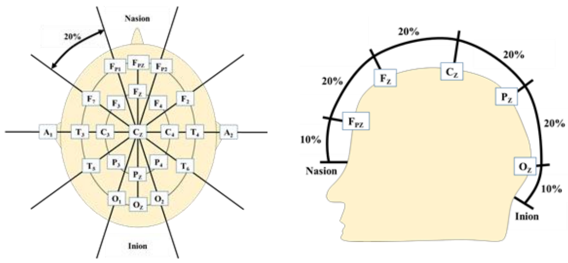

Figure 1: 10-20 electrode placement standardization. Adapted from Schomer and Silva (2010).

The A phases can be categorised into three subtypes, A1, A2 and A3, increasing the percentage of rapid activities, in the alpha or the beta bands from the A1 to A3 (Mendez *et al*., 2014). A non-CAP period happens when the phase duration is higher or lower than the specified. EEG Monopolar derivations (C4-A1 or C3-A2) are frequently used for CAP analysis, being the alpha and beta frequency bands defined differently to include a new band. Therefore, the alpha goes from 8 to 12 Hz, the sigma from 12 to 15 Hz and the beta from 15 to 30 Hz (Mariani *et al*., 2011a).

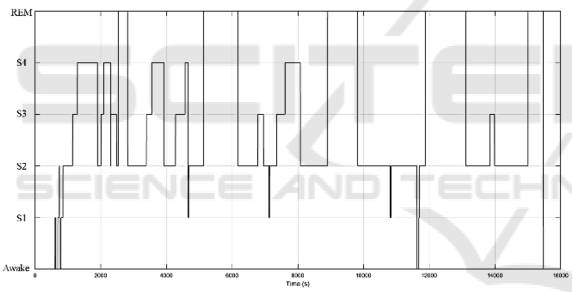

Figure 2: Example of a normal hypnogram.

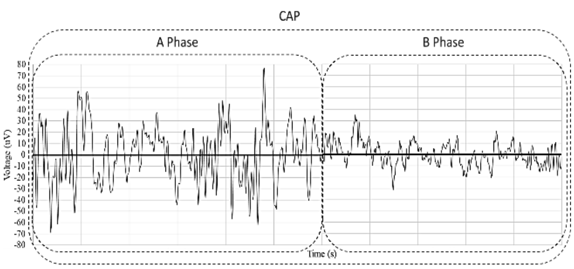

Figure 3: Example of a CAP using a monopolar derivation (C4-A1) signal.

Studies have shown that the main role of CAP in sleep is to generate, consolidate and disrupt the macrostructure of sleep (Halász *et al*., 2004). Therefore, CAP can be seen as a marker of sleep instability. A full night of EEG sleep analysis generates a large quantity of information making manual CAP scoring unpractical with a high susceptibility to miss classification, being the expected specialist agreement, analysing the same results, in the 69% to 78% range (Rosa *et al*., 2006). Therefore, automatic CAP detection algorithms have been proposed.

This paper has the folowing organization: the state of the art is analysed in section 2 being the used methods indicated in section 3; section 4 presents the algorithms performance; comparison with related work is performed in section 5 and the paper conclusion is presented in the next section.

2 STATE OF THE ART

Two main approaches for CAP classification are presented in the bibliography. The first consist in detecting CAP from the EEG data and was used by Karimzadeh *et al.* (2015), employing multiple entropy features to feed the three tested classifiers: linear discriminant analysis (LDA); support vector machine (SVM); k-nearest neighbours (kNN). It was verified that sample entropy, Shannon entropy and Kolmogorov entropy are the most relevant features being kNN the best classifier. The second approach consist in using in a first step a classifier to determine the A and B phases and then applying a finite state machine (FSM) to classify CAP. A total of nine articles were found, through a systematic review, in the state of the art presenting algorithms for A phase detection and five with algorithms to detect each of the three subtypes of the A phase.

The usual approach consist in considering that everything that is not an A phase is a B phase. A simple method, based in frequency band descriptors and thresholds was presented by Navona *et al.* (2002) and Barcaro *et al.* (2004), producing for each of the five bands a descriptor that consists in the value of a short average (two seconds) subtracted by a longer average (64 seconds) and dividing the result by the longer average. Classification was performed using specific thresholds. Mariani *et al.* (2011b) achieved the best results for A phase detection using the Hjorth activity, classifying with a threshold. Niknazar *et al.* (2015) analysed the similarity of the windowed signal with a database of reference A phase windows using statistical behaviour of local extrema (SBLE).

Mariani *et al.* (2010) used five band descriptors, differential variance (difference of the current window and the previous window variance) and the Hjorth activity to feed the classifier, using a three-layer neural network (NN) with Logsig activation function. The same features were used by Mariani *et al.* (2011a) to feed a soft-margin SVM with Gaussian kernel and by Mariani *et al.* (2013), using a variable window, to feed three LDA classifiers (the first for the background classification, the second for the A1 classification and the third for the A2 and A3 classification). The A phase classification was determined by combining the classification vectors. SVM achieved the highest average results.

Mariani *et al.* (2012) used the same features and four classifiers (NN, LDA, SVM and the Adaptive Boosting classifier, AdaBoost, with 20 weak learners) verifying that LDA provided the best results. Machado *et al.* (2016) used a macro-micro structure descriptor, the Teager energy operator (TEO), Lempel-Ziv complexity, Zero-Crossing, empirical mode decomposition, Shannon entropy and variance as features to feed three classifiers, LDA, SVM and kNN. It was determined that SVM produces the highest accuracy.

By analysing the A phase detection proposals it was possible to identify the features indicated as the most relevant: five frequency band descriptors; Hjorth activity; differential variance; TEO; Lempel-Ziv complexity; Zero-Crossing; Shannon entropy; empirical mode decomposition; macro-micro structure descriptor. It is also possible to determine that LDA, SVM, kNN and NN are the most suited classifiers.

The main objective of this work is to propose new features using the LDA, since it was determined to be the classifier that achieved the highest performance in the state of the art analysis. A comparison with the features indicated by Mariani *et al.* (2012) was also implemented since this work reported the highest performance of the bibliographical analysis. The results were achieved using the LDA.

The majority of the presented works remove the REM periods from the analysis, increasing the overall performance of the algorithms. In this work a different approach was used, keeping all the sleep data, making the developed algorithms of this work more suitable for automatic system implementation.

3 MATERIALS AND METHODS

A systematic review was performed to determine the best approach for CAP classification. The chosen method first classifies the A and B phases and after uses a FSM to determine the CAP. A public database was used for training and testing the classifier and the FSM in a programming environment.

The employed features are a mix of some identified in the state of the art as the most relevant and some new ones proposed. The first test involved the use of all features and sequential feature selection (SFS) was applied in the second test to choose the best features for the classifier.

Principal component analysis (PCA) was used in the third test to generate the features independently from the classifier and the final test was the use of the features indicated by Mariani *et al.* (2012) in the developed algorithm.

3.1 Database

A public database from PhysioNet (Terzano et al., 2001), with specific annotations of the macro and microstructure made by trained neurologists, was employed in the tests. A total of 14 recordings were used, being recorded using the 10-20 international system and monopolar derivations (C4-A1 or C3-A2). The annotations include the sleep stage, event description and duration.

The sleep analysis varies between six hours and thirty minutes and nine hours and fifty minutes. The subjects age varies between 23 and 78 years, being nine males and five females. 50000 samples were used in average in each of the employed datasets (data from three subjects), either for test or training. In both cases train/test with two datasets and validate with the left off subject, repeating multiple times until all subjects were used at least one time for validation. The EEG signals were imported to the programming environment Matlab 9.0 (The Mathworks Inc.) for the analysis.

3.2 Feature Set

The features determined in the review as the best ones for A phase detection were tested. A two second time window was used, chosen due to be the minimum A phase duration.

TEO and Shannon entropy presented good discriminatory capabilities. The five band descriptors provided a lower accuracy when compared to the analysis of power spectral density (PSD) of each band. The same conclusion occur when comparing the differential variance with the autocovariance. The time series analysis could also be used, since the average power and the standard variation presented a good correlation with the presence of the A phases. Other relevant feature used in other EEG analysis is the log-energy entropy (Aydin *et al.*, 2009).

A total of 11 features were analysed in this work. Specifically: average power; standard variation; Shannon entropy; autocovariance; log-energy entropy; TEO; PSD in the delta, theta, alpha, sigma and beta bands.

The feature selection was performed with a classifier dependent method (the SFS using the sequential forward selection method) and a classifier independent method (the PCA). The seven features used by Mariani *et al.* (2012) were also tested in the developed algorithm.

3.3 Sequential Forward Selection

The implemented sequential forward selection algorithm initiates with two sets of variables, the first is empty and the second has all the features.

The most relevant feature is determined in the first iteration considering the ratio Total= (Acc+Sen+Spe)/3 and moved from the second set to the first set.

During the second iteration the algorithm looks for the second most relevant feature that has the best compatibility with the first feature, providing the highest value for Total. This feature is moved from the second set to the first set and placed after the first feature.

The Algorithm is repeated until all the features were moved to the first set, being ordered according to their relevance.

3.4 Classifier

The discriminant analysis, a supervised learning classifier, was employed for classification. This classification method assumes the data to be produced based on Gaussian distributions. The linear model (LDA) first determines the mean of each class and then computes the covariance. Therefore, each class has the same covariance matrix but with different means.

The aim of the classifier is to produce a hyperplane decision surface that divides the feature space, maximizing the ratio of between-class variance to within-class variance (Murphy, 2012). In this work LDA was used in a binary classification where the results are either an A phase or not an A phase (considered to be a B phase).

The classifier was tested and validated using a cross validation scheme (validate with one subject and train with the others, being used 7 subjects for training and 7 subjects for testing), producing the average accuracy (Acc), sensitivity (Sen), specificity (Spe) and area under the curve (AUC). A FSM was used to classify the CAP, by implementing the rules of CAP, being the accuracy (CAPacc) of the results evaluated.

3.5 Post-processing

A post-processing procedure was introduced to reduce the outliers of the classification, improving the CAP accuracy. This procedure considers as a misclassification an isolated A phase, with only two seconds, surrounded by two b phases and an isolated B phase, with only two seconds, surrounded by two A phases. The misclassified data is converted into the opposite phase (an A into a B and a B into an A).

3.6 Finite State Machine

The FSM was developed to implement the two rules of CAP: the first dictates the validity of the A and B phases by specifying the minimum duration of 2 s and a maximum of 60 s of each phase; second rule indicates that a B phase needs to separate two successive A phases. The FSM algorithm flowchart is represented in figure 4.

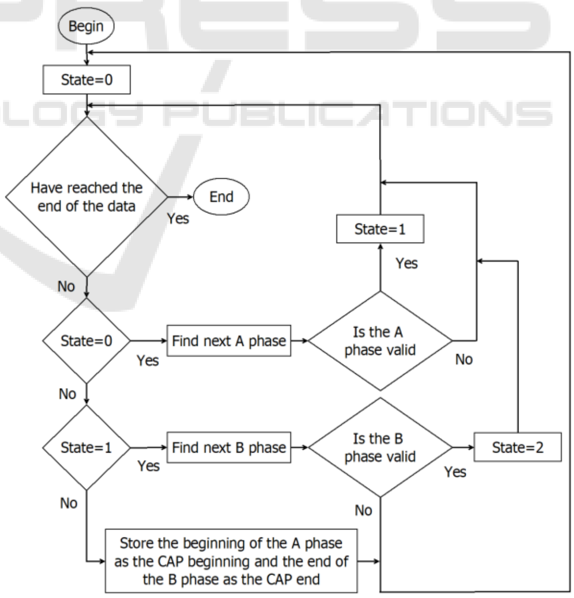

Figure 4: FSM algorithm flowchart.

4 RESULTS

The influence of the sleep stage in the features was analysed, concluding that average power, standard variation, log-energy entropy and PSD in the delta and theta bands are strongly correlated with the sleep stage. This correlation may affect the classifier performance since the feature behaviour changes according to the sleep stage. It was also determined that all features react to the presence of an A-phase in every sleep stage. However, the highest reaction happen in the second sleep stage.

The 11 features were used in the first test and the classifier average accuracy was 72% with a sensitivity of 82% and specificity of 70%. The CAP accuracy was 67%. SFS was applied in the second test being presented in table 1 the order of the features by relevance (from 1 to 11) and in figure 5 the average results. The best results were achieved using the first six features with a Total ratio of 76. PCA was employed in the third test and the best results were produced using the first three components (variance of 78%).

Table 1: Features ordered according to the SFS results.

Features	Order
PSD beta	1
Average power	2
PSD theta	3
TEO	4
Standard variation	5
PSD alpha	6
PSD sigma	7
Shannon entropy	8
Log-energy entropy	9
Autocovariance	10
PSD delta	11

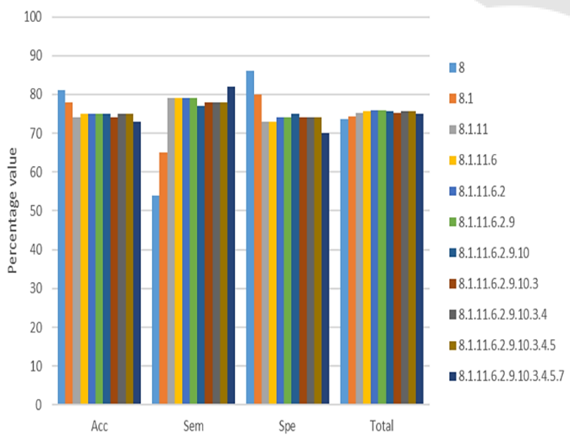

Figure 5: Results of the SFS. Legend: 1 - average power; 2 - standard variation; 3 - Shannon entropy; 4 - log-energy entropy; 5 - autocovariance; 6 - TEO; 7 - PSD delta; 8 - PSD beta; 9 - PSD alpha; 10 - PSD sigma; 11 - PSD theta.

The final test was the application of the features used by Mariani *et al.* (2012) in the developed algorithm. However, Mariani *et al.* (2012) used a re-sampled training set from a different source, using the same number of samples belonging to the A and B phases, to avoid biasing the classifier and the wake and REM periods were removed. The obtained results are presented in table2.

Table 2: Results of the implemented classifier achieved with different features.

Employed features	Acc (%)	Sen (%)	Spe (%)	AUC	CAPacc (%)
Selected by SFS	75 ± 5	78 ± 2	74 ± 7	0.76 ± 0.02	75 ± 7
Produced by PCA	74 ± 6	71 ± 5	75 ± 8	0.73 ± 0.02	76 ± 6
Proposed by Mariani *et al.* (2012)	67 ± 3	79 ± 15	64 ± 4	71 ± 0.07	68 ± 6

The highest accuracy and AUC was achieved using SFS while PCA provided the best specificity and CAP accuracy (since the data is unbalanced, having more B phases then A phases). The features proposed by Mariani *et al.* (2012) provided the maximum sensitivity but with a great variation in the results.

5 DISCUSSION

Multiple approaches have been presented in the analysed bibliography for the A-phase detection. Table 3 summarizes the analysis of the reported results from papers that have used LDA for classification and compares with the average results achieved in the work.

Table 3: Results comparison.

Paper	Method	Acc (%)	Sen (%)	Spe (%)
(Mariani *et al.*, 2013)	LDA	86	67	90
(Mariani *et al.*, 2012)	LDA	85	73	87
(Machado *et al.*, 2016)	LDA	68	-	-
This work	LDA with SFS	75	78	74

From table 3 analysis is notorious that our method produced the highest sensitivity but a lower accuracy then Mariani *et al.* (2013) and Mariani *et al.* (2012) that have removed the REM periods, leading to an increase in the overall performance of the proposed method. The approach of not removing the REM periods was also employed by Machado *et al.* (2016), however the reported accuracy has the lowest value.

A more detailed comparison between the results achieved using the features proposed by Mariani *et al.* (2012) is presented in table 4. The achieved results have a lower accuracy and specificity but a higher sensitivity. However, the variation of the results is similar to the variation presented by Mariani *et al.* (2012), having sensitivity the more significant variation. The difference in the results could be due to the fact that Mariani *et al.* (2012) employed a re-sampled training set to balance the data since, usually, there are much more B phases than A phases so a low specificity will lead to a lower accuracy. Therefore, the AUC would provide a better comparison but this information is not reported by Mariani *et al.* (2012). The other relevant factor is the removal of the REM periods that leads to better results.

Table 4: Comparison between the results achieved using the features proposed by Mariani *et al.* (2012).

Paper	Acc (%)	Sen (%)	Spe (%)
(Mariani *et al.*, 2012)	85 ± 5	73 ± 11	87 ± 6
This work	67 ± 3	79 ± 15	64 ± 4

Comparing the CAP accuracy of the developed work with the proposal of Karimzadeh *et al.* (2015), consisting in classifying directly CAP from the EEG data, is possible to verify that our results are 4% lower when comparing with the LDA classifiers. However, Karimzadeh *et al.* (2015) have also removed the REM periods in the analysis so the direct comparison is not appropriated. Figure 6 summarizes the results with SFS.

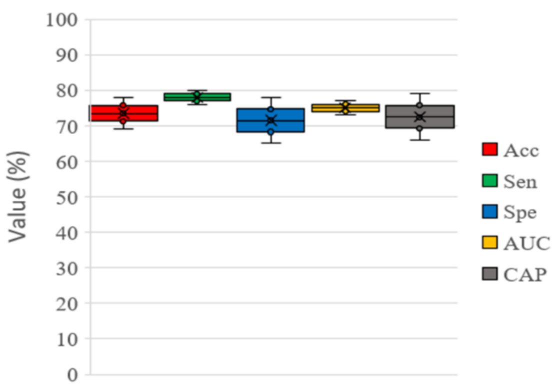

Figure 6: Global results with SFS.

6 CONCLUSIONS

This work was produced with the goal of developing an algorithm capable of detecting the CAP using first a classifier for the A phase detection and then apply a FSM to implement the rules of CAP. It was verified that a combination of SFS, for selecting the best features, and a post processing procedure produces the best results. Comparing with the alternative approach, presented by Karimzadeh *et al.* (2015), of directly classify the CAP from EEG, it was determined that our method produces a similar accuracy but with simple features.

By comparing with the articles in the state of the art it was determined that the developed algorithm has comparable performance without the need to manually manipulate the database to remove the REM periods, making the approach of this work more suitable for automatic system implementation.

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