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Automatic detection of cyclic alternating pattern

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Abstract

The cyclic alternating pattern is a microstructure phasic event, present in the non-rapid eye movement sleep, which has been associated with multiple pathologies, and is a marker of sleep instability that is detected using the electroencephalogram. However, this technique produces a large quantity of information during a full night test, making the task of manually scoring all the cyclic alternating pattern cycles unpractical, with a high probability of miss classification. Therefore, the aim of this work is to develop and test multiple algorithms capable of automatically detecting the cyclic alternating pattern. The employed method first analyses the electroencephalogram signal to extract features that are used as inputs to a classifier that detects the activation (A phase) and quiescent (B phase) phases of this pattern. The output of the classifier was then applied to a finite state machine implementing the cyclic alternating pattern classification. A systematic review was performed to determine the features and classifiers that could be more relevant. Nine classifiers were tested using features selected by a sequential feature selection algorithm and features produced by principal component analysis. The best performance was achieved using a feed-forward neural network, producing, respectively, an average accuracy, sensitivity, specificity and area under the curve of 79, 76, 80% and 0.77 in the A and B phases classification. The cyclic alternating pattern detection accuracy, using the finite state machine, was of 79%.

Keywords Automatic classification · CAP · A phase

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1 Introduction

During sleep, the brain oscillates between two major states, the rapid eye movement (REM) and the non-REM (NREM). Cyclic patterns of REM and NREM define the sleep macrostructure, organized in discrete levels that are directly related to the sleep deepness. NREM is divided into three stages (N1, N2 and N3), increasing from stage to stage the slow-wave activity.

Stage N1 is commonly characterized by mixed frequency activity with low amplitude and constitutes between 2 and 5% of the total sleep time. The energy in the lower frequencies increases during the second sleep stage (N2) that occupies between 45 and 55% of the total sleep. High-amplitude waves with low frequency characterize stage N3. During REM sleep, the cerebral activity increases, presenting mixed wave frequencies with low amplitude [1].

Transitional states are defined by the sleep microstructure, describing the transient and phasic events in the brain electrical activity that can be measured by electroencephalography. This imaging technique belongs to the electrobiological measurements group, and the electroencephalogram (EEG) is one of the most commonly used techniques in this field. EEG is registered, at the surface of the scalp, using metal electrodes and conductive media [2]. The most common scalp electrodes distribution is the 10–20 electrode placement standardization [3].

A relevant microstructure phasic event, defined in the NREM sleep, is the cyclic alternating pattern (CAP), characterized by cycles of an activation (A phase) phase followed by a quiescent (B phase) phase. Each phase duration can vary between 2 and 60 s [4]. A non-CAP period occurs when the duration of the phases is higher or lower than the specified one and a CAP sequence is a succession of two or more CAP cycles. The mean duration of a CAP sequence, in healthy adults, is estimated to be 2 min and 33 s, composing in average to 5.6 CAP cycles, having each cycle a mean duration of 26.9 ± 4.1 s [5].

Three subtypes, A1, A2 and A3, were defined according to the A phase characteristics, increasing the energy, in the alpha or beta bands from subtypes A1–A3 [6]. The EEG monopolar derivations, C4-A1 or C3-A2, are often used for CAP analysis, and the sigma band is introduced. Therefore, the EEG power spectrum is subdivided into five bands, delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), sigma (12–15 Hz) and beta (15–30 Hz) [7]. A detailed analysis of CAP origin and its significance was produced by Terzano and Parrino [8]. An example of a B phase and the three subtypes of the A phase is presented in Fig. 1.

Studies have indicated that CAP is a relevant process to generate, consolidate and disrupt the sleep macrostructure [9]. The CAP rate is defined by the ratio of the total CAP time, in NREM sleep, to total NREM sleep time. When sleep is disturbed, by induced vigilance instability, the CAP rate increases. Hence, there is a temporal relation between autonomic functions, behavioural activities and CAP [10]. A poorer sleep quality is related to higher values of CAP rate; therefore, CAP is the EEG marker of sleep instability [11] and measures the effort of the brain to maintain sleep [12]. CAP cycles have been associated with sleep apnea [13], bruxism [14], insomnia [12, 15], periodic limb movements [12, 16], restless leg syndrome [17], idiopathic generalized epilepsy [18] and nocturnal frontal lobe epilepsy [17]. Therefore, scoring CAP is significant for characterization and diagnosis of such pathologies.

A large quantity of information is produced during a full night of EEG sleep, making the task of manually scoring all the CAP cycles unpractical, with a high probability of miss classification. Consequently, the specialist agreement, analysing the same EEG results, is in the 69–78% range [19] and automatic CAP detection algorithms have been proposed to address this issue.

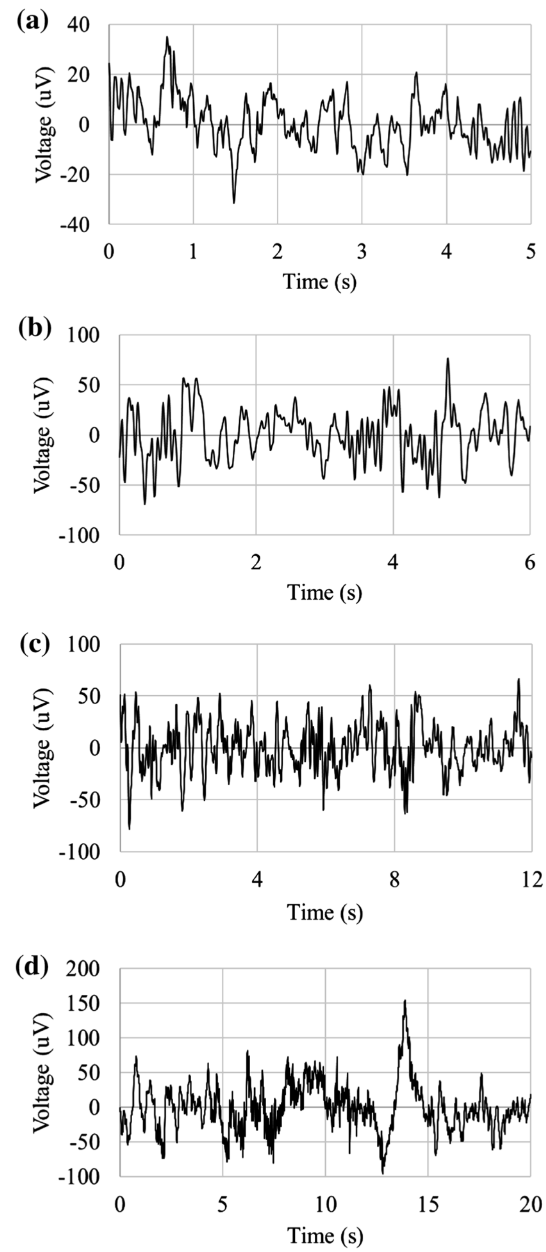

Fig. 1 Example of CAP phases, **a** B phase, **b** A1 subtype, **c** A2 subtype and **d** A3 subtype. From **a** to **c**, it is possible to detect the increase in rapid activities, and from **a** to any of the A phase subtypes (**b–d**), an increase in the signal amplitude variation occurs

Therefore, the objective of this work is to analyse multiple classifiers, proposing algorithms for possible implementation, making an expansion of the previous work [20] where linear discriminant analysis (LDA) was analysed for the CAP phases classification.

The paper is organized as follows: related work is analysed in Sect. 2; employed methods are discussed in Sect. 3; algorithm's performance is examined in Sect. 4; Sect. 5 presents the comparison of the produced results with related work in the state of the art, and the paper conclusion is presented in the final section.

2 Related work

Two main approaches for CAP classification were identified through a systematic review. The first consists in directly classifying the CAP cycles using features extracted from EEG. Karimzadeh et al. [21] have employed this method using multiple entropy features and tested three classifiers, the support vector machine (SVM), the LDA and the *k*-nearest neighbours (kNN). kNN provided the best results, and the most relevant features were Shannon, Kolmogorov and sample entropies. The alternative approach consists in first generating features from EEG to feed a classifier with the aim of determining the A and B phases. Afterwards, a finite state machine (FSM) classifies the CAP cycles. A commonly employed simplification consists of considering that when an epoch is not an A phase, it will be classified as a B phase (binary classification). The second method was employed in this work since it provides more information, specifically the CAP phases and the CAP cycles, that could be useful for medical diagnosis.

Multiple methods for sleep microstructure analysis, and specifically the A phase classification, are presented in the state of the art. Barcaro et al. [22] proposed a technique for the quantitative description of sleep microstructure, based on the computation of descriptors that provide a normalized measure of how much the amplitude of the activity in a specific frequency band differs from its background. Navona et al. [23] and Barcaro et al. [24] used five frequency band descriptors (one descriptor for each of the EEG bands) and thresholds for classification. A threshold classification was also employed by Mariani et al. [25], and Hjorth activity was determined to be the best feature. Largo et al. [26, 27] computed the fast discrete wavelet transform and analysed the signal power in each of the five frequency bands. Two moving averages were calculated, and the relation between the averages (named activity index) was used as a measure of the presence of activation phases by comparing with a threshold. The moving averages and the thresholds were defined by a genetic algorithm.

Ferri et al. [28] presented an algorithm where the user has to choose two threshold values: one for the low-frequency band power (characterizing the A1 and part of A2 phases) and another level for the high-frequency band power (characterizing the A3 and the other part of the A2 phases). A technique based in the similarity analysis of the windowed signal and an A phase windows reference database was presented by Niknazar et al. [29].

Five band descriptors, Hjorth activity and differential variance were used as features to feed classifiers by Mariani et al. [7, 30 31, 32]. In the first work, the employed classifier was a three-layer neural network (NN), and in the second it was a SVM with Gaussian kernel. In the third work, three LDA classifiers were employed (one for B phase classification, other for A1 phase classification and the last for A2 and A3 phases classification) and the A phase classification was generated by a SVM feed by a combination of the classification vectors. The fourth work analysed four classifiers, specifically, LDA, NN, SVM and adaptive boosting (AdaBoost). The best results were produced by LDA.

Teager energy operator (TEO), a nonlinear energy-tracking operator viewed as an instantaneous measure of energy, was used in the discrete form by Machado et al. [33] applying a threshold for classification. LDA, SVM and kNN were tested by Machado et al. [34] using TEO, macro–microstructure descriptor, Lempel–Ziv complexity, empirical mode decomposition, zero crossing, variance and Shannon entropy as features. It was verified that the highest accuracy was achieved by the SVM.

Temporal (skewness, standard deviation, kurtosis and average A phase duration), energy (total EEG energy and power density in four bands: delta; theta; alpha; beta) and complexity (sample entropy, Lempel–Ziv complexity, Tsallis entropy and fractal dimension) measures were computed by Mendez et al. [6] to feed a kNN classifier. It was determined that sample entropy, Lempel–Ziv complexity, standard deviation, EEG energy and power in the beta band were the most relevant features. A method was also proposed to discriminate the A phase borders (onset and offset) that was further analysed by Mendez et al. [35].

The features indicated as the most relevant by the analysed A phase detection proposals were: Hjorth activity; Lempel–Ziv complexity; differential variance; TEO; Shannon entropy; five frequency band descriptors; EEG energy; power in the beta band; empirical mode decomposition. LDA, kNN, SVM and NN were the most significant classifiers. The majority of the analysed papers remove the REM periods from the analysis, leading to an increase in the classifier performance. In this work, all the sleep data of the subjects were kept, making the developed algorithms more suitable for an automatic system implementation.

3 Materials and methods

The implemented method for CAP classification first discriminates each epoch as either A or B phase. Afterwards, a FSM analyses the epochs and determines the CAP cycles.

A public database was used for training and testing the classifier and the FSM.

The employed features and the analysed classifiers are a combination of some that were identified in the systematic review and some new proposals.

Two tests were performed for each classifier using data from a database that contains polysomnographic recordings enclosing subjects with and without pathologies. In the first, features were selected by sequential feature selection, using the best features for each classifier. In the second, the features were produced by principal component analysis (PCA), selecting the features independently from the classifier.

3.1 Database

The CAP Sleep Database from Physionet was used [36] to test the algorithms. This database has annotations concerning the microstructure and macrostructure of sleep inserted by a team of trained neurologists of the Ospedale Maggiore of Parma, Italy. EEG was recorded using the 10-20 international system, and the signals from monopolar derivations (C4-A1 or C3-A2) were used.

Recordings from fourteen subjects were selected for this work. Nine of them are free of any neurological disorders, four have sleep-disordered breathing, and one has bruxism. The recording's duration varies between 6 h and 30 min to 9 h and 15 min. Five subjects were females, and nine were males, having an age variation between 23 and 78 years old. The annotations include the A phase description and duration. However, the CAP cycles are not annotated. Hence, these annotations were made for each subject in agreement with Terzano reference atlas [36].

An average of 50,000 samples was used in each of the employed datasets, consisting of data from three subjects, either for training or for testing. Thus, seven subjects were used for training and the other seven for testing. In each iteration, two datasets were used for training or testing and validation was performed with the left off subject, repeating multiple times with different combinations until all subjects were used at least once for validation.

The programming environment MATLAB (The Mathworks Inc.) was used to produce the analysis, importing the EEG signals.

3.2 Methodology

The employed methodology was based on the processing of the whole EEG signal related to either C4-A1 channel or C3-A2 channel and encompasses the steps: feature extraction; feature selection; classification by a classifier (A and B phases); post-processing; FSM classification (CAP cycles).

3.3 Feature set

A two-second epoch duration was employed since it is the minimum duration of a CAP phase. An individual test of each of the features identified in the systematic review, as the most relevant for A phase detection, was performed.

The five band descriptors, implemented in delta, (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), sigma (12–15 Hz) and beta (15–30 Hz) bands, achieved good discriminatory capabilities in the A phase analysis. However, the power spectral density (PSD) of each band was chosen since they provided a higher accuracy. The same conclusion was obtained when comparing the autocovariance with differential variance. Log-energy entropy was indicated as a significant feature for EEG analysis by Aydin et al. [37] and presented a better performance than Hjorth activity, Lempel–Ziv complexity and empirical mode decomposition for A phase detection. Standard deviation and the average power of the time series also exhibit a good correlation with the A phase presence.

Therefore, a group of eleven features, indicated in Table 1, were used in this work, specifically, the standard deviation and the average power in the time series, autocovariance, Shannon and log-energy entropies, PSD in the five frequency bands (delta, theta, alpha, sigma and beta) and TEO. Feature selection was performed using classifier dependent, sequential forward selection and classifier independent, PCA, methods.

3.4 Sequential feature selection

Feature selection was performed using the sequential forward selection (SFS) method. The algorithm is initiated with two vectors: the first is empty, and the second has all the features with a random order.

Table 1 Analysed features and the respective identification number

Feature	Number
Average power	1
Standard deviation	2
Shannon entropy	3
Log-energy entropy	4
Autocovariance	5
TEO	6
PSD in the delta band	7
PSD in the beta band	8
PSD in the alpha band	9
PSD in the sigma band	10
PSD in the theta band	11

The goal is to produce a feature vector that provides the maximum accuracy (Acc), sensitivity (Sen) and specificity (Spe). Consequently, this is a multi-objective optimization. Therefore, a combined objective (CO) was defined as the sum of accuracy, sensitivity and specificity with equal weight [38].

In the first iteration, the feature that provided the highest value for the CO was selected as the most relevant and was moved from the second vector to the first vector.

In the next iterations, the algorithm looks for the feature, in vector two, that when combined with the feature in vector one provides the highest value for the CO. The selected feature was moved from the second to the first vector and placed after the first moved feature. This process was repeated until all the features have been moved from the second to the first vector. The result was a vector (the first vector) with all features ordered according to their relevance for the classifier. A feature selection process analyses the result vector and chooses the features that contribute to an increment of the CO. The final feature vector keeps the features that, when combined, provided the maximum achieved value of the CO.

3.5 Classifiers

A binary classification was employed in this work since the results of the classifier are either an A phase or not an A phase (considered to be a B phase). In the previous work [20], LDA was analysed. It is a supervised learning classifier that assumes the data to be produced based on Gaussian distributions [39].

Nine classifiers were tested in this study with the aim of covering multiple possible solutions, from simple to complex implementations. Two classifiers based in unsupervised learning were selected: the first was the self-organizing map (SOM), a type of NN that analyses topographic relationships of the input data [40]. The second classifier was *k*-means clustering (kMC) that consists in determining cluster means and then assigning the data points to the clusters [41]. The other seven classifiers, based on supervised learning, were logistic regression (LR), classification tree (CT), ensemble of decision trees (ET), SVM, kNN, feed-forward NN (FFNN) and cascade-forward NN (CFNN).

LR uses the logistic function to predict the output probability given the model parameters. A different approach is followed by CT, dividing the dataset into smaller subsets, and generates an associated decision tree with decision nodes and leaf nodes that produces the classification [39]. An ET was also analysed, consisting of a combination of multiple decision trees (weak learners) to implement a classifier combination strategy [40].

The kNN algorithm classifies the data by analysing the dominant class among its *k*-nearest neighbour points in the training set. A more complex approach is employed by SVM, representing the input data in a multidimensional space that is divided by a discriminant hyperplane to identify classes. The FFNN can be seen as series of logistic regression models connected in layers to form a directional network [39]. CFNN is similar to FFNN but has a connection from every previous layer to the next layer.

A cross-validation scheme, where validation was performed with one subject and training or testing with the others, was used for each classifier performance analysis, producing the average Acc, Sen, Spe and area under the curve (AUC). The FSM was then fed with the classifier output to determine the CAP cycles, and the accuracy of the results (CAPacc) was evaluated.

3.6 Post-processing and finite state machine

A post-processing procedure was implemented to reduce the CAP phases classification outliers, leading to an improvement in the accuracy of CAP detection.

An epoch was considered as a misclassification if the previous and the next epochs are from the opposite phase. Therefore, if the epoch was classified as an A or B phase, then the epoch label is changed to a B or A phase, respectively.

After the post-processing, a FSM was employed to classify the CAP cycles in agreement with Terzano reference atlas [36]. First, the algorithm verifies whether the A and B phases are valid, using the specifications of minimum (2 s) and maximum (60 s) duration of a phase. Afterwards, the cycles are defined by applying the rule that an A phase needs to separate two consecutive B phases.

4 Results

It was verified that the features have different behaviours in each sleep stage and this effect decreases the classifier performance. However, all features react to the occurrence of an A phase in every sleep stage.

The performance of the classifiers was analysed in two tests, with a cross-validation scheme in each test. The features selected by SFS were employed in the first test, and the features produced by PCA were used in the second test.

The SFS results of each classifier are presented in Table 2. The order of selection is from the most relevant (first feature) to the less relevant (last feature), and the feature number indicates the feature according to Table 1. Figure 2 presents the number of times each feature was selected by the classifiers. It is possible to determine that

Table 2 SFS result of each classifier, using the feature identification number present in Table 1

Classifier	SFS order
LR	8, 1, 9, 6
CT	7, 8, 11, 10, 9, 5, 4, 3
ET	9, 7, 11, 10, 4, 8, 6, 5, 3
SVM	1, 8, 11, 4, 6, 2, 10, 5
FFNN	8, 3, 6, 5, 11
CFNN	8, 3, 6, 9, 11, 5, 10
kMC	10, 5, 6, 3, 9, 8, 2
kNN	11, 8, 7, 9, 5, 3, 1, 4, 2
SOM	10, 1, 8, 6, 11, 5, 2

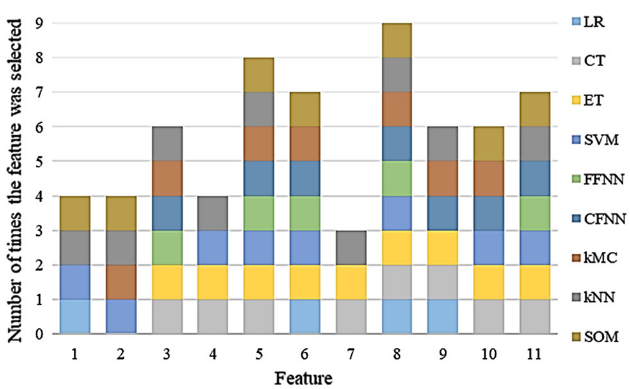

Fig. 2 Number of times the features were selected by each classifier specified by a colour. Features are identified by the identification number present in Table 1 (colour figure online)

PSD in the beta band is the most relevant feature and PSD in the delta band is the less relevant feature. The first three components of PCA were used in the second test. It was verified that the first component was the most relevant. An example of the variation of this component and the PSD in the beta band (most relevant feature) is presented in Fig. 3 and is possible to assess their correlation with the CAP phases. An A phase is represented by the value 1 and a B phase by the value 0.

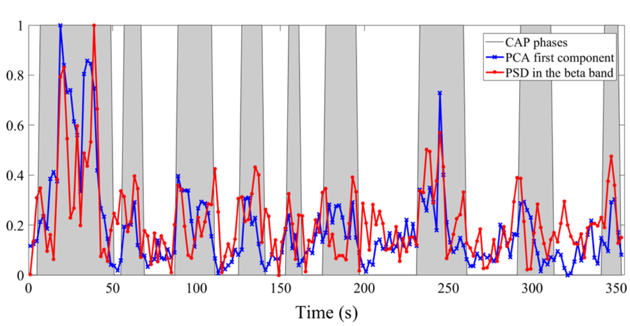

Fig. 3 Example of the variation of the most relevant feature (PSD in the beta band) and PCA first component with the CAP phases

The specifications of each classifier were chosen by performing multiple runs with cross-validation, and the parameters that maximized the CO were kept. For the LR, it was verified that using regularization does not increase the classification performance. The selected split predictor algorithm for the CT minimizes the p value of the Chi-square tests. If the p value is greater than 0.05, then the algorithm stops splitting nodes. The best minimum parent size was varied between 1 and 10.

Best results were produced for the minimum size of 1. For the ET, the best number of trees was evaluated by consecutive increment, from 3 to 30. It was determined that the highest value for the CO was achieved with 10 trees. Three ensemble-aggregation methods were tested, specifically the AdaBoost, LPBoost and TotalBoost [42]. The best results were produced using TotalBoost. Linear and Gaussian kernel functions were tested for the SVM classifier, with the highest CO value obtained using the linear kernel function with a scale of 2 and a 10% outlier fraction.

The best transfer function for both FFNN and CFNN was the hyperbolic tangent sigmoid, and gradient descent was employed for learning adaptation. The chosen training function was Levenberg–Marquardt backpropagation [41]. The number of neurons was varied from 20 to 400, in steps of 10 neurons. The best value of neurons for the FFNN was 280, and for CFNN it was 270.

Three kMC distance measures were analysed, specifically, the squared Euclidean, sum of absolute differences and Hamming [43]. The best results were provided by the squared Euclidean distance. The number of nearest neighbours for the kNN classifier was varied between 1 and 10, with the best result achieved with 4 for the Euclidean distance. The analysed distances were Chebyshev, Euclidean and Hamming [39]. For SOM, the dimension size was varied from 2 to 10. The best result was achieved using a dimension size of 6.

Table 3 Average results of the implemented classifiers using the features selected by SFS

Classifier	Acc (%)	Sen (%)	Spe (%)	AUC	CAPacc (%)
LR	76	80	75	0.77	78
CT	70	58	73	0.66	64
ET	70	64	71	0.67	70
SVM	72	80	70	0.76	75
FFNN	79	76	80	0.78	79
CFNN	76	77	76	0.76	77
kMC	78	67	81	0.74	78
kNN	72	70	72	0.71	70
SOM	67	79	66	0.73	68

Table 4 Average results of the implemented classifiers using the features produced by PCA

Classifier	Acc (%)	Sen (%)	Spe (%)	AUC	CAPacc (%)
LR	67	78	65	0.71	69
CT	74	51	82	0.62	68
ET	74	63	77	0.70	76
SVM	68	84	66	0.74	71
FFNN	75	76	75	0.75	76
CFNN	74	76	74	0.75	76
kMC	61	62	61	0.61	61
kNN	69	65	70	0.67	66
SOM	22	90	08	0.49	60

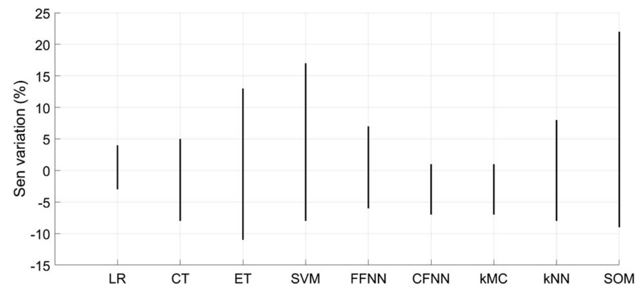

Fig. 5 Variation in percentage of the Sen of each classifier, using features selected by SFS

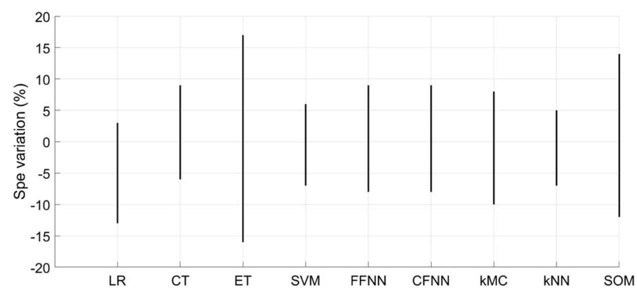

Fig. 6 Variation in percentage of the Spe of each classifier, using features selected by SFS

Tables 3 and 4 present the results of each classifier using the features selected by SFS and the features produced by PCA, respectively. The accuracy of the FSM is also presented. The performance analysis is based in the Acc, Sen, Spe, AUC and CAPacc. Comparing the results of the two tests, it is possible to verify that only the CT and ET achieved better results using PCA.

FFNN with features selected by SFS provided the highest average values for the CO, Acc and AUC. CT with the features produced by PCA attains the highest average Spe but has a poor Sen. The maximum Sen was achieved by SOM, but it has also produced the lowest value for the CO.

It was determined that FFNN is the best classifier to classify the CAP phases and the FSM attains the highest accuracy in the CAP classification (CAPacc) using the results of the FFNN as input. However, LR with features selected by SFS achieved similar results, when comparing with the FFNN, and this algorithm provides a simpler implementation that could be useful in a system with few computational resources.

The variation, around the average value, of Acc, Sen, Spe, AUC and CAPacc (using the results provided by the classifier to feed the FSM), for each classifier using the features selected by SFS, is presented, respectively, in Figs. 4, 5, 6, 7 and 8. By analysis of these figures, it is possible to verify that CFNN has the lowest variation in the results, while ET has the highest.

The estimate of which noise level is tolerable for the proposed method that achieved the best results (FFNN with features selected by SFS), classifying the CAP phases, was performed by introducing additive white Gaussian noise (AWGN) to the EEG signal with different levels of signal-to-noise ratio (SNR) and using the CO as the reference measurement. The results are presented in Fig. 9, and it was verified that below a SNR of 31 dB the performance of the proposed method begins to deteriorate and the lowest admissible SNR was 0.5 dB (CO of 70%).

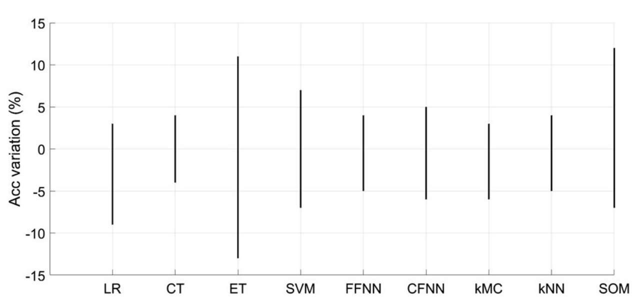

Fig. 4 Variation in percentage of the Acc of each classifier, using features selected by SFS

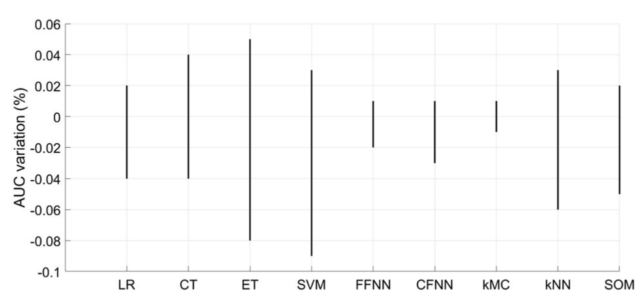

Fig. 7 Variation in percentage of the AUC of each classifier, using features selected by SFS

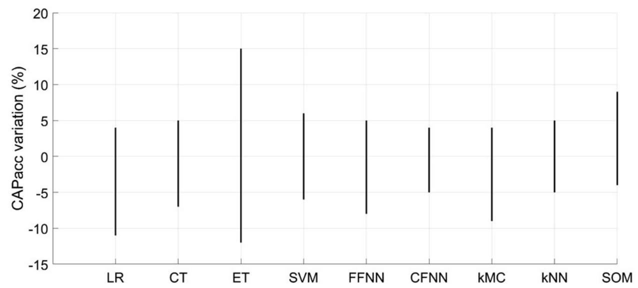

Fig. 8 Variation in percentage of the CAPacc, using the results provided by each classifier, with features selected by SFS, to feed the FSM

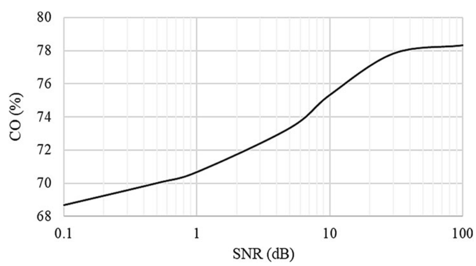

Fig. 9 CO produced by the FFNN with features selected by SFS (method that achieved the best results) in the presence of AWGN, classifying the CAP phases. The noise was introduced in the EEG signal with different levels of SNR

5 Discussion

Multiple approaches for A phase detection are presented in the state of the art. Table 5 summarizes the analysis of the reported results from the articles that have been identified in the review. The average results achieved in this work are also presented to facilitate the comparison. A common approach consists of removing the REM sleep periods, leading to a reduction in the miss classifications and, therefore, an increase in the Acc. From the analysed works in Table 5 only this work, Machado et al. [34] and Mendonça et al. [20] did not follow this approach.

From the group of papers that did not employ a machine learning approach, Barcaro et al. [24] reported the highest Acc using band descriptors. Mariani et al. [31] achieved the maximum reported Acc and Spe using LDA as classifier. However, the approach also reported the lowest Sen, leading to unbalanced results. Using the same classifier, Mariani et al. [32] achieved the second highest Acc with balanced results in Sen and Spe. Comparing these results with the works that have also used LDA, Machado et al. [34] and Mendonça et al. [20], it is possible to verify that a lower performance was achieved possibly due to the effect of not removing the REM sleep periods from the analysis.

Comparing the achieved results, for the kNN and SVM classifiers, with the results reported by Machado et al. [34] it is possible to verify that a higher ACC was achieved in this work. Making the comparison with Mariani et al. [7, 32], for the SVM, it is possible to verify that in this work a lower Acc and Spe were achieved, but the Sen is higher. These results could be due to the typical unbalanced data in a normal subject, having much more B phases than A phases, implying that an increase in Spe has a greater impact in the Acc than an increase in Sen. The other relevant aspect is the removal of the REM sleep periods from the analysis that also leads to an increase in the Acc. The same analysis is valid for the comparison of the achieved results with the FFNN and the NN employed by Mariani et al. [30, 32].

Table 6 presents the analysis for CAP classification. It is possible to verify that the results reported by Karimzadeh et al. [21] are similar to the results achieved in this work for the methods that employ either the LR, FFNN and kMC classifiers or the FSM. However, the proposed implementation in this work is based in features that are obtained more easily.

The higher CAPacc achieved by Karimzadeh et al. [21] could be due to the removal of the REM periods. Mendonça et al. [20] employed the method of first discriminate the CAP phases, with an LDA classifier, and afterwards use a FSM to determine the CAP cycles. Therefore, it is possible to make a direct comparison with this work. Classifying the CAP phases with SVM provides the same accuracy as reported by Mendonça et al. [20]. However, better results are produced using the LR, FFNN, CFNN and kMC classifiers.

6 Conclusions

The goal of this work was to develop algorithms capable of detecting the CAP phases, using a classifier to determine the A and B phases, and the CAP cycles, by employing a FSM. A review was made to assess the most relevant features and classifiers to be analysed in the work. Each classifier was tested with features selected by SFS and PCA. The best results were produced using the FFNN with features selected by SFS. It was verified that the developed algorithms have a comparable performance with the algorithms in the state of the art for the detection of the CAP phases, without the need to remove the REM sleep periods, providing a simpler approach for an automatic system implementation.

According to Rosa et al. [19], the specialist agreement, analysing the same EEG results, is in the 69–78% range. Therefore, the attained results with the LR, FFNN, CFNN and kMC classifiers are above the average specialist agreement, indicating that the presented algorithms could be useful for medical diagnosis.

Table 5 Comparative analysis of the CAP phases classification proposals in the state of the art and the presented methods

Paper	Method	Acc (%)	Sen (%)	Spe (%)
Navona et al. [23]	Band descriptors	77	84	90
Barcaro et al. [24]	Band descriptors	84	–	–
Mariani et al. [30]	NN	82	76	83
Mariani et al. [7]	SVM	84	74	86
Mariani et al. [25]	Band descriptors	69	59	71
	Differential variance	72	55	76
	Hjorth activity	72	70	72
Mariani et al. [32]	AdaBoost	79	69	79
	LDA	85	73	87
	NN	82	73	82
	SVM	82	70	84
Mariani et al. [31]	LDA	86	67	90
Niknazar et al. [29]	Similarity analysis	81	76	81
Machado et al. [34]	kNN	70	–	–
	LDA	68	–	–
	SVM	71	–	–
Mendonça et al. [20]	LDA	75	78	74
This work	LR	76	80	75
	CT	70	58	73
	ET	70	64	71
	SVM	72	80	70
	FFNN	79	76	80
	CFNN	76	77	76
	kMC	78	67	81
	kNN	72	70	72
	SOM	67	79	66

Table 6 Comparative analysis of the CAP classification proposals in the state of the art and the presented methods

Paper	Method	CAPacc (%)
Karimzadeh et al. [21]	kNN	79
	LDA	79
	SVM	82
Mendonça et al. [20]	LDA and FSM	75
This work	LR and FSM	78
	CT and FSM	64
	ET and FSM	70
	SVM and FSM	75
	FFNN and FSM	79
	CFNN and FSM	77
	kMC and FSM	78
	kNN and FSM	70
	SOM and FSM	68

The main limitation of this study is related to the unknown effect that EEG signals provided by subjects with sleep pathologies that were not considered in this study database, such as insomnia, narcolepsy, periodic leg movements, nocturnal frontal lobe epilepsy and REM behaviour disorder, which would produce in the developed methods. Such analysis is the subject of the future work.

A bigger dataset could be a good option to carry out a clinical validation of the method. Regarding physical implementation, either a computer or a dedicated hardware, such as a digital signal processor, is needed to run the algorithm and sensors to produce the EEG signal from either C4-A1 channel or C3-A2 channel.

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Compliance with ethical standards

Conflict of interest All authors declare that they do not have conflict of interest.

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