Detection of CAP sequences in sleep EEG

PDSB 2020 - Group 6
Nina Bach-Gansmo - 97692
Carina Franing Rutledal - 97604
Linnea Wivilson - 97693

Abstract

To extend quantitative sleep analysis and understand human sleep better, study of cyclic alternating pattern sequences (CAPS) is important. CAPS is an indicator of unstable sleep and it is therefore interesting to study a variety of patients ranging from healthy to patients suffering with sleep related diseases, and compare them to study their quality of sleep. In this study, different signal processing tools were used to study CAP sequences. Both bandpass filtering, empirical mode decomposition, Hilbert Huang transform, short time Fourier transfom and discrete wavelet tranform were used to process and analyze the signals. The automatic detection of CAPS did not obtain satisfying results, but are good starting points on the way to more advanced methods.

1. PROBLEM AND MOTIVATION

EEG has been used as a medical technique to study brain activity in over 70 years [1]. Changes in brain activity may indicate brain disorders such as seizure disorders, sleep disorders and much more. By studying the different frequencies in human EEG waves, one can determine the different sleep stages. Observing changes and abnormalities in these frequencies can indicate sleep quality and sleep pathophysiologies. Study of CAP sequences is important to indicate this, and many previous studies have focused on detecting these sequences. However, CAPS studies by visual analysis is a heavy task and reliable automatic detection systems are needed. Previous studies has have mainly focused on using filter banks, FFT and DWT to extract features from the EEG recordings, but in this study EMD, STFT and DWT are studied, to investigate if this can give better detection rate.

2. BACKGROUND AND RELATED WORK

Electroencephalography (EEG) is a medical technique used to analyze the electrical activity in the brain. Human brain waves are commonly divided into five bands based on their frequencies: delta activity ($<$ 4 Hz), theta activity (4-7 Hz), alpha activity (7-13 Hz), beta activity (13-30 Hz) and gamma activity ($>$ 30 Hz) [2]. While alpha activity is most common in resting, awake adults, theta and delta activity are common in the early and deep stages of sleep. The partition between slow and fast brain activity is used to determine the traditional sleep stages N1, N2, N2 and REM sleep. These stages describe the macrostructure of sleep.

CAPS are periodic sleep EEG patterns which consist of transient electrocortical events that can be distinguished from the background activity. Detection of CAP sequences as a measure of the sleep microstructure was proposed by Terzano et al. [3]. A CAP consists of an A phase, with a higher arousal level, and B phase, with a lower arousal level. Each of the two phases have a duration between 2 and 60 seconds. Typical events observed in the A phase are delta bursts, k-comlexes, vertex sharp transients, polyphasic bursts, k-alpha, intermittent alpha and EEG arousals [3].

Several approaches have been proposed for the automatic detection of CAP sequences. The usual approach is to regard everything that is not an A phase as a B phase. The majority of the works also remove the REM sleep form their analysis, in order to improve the performance of the algorithms [4]. EEG filtering and extraction has been performed by the use of filter banks, FFT and DWT. Typically, a classifier to determine the A and B phases are used and then a finite state machine to classify the CAP. Classifiers based on averages, support vector machine (SVM), linear discriminant analysis (LDA) and neural networks have all been used [4].

3. APPROACH AND UNIQUENESS

3.1. Material

20 different all-night recordings were provided to the project, with each recording containing 14 channels including EEG, EMG and EOG. The one of main interest in this subjects is the EEG channel 'C4A1'. The subjects varied from healthy subjects, to subjects with different sleep related disorders such as insomnia and narcolepsy.

In addition, visual detection of CAP sequences in the sleep recordings were provided. Then a comparison between the different automatic detection methods and the visual detection could be calculate to indicate the quality of the automatic methods.

3.2. Methods

The channel of interest, 'C4A1', was extracted from each of the edf-files. A notch filter was then applied to remove the power supply background noise at 50 Hz, and a low-pass filter with cut-off frequency at 60 Hz to remove part of the signal with no interest in this projects.

By applying different signal decomposition methods on the smoothed and extracted channel, the delta and alpha waves got extracted. The alpha- and delta-waves were then analysed to detect A and B phases, and then detect CAP sequences. As long as alpha and delta wave was present, and the amplitude of one of them were higher than 1/3 more than the rms.

When the decomposition was performed with EMD, the data was segmented into 30 seconds epochs before further processing. Then, EMD was applied to each segment at a time. When using DWT and STFT the whole signal was observed at once.

3.2.1. Emprical Mode Decomposition

Emperical mode decomposistion (EMD) was used to distinguish the alpha, beta, delta and theta waves from the signal. By performing EMD and then observing the frequencies from the IMFs, the different waves were determined.

Observing the frequencies from the IMFs was first done by using FFT on the IMFs. However, as some time information was lost when using this transformation, the Hilbert-Haung transform (HHT) was used instead on the IMFs. Therefore, as little time information as possible was lost. The IMF's in the range of the delta frequency band were assigned into a new signal only containing the part of the signal that has delta frequencies, and the IMF's in the range of the alpha frequency range were attached to a new signal only containing the part of the signal in alpha range.

3.2.2. Short Time Fourier Transform

As mentioned, Short Time Fourier Transform (STFT) was applied on data recordings of whole nights. STFT calculates the Fourier transform of local segments separately, in order to obtain time resolution as well as frequency resolution. When applying STFT to the EEG recordings, a Hann window of length 400 was used. The overlap length was set to 75%. The magnitude of the STFT coefficients of frequencies corresponding to delta and alpha waves respectively, was summed. Root mean square values of the delta and alpha magnitudes over the whole night were calculated.

3.2.3. Discrete Wavelet Transform

Another method of obtaining the time variant frequency components is by applying the discrete wavelet transform (DWT) to the signal. DWT is used to deconstruct the signal into an orthogonal set of wavelets. In this study, the wavelet db8 was chosen. DWT is better than FFT when the signal is non-stationary, due to better time-resolution than FFT. The *wavedec* function returns the wavelet decomposition C and the bookkeeping vector L containing the number of coefficients by level. L gives information about the elements in C that corresponds to high and low frequencies, one can therefore eliminate specific frequencies. The function *wrcoef* does the reconstruction, and from this the alpha and delta frequencies were extracted. One can by this method also do filtering by neglecting the high frequencies. This was not done in this study.

A visual detection of CAP sequences was provided for the project, and used to compare with the automatic detection methods as STFT, EMD, bandpass-filtering and DWT. For each of the provided recordings, the correctness, the amount of true detections of A-phases (%True) and the amount of false detection of A-phases (False/Ref) were calculated [5].

3.3. Proposed solution

In the function *rms_general_classifier.m*, the root mean square (RMS) values of the signals are calculated. The parts of the alpha activity and delta activity bands that have an amplitude at least 1/3 higher than the RMS are regarded as potential A phases. The output from this function is sent into the function *events_to_phases.m* which neglects the potential A phases from *rms_general_classifier.m* where the duration of the phase is less than 2 seconds or longer than 60 seconds. It also neglects the A phases that is not followed by a B phase with the same time duration criteria. In *CAPS_classifier.m* only the CAP with two or more repetitions are remained, and the output is a vector with start time and stop time for all the CAPS in that time interval.

4. RESULTS AND CONTRIBUTIONS

Detection of CAP sequences during the whole night for all the provided sleep recordings was performed using the developed CAPS detection algorithm. Bandpass filtering, EMD, STFT and DWT were all used to separate the sleep EEG signals into frequency bands.

The comparison indices between the visual and the automatic CAP detection methods is shown in tables 1-4. Table 1 containing the calculated indices with the bandpass method, table 2 the indices obtained with EMD, table 3 with STFT and table 4 with DWT.

Table 1: Calculated comparison indices between the visual detection of CAP sequences and the bandpass method.

Subjects	% Correctness	% True	False/Ref
brux2	57.37	8.48	0.4905
ins2	82.13	15.12	2.0026
ins3	68.21	5.34	0.8660
ins4	71.53	4.83	0.7056
ins5	74.35	19.95	0.7227
narco1	81.04	9.68	1.468
narco2	55.29	18.19	0.1388
narco3	69.53	3.27	0.4367
narco4	66.36	9.38	0.5771
narco5	72.78	3.50	0.6849
n1	61.18	8.21	0.5963
n2	73.02	8.54	1.2075
n3	72.91	6.62	0.7888
n5	59.49	7.02	0.4804
n11	64.76	11.00	0.7264
nfle1	59.76	1.68	0.0817
plm2	63.14	19.23	0.5185
plm3	43.48	18.06	0.1463
rbd1	78.63	4.62	0.5706
Mean	66.90	8.9	0.68

Table 2: Calculated comparison indices between the visual detection of CAP sequences and Emperical mode detection (EMD).

Subjects	% Correctness	% True	False/Ref
brux2	55.86	5.97	0.3973
ins2	80.53	13.17	2.0921
ins3	69.74	3.58	0.7632
ins4	72.58	3.51	0.5740
ins5	75.05	18.47	0.6609
narco1	84.28	4.19	0.8927
narco2	53.87	17.37	0.1601
narco3	68.75	4.45	0.4879
narco4	67.11	8.36	0.5587
narco5	72.06	4.64	0.6971
n1	61.29	7.36	0.5184
n2	70.75	5.90	1.3584
n3	71.63	6.42	1.0618
n5	58.62	7.77	0.5499
n11	66.44	9.02	0.6980
nfle1	60.81	2.31	0.0862
plm2	63.86	14.86	0.5663
plm3	41.86	18.06	0.1537
rbd1	76.56	4.48	0.9259
Mean	66.99	8.92	0.71

Table 3: Calculated comparison indices between the visual detection of CAP sequences and short-time Fourier transform (STFT).

Subjects	% Correctness	% True	False/Ref
brux2	52.61	15.55	1.0923
ins2	77.64	25.64	2.6689
ins3	57.47	11.79	1.8388
ins4	65.05	8.89	1.1686
ins5	69.63	23.93	1.1252
narco1	80.88	12.88	1.502
narco2	58.57	29.35	0.2372
narco3	70.40	6.64	0.5659
narco4	63.04	16.33	0.97558
narco5	70.49	5.30	1.0344
n1	62.31	10.39	0.6471
n2	72.29	12.75	1.4880
n3	70.73	9.05	1.4222
n5	58.25	7.41	0.5724
n11	67.33	10.04	0.6980
nfle1	59.40	3.41	0.1257
plm2	62.18	34.86	1.0303
plm3	49.64	31.34	0.2600
rbd1	78.20	4.01	0.5689
Mean	65.58	14.71	1.00

Table 4: Calculated comparison indices between the visual detection of CAP sequences and discrete wavelet transform (DWT).

Subjects	% Correctness	% True	False/Ref
brux2	59.87	5.45	0.2564
ins2	82.32	11.36	1.7122
ins3	67.01	4.03	0.9540
ins4	70.07	4.23	0.7890
ins5	72.10	12.39	0.7265
narco1	82.65	4.19	1.0389
narco2	55.66	18.21	0.1279
narco3	67.07	4.90	0.5429
narco4	66.85	10.40	0.5501
narco5	73.93	3.01	0.7174
n1	61.93	8.14	0.5282
n2	72.35	6.89	1.1585
n3	73.20	9.21	0.8966
n5	58.00	6.49	0.4297
n11	65.74	10.50	0.6491
nfle1	60.35	3.42	0.1096
plm2	63.29	14.59	0.4762
plm3	43.02	17.27	0.1571
rbd1	76.14	2.42	0.9259
Mean	67.06	8.47	0.67

5. DISCUSSION AND CONCLUSION

The main aim of this project was to propose a method for automatic detection of CAP sequences in sleep EEG signals. Bandpass filtering, EMD, STFT and DWT was performed to decompose the signals in appropriate frequency bands, and algorithms for phase A and CAPS detection were developed.

It was observed that much false CAP sequences is detected in the start and the end of the recording in some of the patients. In the start of the recording, the patient is still awake. In this time-period higher frequency waves, like alpha and beta, are more present. In addition, there is likely to be more movement in this time-period, and these movement artifacts will affect the amplitude. This may result in many false A-phases getting detected. In the end of the sleep, the situation is alike. The patient is usually awake or in REM sleep at the end of the recording, and higher frequency waves are more present there as well. Therefore, by only looking at non-REM sleep or by using movement artifacts removal, such as ICA, less false A-phases would have been detected.

Another thing that was noticed is how the CAPS found by visual inspection seem to last longer than the ones found automatically. The short duration of the automatically found CAPS may be contribute to the low percentage true calculated. The algorithm for defining CAPS from A- and B-phases might be more strict than possible when studying the signals manually, resulting in excluding more cycles. One reason for this may be that the automatic detection doesn't merge together A-phases that are less than two seconds apart. This gap is not classified as a B-phase, as it is shorter than two seconds, such that this is the probable cause of the detected CAPS being shorter than the visual CAPS. By merging the A-phases, more false A-phases would also be detected.

When considering the comparison indices calculated with the different signal processing methods, as shown in tables 1, 2, 3 and 4, the indices are relatively similar. This might be a sign that the different methods do not differ a lot in their ability to find true events compared to false ones. There are bigger differences between methods in detecting A-phases overall. However, the % true and % Correctness seems to be higher when using the STFT method, this was unexpected as DWT is better for non-stationary signals. However, STFT also gives the highest % False. This indicates that this method detects many CAP sequences during the whole recording.

Also, as described, only alpha- and delta-bursts were analysed to reduce the complexity of the project. Additional A phase characteristics include vertex sharp transients, k-complex and shift to faster rhythms. Since A-phases only consisting of these characteristics are not detected with our algorithm, some CAP sequences may have been neglected. This could be one of the reasons for the low % True values observed in all patients for all methods. To improve these values, more of the A phase features could be included in the analysis.

It is also interesting to discuss how the different patient groups gets affected differently. One can observe that patients with insomnia (ins) generally give high % False. Insomnia is characterized by trouble falling asleep and staying asleep. By studying the visual scoring files for these patients, long awake periods can be observed during the whole night. Since our algorithm do not take these periods into account, CAP sequences will be detected also during these periods and give increased false detections.

The overall results of the different algorithms were not particularly promising. Percentage true A-phases were disappointingly low. However, the algorithms presented may be a good starting point for more advanced detection systems. Several improvements could be implemented on the way to more sophisticated CAPS detection.

Due to the small variations in indices between the methods and the large variations between the different patients, no conclusions can be drawn about which method is the best one for our purpose in this study.

References

[1] Coenen, Anton; Edward Fine; Oksana Zayachkivska (2014). "Adolf Beck: A Forgotten Pioneer In Electroencephalography". Journal of the History of the Neurosciences. 23 (3): 276–286.

[2] (2007), *Brainworks.* https://brainworksneurotherapy.com/what-are-brainwaves Read: May 31. 2020

[3] M. Terzano, L. Parrino, A. Smerieri, R. Chervin, S. Chokroverty, C. Guilleminault, M. Hirshkowitz, M. Mahowald, H. Moldofsky, A. Rosa, R. Thomas, A. Walters (2001), Atlas, rules and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep, *Sleep Medicine 3 (2002), 187-199.*

[4] F. Mendonça, A. Fred, S. Mostafa, F. Morgado-Dias, A. Ravelo-García,(2018). *Automatic Detection of a Phases for CAP Classification.* Proceedings of the 7th International Conference on Pattern Recognition Applications and Methods - Volume 1: ICPRAM, 394-400.

[5] R. Largo, C. Munteanu, A. Rosa,(2005). *Wavelet Based CAP Detector with GA Tuning.* Proceedings of the 6th WSEAS Int. Conf. on EVOLUTIONARY COMPUTING, Lisbon, Portugal, June 16-18, 2005 (pp10-14)

6. ABOUT THE AUTHORS

Nina Bach-Gansmo

Nina is currently attending the study program Physics and Mathematics at NTNU in Trondheim, Norway. In addition, Nina has always been interested in medicine, which resulted in choosing the biophysics and medical techniques path. Nina is now in year 4 in this integrated master program, and is next year going to write her thesis about MRI. She is studying at IST this semester under the ERASMUS+ exchange program.

Carina Franing Rutledal

Carina also has an interest in medical physics, and is also studying Biophysics and medical techniques at NTNU in Trondheim. In addition, she has an interest for machine learning and computer science. Last summer she had a summer internship where she was working with neural network and other supervised methods. This semester she is studying at IST under the ERASMUS+ exchange program, and looking forward to her thesis next year when she is going to write about how to optimize VMAT in external radiation therapy of cervical cancer.

Linnea Wivilson

Linnea is on her 4.th year of the study biophysics and medical technology at NTNU, now studying one semester at Instituto superior tecnico under the ERASMUS+ Exchange program. Linnea is looking forward to working with PET optimizing in her thesis next year