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Assessment of Sleep Quality in Powernapping

Bashaer K. Takhtsabzy[a], Carsten E. Thomsen[b]

Abstract—**The purpose of this study is to assess the Sleep Quality (SQ) in powernapping. The contributed factors for SQ assessment are time of Sleep Onset (SO), Sleep Length (SL), Sleep Depth (SD), and detection of sleep events (K-complex (KC) and Sleep Spindle (SS)). Data from daytime nap for 10 subjects, 2 days each, including EEG and ECG were recorded. The SD and sleep events were analyzed by applying spectral analysis. The SO time was detected by a combination of signal spectral analysis, Slow Rolling Eye Movement (SREM) detection, Heart Rate Variability (HRV) analysis and EEG segmentation using both Autocorrelation Function (ACF), and Crosscorrelation Function (CCF) methods. The EEG derivation FP1-FP2 filtered in a narrow band and used as an alternative to EOG for SREM detection. The ACF and CCF segmentation methods were also applied for detection of sleep events. The ACF method detects segment boundaries based on single channel analysis, while the CCF includes spatial variation from multiple EEG derivation. The results indicate that SREM detection using EEG is possible and can be used as input together with power spectral analysis to enhance SO detection. Both segmentation methods could detect SO as a segment boundary. Additionally they were able to contribute to detection of KC and SS events. The CCF method was more sensitive to spatial EEG changes and the exact segment boundaries varied slightly between the two methods. The HRV analysis revealed, that low and very low frequency variations in the heart rate was highly correlated with the EEG changes during both SO and variations in SD. Analyzing the relationship between the sleep events and SD showed a negative correlation between the Delta and Sigma activity. Analyzing the subjective measurement (SM) showed that there were a positive correlation between the SL and rated SQ. This preliminary study showed that the factors contributing to the overall SQ during powernapping can be assessed markedly better using a fusion of multiple methods. Future studies will include measures of individual performance before and after powernapping and investigate its relation to the assessed SQ.**

I. INTRODUCTION

TAKING a short daytime nap can improve the mood, alertness, and performance [1]. For Sleep Quality (SQ) assessment in powernapping, several factors, which have influence on SQ, can be analyzed. Some of these factors are the time of Sleep Onset (SO), the Sleep Length (SL), the Sleep Depth (SD) or amount of Delta activity, the sleep events (such as the K-complex (KC) and the Sleep Spindle (SS)), and the Heart Rate Variability (HRV). The HRV analysis can contribute to SO and SD analysis.

Corresponding authors: Bashaer k. Takhtsabzy, bashaer.kt@gmail.com, and Carsten E. Thomsen, cet@sund.ku.dk

[a] Technical university of Denmark (DTU) electrical engineering, ØrstedsPlads, building 349, DK-2800 Kgs.Lyngby

b Faculty of Health Sciencel, Nørre Alle 20, DK-2200 Copenhagen

There are several methods for SO detection. One of these methods is to calculate the elapsed time between the light off to the first Slow Rolling Eye Movement (SREM) event [2]. The SREM is known to be the typical phenomenon of sleep-wake transition. Another method for SO detection (and SD analysis) is to analyze the HRV that can be divided in three frequency bands: The Very Low Frequency (VLF - 0.003-0.04 Hz) is related to long-term regulatory mechanisms (activity of the rennin-angiotensin system); the Low Frequency (LF - 0.04-0.15 Hz) is related to both sympathetic and parasympathetic influence on the sinus node; and the High Frequency (HF - 0.15-0.4 Hz) is linked to the parasympathetic (vagal) activity [3]. Previous studies of HRV during SO (SO defined as the first 60 seconds of consecutive stage 1) have showed that the amount of VLF and LF activity decreased 2 min before SO [3]. At deeper sleep stages there is negative relation between progressing Non Rapid Eye Movement (NREM) sleep stage 1 to 4 and the amount of both VLF and LF activity, while there is a marked increase during Rapid Eye Movement (REM) sleep stage [4]- [5].

The sleep EEG signal can be analyzed by applying spectral power analysis including of Alpha (8-12 Hz), Theta (3.5-8 Hz), Sigma (12-14.5 Hz), and Delta (0.5-3.5 Hz) activity [10]. The Sleep events (included in Sigma and Delta) can be detected by signal segmentation and finding the significant changes in signal properties. Previous studies have shown that there is a negative correlation between the Sigma activity and the delta activity (deep sleep in nap) [6].

The aim of this study is to assess the SQ in powernapping. Some of the factors which can affect the SQ are selected. The contributed factors are the time of SO, the SL, the SD, and the sleep events. For SO detection, the SREM detection, the HRV analysis, the Autocorrelation Function (ACF), and the Crosscorrelation Function (CCF) methods are applied. The last two mentioned methods are also applied for sleep events detection. Another important aim is to apply scalp EEG (derivation of FP1-FP2) as an alternative to EOG for SREM detection. Finally the relationship between the SD and sleep events (linear regression method) and between the SL and the rated SQ (subjective analysis) is analyzed.

II. METHOD

A. Clinical Data

A 40-60 min daytime nap (between 17-18 h) was recorded in two days (one habituation day for adaptation effect analysis) from 10 normal healthy subjects (4 males), with the age ranging from 18-32 years. A subjective measurement (rating the sleep quality from 0- 100) was applied after napping session. The Polysomnography (PSG) recording included 14 channels of scalp EEG (10-20 system) and chest

ECG, and was performed using the CADVELL® Easy II EEG system. The data were sampled at 400 Hz and filtered by 50 Hz notch filter. The EEG and ECG signals were pre-filtered by a band-pass filter of 0.53-70 Hz and 0.16-35 Hz, respectively. The software MATLAB 7.0.4 was applied for signal processing. All the EEG signals were divided to small segment of 2 seconds and the Root Mean Square (RMS) value of each segment's frequency components was calculated. The Fast Fourier Transform (FFT) function was used to power spectral analysis of each segment and finding its frequency components.

B. Data Processing

1) SREM Detection

To detect and analyze the SREM, the signal from FP1-FP2 channel was filtered from 0.16-1Hz. The Alpha and Delta activities (derivation of C4-P4) were analyzed concurrently with SREM analysis. The RMS value for SREM, Alpha, and Delta activity was calculated and median filtered (order=3) for smoothing the signal.

2) HRV Analysis

In the ECG channel all R waves are detected using a crosscorrelation method. One selected heart cycle (containing R wave) was correlated with the entire signal locating the time points with the maximum values in the crosscorrelation signal. Each R point was plotted against its time interval with the previous R point. The obtained plot was then interpolated (Cubic Spline) and re-sampled by a sampling frequency of 2 Hz. The three frequency components of HRV were determined using FFT.

3) ACF Method

The ACF method was applied for single signal segmentation aiming at detecting both SO and sleep events [7]. The method is based on calculating the ACF between a test and a moving window. The test window is initially placed at the beginning of the signal, while the moving window starts from the beginning of the signal and scans whole the signal. If any significant variation (in amplitude and frequency) was found between the moving and test window, a new segment boundary will be inserted and the test window will be placed at the beginning of the new boundary. The process will be repeated until the entire signal is analyzed. The length of the moving and test window was 2 seconds and the threshold for frequency and amplitude (Th_f and Th_p) varied between 2-2.5. The variation in amplitude, $d_p(n)$ can be found by calculating the square root of the power (the ACF at lag zero):

$$d_p(n)=\frac{\left|\sqrt{\varphi_T(n,0)}-\sqrt{\varphi_R(0)}\right|}{\min\left\{\sqrt{\varphi_T(n,0)},\sqrt{\varphi_R(0)}\right\}} \quad (1)$$

Where $\varphi_T(n,0)$ and $\varphi_R(0)$ denote the ACF for the test and test window, respectively. The frequency changes, $d_f(n)$ can be obtained by calculating the difference in ACF coefficients only up to lag q which is where the ACF's for the first time crosses the abscissa:

$$d_f(n)=\frac{\sum_{K=1}^{q}\left|\overline{\varphi}_T(n,K)-\overline{\varphi}_R(K)\right|}{0.5+\sum_{K=1}^{q}\min\left\{\overline{\varphi}_T(n,K),\overline{\varphi}_R(K)\right\}} \quad (2)$$

Finally the net ACF distance $d(n)=\frac{d_P(n)}{Th_P}+\frac{d_f(n)}{Th_f}$, is calculated. As soon as $d(n)>1$, a new segment boundary is drawn [7].

4) CCF Method

The CCF method was applied in this study for multi signal segmentation as an alternative to the ACF Method [8]. This method is based on calculating CCF between several channels and finding the time of activity shift across channels. The first step of implementation is to find the Normalized Crosscorrelation Coefficient (NCCC) between two different times, i and j [9]:

$$c_{ij}=\frac{E_i^T\cdot E_j}{\sqrt{(E_i^T\cdot E_i)\cdot(E_j^T\cdot E_j)}} \quad (3)$$

Where the vector E_i, taken from the time i, can be defined as:

$$E_i=\left[e_{i,1}e_{i,2}\ldots e_{i,N_S}\right] \quad (4)$$

The $e_{i,1}$ represent the potential fields recorded at time i and the N_S, indicates the number of electrodes. The vector E_j is similar to E_i, but is taken from the time= j. All the NCCC values from sample 1 to N (N is the segment length in samples) will be included in a $N\times N$ normalized crosscorrelation Matrix (C). This matrix contains the values between 1 to -1 and a diagonal values equal to 1(equation 5). This matrix is symmetric compared to diagonal axis and is divided to four main areas; two rectangle areas close to diagonal containing the values closed to 1 (high similarity between the signals), and two rectangle areas close to off diagonal containing values close to -1 (low similarity).

$$C=\begin{bmatrix} c_{11} & \cdots & c_{1N} \\ \vdots & \ddots & \vdots \\ c_{N1} & \cdots & c_{NN} \end{bmatrix} \quad (5)$$

Finally the error function of the C will be calculated:

$$e(n_b)=\sum_{n=1}^{n_b}\sum_{m=1}^{n_b}\frac{(1-c_{nm})^2}{n_b^2}+\sum_{n=n_b+1}^{N}\sum_{m=n_b+1}^{N}\frac{(1-c_{nm})^2}{(N-n_b-1)^2} \quad (6)$$
$$+2\sum_{n=1}^{n_b}\sum_{m=n_b+1}^{N}\frac{(1+c_{nm})^2}{n_b\cdot(N-n_b-1)}$$

The error function contains several minima representing the transition from one microstate to another. By detecting

these minima, the time for new event in EEG signals is found. The value of the locale minima should be lower than the values of its previous and its following samples. To decrease the sensitivity for error minima detection, a threshold value was selected for the ratio between the error value of 25 samples around the detected minima and the error value of 25 samples of its previous and its subsequent samples. Fig. 1 shows an example of CCF method application. The first graph shows 0.5 sec (contains KC) of the EEG signal with the detected boundary (the red dashed line). The second graph shows the C matrix, while the last graph shows the error function and the detected minima. This algorithm is applied for all the channels at the same time, but in this example, only the C4-P4 channel is shown.

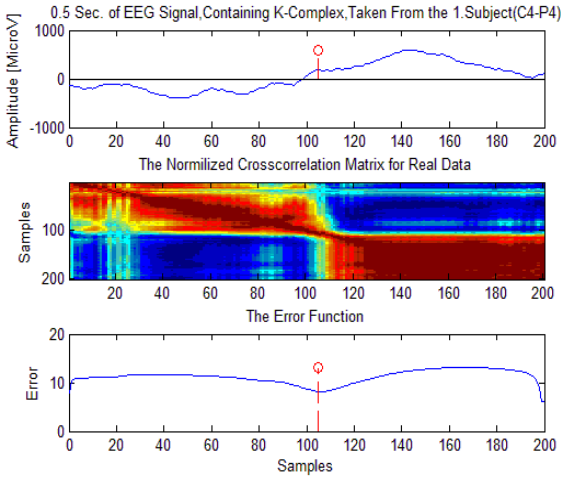

Fig. 1. An example of CCF algorithm application; The first graph shows 0.5 sec (contains KC) of the original signal with the detected boundary (the red dashed line). This algorithm is applied for all the channels at the same time, but in this example, only the C4-P4 channel is extracted. The second graph shows the C matrix which contains the values between 1 to -1 and a diagonal values equal to 1. This matrix is symmetric compared to diagonal axis and is divided to four main areas; the red rectangles (close to diagonal), which their values are closed to 1, and the blue rectangles (close to off-diagonal), which their values are close to -1. The last graph shows the error function with the detected minima (the red dashed line). X- axis indicates samples and the y- axis shows the amplitude of the original signal, the samples of matrix, and the error value for the matrix, respectively.

5) *Sleep Events and SD*

To find the relationship between the sleep events and SD, the RMS amount of Sigma activity for each subject was plotted against the RMS amount of Delta activity (linear regression analysis).

III. Result and Discussion

A. *SO Detection by Applying SREM Algorithm*

Fig. 2 shows an example of the result of calculating the RMS of SREM and Alpha activity. Decrease in Alpha-RMS from segment number 106-120, happens concurrently with increase in SREM- RMS. This time interval represents the SO time. Performing the paired t-test showed that there was a significant increase (P value= 0.004) in SREM- RMS signal, and there was a decrease in Alpha- RMS, 5 seconds after SO time. This result is similar to the study of [2] which applied EOG for SREM analysis in SO detection. In addition we have improved SREM based SO detection a by concurrent analysis of Alpha variations. Excluding the EOG make the subjects feel more comfortable to fall asleep. Another difference between this study and the study of [2] is that in this study, an extra tool (Alpha variation analysis concurrently with SREM variation), have been used for SO detection.

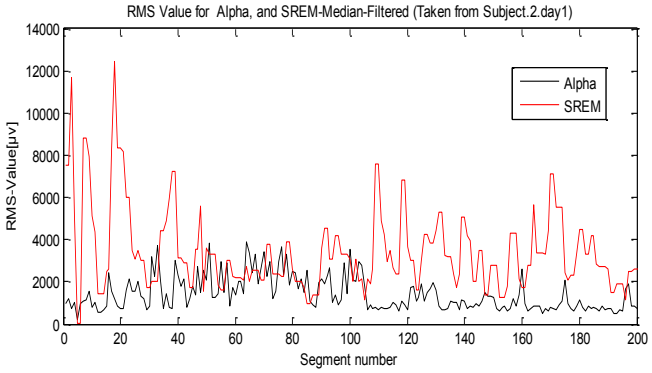

Fig. 2. The calculated RMS value for the signal generated from FP1-FP2 (red) and C4-P4 (black). This is the first 6.6 min of the signal (includes SO). The x- axis shows the segment number. Each segment has a length of 2 seconds; y- axis shows the amplitude.

B. *HRV Analysis*

The result of HRV analysis for SO detection showed that there was a significant (P value=0.05) decrease in VLF band during the SO time. This result is similar to the study of [3]. This means that during the SO there might be a decrease in long-term regulatory mechanisms. Analyzing the HRV during other stages of sleep showed that the VLF and the LF increased during the light sleep (first 20 min) and decreased during the deeper stages of sleep (last 20 min). Comparing this result with the result of the study of [4] and [5], showed that at deeper sleep stages there is negative correlation between progressing NREM sleep stage 1 to 4 and the amount of both VLF and LF activity, while there is a marked increase during REM sleep stage [4]- [5]. The mentioned studies had analyzed an 8h night sleep and divided it in two stages (NREM and REM), while a 60 min daytime nap does not include of NREM stage. Dividing the nap procedure in two stages (light and deep nap) showed a similar result to the result of the [4] and [5]. This means that there is an increase in VLF (or long-term regulatory mechanisms) and LF (or sympathetic and parasympathetic activity) during the light sleep, and there is a suppression in the mentioned activities during the deep sleep. According to [4] and [5], if the sleep procedure in this project included of REM, the VLF and LF activity might increase in REM stage.

C. *The ACF*

Applying the ACF method showed that it is able to detect the SO and sleep event. Fig. 3 shows an example of applying the ACF algorithm for KC detection. Three segment boundaries were found: one before, and two after the KC occurrence. The first boundary was detected 1.2 seconds before the main component of KC. That could be because of some brain preparation for KC occurrence, which leads to signal variation before the KC occurs. It could also be because of the KC occurs in longer period than what it is

defined and the detected boundary is the real time of KC start. The second boundary shows when the KC terminated, while the last boundary is detected one second after the KC occurrence.

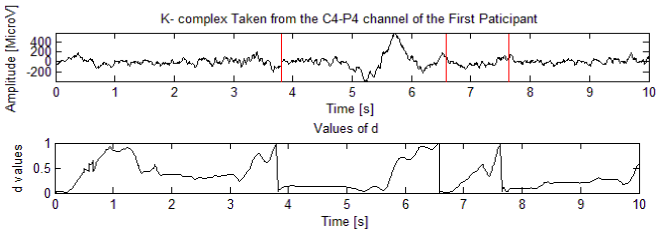

Fig. 3. An example of KC detection by ACF method: The first graph shows the EEG signal (includes KC) taken from the C4-P4 channel with the estimated segments boundaries. The second graph shows the summation of variation in segment amplitude and frequency. X- axis shows the time and the y- axis shows the amplitude d values, respectively.

D. The CCF

The CCF method was able to detect the SO and sleep events. Fig. 4 shows an example of CCF method application for KC detection on the same signal selection as in Fig. 3. Comparing to Fig. 3, this algorithm has detected one extra boundary and the time of detected boundaries is not the same. The reason of high spatial sensitivity of CCF and detecting extra boundaries is that it scans the variation in all 14 channels (global analysis) and not only C4-P4 channel (local analysis). The reason of not detecting the boundaries at the same time as in the ACF method is because of the KCs do not occur at the same time in all the channels and have delay compared to each other. This method is a kind of micro segmentation of signal, which means dividing a non-stationary signal into small stationary segment (with a length of 2 seconds in this study) and finding the variation on each segment.

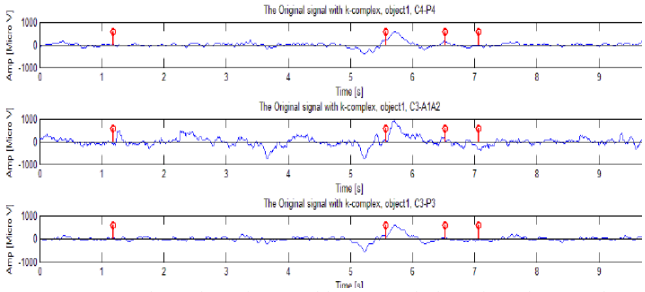

Fig. 4. An example (taken from subject 1) of detecting the KC by applying the CCF method; the algorithm is applied for all the channels at the same time, but in this example, only the C4-P4, C1-A1A2, and C3-P3 channels are shown. X- axis shows the time and the y- axis shows the amplitude. The red dashed line indicates the detected boundary.

E. Sleep Events and SD

Plotting the RMS amount of Sigma activity against the RMS amount of Delta activity showed a linear regression model with a slope value of -0.36. This result is similar to the study of [6] and shows that the SD and sleep events are negatively correlated. This means that if the person fall asleep quickly, and have 1h for sleeping, sleep events will occur at the beginning of the sleep procedure, and there will be higher opportunity for reaching a deep sleep. As long as there is negative correlation between the Delta and Sigma activity, a deep nap would not include so many sleep events. Occurrence of sleep events can be affected by several factors, such as amount of time spending awake, time of sleep events occurrence, and amount of Delta sleep.

F. Subjective Measurement

Analyzing the result of subjective measurement showed that the rated SQ was good (rating value > 70%) for first 9 subjects. Except for subject 10, falling asleep was easy. Analyzing the relationship between the SL and rated SQ showed that there was a positive correlation between the SL and SQ.

IV. Conclusion and Future Works

The results showed that SREM detection using EEG is possible, but the SREM has to be analyzed concurrently with variation in Alpha activity for SO detection. Applying signal segmentation and CCF method showed that it is possible to classify the sleep process in more detailed stages (micro staging the sleep), which differs from the traditional sleep classification. Assessment of SQ in this study leads to analysis of variation in different physiological processes (such as SREM, HRV, local and global EEG). The detected time for SO was not the same in the applied methods. This was because that SO is a time interval and not a defined time. The activity variations in different physiological process do not occur at the same time during SO, but analyzing several activities during the SO make it possible to find the correct time interval for SO. Performing alertness/ performance test before and after taking the nap will be one of our future works. Measuring the performance is another tool for SQ assessment. Currently, we are searching for an optimal simulator to test the performance level.

V. References

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