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Automatic Detection of the Wake and Stage 1 Sleep Stages Using the EEG Sub-Epoch Approach

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Abstract— **Studies by Rechtschaffen and Kales (R&K), rely on 30-sec epochs to score sleep stages. In this paper, we introduce a new approach based on three consecutive and non-consecutive 6-sec sub-epochs for the detection of the wake stage and stage 1 sleep. The Relative Spectral Energy Band (RSEB) is used as a feature extraction from the electroencephalographic (EEG) signal. Spectral estimation is performed using non-parametric and parametric methods. We then compared the performance of the conventional 30-sec epochs with the three consecutive and non-consecutive 6-sec epochs. The outcomes of this study showed that while the accuracy varies between subjects, the non-parametric method proved to be more effective with stage 1 sleep detection and the parametric method was more effective for wake stage detection. The non-consecutive sub-epoch method was more effective and consecutive method was least effective in non-parametric stage 1 detection. Alternatively, the 30-second epoch method was most effective for parametric wake stage detection.**

I. Introduction

For more than two centuries, sleep medicine researchers have attempted to standardise rules for scoring sleep in the investigation of night-time sleep behaviour. In 1968, Rechtschaffen and Kales (R&K) [1] published a first manual on the scoring of sleep stages. They proposed a method based on a set of rules to identify the sleep stages recorded during nocturnal polysomnography (PSG). Sleep stage scoring is reliant on electroencephalographic (EEG), electro-oculographic (EOG) and sub-mental (chin) electromyographic (EMG) criteria. These sleep stages are broken down into two main general stages: non-rapid eye movement (NREM) and rapid eye movement. The R&K method categorises sleep stages into a wake stage, stages 1, 2, 3, 4 and the REM stage, whereas the American Academy of Sleep Medicine (AASM) classifies sleep stages as wake, stages 1 (N1), 2 (N2), 3 (N3) and R (REM) [2].

In general, visual sleep stage scoring is a tedious task. It is time consuming and labour intensive for the physician. Currently, there are numerous developed automatic sleep stage detection methods that are based on R & K 30-second epochs. Various techniques used for automated sleep stage detection are based on various feature extractions (i.e. wavelets [5]) and neural network and pattern recognition [7]. In fact, several studies have criticised the epoch-based method (R & K/AASM) of scoring sleep stages [6,13], claiming the following as: "major drawbacks are associated with their low temporal resolution one label for 30s-and unnatural classification of sleep based on fixed-duration discrete epochs" [13]. Therefore, the tradition of sleep stage scoring based on 30-second epochs might provide less information about brain activities because it uses a fixed duration. It has suggested that EEG epoch duration is reduced to 1, 2 or 5 seconds [14].

In this paper, we introduced a new approach based on three consecutive and non-consecutive 6-second epochs for scoring or detecting the wake stage and stage 1 sleep using a single EEG channel (C3-A2). The three consecutive and non-consecutive epochs were obtained by dividing the 30-second epochs by 5 and then subjecting these sub-epochs to feature extraction. We then attempted to investigate whether there were three consecutive or non-consecutive sub-epochs out of five epochs, indicating wake or stage 1 sleep. Previously, several factors, such as the alpha ratio [8], spectral power and power ratio [5], have been used for feature extraction from EEG signals. In the present study, we used the Relative Spectral Energy Band (RSEB) for feature extraction from the EEG. The activity of the EEG signal uses various frequency bands, such as delta (0.5–4Hz), theta (4–7Hz), alpha (8–12Hz) and beta (13–30Hz).

II. Materials and Methods

A. Subjects & Data Collection

The PSG data used in this study was recorded from 10 healthy adult male subjects, aged 21–43 years old (mean age = 29). None of the subjects had a previously diagnosed sleep disorder. RMIT Ethics approval was granted for the recording of this PSG data and all human subjects signed the consent letters. A single continuous EEG recording of 20 minutes in duration was utilised for each subject. The PSG recording for each subject contained six channels, two EEGs (O2-A1 and C3-A2), two EOGs (ROC and LOC) and an ECG (Lead II using torso electrode placement). The sample frequency was 256 Hz for each signal. Six channels were utilised for automated sleep scoring by Hypnolab (SWS Soft, Italy, 2006-2008), but only one EEG channel (C3-A2) data was used in this analysis. All subjects were exposed to audio and photic stimulation under biofeedback operant conditioning, influencing wake and sleep states. Therefore, the influence of these stimuli may have caused the PSG transients to differ considerably as compared to 'normal' wake and sleep conditions. Also, this PSG data can be considered to be recorded from 20 min napping rather than 20 min sleep – wake and stage 1 were detected only.

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B. EEG Signal Processing

Figure 1 shows the flowchart for the proposed consecutive and non-consecutive 6-second sub-epoch comparison approach comprised of six parts: (part 1) EEG segmentation of the 30-second epochs; (part 2) filtering; (part 3) EEG segmentation of the 30-second epochs into 6-second sub-epochs; (part 4) feature extraction; (part 5) sleep stage scoring rules; and (part 6) checking three consecutive and non-consecutive 6-second sub-epochs.

Part 1 Segmentation of the 30-second epochs: The length of these data was segmented into 30-second epochs for scoring the sleep EEGs prior to pre-processing.

Part 2 Filtering: The entire EEG vector was processed utilising a 6-order Butterworth band pass filter for the different band frequencies, as follows: theta (θ, 4–7Hz), alpha (α, 8–12Hz) and beta (β, 13–30Hz).

Part 3 EEG segmentation of 30-second epochs into 6-second sub-epochs: Prior to feature extraction, the 30-second epochs were divided into five sub-epochs of 6 seconds each.

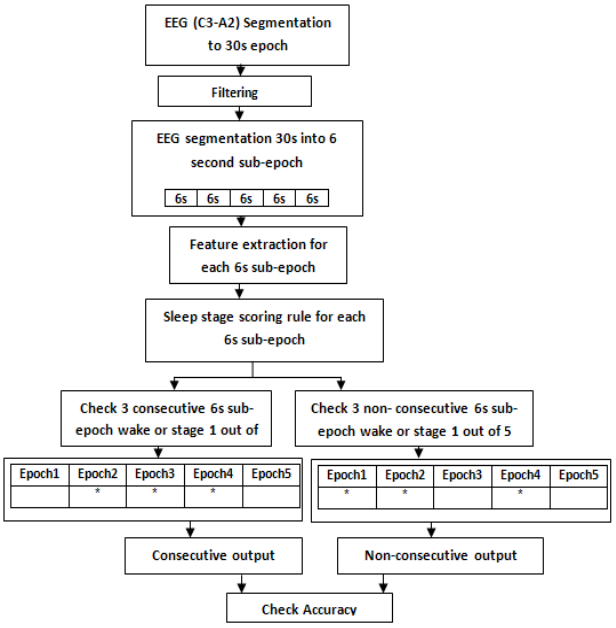

Figure 1. Flow-chart describing the consecutive and non-consecutive 6-second EEG epoch comparison.

Part 4 Feature extraction: Frequency domain feature extraction was applied, calculating RSEB for the θ, α and β EEG bands from the computations of parametric and non-parametric Power Spectral Densities (PSD_θ, PSD_α, PSD_β). The RSEB can be calculated as follows:

$$\text{Total power} = PSD_\theta + PSD_\alpha + PSD_\beta$$

$$\text{RSEB}(\theta) = PSD_\theta \,/\, \text{Total power}$$

$$\text{RSEB}(\alpha) = PSD_\alpha \,/\, \text{Total power}$$

$$\text{RSEB}(\beta) = PSD_\beta \,/\, \text{Total power}$$

Part 4.1 Non-parametric method: Thomson's multi-taper method (MTM) [15] was used to estimate the PSD. The advantage of using the MTM is that it reduces the variance of the spectral estimate by utilising a few groups of tapers, as proposed by Thomson (1982) and Percival and Walden (1992) [10]. The computation of the Power Multi-Taper (PMT) method was put forward in [16].

Part 4.2 Parametric method: Non-parametric methods have the drawback of spectral leakage effects because of windowing, which can result in a weakening of the signal components. Using parametric methods to compute PSD is a solution to spectral leakage and provides optimal frequency resolution. In this paper, we used Burg's Auto Regressive (AR) method to calculate the PSD. The main concept of Burg's method is that it attempts to reduce the forward and backward prediction errors by accepting the Levinson-Durbin recursion [11]. The reflection coefficients are estimated directly in Burg's method rather than calculating the autocorrelation function.

Part 5 Sleep stage scoring rule: In this part, we applied the rule for scoring sleep stages in each 6-second epoch. For example, according to the R&K rule, an epoch is scored as a wake stage if RSEB(α) represents more than 50% of the epoch. On the other hand, the epoch is scored as stage 1 when the RSEB(θ) is more than 50% of the epoch. In addition, stage 1 can be scored when the RSEB(α) is less than 50% of the epoch.

Part 6 Checking the three consecutive and non-consecutive 6-second sub-epochs. This was accomplished by investigating whether three out of five consecutive or non-consecutive 6-second sub-epochs indicated wake or stage 1 sleep. The three out of five consecutive and non-consecutive 6-second sub-epochs characterised 60% of predominant band power in its total 30 sec epoch, making the detection more difficult based on the rule criteria of 50% predominant power.

III. RESULTS

Figure 2 shows the hypnograms for subject 22 using the parametric and non-parametric methods, respectively. The figure also shows the difference between using 30-second epochs and three consecutive and non-consecutive 6-seconds epochs for identification of the wake stage and sleep stage 1. From Figure 2, it is clear that the three consecutive and non-consecutive 6-second sub-epochs provide slightly better results than the 30-second epoch method. In addition, the non-parametric method showed lower detection accuracy for the wake stage but higher detection accuracy for sleep stage 1. It is clear from Table II, that the non-consecutive 6-second epoch method was able to detect both sleep stages better than the 30-second epoch method.

Table I describes the count of wake and stage 1 (S1) epochs automatically detected by parametric, non-parametric methods and compared to commercial 'Hypnolab' tool. The 20 min PSG recording translated into 39 30-second epochs (last 30 min was not scored). While the sum of wake and stage 1 epochs was expected in all subjects (there were no other stages present), the wake stages were all accounted in both parametric and non parametric and its three methods (30-sec epoch, consecutive and non-consecutive sub-epochs). However, for stage 1, not all epochs were detected with the three epoch/sub-epoch methods. Some subjects did not have any stages detected by Hypnolab, such as S18, S23,

S29 and S30. Therefore, the validation for stage 1 for those subjects was not available (noted by N/A in Table I). Also, for some subjects the consecutive and non-consecutive sub-epoch methods showed instances of not classified or misclassified, noted by M/C in Table I.

Table II revealed with the non-parametric spectral density 30-second epoch method, an accuracy of 71.4% in the wake stage and 47.5% in stage 1. While the accuracy of the three consecutive 6-second sub-epoch method was slightly lower than the 30-second method, as 59.3% in the wake stage and 35% in stage 1. The three non-consecutive 6-second method revealed a slight improvement in accuracy as compared to 30-second epoch method (non-parametric), at 77% (increase by 5.6%) for the wake stage and 55.8% (increase by 8.3%) for stage 1. Moreover, for some subjects, the three consecutive and non- detection method for stage 1 proved to be more effective over the conventional 30 s method. For example, from Table II, the accuracy of detection of stage 1 for subjects S20 and S22 was higher with by 80% with the three consecutive and non-consecutive 6-seconds method, while the accuracy of 30 s method was 60% in subject S20 and 25% in subject S22. However, the average accuracy for all 10 subjects was higher with 30-second method as compared to consecutive and non-consecutive methods but also with a larger standard deviation. S.D was 25-30% for 30-second epoch and 40-46% for consecutive and non-consecutive 6-second sub-epoch methods.

On the other hand, the parametric method revealed a significant accuracy in detection of the wake stage, wherein the accuracy of the 30-second method was 98.5%, the three consecutive 6-seconds method was 75.6% and the three non-consecutive 6-seconds method the accuracy was 95.1%. The stage 1 detection was 0% for both 30-second epoch and 6-second consecutive sub-epoch methods, and 10.8% for 6-second non-consecutive sub-epoch.

IV. Discussion and Conclusion

The results of this study confirmed the possibility of using the 30-second epoch and the three consecutive or non-consecutive 6-second epoch methods for scoring of wake and stage 1 sleep. While the accuracy varies between subjects, the non-parametric method proved to be more effective with stage 1 sleep detection. Whereas, the parametric method was more effective for wake stage detection. The non-consecutive sub-epoch method was more effective and three consecutive method was least effective in non-parametric stage 1 detection. The 30-second epoch method was most effective for parametric wake stage detection.

There is a need to design an adaptive detector intelligent enough to know when to apply the non-parametric and parametric 30-second and the consultative/non-consecutive sub-epoch methods. We also calculated accuracy independently for wake and stage 1, rather than combined. The PSG data may need to be recorded by normal (non-stimulation) conditions, so that subjects can exhibit non-induced wake and stage EEG activity. Other improvements to these results may be found in including delta power in the total power, even though the relative power is not required in this approach. The pre-processed step of filtering may also need to be excluded to improve the EEG bands power computations. Obviously, the wake and stage 1 automatic detection will also improve by adding EOG and EMG signals analysis and implementation of its rules based on AASM criteria.

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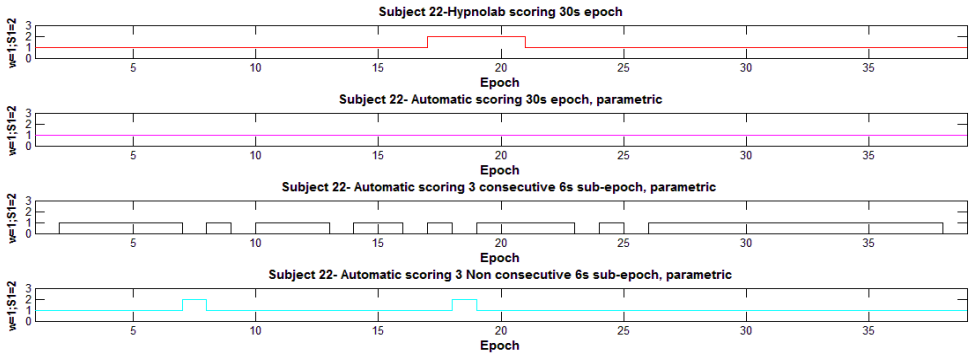

Figure 2. The hypnograms for subject S22 using the parametric approach, comparing the 30-second and the three consecutive and non-consecutive 6-second epochs methods. 'W' indicates the wake stage; 'S1' indicates stage 1; and 0 indicates misclassification.

TABLE I. THE COUNT OF WAKE AND STAGE 1 SCORED EPOCHS FROM THE THREE AUTOMATED DETECTION METHODS USING PARAMETRIC AND NON-PARAMETRIC SPECTRAL DENSITY FUNCTIONS, AND COMPARED WITH THE COMMERCIAL 'HYPNOLAB' SLEEP SCORING. NOTE: N/A – SLEEP STAGE 1 IS NOT AVAILABLE IN SUBJECT FILE; & M/C – MISCLASSIFICATION.

Method	Non-Parametric						Parametric						'Hypnolab'	
	Wake stage scored epochs			Stage 1 stage scored epochs			Wake stage scored epochs			Stage 1 stage scored epochs			Wake & Stage 1 scored epoch	
Subject	30-s epoch	3 consecutive 6-s sub-epoch	3 non-consecutive 6-s sub-epoch	30-s epoch	3 consecutive 6-s sub-epoch	3 non-consecutive 6-s sub-epoch	30-s epoch	3 consecutive 6-s sub-epoch	3 non-consecutive 6-s sub-epoch	30-s epoch	3 consecutive 6-s sub-epoch	3 non-consecutive 6-s sub-epoch	Wake 30-s scored epochs	Stage 1 30-s scored epochs
S18	39	38	39	N/A	N/A	N/A	39	36	39	N/A	N/A	N/A	39	N/A
S19	13	12	21	26	9	18	35	26	35	4	M/C	4	34	5
S20	27	14	20	12	11	19	39	23	35	M/C	M/C	4	33	6
S21	25	30	36	14	1	3	39	30	37	M/C	M/C	2	35	4
S22	35	25	36	4	2	3	39	30	37	M/C	M/C	2	35	4
S23	8	2	6	31	2	33	39	31	37	M/C	1	2	39	N/A
S25	33	16	26	6	M/C	13	39	30	38	M/C	M/C	1	38	1
S27	34	34	38	5	1	1	39	28	36	M/C	1	3	28	11
S29	33	25	34	6	M/C	5	39	33	39	M/C	M/C	-	39	N/A
S30	33	36	39	6	M/C	M/C	39	31	38	M/C	M/C	1	39	N/A
Mean	**28**	**23**	**29**	**12**	**4.3**	**11.8**	**38.6**	**29.8**	**37.1**	**4**	**1**	**2.37**	**35.9**	**5.1**
S.D.	**10**	**11**	**10**	**9**	**4.4**	**11**	**1.26**	**3.58**	**1.44**	**0**	**0**	**1.18**	**3.6**	**3.3**

TABLE II. THE COMPARISON OF THE ACCURACY BETWEEN THE THREE AUTOMATED DETECTION METHODS USING PARAMETRIC AND NON-PARAMETRIC SPECTRAL DENSITY FUNCTIONS. NOTE: N/A – SLEEP STAGE 1 IS NOT AVAILABLE IN SUBJECT FILE.

Method	Non-Parametric						Parametric					
	30-s epoch		3 consecutive 6-s sub-epochs		3 non-consecutive 6-s sub-epochs		30-s epoch		3 consecutive 6-s sub-epochs		3 non-consecutive 6-s sub-epochs	
Subject /W&S1 %(*)	W (%)	S1 (%)	W (%)	S1 (%)	W (%)	S1 (%)	W (%)	S1 (%)	W (%)	S1 (%)	W (%)	S1 (%)
S18	100	N/A	97.4	N/A	100	N/A	100	N/A	92.3	N/A	100	N/A
S19	38.2	100	32.3	80	58.8	80	88.2	0	67.6	0	88.2	0
S20	70.5	60	35.2	80	53.9	80	97	0	61.7	0	91.1	40
S21	60	0	74.2	0	91.4	0	100	0	74.2	0	94.2	0
S22	91.4	25	68.8	50	100	75	100	0	77.1	0	97.1	25
S23	20.5	N/A	5.1	N/A	15.3	N/A	100	N/A	79.4	-	97.4	-
S25	86.8	100	42.1	0	68.4	100	100	0	76.3	0	97.3	0
S27	82.1	0	82.1	0	96.4	0	100	0	64.2	0	89.2	0
S29	84.6	N/A	64.1	N/A	87.1	N/A	100	N/A	84.6	N/A	100	N/A
S30	84.6	N/A	92.3	N/A	100	N/A	100	N/A	79.4	N/A	97.4	N/A
Mean	**71.4**	**47.5**	**59.3**	**35**	**77**	**55.8**	**98.5**	**0**	**75.6**	**0**	**95.1**	**10.8**
S.D.	**25.2**	**46.2**	**28.1**	**39.8**	**27.9**	**44.9**	**3.74**	**0**	**9.3**	**0**	**4.3**	**17.4**