The development of automated sleep apnea detection algorithms is an emerging topic of interest [1, 2]. The main aim of automation is to reduce the time and cost associated with manually scoring polysomnogram (PSG) tests [3]. To automate the process, traditional algorithms attempt to mimic the human observer by implementing a series of predefined rules, such as the American Association of Sleep Medicine’s (AASM) scoring guidelines [4]. Recently, data driven methods have emerged [5]. Electroencephalogram (EEG) frequency is known to be an important feature for both the human observer and data driven methods for sleep staging classification. This study presents the initial findings for a novel approach to sleep stage analysis. EEG time-frequency analysis is used to characterise the dominant frequency with respect to time, specifically at the point of sleep stage transition. The goal of this study is to further discuss on the topic of sleep staging automation and explore alternative and novel features to improve sleep stage detection.

Clinically annotated PSG data was acquired from the “You Snooze You Win: The PhysioNet/Computing in Cardiology Challenge 2018” [6, 7]. EEG channel O1-M2 was selected for initial investigation. The dataset contains 994 overnight PSG recordings of approximately eight hours each, with clinical annotations provided. Sleep stages were scored in 30 second windows as recommended [4]. Given the annotations provided, six sleep stages were possible, for a total of 36 transition categories. Sleep stage transitions were grouped by category as shown in Table 1.

Sixty seconds of data were acquired for each sleep stage transition, 30 seconds before and after the point of transition. This windowing gave two epochs as defined by the AASM scoring guidelines. A continuous wavelet transform was performed on each windowed signal. Time-frequency ridge analysis was subsequently performed on the CWT data, per windowed signal. An example of the CWT output, with sleep stage transition centered in the x-axis, and dominate time-frequency ridge marked as a solid black line, shown in Figure 1. The time-frequency ridges were segregated by sleep stage transition categories. While 36 categories were possible, 23 were populated based on the data.
on the sleep stage transitions within the data. Sleep stage category transitions varied from 10,000 sleep stage transitions (truncated for computation purposes), to 0 sleep stage transitions. Presentation of all 23 populated stages is outside the scope of this poster. Two stages with a truncated maximum value of 10,000 will instead be considered. These transitions were N1->to->N2 and N2->to->N1.

The input EEG data is raw with no filtering as the frequency characteristics were the main point of interest. Electromyography artifact noise is clearly visible as a high frequency energetic band (yellow band, top) as shown in Figure 1. To prepare the data for final analysis - without introducing filtering bias - all 10,000 samples (n) were sorted in ascending order based on the median value of the signal as shown in Figure 2. Vertical lines are placed at n = 250, 500, 9500 and 9750 in Figure 2. The 250 lowest and highest samples based on median value were excluded from analysis, effectively giving a 95% confidence interval. The remaining data was approximately linear.

With the data distilled, the median and 95% confidence intervals were generated for transitions. For illustrative purposes, transitions N2->to->N3 and N3->to->N2 are shown in Figure 3. Dominant ridge patterns were clear in Figure 3, in addition there was frequency correlations between reversal of sleep stage transitions which is promising. It should be noted that Figure 3 plots 90% confidence intervals to allow for obvious visual interpretation. A detailed results section is beyond the scope of this poster, thus has been excluded.
The author notes a few limitations of this work; firstly the selected database contains individuals who are undergoing an overnight PSG to assess for sleep disordered breathing conditions. While this could skew data, it is not expected to be significant. In addition, sleep disordered breathing conditions are highly prevalent as discussed in [8], and therefore should be considered for generalised models. Secondly, distilling temporal data by a single average could remove data of interest. While limiting this data to 95% confidence intervals should ensure sufficiently generalised data is retained. This method offers a means to filter data without applying filter bias. The primary goal of this poster presentation is to generate discussion around the suitability of time-frequency analysis for analysing EEG signals for automated detection of sleep arousals.

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REFERENCES


