Time-Frequency Ridge Analysis of Sleep Stage Transitions

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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 Academy 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. Poor inter-scorer agreement at sleep stage transitions is a noted limitation of current manual and automated methods as the point of transition is poorly defined [6]. The goal of this study is to further discuss on the topic of sleep staging automation and explore alternative and novel features to improve the inter-scorer reliability of sleep staging.

Clinically annotated PSG data were acquired from the "*You Snooze You Win: The PhysioNet/Computing in Cardiology Challenge 2018*" [7, 8]. 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. Six sleep stage annotations were possible (N1, N2, N3, R, U, W) Stages N1, N2 and N3 represent progressively deeper sleep, R represents REM sleep, U represents an undefined sleep stage, used for clinical ease and W represents wakefulness. All 994 recordings were used in this study. 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. It should be noted that successive annotations occurred e.g., N1→N1 in the data, however, as no sleep stage transitions occurred these instances were excluded from analysis.

Table 1. Exhaustive Sleep Stage Transition Categories

	N1	N2	N3	R	U	W
N1	N1 → N1	N1 → N2	N1 → N3	N1 → R	N1 → U	N1 → W
N2	N2 → N1	N2 → N2	N2 → N3	N2 → R	N2 → U	N2 → W
N3	N3 → N1	N3 → N2	N3 → N3	N3 → R	N3 → U	N3 → W
R	R → N1	R → N2	R → N3	R → R	R → U	R → W
U	U → N1	U → N2	U → N3	U → R	U → U	U → W
W	W → N1	W → N2	W → N3	W → R	W → U	W → W

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 (CWT) with frequency bounds of 0.05-86.8 Hz was performed on each windowed signal. For ease of comparison, figures referring to 'standardisation' were re-scaled from 0.05-86.8 Hz to between 0 and 1, using $(value - min)/(max - min)$. In this study, CWT was used due to its time and frequency localisation and hence ability in analysing non-stationary signals. 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 dominant time-frequency ridge marked as a solid black line, is

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 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 N2→N3 and N3→N2.

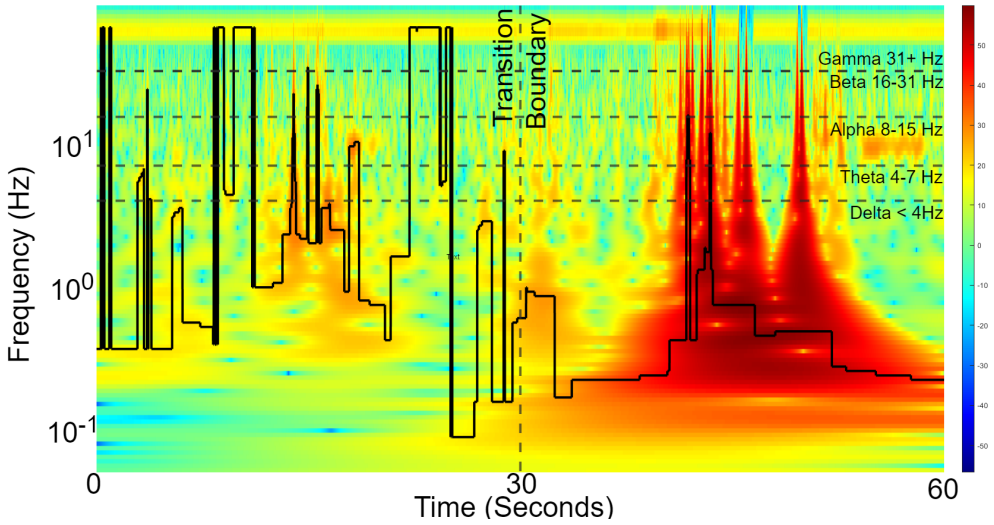

Figure 1. An example of a 60 second EEG CWT with subsequent time-frequency ridge shown as a solid black line.

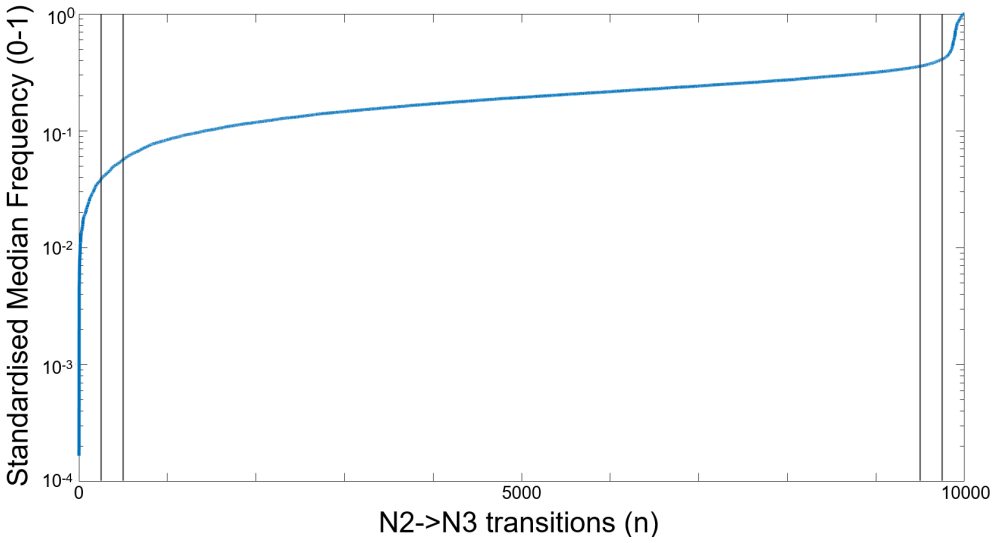

Figure 2. Ascending median values of 10,000 time-frequency ridges for N2→N3 sleep stage transitions

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. Several other noise sources were also expected including but not limited to; 50 Hz hum, low frequency/DC noise due to central apnea and high frequency noise due to poor electrode contact. To prepare the data for final analysis it was important to remove outliers - without introducing filtering bias - all

10,000 samples (n) were sorted in ascending order based on the median value of the time-frequency ridge, as shown in Figure 2. Extremely high and low frequency transitions were excluded from analysis. 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 90% confidence interval. The remaining data was approximately linear.

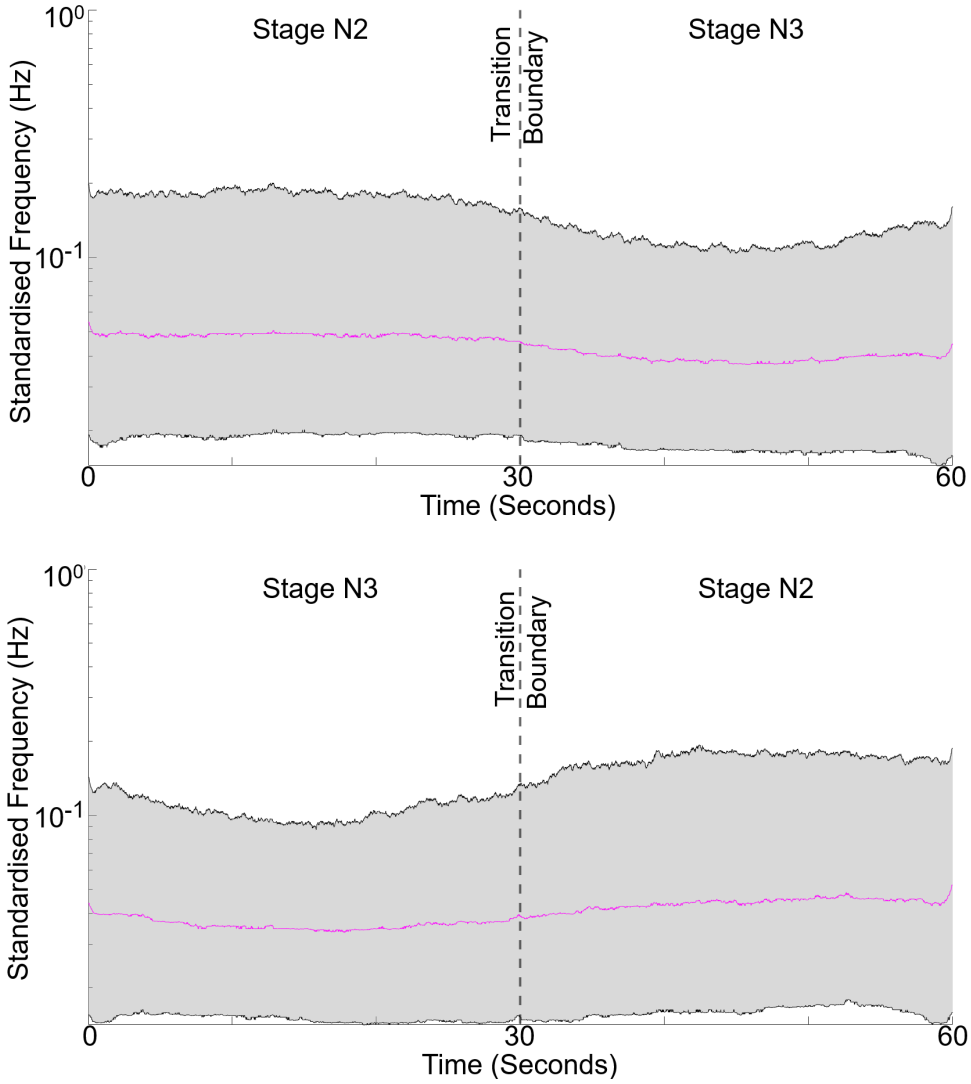

Figure 3. The median time-frequency ridge (magenta) for transition N2→N3 (top) and transition N3→N2 (bottom) with 90% confidence intervals in grey against standardised frequency

With the data distilled, the median and 90% confidence intervals were generated for transitions. For illustrative purposes, transitions N2→N3 and N3→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. However, the reader should note that for N2→N3 and N3→N2, a median difference of approximately 25% was reported. This is statistically significant. The methodology could lend itself to future automated pattern matching or an additional channel for clinicians to offer better interscorer reliability at the point of transition.

The author notes a few limitations of this work; firstly, the selected database contains individuals who underwent an overnight PSG study to assess 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 [9], 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 90% confidence intervals should ensure sufficiently generalised data is retained. This method offers a means to filter data without applying filter bias.
In conclusion, time-frequency ridge analysis is a promising approach to improving interscorer reliability due the observable, statistical changes in the time-frequency ridges at the point of transition. Future work will focus on fully quantifying ridges, generating all transition patterns and implementation for automation. Thus, advancing the current knowledge base of the physiological underpinning of sleep.

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Abstract

1. Sleep apnea is a highly prevelent condition in which breathing reduces or ceases during sleep [1].
2. An overnight polysomnogram (PSG) test is the current gold standard for clinical detection and severity.
3. Overnight PSG tests are currently manually scored, a process that takes approximately 2 clinical hours per recording. Inter-scorer reliability (ISR) is only ∼80% [2].
4. Automating clinical sleep stage scoring has the potential to revolutionise the field and reduce the clinical burden of manual scoring.
5. The majority of inter-scorer disagreement comes from transitions between sleep stages.
6. With these limitations in mind; robust simple features to determine the point of transition could significantly improve the ISR.

Introduction

Clinically annotated PSG data were acquired from the Computing in Cardiology Challenge 2018 [3]. EEG channel O1-M2 was selected for investigation. The dataset contained 994 overnight PSG recordings with clinical annotations. From this data time frequency ridges were generated based on each sleep stage transition.

Table 1. Exhaustive Sleep Stage Transition Categories

	N1	N2	N3	R	U	W
N1	N1 → N1	N1 → N2	N1 → N3	N1 → R	N1 → U	N1 → W
N2	N2 → N1	N2 → N2	N2 → N3	N2 → R	N2 → U	N2 → W
N3	N3 → N1	N3 → N2	N3 → N3	N3 → R	N3 → U	N3 → W
R	R → N1	R → N2	R → N3	R → R	R → U	R → W
U	U → N1	U → N2	U → N3	U → R	U → U	U → W
W	W → N1	W → N2	W → N3	W → R	W → U	W → W

Aims and Objectives

The aim of this study was to explore alternative and novel features to improve the inter-scorer reliability of sleep staging and generate discussion on the topic. Several objectives were identified to meet this aim;

1. Characterise the profile of sleep stage transitions though the use of time-frequency transform analysis.
2. Propose the use of this characterisation for future work such as artificial intelligence approaches for determining sleep stages and improving ISR.

Methodology

Sixty seconds of data were acquired for each sleep stage transition. A continuous wavelet transform (CWT) with frequency bounds of 0.05-86.8 Hz was performed on each windowed signal. This windowing gave two 30 second epochs as defined by the AASM scoring guidelines. A time-frequency ridge was then generated. Time-frequency ridge analysis was subsequently performed on the CWT data, per windowed signal.

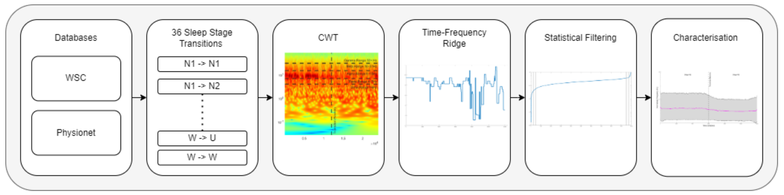
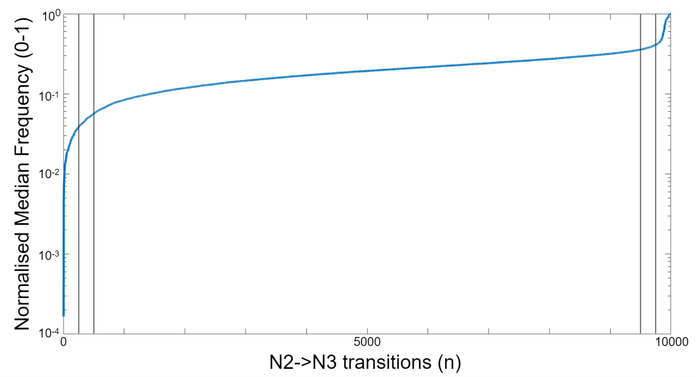


Figure 1. An overview of the processing pipeline

Figure 2. An example of a 60 second EEG CWT with subsequent time-frequency ridge shown as a solid black line.



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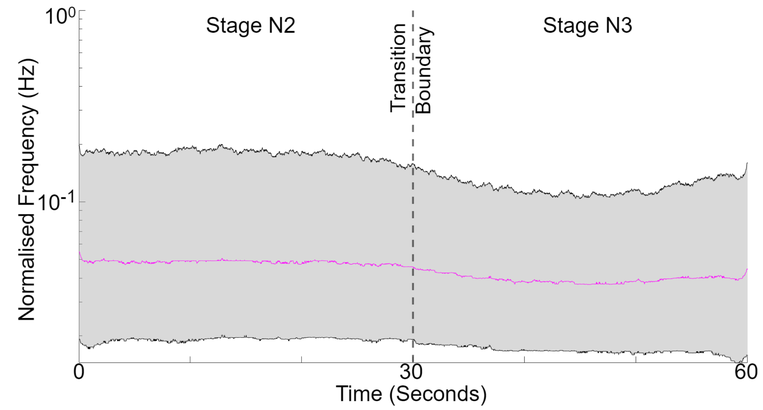
Results and Conclusions



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In conclusion, time-frequency ridge analysis is a promising approach to improving interscorer reliability due the observable, statistical changes in the time-frequency ridges at the point of transition. Future work will focus on fully quantifying ridges, generating all transition patterns and implementation for automation. Thus, advancing the current knowledge base of the physiological underpinning of sleep.

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