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Transforming Polysomnography: Time-Frequency Transforms to Visualise and Classify Polysomnography Data

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INTRODUCTION

Data transforms simplify signals while preserving essential information [1]. Polysomnography (PSG) is an example of several complex signals recorded simultaneously, which require classification into sleep stages and arousal events per epoch. This study outlines the initial investigation of a **novel technique to visualise PSG data in a more human intuitive manner**, considering the American Academy of Sleep Medicines (AASM) scoring guidelines [2]. It is proposed that this visualisation offers improved separation between classes (sleep stages) thus offering a chance to improve interscorer reliability. For this initial study, a machine learning classifier was employed to ensure epochs were accurately classified post transform. Mean sensitivity, specificity and Cohen's kappa were 0.79, 0.95 and 0.62 respectively.

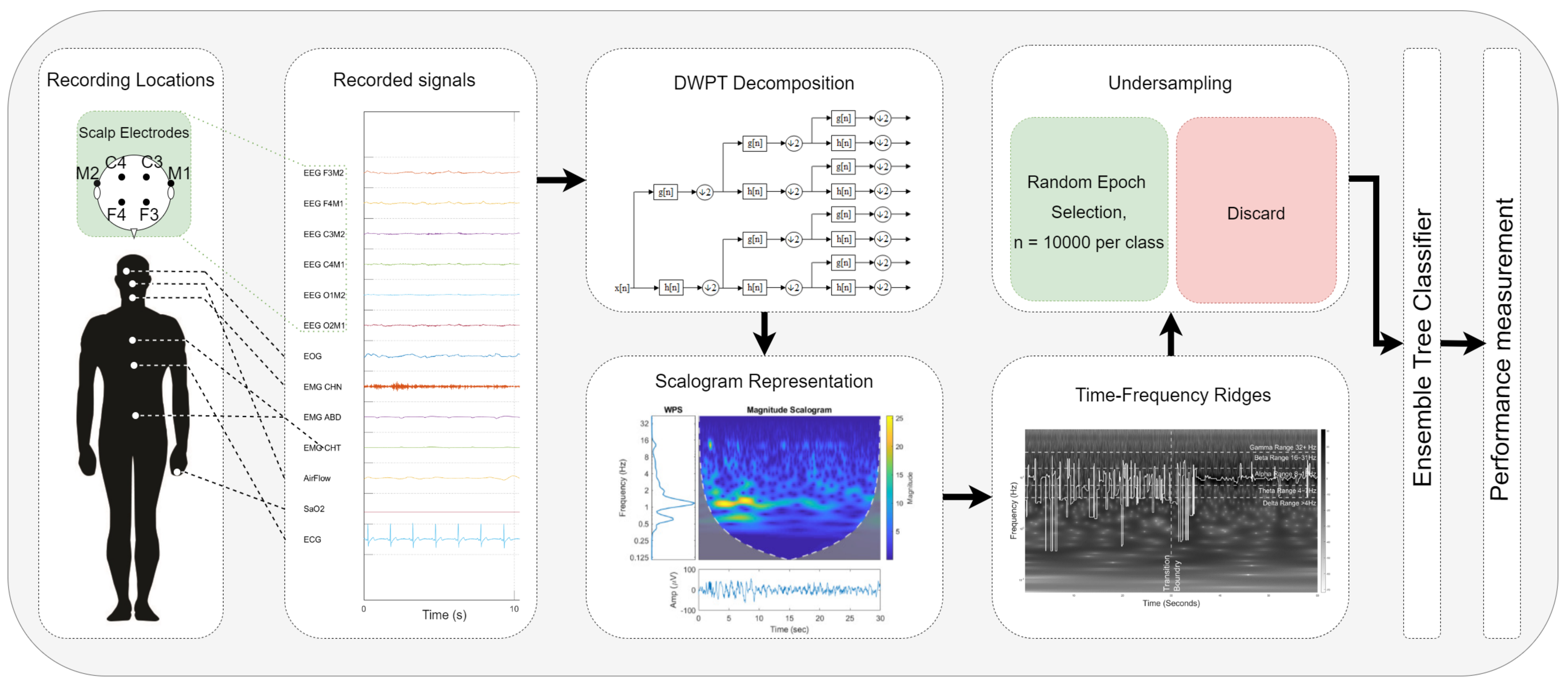

Figure 1: An overview of the processing pipeline

METHOD

An overview of the methodology is shown in Figure 1:

1. One hundred overnight PSG recordings were randomly selected from the dataset [3].
2. Each recording was split into 30 second epochs.
3. The continuous wavelet transform (CWT) was preformed per epoch.
4. Time-frequency (TF), and time-frequency-amplitude (TFA) ridges were computed from CWT shown in Figure 2.
5. Simplified visual signal representation of the PSG data (Figure 3), focusing on instantaneous frequency and energy magnitude were produced; aligning with the AASM scoring manual [2], and reducing the need for extensive clinician interpretation.

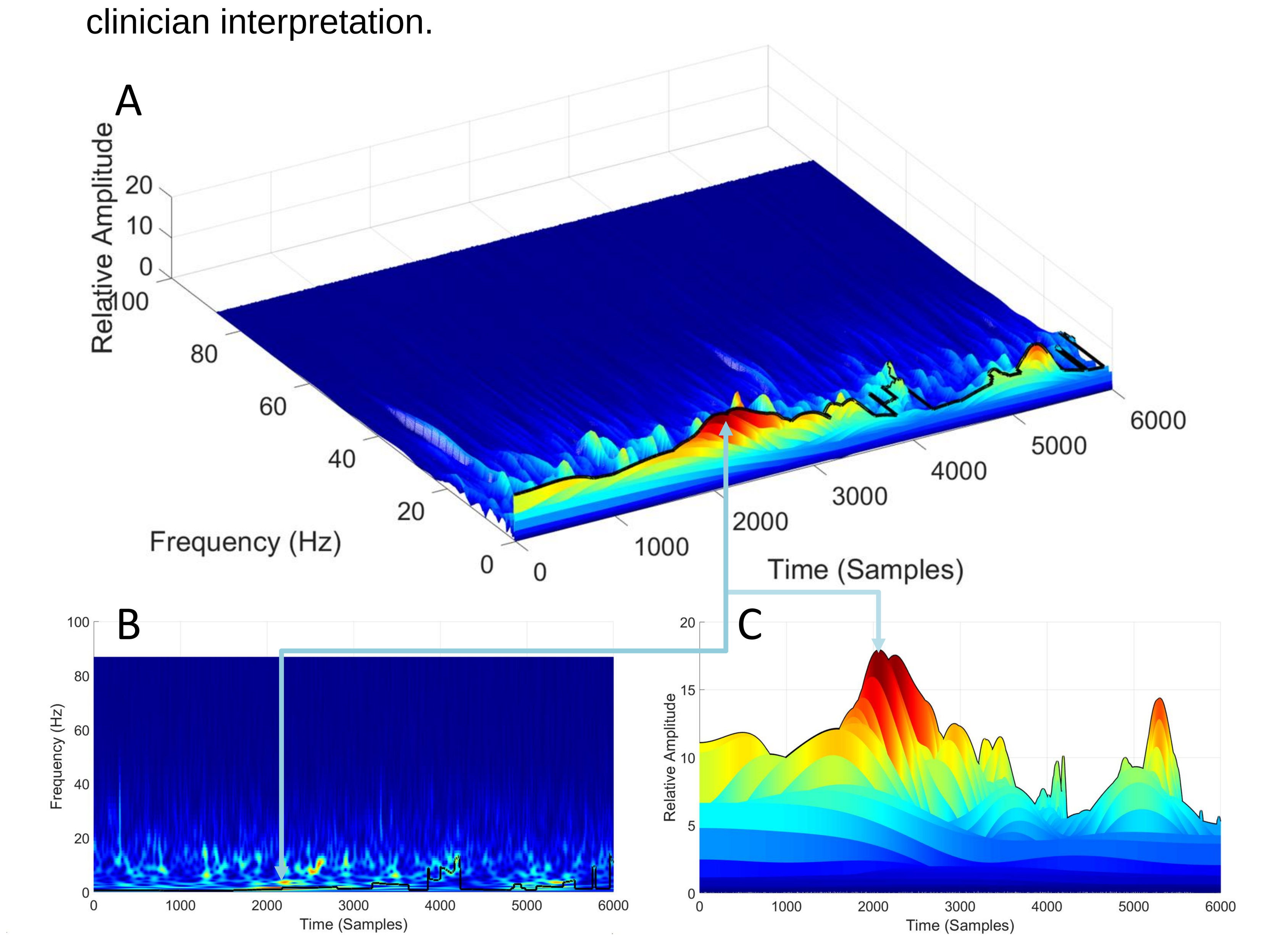

Figure 2: Top: A) A three-dimensional plot of the continuous wavelet transform of a 30 second epoch of stage N3 data. Time-frequency (B) and time-frequency amplitude ridge (C) are shown as a solid black line. Note the frequency of the black line, which is mainly in the 0.5-2Hz region, consistent with slow wave, stage N3 sleep and relatively high amplitude with occasional spiking.

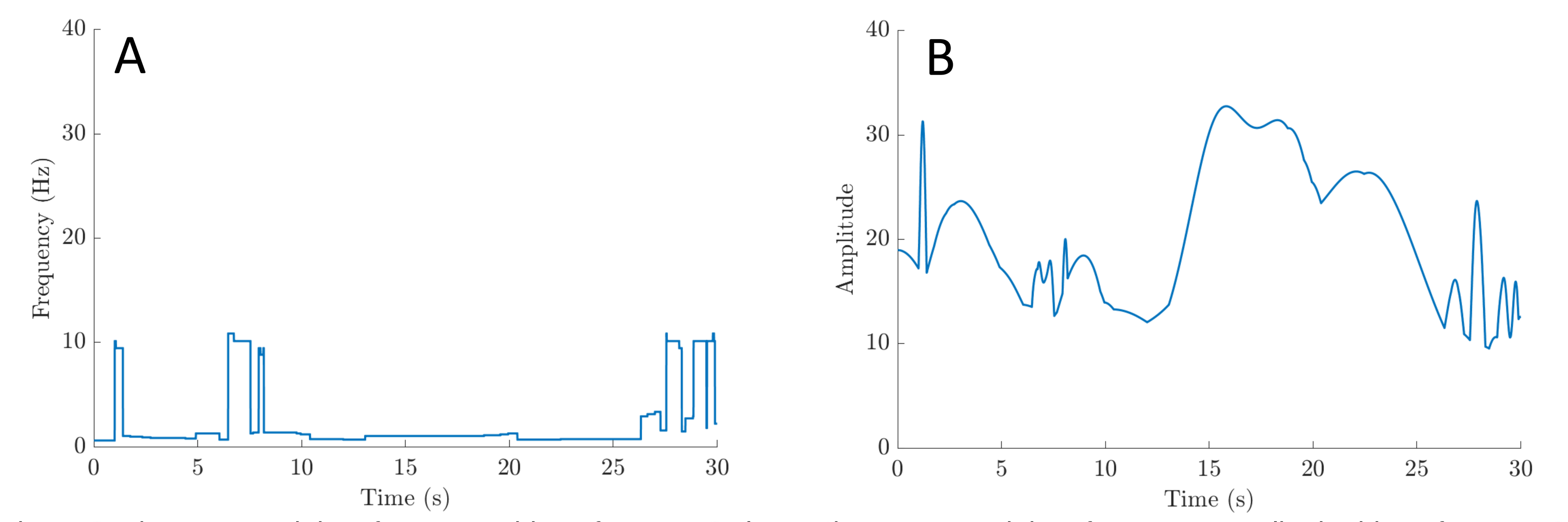

Figure 3: A) A extracted time-frequency ridge of stage N3 sleep. B) An extracted time-frequency amplitude ridge of stage N3 sleep.

RESULTS & DISCUSSION

To generate results for all 100 patients:

1. Time-frequency ridges were generated for each sleep stage for the following signals; F3-M2, C3-M2, O1-M2, E1-M2 and Chin1-Chin2.
2. Nine statistical features were calculated: kurtosis, maximum, mean, median, minimum, RMS, skewness, standard deviation and variance.
3. Undersampling techniques were used to balance the dataset. Each class was reduced to 10000 samples.
4. Results are displayed as a confusion matrix in Figure 4 for the five-fold cross validation process.

For sleep stages N1, N2, N3, R and W performance metrics were calculated:

- Sensitivity; 0.66, 0.71, 0.91, 0.86 and 0.82.
- Specificity; 0.92, 0.94, 0.97, 0.97 and 0.94.
- Cohen's Kappa; 0.63, 0.63, 0.61, 0.61 and 0.61.

Thus, the ensemble tree classifier preforms on par with computationally heavier algorithms presented in literature, largely due to the time frequency transforms. However, the TF and TFA signals are '*interpretable*', in the sense of artificial intelligence approaches. i.e., the system is "comprehensible to humans" [4]. This is an important divergence from existing AI approaches which are 'black boxes' and therefore clinically mistrusted.

True Class \ Predicted Class	N1	N2	N3	R	W	TPR	FNR
N1	6652	934	34	764	1616	66.5%	33.5%
N2	1051	7150	987	420	392	71.5%	28.5%
N3	15	772	9073	19	121	90.7%	9.3%
R	661	496	44	8552	247	85.5%	14.5%
W	1436	144	64	121	8235	82.3%	17.6%
PPV	67.8%	75.3%	88.9%	86.6%	77.6%		
FDR	32.2%	24.7%	11.1%	13.4%	22.4%		

TPR = Sensitivity
FNR = False Negative Rate
PPV = Positive Predictive Value
FDR = False Discovery Rate

Figure 4: A confusion matrix for the features generated from the time-frequency transformed data

CONCLUSION & FUTURE WORK

In conclusion:

- TF and TFA ridges provide a novel visual methodology for PSG data which could offer easier interpretation and improve inter-score reliability.
- Therefore, the use of TF and TFA ridges may offer a new approach to sleep study scoring which requires less subjective visual interpretation from a sleep technologist.
- Considering sensitivity and specificity, the classification is on par with literature; sufficient signal information has been retained by the transform.
- It is hoped that this poster will further discussion of novel visualisations for PSG data to improve interscorer reliability.
- Future work will focus on establishing side-by-side comparison with raw EEG data.

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