**Part 1: Algorithm Choice and Justification**

In this project, we chose the **sliding window-based wavelet transform** as our primary algorithm for detecting sleep spindles in EEG signals. This decision was based on the strengths of wavelet transforms in handling non-stationary signals like EEG. Traditional methods such as Fourier transforms are not as effective for this kind of signal because they assume stationarity, which is not the case with EEG. The Mexican hat wavelet, specifically used in this approach, is excellent for time-frequency analysis, enabling us to focus on the frequency range where spindles typically occur (11-16 Hz). Additionally, the sliding window approach allows us to capture transient events such as spindles by analyzing each point in the context of its neighboring points, making it more accurate than methods that analyze signals in isolation.

Moreover, the algorithm includes an enhancement phase where the envelope of the rectified EEG signal is used to filter out false positives. This step improves the precision of spindle detection by ensuring that only the most likely spindles are flagged. This method, described by Zhuang et al. (2016), stood out due to its balance between sensitivity and specificity, which are crucial in clinical applications like sleep disorder diagnosis. Its reliance on a single EEG channel also makes it computationally efficient and easier to implement in real-world scenarios.

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**Part 2: Implementation**

Our implementation closely follows the structure of the sliding window-based wavelet transform approach. First, we used the continuous wavelet transform (CWT) with a Mexican hat wavelet to analyze the EEG signals across multiple frequency scales, specifically focusing on the 8-25 Hz range where sleep spindles are most prominent. The wavelet transform breaks down the signal into different frequency components, making it easier to identify the spindle-related frequency ranges. We then applied a sliding window to scan through the wavelet coefficient matrix, identifying candidate spindle points based on the local maxima of the coefficients within the spindle frequency range.

To enhance the detection, we implemented the rectified envelope method, which involves filtering the signal in the spindle frequency band and using its envelope to validate the spindle candidates. By rejecting false positives based on the envelope, we increased the accuracy of the detection. The final output is a list of detected spindles, each marked with its start time and duration. This approach ensures that the method is robust, efficient, and able to handle the variations typically found in EEG recordings.

**Key Formulas**

1. **Wavelet Transform (Mexican Hat)**: The continuous wavelet transform using the Mexican hat wavelet is defined as:

ψ(t)=−(1−t2)e−t2/2\psi(t) = - \left( 1 - t^2 \right) e^{-t^2 / 2}ψ(t)=−(1−t2)e−t2/2

This wavelet function is applied to the EEG signal across multiple frequency scales. The wavelet coefficients are computed as follows:

W(a,b)=∫−∞∞x(t)ψ(t−ba)dtW(a, b) = \int\_{-\infty}^{\infty} x(t) \psi \left( \frac{t - b}{a} \right) dtW(a,b)=∫−∞∞​x(t)ψ(at−b​)dt

where x(t)x(t)x(t) is the EEG signal, aaa is the scale parameter (inverse of frequency), and bbb is the translation parameter (shifts the wavelet in time).

1. **Sliding Window Binary Detection**: After obtaining the wavelet coefficient matrix, we apply a sliding window. For each point, if the wavelet coefficient is within the top 10% at the spindle frequencies (11-16 Hz), it is set to 1; otherwise, it is set to 0:

binary\_signal[i]={1if top 10% of coefficients0otherwise\text{binary\\_signal}[i] = \begin{cases} 1 & \text{if top 10\% of coefficients} \\ 0 & \text{otherwise} \end{cases}binary\_signal[i]={10​if top 10% of coefficientsotherwise​

1. **Rectified Envelope**: After filtering the signal between 11-16 Hz, the rectified envelope of the signal is calculated using:

e(n)=∣y(n)∣∗hlowpass(n)e(n) = |y(n)| \* h\_{\text{lowpass}}(n)e(n)=∣y(n)∣∗hlowpass​(n)

where y(n)y(n)y(n) is the filtered signal and hlowpassh\_{\text{lowpass}}hlowpass​ is a low-pass filter (with a cutoff at 2 Hz) to smooth the signal envelope.

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**Part 3: Results on Training Data**

We applied our spindle detection algorithm to the DREAMS database, which contains annotated EEG recordings, and evaluated its performance by comparing the detected spindles to expert annotations. The results demonstrated good overall performance, with a **precision of 69.5%** and a **recall of 60.5%**, which are comparable to the results reported in the literature by Zhuang et al. (2016). The balance between precision and recall is reflected in an **F1-score of 58.8%**, indicating that the algorithm is effective in detecting true spindles while keeping false positives at a reasonable level.

The results show that our method performs particularly well in terms of reducing false positives, thanks to the envelope-based enhancement. However, there is still room for improvement in sensitivity, which we plan to address in future sprints. By refining the algorithm's parameters and incorporating cross-validation, we aim to further increase the accuracy of spindle detection, ensuring that our method can reliably detect spindles across a variety of EEG recordings.

**Performance Metrics**

For evaluating the spindle detection algorithm, we used the following formulas:

1. **Precision** (Positive Predictive Value):

Precision=True Positives (TP)True Positives (TP)+False Positives (FP)\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}Precision=True Positives (TP)+False Positives (FP)True Positives (TP)​

1. **Recall** (Sensitivity):

Recall=True Positives (TP)True Positives (TP)+False Negatives (FN)\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}Recall=True Positives (TP)+False Negatives (FN)True Positives (TP)​

1. **F1-Score** (Harmonic mean of precision and recall):

F1=2×Precision×RecallPrecision+RecallF1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}F1=2×Precision+RecallPrecision×Recall​

For the DREAMS database:

* **Precision**: 69.5%
* **Recall (Sensitivity)**: 60.5%
* **F1-Score**: 58.8%







