UNSW AUSTRALIA

BE Thesis 2019 – *Poster #120*

Never Stand Still | Faculty of Engineering | School of Electrical Engineering and Telecommunications

Investigating The Feasibility Of Using Non-Linear Least Squares To Predict Sleep Spindles In EEG

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Background and Motivation

- Sleep spindles are oscillations generated in brainwaves in *Stage N2* sleep.
- Generally are 0.5 – 2.0 second in duration and have a frequency between 11-16 Hz.
- Correlated with a higher quality of sleep and long-term memory consolidation.
- Spindle detection and classification is currently performed visually by trained sleep technicians as the *gold standard*.
- Existing mathematical models and time-frequency methods detect spindles but are limited in describing the temporal features of spindles.
- The *Quadratic Parameter Sinusoid (QPS)* developed by *Palliyali et. al. (2015)* is a candidate model for spindles.

$$s(t) = e^{a+bt+ct^2} cos(d + et + ft^2)$$

- Model serve to not only describe spindles in richer detail but classify spindles found in EEG.

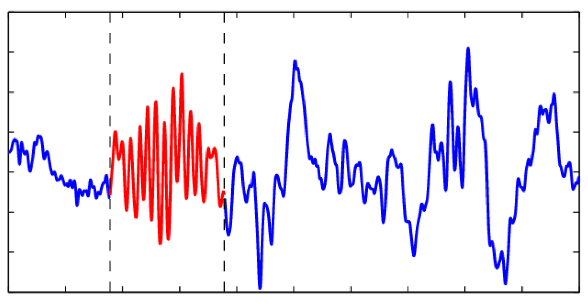


Fig 1: Raw spindle detected in an EEG segment

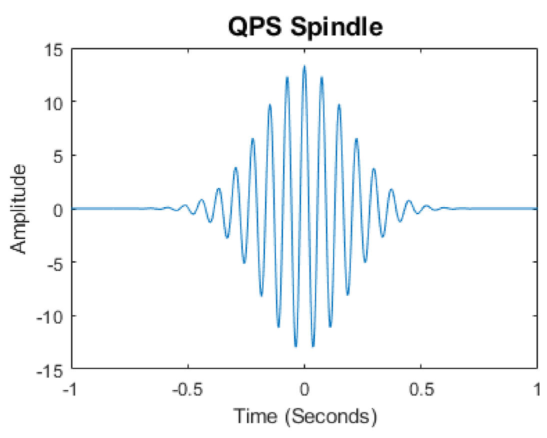


Fig 2: A QPS spindle generated with set parameter values

Aim and Objectives

- Develop a frame acquisition process to extract spindles and non-spindles based on a threshold or power-based criterion using expert scorers as manual classification.
- Compute QPS parameters as well as energy and frequency characteristics from extracted spindles and non-spindles via NLLS initialisation.
- Use the QPS parameters and features to train a neural network model to classify spindles from non-spindles
- Perform feature selection to optimise the neural network model in classifying spindles

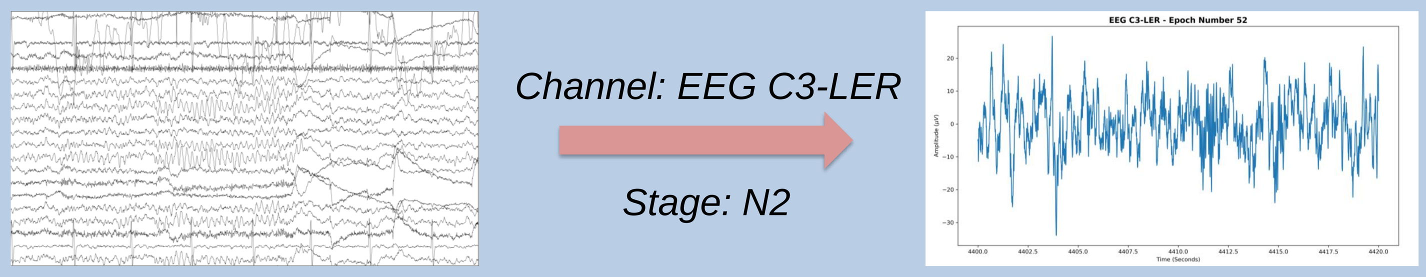
Distribution Of QPS Parameter Values Used For NLLS Initialisation

Mean Values (With Standard Deviation)

a	*b*	*c*	*d*	*e*	*f*
0.82 (1.78)	1.05 (9.05)	-10 (3.87)	0 (4.69)	84.5 (3.86)	-0.9 (4.96)

Methodology

Step 1: *Extracting 30 second 'Stage N2' epochs from the EEG*



Step 2: *QPS Parameter Calculations and Manual Classification*

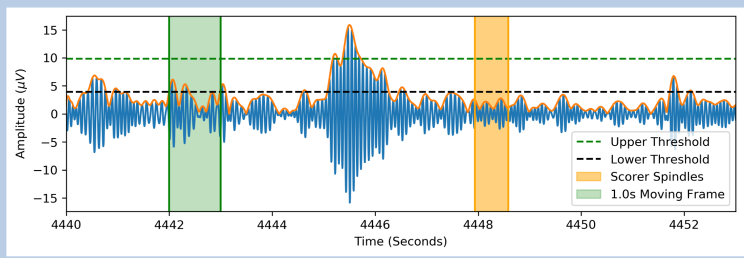


Fig 3: A 20.0 second epoch with an 11-16 Hz zero-phase bandpass filter applied. the spindle found by the scorers is shown in the time-domain plot of the signal.

Cost Function Minimisation

$$\frac{\partial S(\mathbf{p})}{\partial \mathbf{p}} = \mathbf{J}^T(\mathbf{y} - \hat{\mathbf{y}}) = 0$$

Levenberg – Marquadt Algorithm

$$\mathbf{h}_{lm} = (\mathbf{J}^T\mathbf{J} + \lambda \mathbf{I})^{-1}\mathbf{J}^T(\mathbf{y} - \mathbf{y}(\mathbf{p}_n))$$

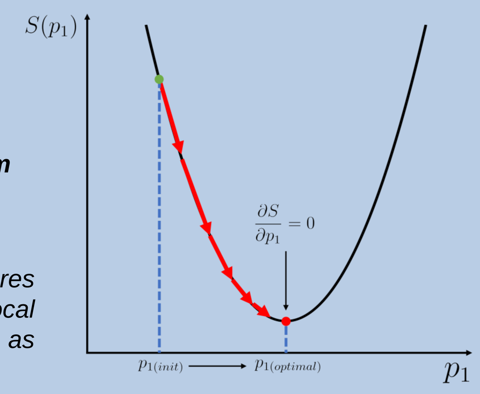
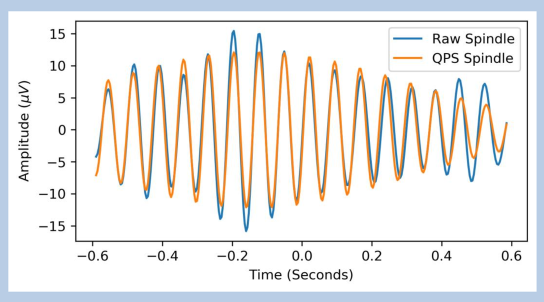


Fig 4: Non-Linear Least Squares Regression (NLLS) finds the local minima of the cost function as fast as possible.



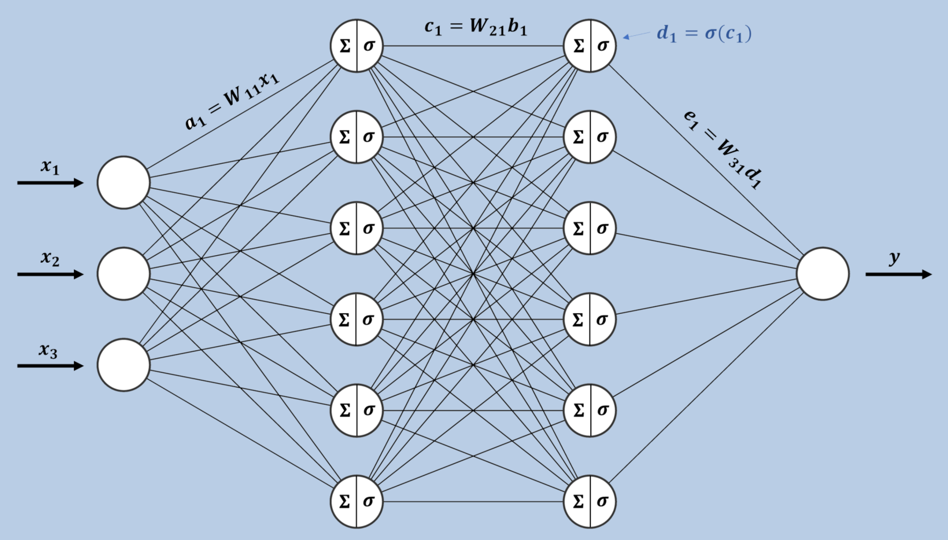
Estimated Parameter Values After NLLS Regression

Param	*a*	*b*	*c*	*d*	*e*	*f*
Initial	2.5921	2.9055	-14.2400	0.0027	84.6602	-1.4241
Final	2.4547	-0.7004	-2.5863	-1.8804	86.9666	-0.3235
Error (%)	0.98	-10.74	-8.83	-1.28	0.09	-70.15

Fig 5: The raw spindle captured by the detection algorithm and the best-fit QPS with an example of initialised values for the NLLS regression algorithm. The initial and final values of the QPS parameters are shown on the table to the right.

Step 3: *Classification Using An Artificial Neural Network*

Feature vectors including QPS parameter values serve as inputs to the classifier



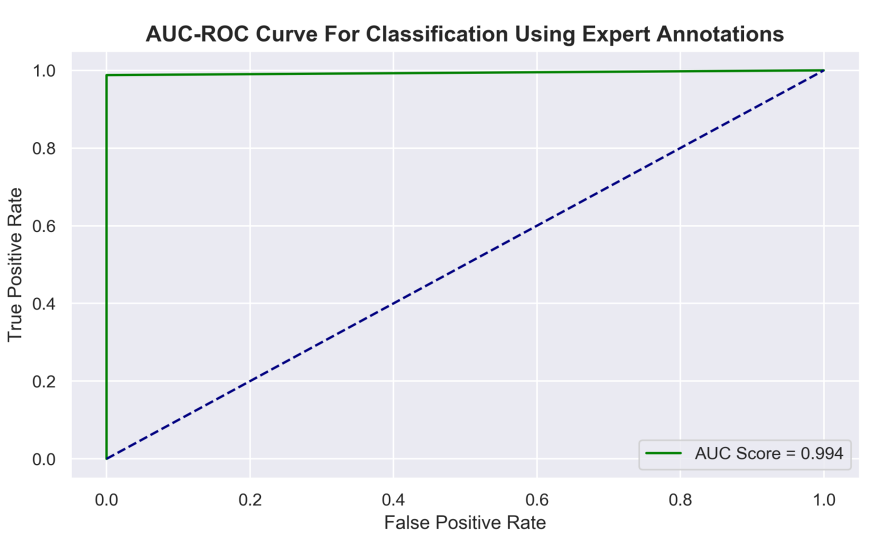
Binary output that predicts a spindle (1) or non-spindle (0)

Performance using expert scorer for NLLS initialisation AND manual classification

(Intersection of Scorer 1 and 2 as annotations)

- QPS parameters for **spindles** were set to the mean values known a priori while non-spindles had theirs set all to 0.
- Clear separation due to bias between the two classes.
- NLLS regression fails for non-spindles since initial values were far from optimum.

Metric	Result (%)
Accuracy	99.17
Precision	98.44
Recall	100.0
F1 Score	99.21
AUC Score	99.4



Performance Using *SDT Ratio* For NLLS parameter initialisation

- Spindles in EEG have a high localised power in the 11-16 Hz range relative to the power in the *delta* band (0.5 – 4 Hz) and the *theta* band (4 – 7 Hz). From this, we can compute the SDT ratio as:

$$SDT\ Ratio = \frac{P_{spindle}}{P_{delta} + P_{theta}}$$

- All powers are *relative* (to the total power captured by the frame) and are computed as the integral of the power spectral density in the relevant bands for each frame using a 0.5 second window with 0.25 second overlap.

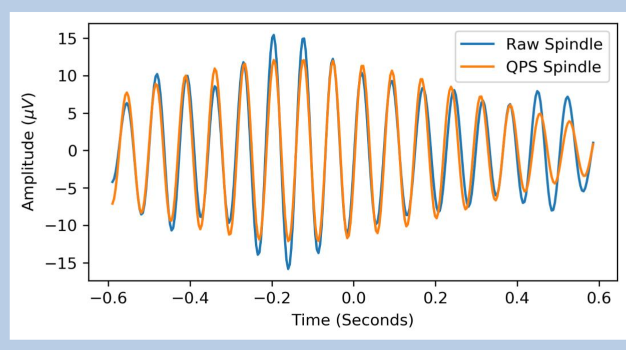
$$P_x = \int_{f_l}^{f_h} S_x(f) \cdot df$$

- Mean SDT ratio (percentage value) for spindles (marked by experts) was found to be 0.3682 ± 0.2635.
- Poor performance; no guarantee of correlation with actual spindles marked by experts.

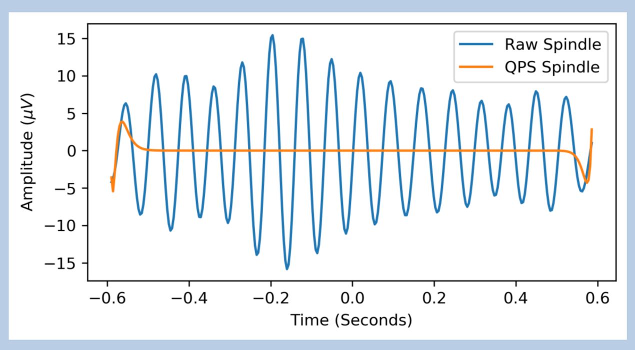
Metric	Result (%)
Accuracy	55.40
Precision	40.55
Recall	57.67
F1 Score	47.6
AUC Score	55.9

Sensitivity of the NLLS Regression

- QPS initialised at the *full* mean values shows good spindle reconstruction



- Initialisation at a fraction (a sixth in this case) of the mean values causes QPS to fail in the regression process.



Consequences

- Not all spindles are generated the same physiologically and may not correlate with the morphology of the QPS model.
- Moving window may capture a spindle but its signal characteristics may not be in the range of the mean parameter values.
- As a result, the Gauss-Newton optimisation will never reach the optimum QPS parameter values for the spindle captured.
- May lead to wrong classification which affects the class separation between spindles and non-spindles and the ability of the neural network to differentiate between the classes.

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN} \qquad AUC\ Score = P(X_1 > X_0)$$

(Where X_1 is a positive instance and X_0 is a negative instance)

$$F_1\ Score = 2 \times \frac{Precision\ * Recall}{Precision + Recall} \qquad Accuracy = \frac{\text{Correct Predictions}}{Total\ Number\ Of\ Predictions}$$

Conclusions

- The NLLS allows for effective reconstruction of sleep spindles when parameters are initialised near their optimum values.
- However, the NLLS parameter initialisation is a sensitive process. If parameters are not near the optimum values, the regression performs very poorly
- Poor regression of the QPS model reduces the model's ability to classify spindles

Further Work

- Further investigate the characteristics of spindles detected by expert scorers to determine other possible criteria for NLLS parameter initialisation.
- Develop another analytical method that is not reliant on NLLS for parameter initialisation due to its sensitive performance.