A Comparison of EEG Power Spectral and Wavelet Features in Concussed Cohorts Using Support Vector Machine

Saurabh Garg[1], Arnold Yeung[2], Harinath Garudadri[3], and Naznin Virji-Babul[4]

[1]Department of Electrical and Computer Engineering, University of British Columbia; [2]Department of Mechanical Engineering, University of British Columbia; [3]Qualcomm Institute of Calit2, University of California San Diego; [4]Department of Physical Therapy, University of British Columbia

Introduction

- **EEG** has shown potential to be a **diagnostic tool** for **concussion**
- Many studies have shown that **stationary power spectral features** may indicate brain activity changes due to concussion [1, 2, 3]
- Further studies have noted that **non-stationary wavelet features** may also be used to diagnose concussion [3]

Purpose

1. To **compare** the performances of **power spectral features** and **wavelet features** in **concussion classification**
2. To assess the **accuracies of these 2 feature sets** in concussion classification using **linear SVM**

Methods

Participants
- **27 concussed subjects** (mean age: 16.0 ± 0.9)
- **33 healthy controls** (mean age: 15.8 ± 1.3)

EEG Data Acquisition and Processing
- Sampled at 250 Hz
- Interpolated to **10-20 International System**
- Filtered with **Butterworth band-pass filter** from **4 to 40 Hz**

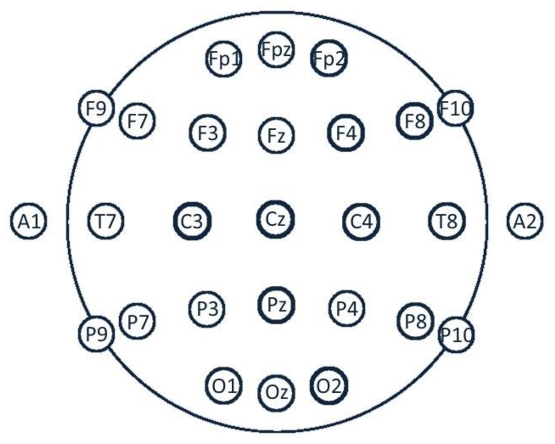

Figure 1. Electrode Placement of 10-20 International System.

Frequency Bands Analyzed
- Delta (0.5 to 4 Hz)
- Theta (4 to 7 Hz)
- Alpha (7 to 14 Hz)
- Beta (15 to 30 Hz)
- Gamma (30 to 40 Hz)

Stationary **Power Spectral Feature Set**
- **Average powers** of the 5 frequency bands
- Average **power ratios** of neighboring frequency bands

Non-Stationary **Wavelet Feature Set**
- Order 8 Daubechies wavelets
- Mean, standard deviation, number of zero-crossings, and energy of **wavelet coefficients**
- **Shannon entropy**

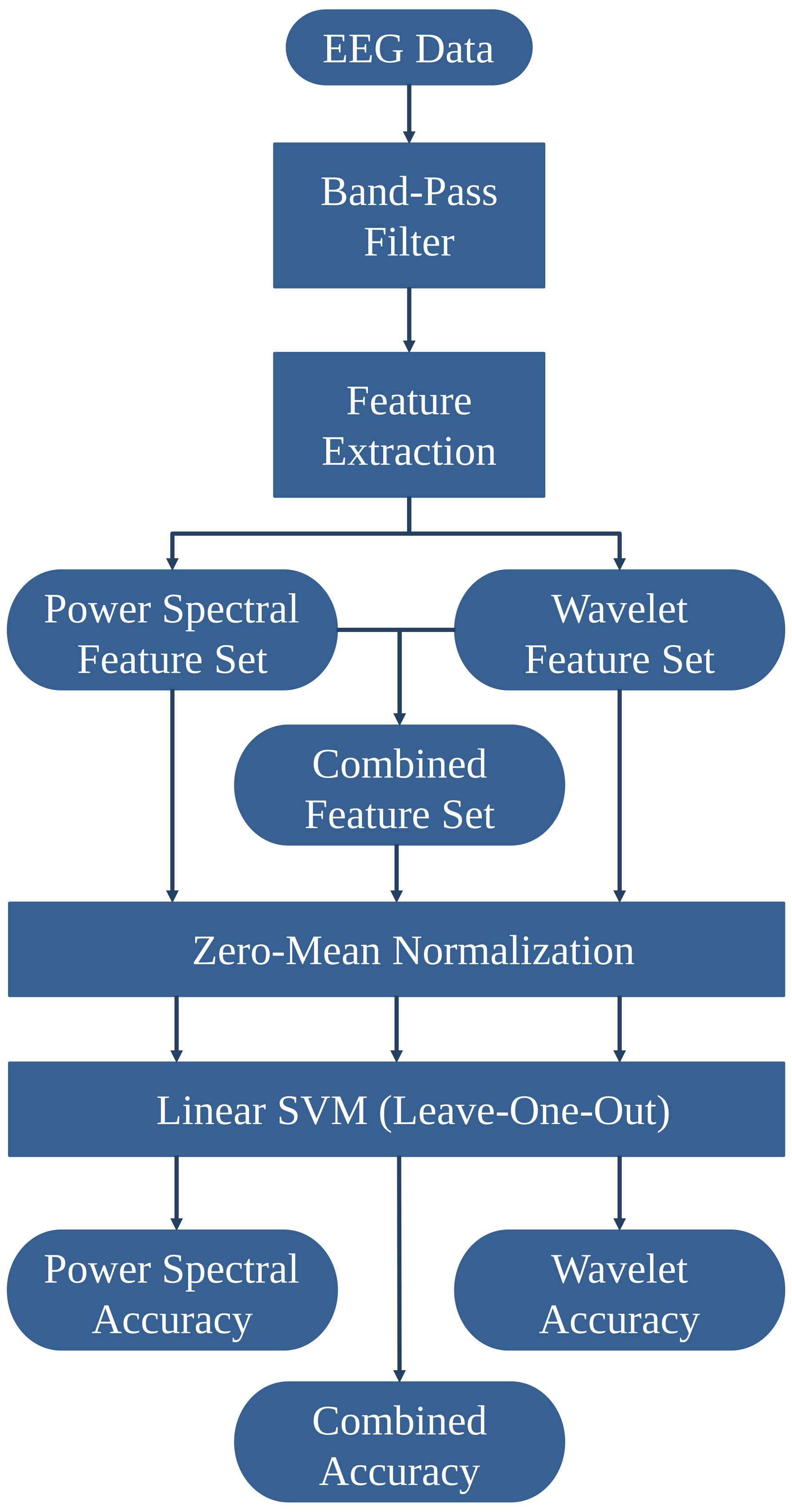

Figure 2. Process of feature extraction and concussion classification.

Linear Support Vector Machine (SVM):
- **Supervised machine learning model** used for classification between different cohorts
- Optimized **linear boundary** between the 2 different cohorts was drawn
- **Leave-One-Out cross-validation** was used for each feature set

Results

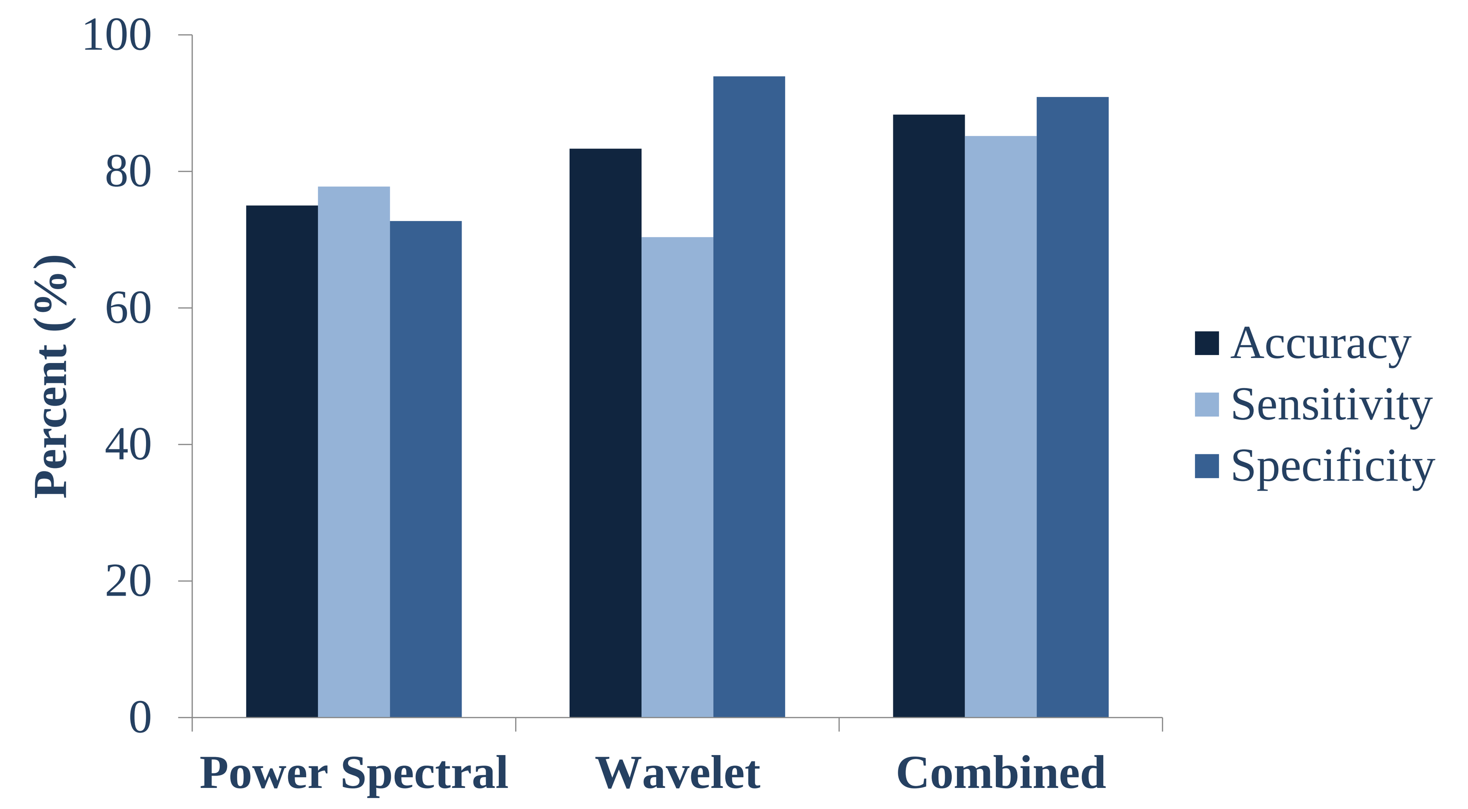

Figure 3. Accuracies of power spectral feature set, wavelet feature set, and the combination of both feature sets.

Table 1. Linear SVM Classification Accuracies for Different Feature Sets

Feature Set	Accuracy (%)	Sensitivity (%)	Specificity (%)
Power Spectral	75.00	77.78	72.73
Wavelet	83.33	70.37	**93.94**
Combined	**88.33**	**85.19**	90.91

- The **combined feature set** obtained the **highest overall accuracy (88.33%)** and the **highest sensitivity (85.19%)**
- The **wavelet feature set** obtained the **highest specificity (93.94%)**

Discussion

- The **combined feature set** had the overall **best accuracy**
  - **sensitivity of 7.41% higher** than that of the power spectral feature set
  - **specificity of 3.03% lower** than that of the wavelet feature set
- The **combined feature set** may provide an **accurate method for identifying brain changes due to concussion**
- **Increased overall accuracy** of the combined feature set suggests the **importance of both the power spectral feature set and the wavelet feature set** in concussion-based EEG analyses

References

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