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

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***Abstract*— EEG power spectral features and wavelet features have independently shown changes in brain activity due to concussions. In this study, we compared the performances of these feature sets with a linear SVM classifier to determine the optimal feature set for concussion classification. Our results show that the power spectral feature set had the higher sensitivity and the wavelet feature set had the higher specificity in classifying concussed subjects. When both feature sets were combined, the overall accuracy improved by 5% due to higher sensitivity, suggesting the relevance of both feature sets.**

I. Introduction

Electroencephalography (EEG) has shown potential to be used as a diagnostic tool for concussions. Numerous studies have used stationary power spectral features to detect changes in brain activity due to concussion [1, 2, 3]. Some studies have used wavelet features [3, 4], as they capture the non-stationary properties of EEG. To our knowledge, this study is the first attempt to compare the performances of the 2 feature sets in classifying concussed and healthy subjects.

II. Materials and Methods

Five minutes of resting state EEG data was collected from 33 healthy controls (mean age: 15.8 ± 1.3) and 27 concussed subjects (mean age: 16.0 ± 0.9). EEG data was sampled at 250 Hz, interpolated to the International 10-20 System, and filtered using a 4 to 40 Hz Butterworth band-pass filter.

For each electrode, the spectral powers of the 5 frequency bands (δ, θ, α, β and γ; [2]) and the 4 ratios between the powers of the neighboring bands were calculated. In total, each electrode had 9 power spectral features.

The wavelet decomposition at each electrode was calculated using order 8 Daubechies wavelets. The wavelet features included the mean, standard deviation, number of zero-crossings, and energy of the wavelet coefficients for each of the 5 frequency bands. Shannon entropy was also included in this feature set. In total, each electrode had 21 features (20 wavelet; 1 entropy).

All features were then normalized to have zero mean and unit variance. Linear support vector machine (SVM) was used as a classifier for each feature set independently and for both feature sets combined. Leave-one-out cross-validation was then used to determine the accuracies for the 3 feature sets.

III. Results and Discussion

The accuracies of the SVM classifiers with the 3 different feature sets are presented in Table 1. The results show that all 3 feature sets were suitable for differentiating between concussed and healthy subjects. Of the 2 independent feature sets, the power spectral feature set displayed higher sensitivity and the wavelet feature set displayed higher specificity. This suggest that the power spectral feature set may be more accurate in detecting concussed subjects, whereas the wavelet feature set may be more accurate in detecting healthy subjects.

TABLE I. SVM Results 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 accuracy (88.3%). The sensitivity of the combined feature set was 7.41% higher than that of the power spectral feature set and 14.82% higher than that of the wavelet feature set. Moreover, the specificity of the combined feature set was vastly higher (18.18%) than that of the power spectral feature set and slightly lower (-3.03%) than that of the wavelet feature set.

IV. Conclusion

Our results suggest that the combined feature set may provide an accurate method for identifying brain changes due to concussion using resting state EEG data. The increased accuracy, when both feature sets were combined, suggests the importance of both the power spectral and wavelet feature sets in EEG analyses for concussion-related studies.

References

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