우울증의 일관성 패턴에 대한 뇌파 통계 분석 및 기계 학습 분류

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EEG Statistical Analysis of Coherence Patterns in Depression and Machine Classification

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Abstract

Depression's neurophysiological basis remains poorly understood, particularly regarding functional connectivity patterns. This study examines EEG coherence differences between 46 major depressive disorder (MDD) patients and 75 healthy controls (HC) from the PRED+CT dataset. Statistical analysis revealed significant reductions in global coherence across all frequency bands in depression, with the strongest effects observed in theta and delta bands. Support Vector Machine classification achieved promising performance, with the best results in the beta band (accuracy=83.28) despite this band showing the smallest statistical effects. This discrepancy suggests that different aspects of coherence data may contribute to biomarker development versus neurophysiological understanding of depression.

1. Introduction

Despite the prevalence of Major Depressive Disorder (MDD), objective biomarkers for depression remain poorly identified [1]. Electroencephalography (EEG) offers insights into depression's neurophysiology through functional connectivity analysis, which may be disrupted in mental disorders such as depression.

EEG coherence measures the phase relationships between different brain regions and has emerged as a promising approach for investigating altered neural communication in depression. Previous studies report mixed findings, with some indicating reduced frontoparietal coherence [2] and others showing increased connectivity in specific frequency bands [3]. However, methodological differences and small sample sizes have limited generalizability.

This study presents a statistical analysis of coherence differences between depression patients and healthy controls across multiple frequency bands. Furthermore, we implement machine learning to assess the diagnostic potential of coherence features and evaluate their usability as viable depression biomarkers.

2. Method

2.1 Dataset and Preprocessing

We utilize the PRED+CT dataset [4], comprising resting-state EEG recordings from 46 MDD patients and 75 healthy controls. Depression was determined using the Beck Depression Inventory (BDI); (BDI >7 = MDD and ≤7 = healthy controls) [5]. We then preprocessed the EEG data using standard procedures including bandpass filtering, artifact removal, and segmentation into four frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (13-30 Hz) [6-12].

2.2 Coherence Analysis and Statistical Approach

We calculated magnitude-squared coherence [13] matrices for each subject and frequency band, defined as:

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}$$

where $P_{xy}(f)$ is the cross-spectral density. From these matrices, we extracted metrics including global coherence (mean of all connections) and the proportion of high (>0.7), medium (0.4-0.7), and low (<0.4) synchronization connections.

Mann-Whitney U tests compared metrics between groups, with effect sizes calculated using Cohen's d, and Statistical significance was established at p<0.05 with Bonferroni correction.

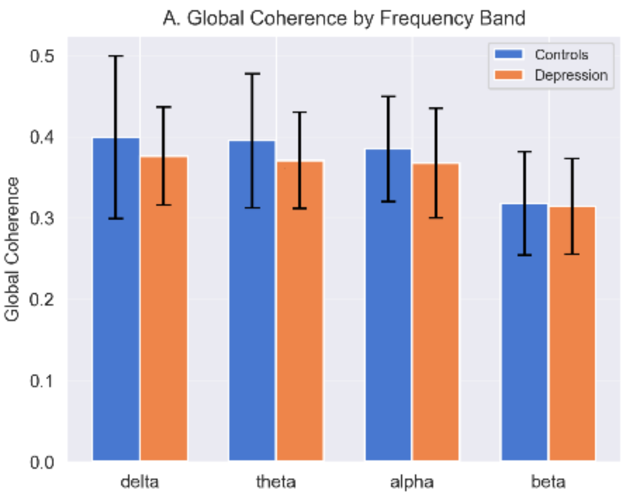
2.3 Classification Approach

We performed SVM [14] classification with radial basis function kernel using coherence-derived features to differentiate MDD and healthy controls. 5-fold cross-validation [15] with standardization was implemented, evaluating performance via accuracy, precision, recall, and F1-score [16].

3. Results and Discussion

3.1 Statistical Comparison

Statistical analysis revealed consistent patterns of altered connectivity in depression across frequency bands (Figure 1).

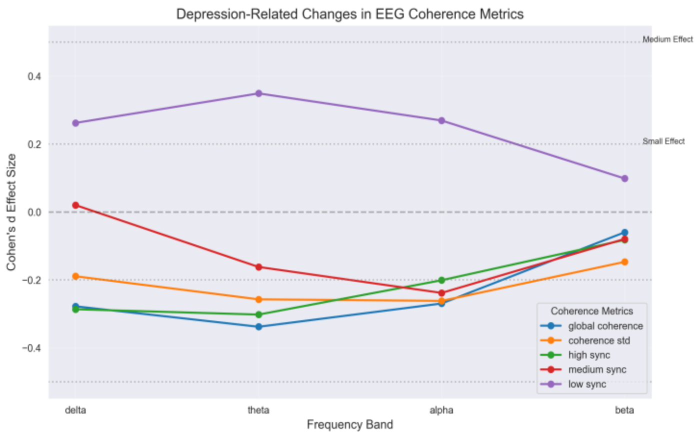


MDD patients showed reduced global coherence compared to controls, with the strongest effects in theta (d=-0.34, p<0.001) and delta bands (d=-0.28, p<0.001), and weakest in beta (d=-0.06, p=0.03).

(Figure 1) Global coherence comparison across bands.

Depression was associated with decreased high synchronization connections (>0.7) across all bands, particularly in theta (d=-0.30) and delta (d=-0.29). Conversely, low synchronization connections (<0.4) showed significant increases, especially in theta (d=0.35). This shift indicates less coordinated neural activity, potentially reflecting network dysregulation underlying depressive symptoms.

Theta band [9] demonstrated the most consistent effects across metrics, suggesting relevance to depression identification. The effect size gradient (Figure 2) shows the differences from delta to beta bands. Also, the standard deviation of coherence values was reduced in depression across all bands (d=-0.19 to -0.26), indicating more uniform connectivity patterns in MDD patients.



(Figure 2) Depression-related changes in EEG coherence metrics across frequency bands.

3.2 Classification Performance

SVM classification achieved promising results, with band-specific patterns. Interestingly, the beta band showing the weakest statistical effects yielded the best classification performance (Table 1). This highlights that, features characterizing group-level differences (theta band) may differ from those with optimal discriminative value for individual classification (beta band). Classification metrics showed progressive improvement from delta to beta frequencies, contrasting with statistical findings where stronger effects appeared in lower frequency bands.

(Table 1) SVM Classification Performance Metrics Across Frequency Bands

Frequency Band	Accuracy	Precision	Recall	F1-Score
Delta (1-4)	72.20	52.80	64.30	67.96
Theta (4-8)	72.69	53.44	66.72	59.33

Alpha (8-13)	78.05	61.73	69.48	65.36
Beta (13-30)	83.28	69.26	79.14	73.84

A key limitation of this study is the reliance on coherence measures, which capture only linear relationships between signals. In the future, we will incorporate directional connectivity measures to provide a more comprehensive characterization of network disruptions in depression.

4. Conclusion

In this study, we present compelling evidence that EEG coherence patterns can vary significantly between depression (MDD) and healthy control patients. Our study showed reduced global coherence across all frequency bands, particularly in the delta and theta bands. Furthermore, we noticed the strongest statistical effects in lower frequency bands, and our classification performance with SVM achieved the best performance on the beta band features with an accuracy of 83.28%. This suggests that different aspects of coherence data contribute to the neurophysiological understanding of depression and suggests that coherence could serve as a potentially reliable tool for depression detection. In the future, we will incorporate directional connectivity measures to better characterize network disruptions in depression.

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