

Application of machine learning and long-range temporal correlations in EEG for the diagnosis of focal epilepsy

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Abstract—We demonstrate that long-range temporal correlations, quantified via detrended fluctuation analysis of EEG during intermittent photic stimulation, outperform traditional spectral features for classifying non-photosensitive focal epilepsy. In a cohort of 54 patients and 54 controls, DFA-based SVM classifiers achieved an F1-score of 0.83, significantly surpassing spectral (CWT-based) classifiers ($F1 = 0.75$). Key discriminative features were LRTC reductions in central α -band and increases in occipital β -band - patterns invisible to spectral analysis. This reveals LRTC as a sensitive biomarker of excitation-inhibition imbalance and unlocks the latent diagnostic power of routine IPS.

Index Terms—EEG, epilepsy, photic stimulation, long-range temporal correlations, detrended fluctuation analysis, machine learning

I. INTRODUCTION

Diagnosis of focal epilepsy, along with other neurological diseases [1]–[3], particularly its non-photosensitivity forms, remains one of the most challenging tasks in modern neuroscience. Although intermittent photic stimulation (IPS) has long been used as a standard provocative procedure in electroencephalography (EEG), its diagnostic value has traditionally been limited to the detection of the photoparoxysmal response (PPR) [4], which is characteristic of only 2-5% of patients [5]. This leaves the vast majority of cases without a reliable tool for rapid diagnosis based on IPS, despite the fact that this procedure is routine, safe, and easily reproducible in clinical settings.

In recent years, increasing attention has been paid to the analysis of photic driving (PD) - a sustained brain response to rhythmic visual stimulation [6]. However, attempts to employ traditional spectral analysis, such as continuous wavelet transform (CWT), for the quantitative assessment of PD [7] and for

differentiating patients with epilepsy from healthy individuals have yielded inconsistent results. This suggests that changes in oscillatory power captured by CWT may not represent a sufficiently sensitive or specific marker for non-photosensitive epilepsy, highlighting the need for alternative approaches to EEG data analysis.

A promising direction involves the investigation of long-range temporal correlations (LRTC) in neural signals [8]. LRTC reflect the complex, self-similar dynamics of the brain, which, according to contemporary theories, are associated with the critical state [9] of neuronal networks and the optimal balance between excitatory and inhibitory processes [10]. This balance is considered a key factor disrupted in epilepsy [11]. The detrended fluctuation analysis (DFA) method enables a quantitative assessment of the degree of LRTC [12], providing information fundamentally different from spectral power and thus potentially more relevant for detecting pathological alterations.

In this study, we hypothesize that DFA, by analyzing LRTC in the amplitude envelopes of EEG signals, can reveal hidden patterns of brain activity that are more informative for epilepsy classification than traditional spectral features. We further propose that disruptions in LRTC, driven by an excitation/inhibition imbalance, will manifest more prominently in response to a provocative challenge such as IPS, even in the absence of a classical PPR.

The aim of this study is to comprehensively test this hypothesis. We not only compare statistically significant differences in features derived from CWT and DFA, but also assess their practical applicability through the lens of machine learning. By building and comparing classifiers trained on these two types of features, we seek to demonstrate that LRTC analysis using DFA does not merely complement spectral analysis, but provides a qualitatively novel and more effective tool for the

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diagnosis of non-photosensitive epilepsy, with the potential to expand the clinical utility of routine IPS procedures.

II. MATERIALS AND METHODS

A. Experiment

The study was conducted at the N.I. Pirogov National Medical and Surgical Center (Moscow, Russia) in accordance with ethical standards and the principles of the Helsinki Declaration. It included two comparable groups of 54 participants each: patients with confirmed drug-resistant focal epilepsy (without a photoparoxysmal response) and healthy volunteers recruited from the medical staff of the center. The experimental procedure involved IPS using a lamp with a circular reflector (flash intensity ~ 0.70 J) at nine discrete frequencies (1, 3, 8, 10, 15, 18, 20, 25, and 30 Hz). Each stimulation session lasted 8 seconds with 5-second intervals between frequencies, and baseline EEG (at least 30 seconds) was recorded prior to stimulation for subsequent data correction.

B. EEG recording and preprocessing

EEG data were recorded using a "Micromed" system (Italy) with a sampling rate of 128 Hz. Signals were acquired from 25 electrodes positioned according to the international 10–10 system [13], providing sufficient cortical coverage for the analysis of local responses to photic stimulation. To register EEG data, cup adhesive Ag/AgCl electrodes were placed on the scalp with the help of "Tien-20" paste [14]. Reference electrodes were placed on the ears (A1/A2), and the ground electrode was positioned at Fpz.

Raw EEG data underwent standard preprocessing to remove artifacts and noise. First, band-pass filtering (Butterworth filter, 1–60 Hz) was applied to suppress low-frequency drift and high-frequency disturbances such as muscle artifacts. A notch filter at 50 Hz was used to eliminate power line interference. Remaining physiological artifacts (e.g., eye movements and cardiac activity), overlapping in frequency with the relevant signal (1–40 Hz), were removed using Independent Component Analysis (ICA). All preprocessing steps were performed in MATLAB using the FieldTrip toolbox [15].

C. Data processing

EEG signal analysis was performed using two independent methods: continuous wavelet transform (CWT) for spectral power estimation and detrended fluctuation analysis (DFA) for quantitative assessment of long-range temporal correlations. Both methods were applied to data from each of the 25 EEG channels for all 9 photic stimulation frequencies (1, 3, 8, 10, 15, 18, 20, 25, and 30 Hz) across five frequency bands: δ (1–4 Hz), θ (4–7 Hz), α (8–12 Hz), β (13–30 Hz), and the stimulation frequency band ($f_{IPS} \pm 0.5$ or 1 Hz).

For CWT, the complex Morlet wavelet was used as the mother function. Spectral power (Event-Related Spectral Perturbation, ERSP) was computed with baseline correction relative to pre-stimulation activity [16]. For each channel, stimulation frequency, and frequency band, the mean power ω_f^i was calculated over the 8-second stimulation interval.

For DFA, the signal was first band-pass filtered within the specified frequency range using an FIR filter. The amplitude envelope was then computed via the Hilbert transform. A cumulative series was constructed from this envelope, and the root-mean-square fluctuation $F(s)$ was calculated over different time scales s . The scaling exponent μ_f^i was determined as the slope of the linear regression of $\log(F(s))$ versus $\log(s)$, providing a quantitative measure of the degree of LRTC in the signal.

Statistical significance of group differences between patients and controls was assessed using a permutation cluster test (1000 permutations, point-wise threshold $p < 0.01$, cluster-level threshold $p < 0.025$), allowing the identification of spatiotemporal clusters with robust differences. For machine learning, four classifiers based on linear-kernel support vector machines (SVM) [17] were constructed: two using all features (ω_f^i or μ_f^i , with dimensionality reduction via PCA retaining 85% of explained variance) and two using only features from statistically significant clusters. Classification performance was evaluated using F1-score, accuracy, recall, and precision with 10-fold cross-validation. Feature importance was determined using the Boruta method [18].

III. RESULTS

Statistical testing. Statistical cluster analysis revealed significant differences between groups for both spectral features (CWT) and long-range temporal correlation features (DFA); however, their spatial distribution and characteristics were fundamentally different. CWT analysis showed that photic driving (PD) was generally stronger in healthy controls than in patients, except in the α band. At low (1, 3 Hz) and high (18–30 Hz) stimulation frequencies, increased power in controls was primarily observed in frontal and temporal regions. In contrast, in the α band, patients exhibited increased spectral power in central and centro-temporal regions, which may indicate abnormal hypersynchronization.

DFA-based analysis revealed a different pattern, focusing on changes in the temporal structure of the signal. The most pronounced differences were observed in central and occipital regions. In the α band, patients showed a significant reduction in LRTC (negative clusters) at the central C4 channel across most stimulation frequencies. In contrast, in the β band at 15–25 Hz stimulation frequencies, patients exhibited increased LRTC in occipital regions (O1, O2 channels). These findings indicate that DFA is sensitive to pathological alterations in brain dynamics that are not captured by traditional spectral analysis and are localized in more posterior cortical areas.

Classification. To evaluate the diagnostic value of features obtained with CWT and DFA, four linear-kernel SVM classifiers were constructed and compared. Two classifiers were trained on the full feature set (1125 features: 25 channels $\times$ 9 stimulation frequencies $\times$ 5 frequency bands), reduced via PCA to 85% of explained variance (15 components for CWT, 46 for DFA). The other two classifiers were trained only on features belonging to statistically significant clusters identified by the permutation test (132 features for CWT, 36 for DFA).

The classification results, averaged across 10-fold cross-validation, demonstrated a clear superiority of classifiers based on DFA features. The classifier trained on all DFA features achieved an F1-score of 0.78, compared to 0.70 for the corresponding CWT-based classifier. The highest performance was observed for the classifier trained on DFA features from significant clusters, yielding an F1-score of 0.83. In contrast, the best-performing CWT-based classifier (trained on significant clusters) reached an F1-score of 0.75 [19].

IV. CONCLUSION

In this study, we demonstrated that the analysis of LRTC using DFA is a significantly more effective tool for classifying non-photosensitive focal epilepsy compared to traditional spectral analysis. Although both methods revealed statistically significant differences between patients and healthy controls, only the classifier based on DFA features achieved high performance (F1-score = 0.83). This indicates that LRTC, reflecting the fundamental balance of excitation and inhibition in neuronal networks, represent a more sensitive and specific biomarker of epileptic status than oscillatory spectral power.

The practical significance of this study lies in its potential to substantially enhance the diagnostic value of a routine clinical procedure - intermittent photic stimulation. Even in the absence of a photoparoxysmal response, EEG analysis using DFA during IPS enables highly accurate differentiation of patients with epilepsy. This paves the way for the development of a novel rapid diagnostic tool that does not require additional procedures but instead utilizes an already established and safe method, thereby making it applicable to a much broader group of patients with non-photosensitive epilepsy.

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