

Recurrence Quantitative Analysis of Resting State Electroencephalography for Parkinson's disease Detection

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Extended Abstract

Parkinson's disease (PD) is the second most common neurodegenerative disorder, affecting approximately 8.5 million people worldwide [1]. It affects approximately 0.2% of the global population and up to 1% of individuals over 60 years of age [2]. The current diagnosis of PD is primarily based on motor symptoms and neurological examination and is typically diagnosed only after >60% of dopaminergic neurons have been lost [3]. Increasing evidence suggests that resting-state electroencephalography (EEG) may be a valuable tool for assessing abnormal neural dynamics associated with PD [1]. Most previous studies have focused on spectral power analysis and functional connectivity measures. These linear methods may be insufficient for capturing the subtle, nonstationary, and nonlinear characteristics typical of early-stage PD. Recurrence Quantitative Analysis (RQA), a nonlinear technique, enables the identification of hidden patterns, transitions, and structural changes in complex EEG time series [4]. By quantifying temporal recurrence patterns in brain activity, RQA can reveal alterations in neural synchronization and signal complexity that may reflect the underlying pathophysiology of PD—potentially providing novel biomarkers for early detection and disease monitoring.

This study aims to characterize alterations in neural dynamics associated with Parkinson's disease by applying recurrence quantification analysis (RQA) to resting-state EEG recordings to identify potential biomarkers for early PD detection.

A publicly available database comprising EEG recordings from 13 PD patients and 19 healthy control subjects was used for this study [4]. EEG signals were acquired using a 64-channel setup during both eyes-closed and eyes-open resting-state conditions, with a sampling rate of 100 Hz. The EEG data were preprocessed to eliminate artifacts and non-neural activity, then segmented into 28-second epochs. Subsequent analyses were conducted across conventional EEG frequency bands: delta, theta, alpha, beta, and the full bandwidth. We analysed the recurrence characteristics of the 64-dimensional EEG data to compute key quantitative metrics—determinism (DET), mean diagonal line length (L_{mean}), maximum diagonal line length (L_{max}), entropy (ENT), trapping time (TT), recurrence rate (RR), and laminarity (LAM)—to assess the underlying EEG dynamics [5]. Mann-Whitney tests were conducted to identify statistically significant differences between PD and control group for each RQA metric.

We observed that at rest, PD exhibited similar RQA metrics than control group. In eyes-open condition, no statistically significant differences were found between PD and control group in delta, theta and alpha bands. As for the beta band, PD showed significantly higher L_{mean} , ENT, and TT than control group, reflecting lower complexity in the neural activity and more persistent states [5]. By contrast, PD patients presented significantly higher L_{max} for the whole bandwidth (p -value<0.05), indicating greater stability in the signal [5]. Our results suggest an increase in neural synchronization and a decrease in signal complexity, as shown in various studies analyzing the complexity of signals [6].

Our findings support the hypothesis that RQA of resting-state EEG reflects neural dynamic abnormalities in Parkinson's disease and could provide a cost-effective and reliable method for early-stage detection. This approach could enable clinicians to design personalized strategies for slowing or potentially halting the progression of Parkinson's disease.

References

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