Bibliographical references

Frolov et al.[1] (2020) proposed a novel approach to analyze multiplex brain networks using recurrence quantification analysis (RQA) on EEG data. The authors demonstrated how recurrence-based synchronization indices can effectively capture both within-frequency (intralayer) and cross-frequency (interlayer) functional connectivity during cognitive tasks. Their work showed that RQA is particularly suitable for analyzing non-stationary EEG signals and revealed important insights about the evolution of functional connectivity patterns during prolonged cognitive tasks.

Kang et al. (2023)[2], in their study investigate the periodic dynamics of the Default Mode Network (DMN) in schizophrenia using RQA and Cross-Recurrence Quantification Analysis (CRQA) on resting-state fMRI data. Findings include decreased determinism (DET) between key DMN regions (vMPFC-PCC and vMPFC-precuneus) in first-episode schizophrenia patients, indicating disrupted predictability of functional interactions. The study highlights the potential of RQA/CRQA as tools for capturing nonlinear brain dynamics and their utility in distinguishing schizophrenia patients from healthy controls with 77% classification accuracy.

Researchers in [3], have applied RQA on resting-state fMRI data from TgF344-AD rats in order to detect early stage of Alzheimer's disease biomarkers. Analysis has been conducted on the Default Mode-Like Network (DMLN) using RQA metrics(entropy, recurrence rate, determinism and average diagonal line length) and revealed significant changes in regions like the basal forebrain (BFB), hippocampal fields (CA1, CA3), and visual cortices (V1, V2). On the study's findings are included reduced predictability in wild-type (WT) rats with aging, while AD rats exhibited less decline in predictability, suggesting compensatory mechanisms. The study highlights RQA's sensitivity to nonlinear dynamics in preclinical AD, offering potential for early diagnosis. Also the code of the research is publicly available.

Lameu et al.[4] investigated burst phase synchronization in neural networks using RQA. The authors employed coupled Rulkov maps to model bursting neurons in both single small-world networks and clustered network-of-networks architectures. Their spatial RQA approach successfully identified synchronized neuron groups and quantified their sizes during synchronization transitions. The study demonstrated that RQA measures (recurrence rate, laminarity, and structure size) provide complementary information to traditional order parameters, particularly for detecting localized synchronization patterns. This work is significant for EEG analysis as it shows RQA's capability to detect phase synchronization in complex networks - a key feature in functional brain connectivity studies.

Lombardi et al.[5] investigate the nonlinear properties of fMRI BOLD signals during a working memory task in schizophrenic patients and healthy controls. Using RQA, analysis has been performed on the recurrence plots for the quantification of determinism (D), trapping time (TT), and maximal vertical line length ($V_{\max}$) in functionally relevant brain clusters. Outcome revealed differences in nonlinear dynamics among the groups, and more specific in working memory and default mode network areas. This study highlights the potential of RQA for discriminating pathological brain states and understanding functional connectivity in complex systems. While their work focused on fMRI, the methodology is adaptable to EEG, which offers higher temporal resolution for capturing rapid neural dynamics.

Author in[6] (2025), investigated changes related to aging in brain sensorimotor systems using RQA and theta-band functional connectivity in EEG signals. In the study a VR experimental paradigm was utilized with auditory stimuli across different age groups. Key findings revealed that elderly subjects showed decreased EEG complexity during motor preparation stages as measured by RQA metrics (ΔRR and ΔRTE), and had increased theta-band functional connectivity highlighting the potential of RQA in detecting age-related biomarkers that were not evident in conventional spectral analysis.

Guglielmo et al. (2022)[7] demonstrated the capability of RQA features which were extracted by EEG signals for the purpose of classification of cognitive performance during mental arithmetic tasks. Frontal and parietal EEG signals have been analyzed from 36 participants by extracting six RQA metrics (recurrence rate, determinism, laminarity, entropy, maximum diagonal line length and average diagonal line length) from four electrodes (F7, Pz, P4, Fp1). By further application of machine learning(ML) classifiers such as SVM, Random Forest, and Gradient Boosting, researchers they reached accuracy of classification above 0.85, showing the potential that RQA hold for generalizing on nonlinear dynamics.

Lopes et al. (2020)[8] have proposed a combinatorial framework mixing RQA with dynamic functional network (dFN) analysis, applying it to both MEG and stereo EEG data. The methodology they described is split into five steps: data segmentation, functional network inference, distance computation alongside networks, recurrence plot construction and finally RQA. The study demonstrated that functional networks in epilepsy patients recur more quickly than in healthy controls, suggesting RQA of dFNs could serve as a potential biomarker. For EEG applications, they showed that pre-ictal networks exhibit higher recurrence rates than post-ictal periods, with the τ-recurrence rate (RR_τ) proving particularly effective for seizure detection. In their research, Pentari et al.[9] have applied CRQA to resting-state fMRI data for examining the dynamic functional connectivity on patients with neuropsychiatric systemic lupus erythematosus (NPSLE). Results contain the fact that CRQA metrics, such as determinism, appear more sensitive than conventional static functional connectivity methods in order to identify aberrant connectivity patterns that correlated with visuomotor performance. The study focused on 16 frontoparietal regions and found that CRQA could detect both increased and decreased connectivity in NPSLE patients compared against the healthy controls. Building on these findings, Pentari et al.[10] subsequently expanded the investigation to whole brain network analysis in a larger cohort. In this study they demonstrate the capability of CRQA to integrate multiple recurrence metrics for revealing both hyperconnectivity in parietal regions (angular gyrus and superior parietal lobule) and hypoconnectivity in medial temporal structures (hippocampus and amygdala). Notably, the dynamic connectivity measures showed stronger associations with cognitive performance than structural measures, particularly for verbal episodic memory.

Recent studies have demonstrated the effectiveness of RQA in analyzing EEG signals for epilepsy detection. Gruszczyńska et al.[11] have applied RQA in order to distinguish epileptic from healthy patients using EEG recordings from frontal and temporal lobe electrodes (Fp1, Fp2, T3, T4). In their findings they have showed that the epileptic signals present more periodic dynamics in comparison to healthy controls, by as evidenced by higher values of RQA parameters such as determinism, laminarity, and longest diagonal line. The study combined RQA with Principal Component Analysis for dimensionality reduction and visualization, achieving 86.8% classification accuracy with SVM. This work is particularly relevant as it demonstrates RQA's capability to identify pathological patterns in resting-state EEG without requiring seizure events during recording.

Another study utilizing advanced nonlinear analysis techniques for neural correlation investigation to cognitive functions [12] used *stereoelectroencephalography (sEEG)* combined alongside RQA for the examination of the relationship of the DMN and empathy. Correlations have been detected relating specific RQA metrics (mean diagonal line length, entropy of diagonal line lengths, trapping time) and empathy scores, particularly within DMN subsystems.

Regarding epilepsy diagnosis, authors in [13] proposed a new framework utilizing the combintation of RQA with genetic algorithms and Bayesian classifiers for identifying corresponding biomarkers for seizure detection. They utilized five distance norms (e.g., Euclidean, Mahalanobis) and multiple thresholds for extracting recurrence features from EEG signals, achieving 100% classification accuracy. More specific, the *transitivity* feature has shown capability of a highly discriminative biomarker, performing better compared to traditional linear methods.

Ngamga et al.[14] studied the performance achieved of RQA and Recurrence Network (RN) measures in identifying pre-seizure states from multi-day, multi-channel intracranial EEG (iEEG) recordings of epilepsy patients. Results highlighted the correlation among RQA measures (determinism, laminarity, and mean recurrence time) in detecting seizure precursors, while RN measures (average shortest path length and network transitivity) provided complementary but not so consistent insights than using the application of RQA measures alone.

Table 1: Comparison among the retrieved studies using recurrence analysis

#	Reference	Modality	Analysis Methods	Network Type
1	Frolov et al. (2020)	EEG	RQA, CRQA	Multiplex functional networks
2	Kang el al. (2023)	fMRI	RQA, CRQA	DMN, schizophrenia
3	Rezaei el al. (2023)	fMRI	RQA	Default model-like network
4	Lameu et al. (2018)	—	RQA	Small-world & clustered networks
5	Lombardi et al. (2014)	fMRI	RQA	schizophrenia,working memory
6	Pitsik E. (2025)	EEG	RQA	aging
7	Guglielmo et al. (2022)	EEG	RQA	cognitive tasks
8	Lopes et al. (2020)	sEEG, MEG	RQA	epilepsy
9	Pentari et al. (2022)	fMRI	RQA, CRQA	NPSLE
10	Pentari et al. (2023)	fMRI	CRQA	NPSLE
11	Gruszczyńska et al. (2019)	EEG	RQA	epilepsy
12	Mo et al. (2022)	sEEG	RQA	DMN, epilepsy
13	Palanisamy et al. (2024)	EEG	RQA	epilepsy
14	Ngamga et al. (2016)	EEG	RQA,RN	epilepsy

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