

RQA-based brain network analysis reveals abnormal connectivity patterns in epileptic patients

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Abstract—This paper explores the method for EEG-based resting state functional connectivity analysis in epileptic patients based on recurrence quantification analysis. We aim to uncover altered network interactions that underlie epileptic pathology using recurrence properties of EEG time series. We show the potential of joint recurrence plots in the task of detection of the differences between healthy control and epileptic resting state EEG functional connectivity network topologies. This work highlights the importance of innovative methods to better understand and manage epilepsy through non-invasive brain network assessment.

Index Terms—recurrence quantification analysis, joint recurrence plots, functional connectivity, epilepsy, EEG

I. INTRODUCTION

In EEG-based epilepsy and fMRI research, analysis of resting state functional connectivity (rs-FC) is a crucial tool in understanding the intrinsic brain network alterations [1]–[9]. Unlike task-based paradigms, resting state analysis captures the brain's spontaneous activity, offering a non-invasive means to probe the disrupted communication pathways that underlie epileptic pathology [10]–[12]. Recent advances in neuroimaging have revealed characteristic patterns of functional dysconnectivity in epileptic patients, which can provide invaluable biomarkers for diagnosis, prognosis, and treatment monitoring.

However, the application of resting state functional connectivity analysis to EEG data in epilepsy faces substantial challenges. The inherently low spatial resolution of EEG complicate the accurate inference of connectivity between brain regions [13]. Additionally, EEG recordings suffer from considerable amount of artifacts that can be challenging to remove using modern mathematical methods such as ICA. These issues necessitate the application of novel approaches that can restore functional networks with greater robustness.

In the present paper, we propose an approach based on recurrence quantification analysis (RQA) to restore rs-FC. We show the advantages of recurrence-based measure of synchronization in analysis of EEG time series and reveal it's

potential in revealing new biomarkers associated with rs-FC in epileptic patients.

II. METHODS

A. Dataset

In the present study, we used resting state EEG recordings. The dataset was provided by the Pirogov National Medical and Surgical Center (Moscow, Russia) and consisted of 116 subjects (58 epileptic patients). During the experiment, the Micromed EEG amplifier was used to record EEG time series samples at 128 Hz from 25 EEG channels according to the international 10-10 system. The dataset was filtered using Butterworth bandpass filter in the range 1-60 Hz, the 50 Hz component was removed to eliminate power grid interference. Blinks, cardiac and muscle activity and other physiological artifacts were removed using Independent Component Analysis.

The pre-processing was carried out using MNE and scikit-learn libraries for Python [14], [15].

B. RQA-based measure of connectivity

We employed RQA-based measure of connectivity based on joint recurrence plots (JRP) [16]. The approach is described in more detail in [17]. We used the same multivariate approach to determine the appropriate embedding for further use in JRP calculation. With this goal, we selected 7 triads of EEG sensors based on their respective placement on the head:

- Frontal left (F_l) – F9, F7, F3;
- Frontal right (F_r) – F10, F8, F4;
- Central (C) – C3, Cz, C4;
- Pareto-temporal left (PT_l) – T9, T7, P9;
- Parieto-temporal right (PT_r) – T10, T8, P10;
- Parieto-occipital left (OP_l) – P7, P3, O1;
- Parieto-occipital right (OP_r) – P8, P4, O2.

When performing RQA on EEG data, there are several reasons to choose the multivariate approach over the traditional method based on Taken's theorem. Embedding parameters restored from fragments of EEG time series may not represent the underlying dynamics of the system reliably due to the non-stationarity of EEG [18]. Besides, by employing the

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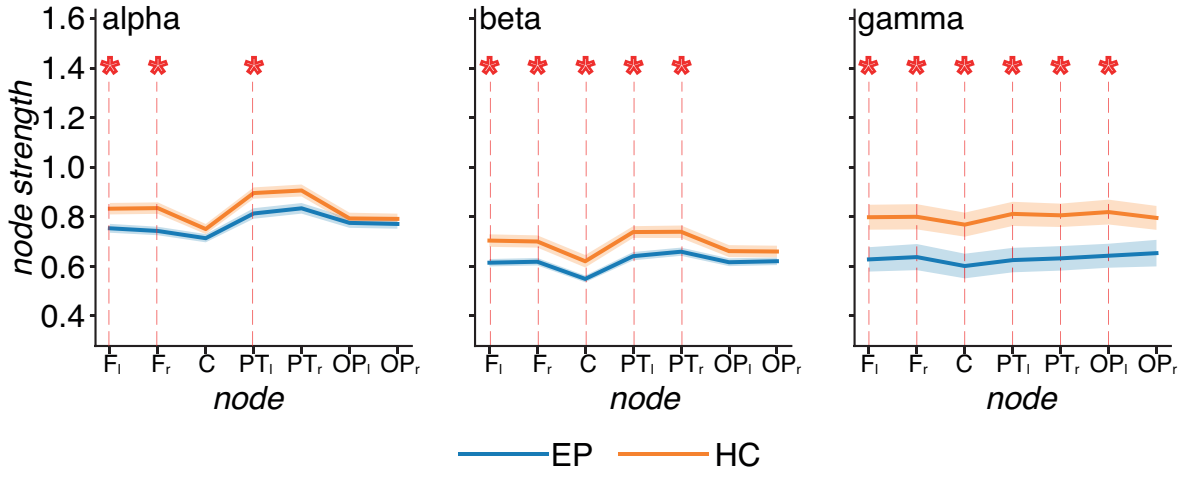


Fig. 1. Node strength for EP (epileptic patients) and HC (healthy controls) groups (mean $\pm$ SE). Red * indicates the presence of statistical differences between the groups.

multivariate embedding approach, we reduce the impact of field spread, which is a common problem when performing sensor-level analysis of functional connectivity.

Each of the 7 triads of sensors above represents a region of interest (ROI) as a three-dimensional state space trajectory which we use to calculate recurrence matrix for each ROI:

$$R_{i,j}^x = \Theta(\epsilon - \|x_i - x_j\|), \quad (1)$$

where $x_i \in \mathbb{R}$, $i, j = 1, 2, \dots, N$, with N representing the number of states x_i and ϵ being the threshold that determines the size of the neighborhood used to search for the recurrent states. Using recurrence matrices, we can calculate joint recurrence matrices for each pair of ROIs by multiplying corresponding recurrence matrices. For threshold, we use a fixed number of nearest neighbors N_N and fix the value $RR = \frac{N_N}{N}$ for both considered systems. Then, joint recurrence rate can be calculated as

$$JRR = \frac{1}{N^2} \sum_{i,j=1}^N JR_{i,j}. \quad (2)$$

From here, we calculate the recurrence-based index of synchronization as $S = \frac{JRR}{RR}$.

We reconstructed sensor-level brain functional connectivity network using the approach described above in different frequency ranges. We selected delta (1-4 Hz), theta (5-7 Hz), alpha (8-14 Hz), lower beta (15-25 Hz) and gamma (30-50 Hz) frequency ranges for this study. The recurrence-based measures of connectivity was calculated for each pair of ROIs, the obtained value was assigned as a corresponding element of 7x7 adjacency matrix.

All calculations were performed using DynamicalSystems package for Julia [19].

III. RESULTS

To evaluate the differences between network structures we calculated node strength for each ROI for both groups of

subjects and performed statistical analysis. To reveal between-groups differences, we applied t-test for independent subjects and applied Benjamini-Hochberg procedure to control false discovery rate [20]. The results are presented on Fig. 1.

While delta and theta rhythms networks yielded no statistical differences between groups of subjects, we show increased node strength in healthy controls in alpha, beta and gamma bands.

Studies of rs-FC based on various data modalities report different topological effects associated with epilepsy. Many studies describe disrupted local functional connectivity associated with different brain functions such as language processing [21] and plays a part in cognitive and executive dysfunctions [22]. A bulk of studies report enhanced functional connectivity in epileptic patients [23], [24].

The RQA-based method shows significant discriminative power between healthy control and epileptic patients groups. The decreased node strength in epileptic patients suggests weakened connectivity mainly in frontal and temporal lobes. Although the sensor-level analysis of restored rs-FC is insufficient for physiological interpretation of uncovered effects due to the low spatial resolution of EEG recordings under study, we reveal the potential for high classifiability of recovered measures, which is significant for development of potential automatized early detection of epileptic activity.

IV. CONCLUSION

In the present paper we report results of applying relatively under-researched technique for restoration of resting state functional connectivity based on joint recurrence plots. We employ multivariate approach to recover state space trajectories of EEG signals in wide frequency range and calculate recurrence-based measure of synchronization. Although our results allow limited opportunities for physiological interpretation of uncovered effects, we show significant discriminative power between healthy controls and epileptic patients. Our findings may be significant in the area of early detection

of epileptic biomarkers based on non-invasive assessment of resting state EEG.

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