

MACHINE LEARNING APPROACH FOR LATERALIZATION OF TEMPORAL LOBE EPILEPSY UTILIZING DTI STRUCTURAL CONNECTOME

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Target audience: neurologist, neurosurgeon, and those interested in brain connectomics

Purpose: Recently, connectomics of temporal lobe epilepsy (TLE) is getting a renewed attention, and some studies have applied machine learning approaches to fMRI-derived connectome for detection of epileptogenic focus^{1,2}. This study aimed to investigate the utility of machine learning approach with DTI structural connectome for lateralization of epileptogenicity in TLE.

Methods: Forty-one patients with TLE (right/left, 13/28; 34±11.5 years-old; male/female, 19/22; 28 hippocampal sclerosis, 3 amygdala enlargement, 1 FCD, 9 MRI-negative) were involved. DTI (b=0, 1000 s/mm²; 13 MPGs; 3mm iso-voxel) and 3D-T1WI were obtained using GE 3T system. The laterality of TLE was determined clinically by comprehensive assessment of seizure semiology, MR imaging, long-time video-EEG, FDG-PET, SPECT, and intracranial EEG. For each patient, an 83x83 connectome matrix was generated with the Connectome Mapper pipeline³ using the Freesurfer default cortical parcellation and deterministic tractography (Fig.1). Graph theoretic regional network measures (degree, clustering coefficient, local efficiency, and betweenness centrality) were calculated using the Brain Connectivity Toolbox⁴. Therefore, 332 features per patient were obtained. As our data contained too many features for the number of patients, feature selection was necessary to avoid over-fitting (curse of dimensionality). After feature selection using the sparse linear regression method (SQRT Lasso), the selected features were used to train the support vector machine (SVM) classifier. The performance of classifier was evaluated by leave-one-out cross validation (LOOCV).

Results: Regional measures of the nodes located in the temporal and occipital lobes were identified as the main discriminating features (Fig.2). SVM demonstrated excellent discrimination between left and right TLE, with 92.7% accuracy in LOOCV.

Discussion: SVM using graph theoretic measures demonstrated excellent discrimination between left and right TLE. From the clinical viewpoint, it is noteworthy that MRI-negative patients could be classified correctly in our study. The performance of the classifier is expected to improve by increasing the number of MPGs and applying probabilistic tractography to ameliorate the crossing-fiber issue. Further studies involving normal controls and 3-class SVM are needed to validate the SVM approach and to give meanings to the identified discriminating features.

Conclusion: Our results suggest possibility that machine learning with DTI structural connectome can distinguish left and right TLE with promising accuracy.

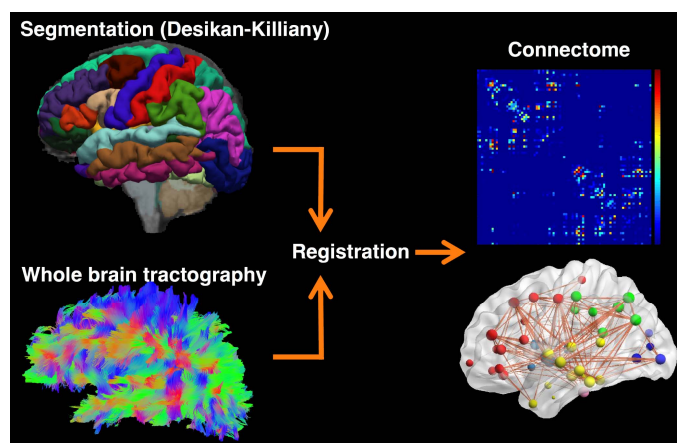


Fig.1. Workflow to create a connectome. Morphological and diffusion data are processed with Freesurfer and Diffusion Toolkit, respectively.

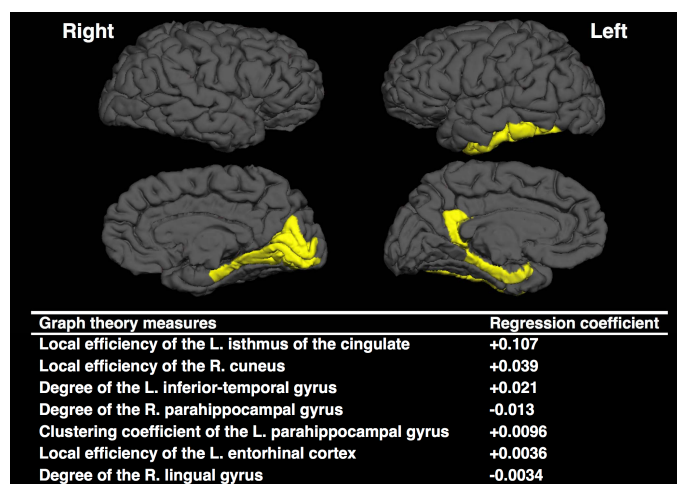


Fig.2. The discriminating features identified by sparse linear regression. Positive value of regression coefficient indicates the regional measure is larger in right TLE than left TLE.

References

1. Chiang S, et al. J Magn Reson Imaging 2014 (ahead of print).
2. Sweet A, et al. Med Image Comput Comput Assist Interv. 2013;16(Pt 1):98–105.
3. Daducci A, et al. PLoS One. 2012;7(12):e48121.
4. <https://sites.google.com/site/bctnet/>