

Discovering Pathophysiologic Networks of Temporal Lobe Epilepsy using the BrainMap Community Portal through the Texas Advanced Computing Center

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Introduction

Medial temporal lobe epilepsy (MTLE) seizures cause regional damage (Barron et al., 2013), detectable on imaging of brain structure (VBM; Ashburner et al., 2000) and function (VBP; Deng et al., 2022). Damage is mediated by aberrant neuronal activity propagating along existing network architecture (Barron et al., 2014). However, MTLE disease networks remain illdefined and are of great interest to diagnostic and therapeutic development.

Independent component analysis (ICA; Beckmann et a., 2004) can detect neural-networks by computing multi-variate cooccurrence patterns across a volume and is validated for coordinate-based meta-analysis (CBMA/Meta-ICA; Fox et al., 2014: Vanasse et al., 2021). Meta-ICA is methodologically distinct from mass-univariate meta-analytics (Activation Likelihood Estimation (ALE); Eickhoff et al., 2016) that simply detect robust regions/hubs of pathology. Although meta-ICA is typically used to extract many (>20) healthy canonical networks (Smith et al., 2009), we applied low-dimensional meta-ICA to VBM/VBP reports of MTLE-pathology, to infer TLE-specific network anomalies.

Canonical vs. Disease Networks

Neural networks derived from imaging have revolutionized the field of neuroscience, a field relying increasingly on high performance computing. (Bassett & Sporns 2017 - Nature neuroscience). The intrinsic connectivity of the brain (Seeley et al., 2007) presents a robust functional architecture, with networks that are detectable both in resting-state and task-based neuroimaging (Smith et al., 2009 - PNAS), and are consistent across analytic modalities (Crossley et al., 2013 - PNAS).



These "canonical" networks also independently emerge from structural imaging of diseases, as shown by a transdiagnostic meta-analysis of coordinate data (Vanasse et al., 2021 -Communications Biology), supporting the Network Degeneration Hypothesis (Seeley et al., 2009 - Neuron). Canonical networks have immensely enhanced our overall understanding of neurophysiology and neuropathology; however, no diseases map to just a single canonical network and no such network is affected by only one disease (Vanasse et al., 2021).

Canonical networks are therefore inadequate to explain the effects of individual diseases. In order to fully understand the pathophysiology of a neurologic condition, disease-specific networks must be defined.

Materials and Methods

- 1. 74 neuroimaging experiments assessing MTLE disease effects (contrasting patients vs. healthy controls) were obtained from the BrainMap database using Sleuth. All BrainMap Portal applications are shown in Figure 7.
 - 45 structural experiments (voxel-based morphometry; VBM)
 - 29 functional experiments (voxel-based pathophysiology; VBP)

MTLE Network 1

ICA d = 1

- 588 foci of pathology were reported, collectively representing 1599 MTLE subjects
- 2. Coordinate data were modeled as spatial probability maps per-experiment (weighted by sample size) using GingerALE commands.
- 3. Maximally discrete networks were extracted as spatial component-maps by computing spatial co-occurrences within and between experiments in a voxelwise manner, using FSL Melodic as implemented in Meta-ICA (Figure 2).
 - Spatial cross-correlations and the χ^2 Test for Homogeneity were used to compare results.
- 4. Component maps were interpreted using the Behavioral Analysis Plugin from Mango and compared with MTLE pathology hubs that were established in a prior analysis (Towne et al., 2022; cf. Figure 5).

Results

1. Two non-canonical networks are specifically affected by 3. MTLE-networks are spatially distinct beyond the MTLE pathology. main hubs of disease.

MTLE Network 2

ICA d = 2

Spatial cross correlation between Network 1 and Network 2 was minimal (R = 0.042).

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between analyses performed at d = 1 and d = 2



Figure 5. ICA Comparison with Activation Likelihood Estimation (ALE) MTLE-networks (IC1 & IC2) only overlap at two MTLE-hubs: hippocampus and medial dorsal nucleus (MDN) thalamus. Previously identified (Towne et al., 2022) hubs of MTLE pathology are highlighted in the table in orange.

Distribution of VBM and VBP Exper

cent Contribu

Network (independent component)

 χ^2 Test for Homoge

Figure 6. We fail to reject the null

that the distribution of VBM versus

hypothesis (x² test for homogeneity)

VBP experiments is homogenous for the identified networks.

meriment Count

Percent of Total

VBM VBP 45 29

60.8% 39.2%

74.3% 67.5%

0.0695 > 0.05

- 4. Spatial separation between the two networks is not attributable to structural-functional effect modification. The distribution of VBM and VBP experiments to
 - each component network was shown to be homogenous by the χ^2 Test for Homogeneity

BrainMap Community Portal on TACC

- A web-based platform for meta-analysis in human brain mapping
- · This neuroimaging research resource aspires to make cognitive neuroscience and disease-biomarker discovery via coordinate-based meta-analysis (CBMA) widely accessible to the research community
- The database contains >20% of structural/functional imaging literature



Conclusion

- · Meta-ICA identified two physiologically meaningful networks that bear little resemblance to canonical networks and are specific to MTLE pathology
- These MTLE-networks likely represent discrete seizurepropagation routes that originate in the two most significant disease hubs.
- many tools that will soon be available to Big Data Neuroscience researchers on the

BrainMap Community Portal (portal.brainmap.org). This resource will continue to enable rapid, novel discoveries and serve as the modern encyclopedia of the brain.

Future Directions

- · Primary resting-state imaging in MTLE patients should be pursued to determine the diagnostic and prognostic potential of these MTLE networks in per-subject prediction.
 - · MTLE-associated brain changes in individual patients may be biased toward one network or the other and should be correlated with clinical markers
- · Low-d meta-ICA has the potential to elucidate neurodegenerative sub-networks
 - This method should be tested in the other 100+ neurologic diseases cataloged in the BrainMap database (brainmap.org/taxonomy/icd.html).
- · No optimization statistics are established for ICA at low dimensions: it will be critical to validate a method for determining the optimal number of disease sub-networks.

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ICA d = 2

Figure 3. Spatial maps extracted by Meta-ICA when the ICA algorithm was applied for dimensions of d = 1 (first spatial map – MTLE Network 1) and d = 2 (second and third spatial maps - MTLE Networks 1 and 2, respectively)

- 2. Both MTLE networks are congruent with separate subsets of symptoms associated with the disease, as shown by
- analysis of behavioral meta-data in the BrainMap database Network 1 (verbal/motor/visual) explains symptoms of impaired communication, involuntary movements, and visual hallucinosis
 - Network 2 (limbic-attentional) explains symptoms of impaired awareness, social-emotional deficits, transient amnesia



compared with that of the regions of spatial convergence among all imaging studies of MTLE disease effects (computed by activation/anatomic likelihood estimation; ALE).

Figure 2. Adapted from the online description of MELODIC ttps://fsl.fmrib.ox.ac.uk/fsl/fslwiki/MELODIC

s probability distr

per experimen

Meta-Analytic ICA (Meta-ICA)

Experiment maps are

converted to 2D vectors and

combined in a matrix before

applying ICA in the

MELODIC algorithm (FMRIB

Software Library)

Spatial may of disease networks

- Network 1 was stable, showing congruence (R = 0.890)

- Hub 1 · Meta-ICA is only one of the