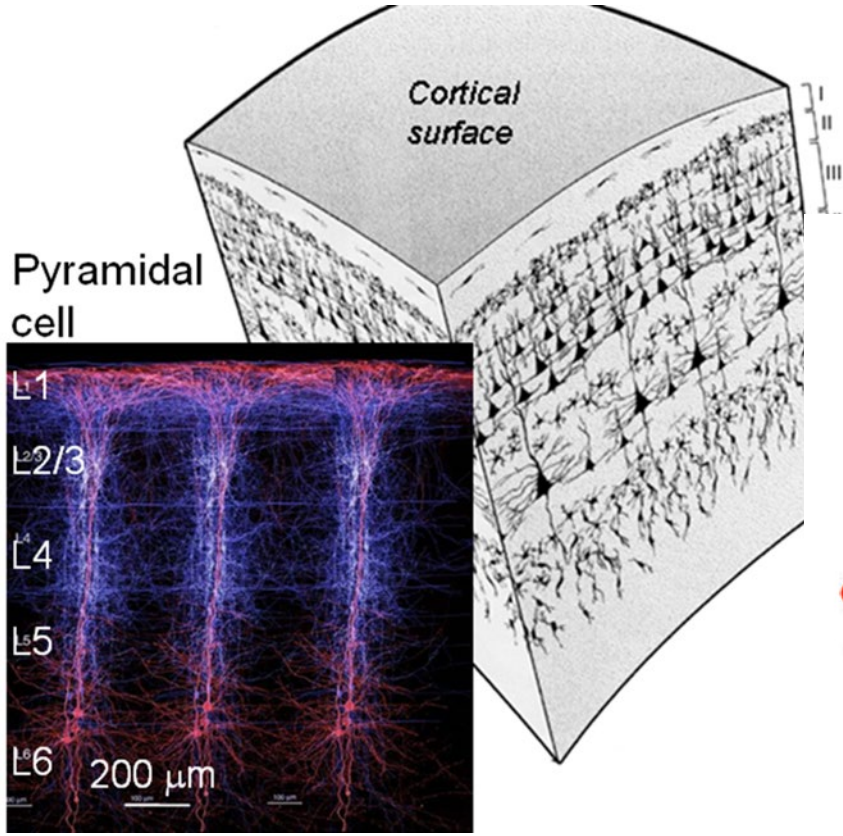
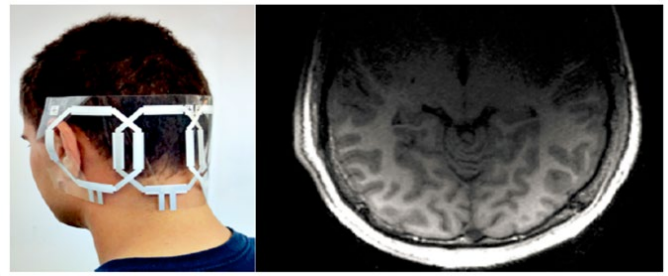
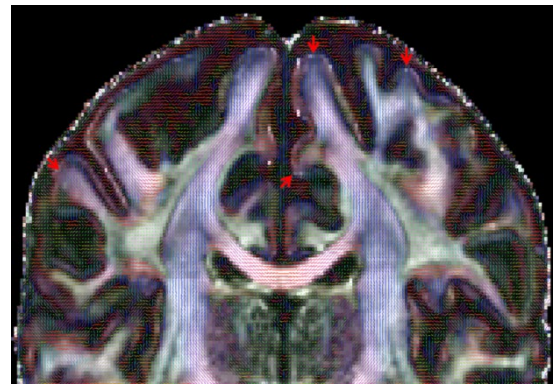
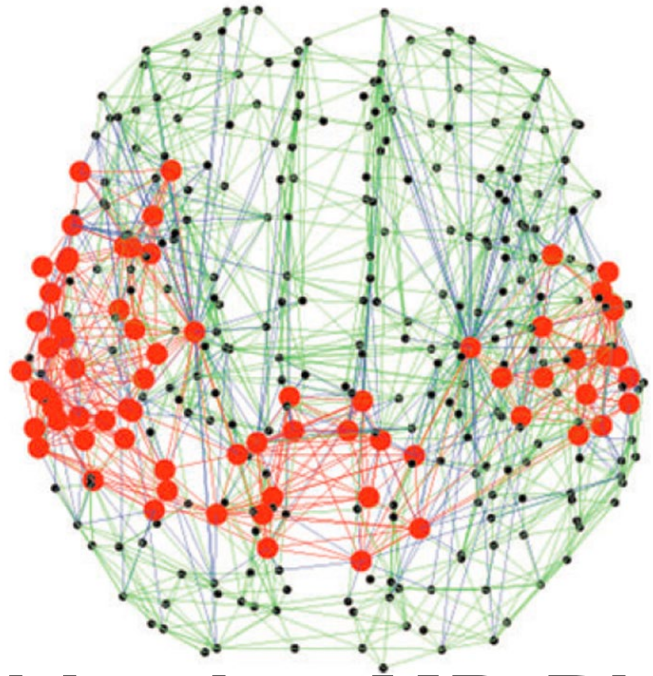
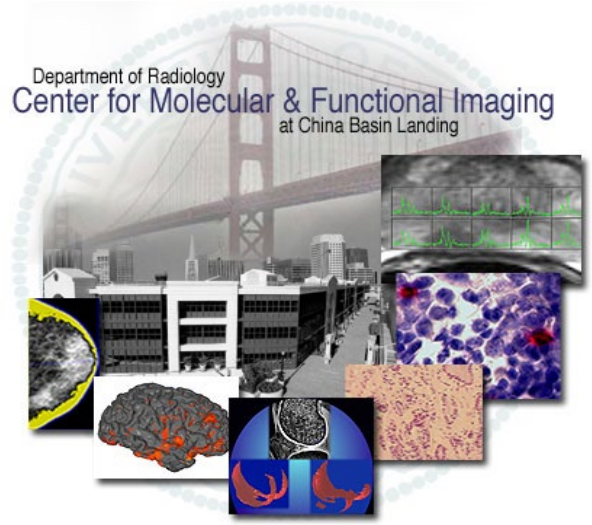
Structural Cortical Mapping: Gradients and Eigenmodes











qb3 ucb·ucsc·ucsf

Pratik Mukherjee MD PhD

Professor of Radiology & Bioengineering

UCSF
University of California
San Francisco

Backwardness of human neuroanatomy

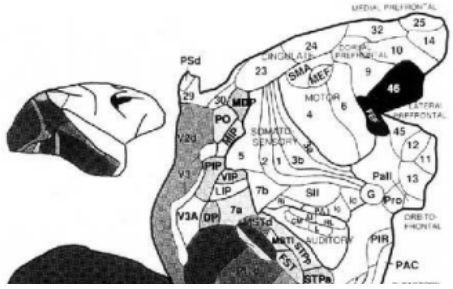
Francis Crick and Edward Jones

Crick & Jones, *Nature* (1993)

To interpret the activity of living human brains, their neuroanatomy must be known in detail. New techniques to do this are urgently needed, since most of the methods now used on monkeys cannot be used on humans.

OVER the past 20 years there have been great advances in understanding the neuroanatomy of the macaque monkey, especially its cerebral cortex. We have learned much about the functional parcellation of the monkey's cortex from both anatomical and physiological studies. We know, for example, that rather more than half the macaque's cortex is predominantly visual and that this visual part comprises more than 20 functional areas. A recent map[1] of these areas is shown in Fig. 1, and a provisional map of some of their interconnections is shown in Fig. 2. We also know something about the cortical layers from which many of these connections originate and to which layers they project. This knowledge, together with that showing the functional connectivity of other parts of the brain, will be essential as a foundation for the many neurophysiological experiments that will eventually show how the macaque brain functions.

In recent years there has also been remarkable progress in looking into the brains of living humans by means of magnetic resonance imaging (MRI)[2] and positron emission tomography (PET)[3].



Most of the MRI scans used, although of high resolution, are static; they show structure but not activity. Such a scan can picture, for example, exactly how the cerebral cortex is folded in a particular individual but not what part is functionally active. The spatial resolution of classical MRI is now 1 mm or less so that the living brain can be seen in much better detail than before. But 1 mm^3 of the human visual cortex may contain more than 40,000 neurons, so we are still looking at a low-resolution image.

A PET scan, although generally of lower resolution than MRI, shows where the brain is more active in particular tasks (or at rest) compared to a control task. By using an isotope of the oxygen of water, for example, the localized increase of capillary blood flow that accompanies local brain activity can be demonstrated. The present spatial resolution of most conventional PET scans is only 7–8 mm, but new photon detectors whose sensitivity approaches that of the theoretical spatial resolution of about 2 mm are being developed. The temporal resolution varies with the isotope used but is commonly minutes. Compare this with the temporal resolution of an electrode picking up the activity of a single neuron — of the order of 1 ms — a factor of 10^5 or better. It is now possible to do both PET scans and an MRI scan on the same brain, so that the localization of activity can be made more precise.

Other types of scans exist, such as those that pick up minute variations of the magnetic field that accompany brain

that for the macaque shown in Fig. 1? And what does the human equivalent of the connectional map of Fig. 2 look like? The shameful answer is that we do not have such detailed maps because, for obvious reasons, most of the experimental methods used on the macaque brain cannot be used on humans.

It is possible to study, postmortem, the appearance of stained sections of the human cortex under the microscope and so observe differences between the basic structure of one region of the cortex and another, a subject called architectonics. It is particularly easy to locate certain cortical areas, for example, the first visual area (the striate cortex). Even with the naked eye one can see the

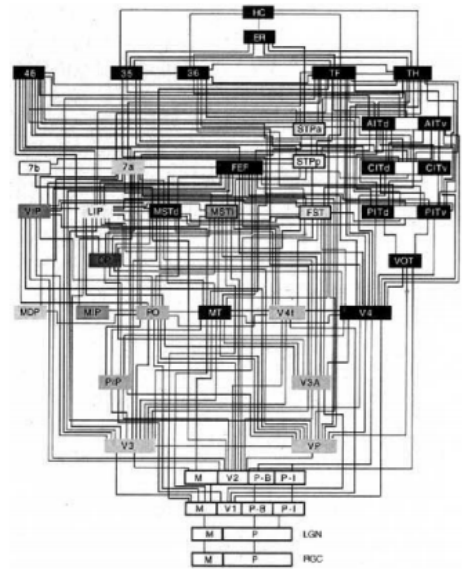


FIG. 2 Some of the intra-cortical connections

'You', your joys and your sorrows, your memories and your ambitions, your sense of personal identity and free will, are in fact no more than the behavior of a vast assembly of nerve cells…"

Crick, *The Astonishing Hypothesis* (1994)

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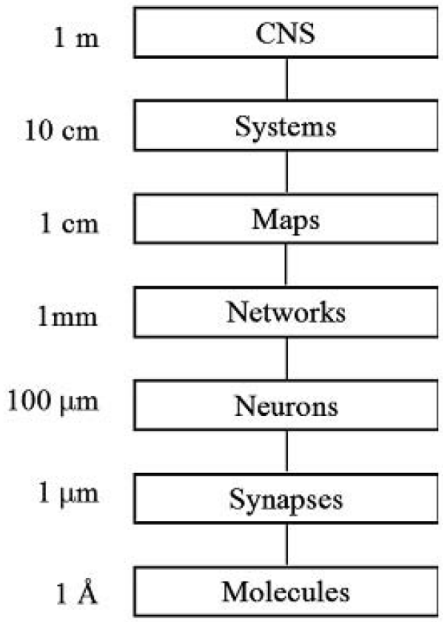
BUILDING NETWORKS ACROSS SCALES & DISCIPLINES: CELLS, BRAINS & POPULATIONS

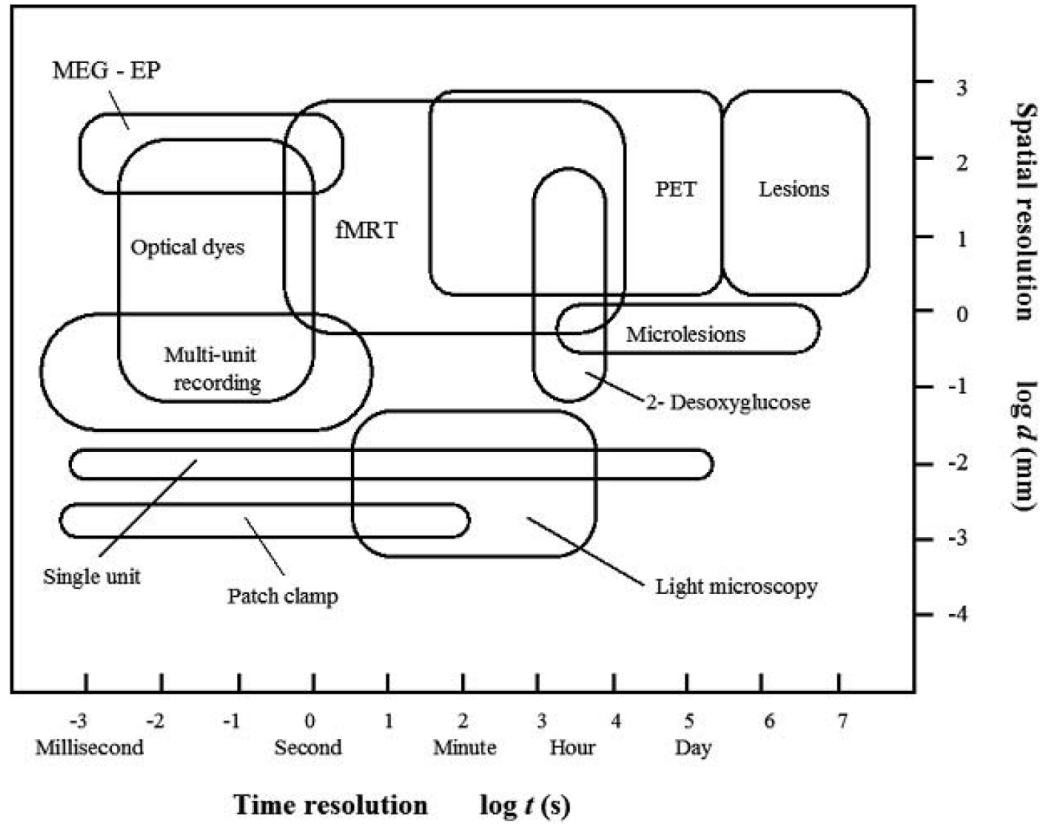
A Future of Convergence

– bridging scales of the connectome: top-down meets bottom-up

– a reconciliation of biological & artificial neural networks

– the connectome as the keystone for clinical/translational neuroscience & neuroengineering





Churchland & Sejnowski
***Computational Brain* (1992)**

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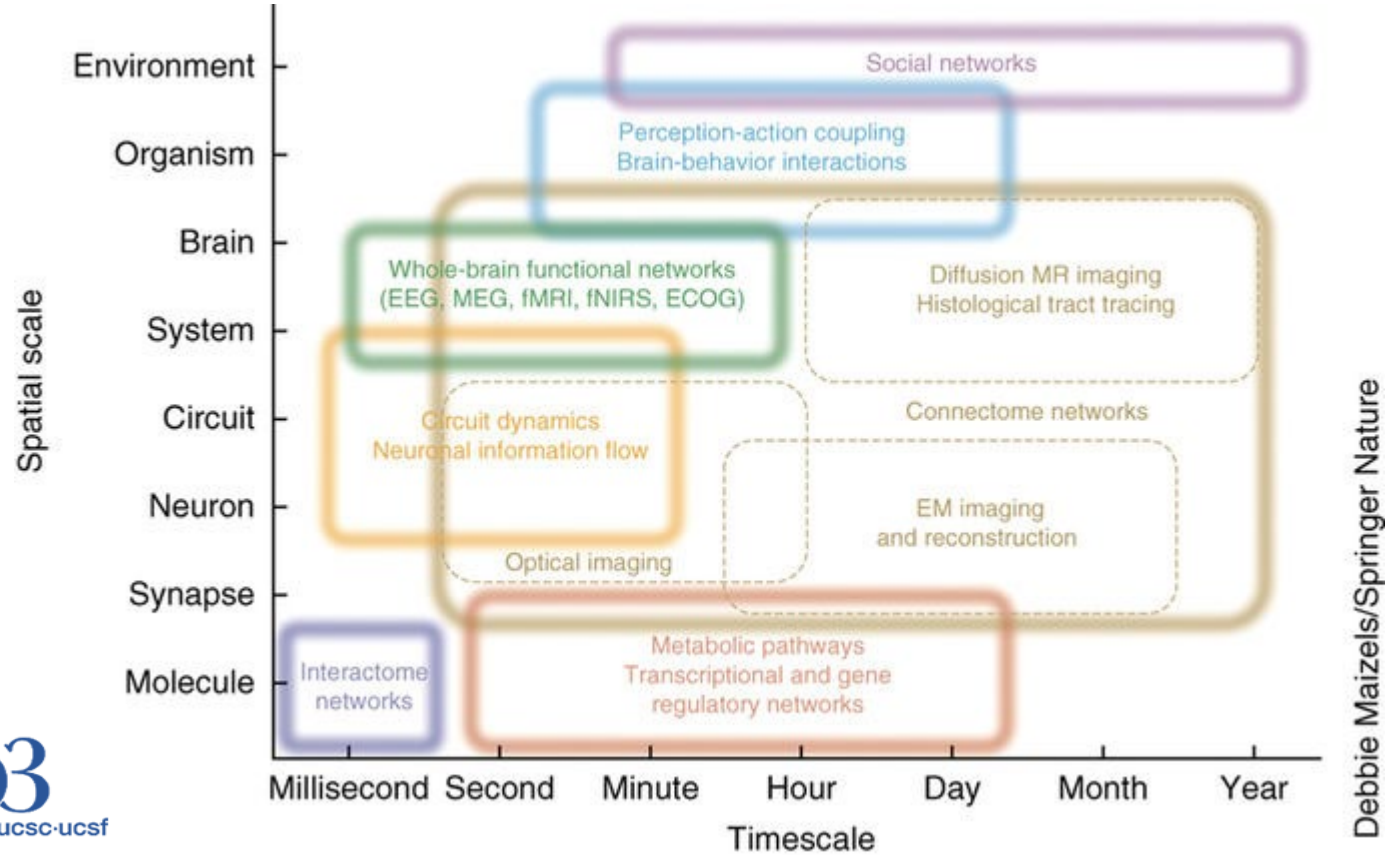
UCSF University of California San Francisco

A Future of Convergence

– bridging scales of the connectome: top-down meets bottom-up

– a reconciliation of biological & artificial neural networks

– the connectome as the keystone for clinical/translational neuroscience & neuroengineering



Bassett & Sporns
***Nature Neurosci* (2017)**

OPEN ACCESS Freely available online

PLoS COMPUTATIONAL BIOLOGY

Review

The Human Connectome: A Structural Description of the Human Brain

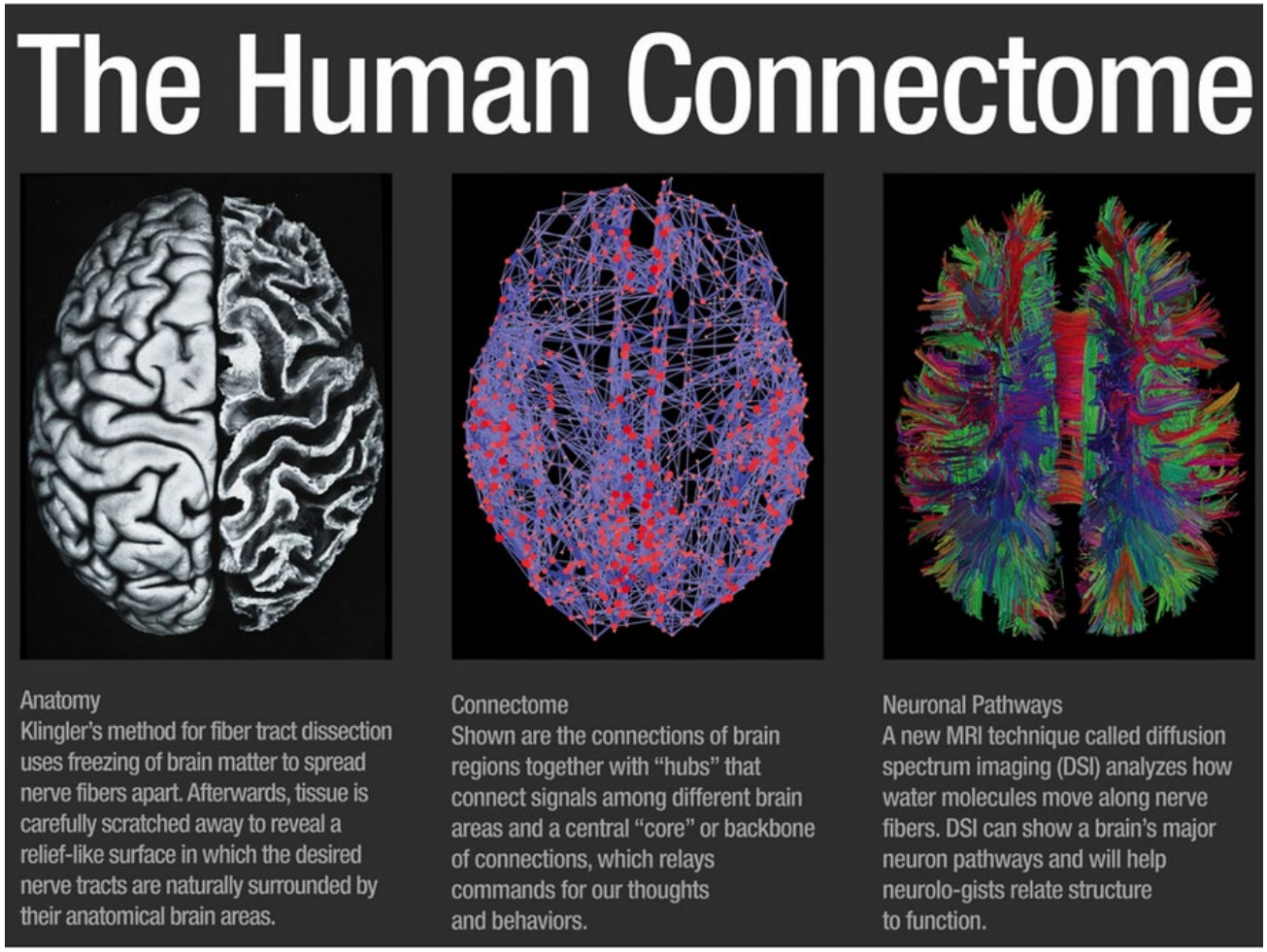
Olaf Sporns*, Giulio Tononi, Rolf Kötter

OPEN ACCESS Freely available online

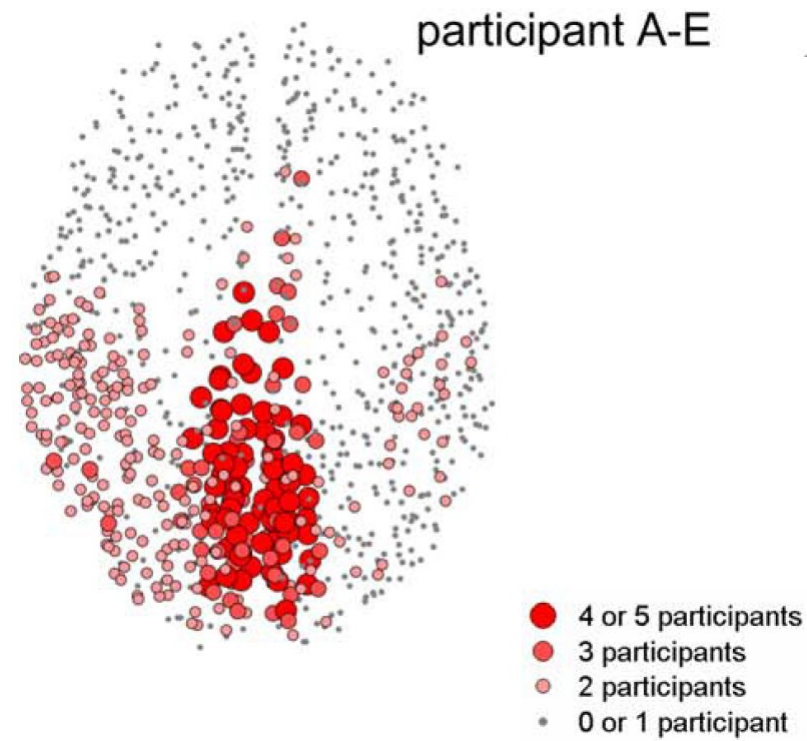
PLoS BIOLOGY

Mapping the Structural Core of Human Cerebral Cortex

Patric Hagmann[1,2], Leila Cammoun[2], Xavier Gigandet[2], Reto Meuli[1], Christopher J. Honey[3], Van J. Wedeen[4], Olaf Sporns[3]*

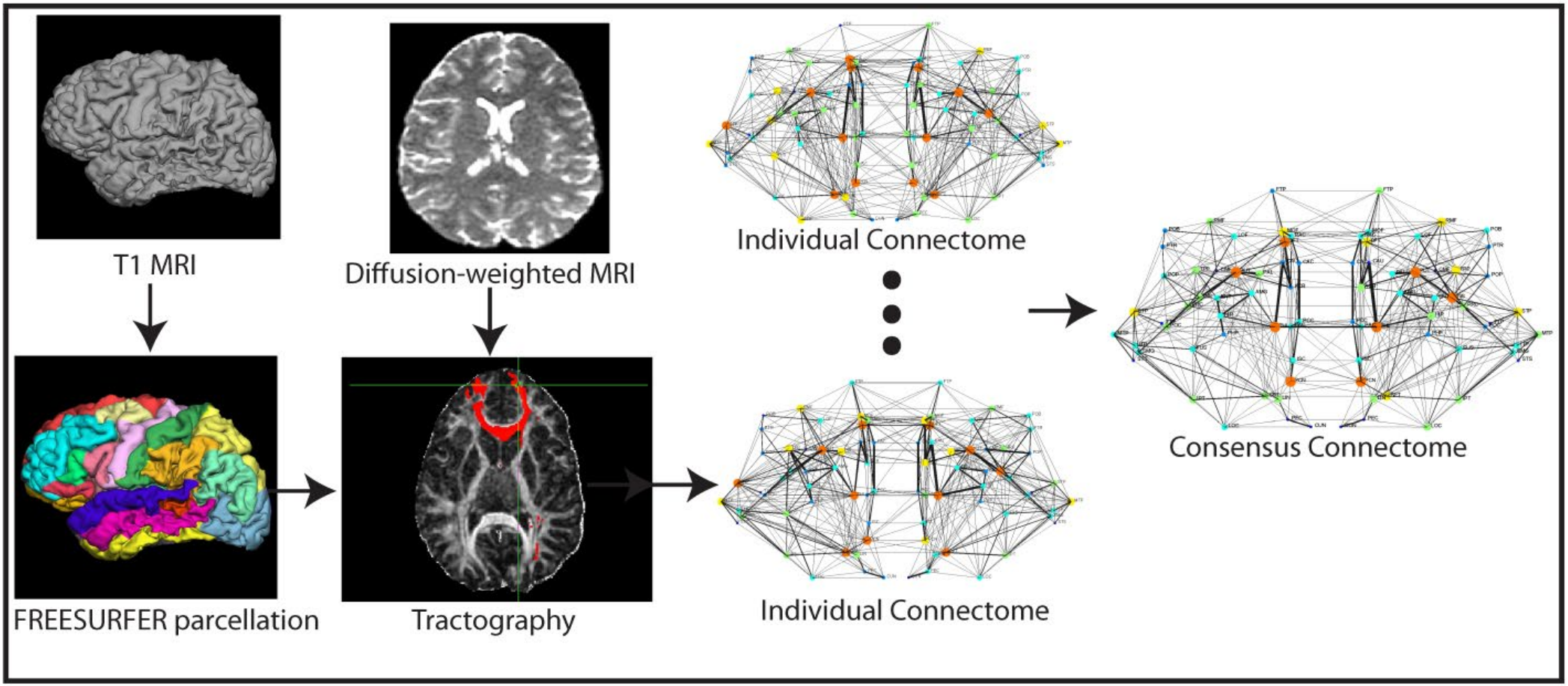


The Human Connectome - Eugen Ludwig, Josef Klingler, Patric Hagmann & Olaf Sporns - 1956, 2008



"Consensus Connectome"

Structural Connectome ("Projectome") Processing Pipeline

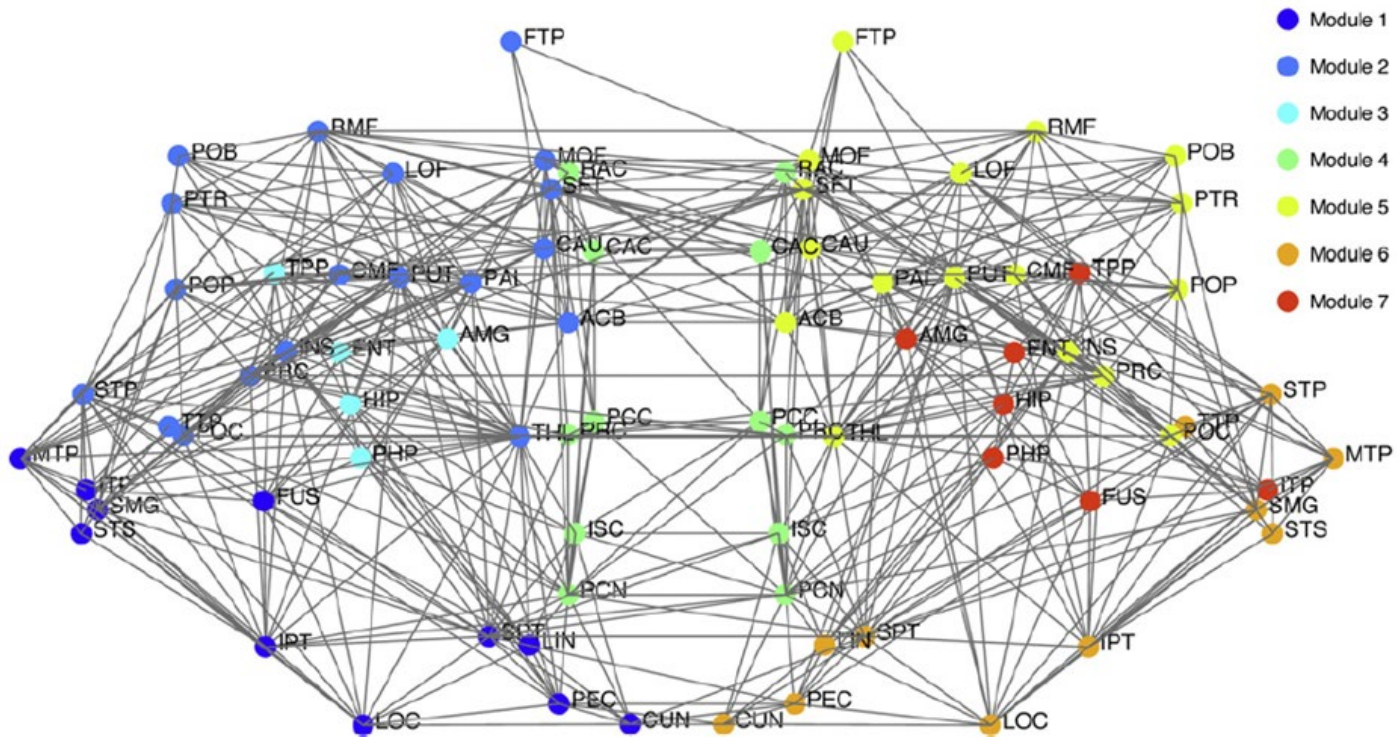


Limitations

- brain network is spatially embedded, not purely topological
- brain regions are heterogeneous in function, not indistinguishable nodes
- therefore, traditional graph theory metrics are not ideal for brain networks

White Matter Connectivity (The Macroscale Connectome)

– anatomic embedding of the connectome within white matter
– importance of spatially-embedded networks in WM diseases (SPD, TBI)
– network eigenmodes: spectral analysis of the macroscale connectome



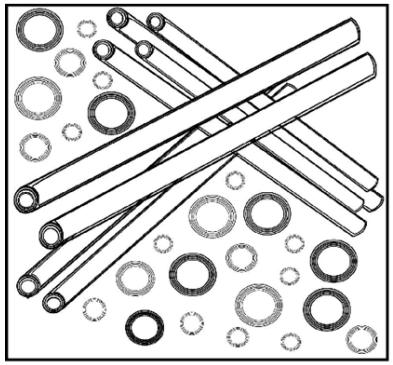
Julia P. Owen, Yi-Shin Chang, Pratik Mukherjee *Neuroimage* (2015)

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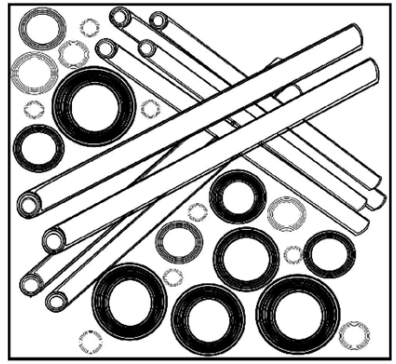
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Are Connectome Edges Uniformly Distributed in White Matter?

- *Hypothesis:* There are **"nexus"** regions of white matter that contain disproportionately large numbers of connectome edges
- These **"nexus" regions of white matter** would be loosely analogous to the **"hub" regions of gray matter** that are the endpoints for large numbers of connectome edges

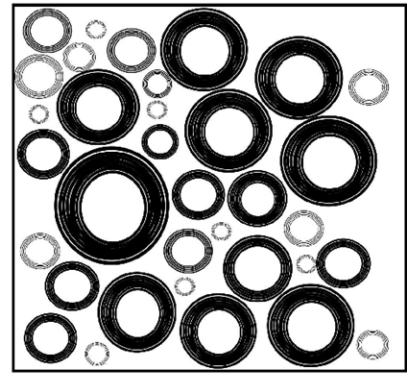


frontal WM



CST - centrum semiovale

Groeschel et al., *PLoS ONE* (2016)



CST - PLIC



"crossing fiber nexus"



"collimated fiber nexus"

Frontiers in Neuroinformatics

ORIGINAL RESEARCH
published: 16 May 2022
doi: 10.3389/fninf.2022.752471

The Case for Optimized Edge-Centric Tractography at Scale

Joseph Y. Moon[1], Pratik Mukherjee[2]*, Ravi K. Madduri[3], Amy J. Markowitz[2], Lanya T. Cai[2], Eva M. Palacios[2], Geoffrey T. Manley[2] and Peer-Timo Bremer[1]*

[1] Lawrence Livermore National Laboratory, Livermore, CA, United States, [2] Department of Radiology and Biomedical Imaging, University of California, San Francisco, San Francisco, CA, United States, [3] Argonne National Laboratory, Lemont, IL, United States

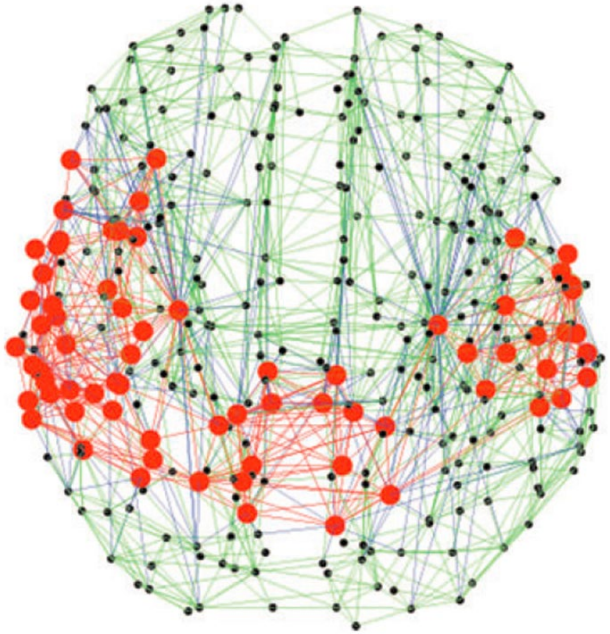
Neuroinformatics
https://doi.org/10.1007/s12021-024-09650-0

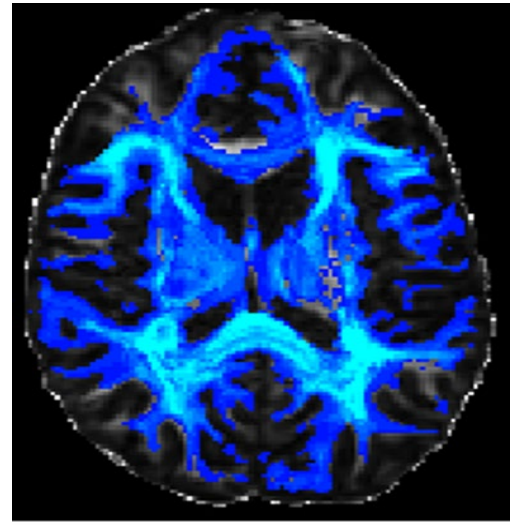
RESEARCH

MaPPeRTrac: A Massively Parallel, Portable, and Reproducible Tractography Pipeline

Lanya T. Cai[1] · Joseph Moon[2] · Paul B. Camacho[3] · Aaron T. Anderson[3] · Won Jong Chwa[4] · Bradley P. Sutton[5] · Amy J. Markowitz[6] · Eva M. Palacios[1] · Alexis Rodriguez[7] · Geoffrey T. Manley[6] · Shivsundaram Shankar[2] · Peer-Timo Bremer[2] · Pratik Mukherjee[1] · Ravi K. Madduri[7] · the TRACK-TBI Investigators

White Matter Network Connectivity: "Structural Connectome"





White Matter Network Anatomy & Connectivity: "Edge Density Imaging"

White Matter Anatomy: "Track Density Imaging"



Contents lists available at ScienceDirect

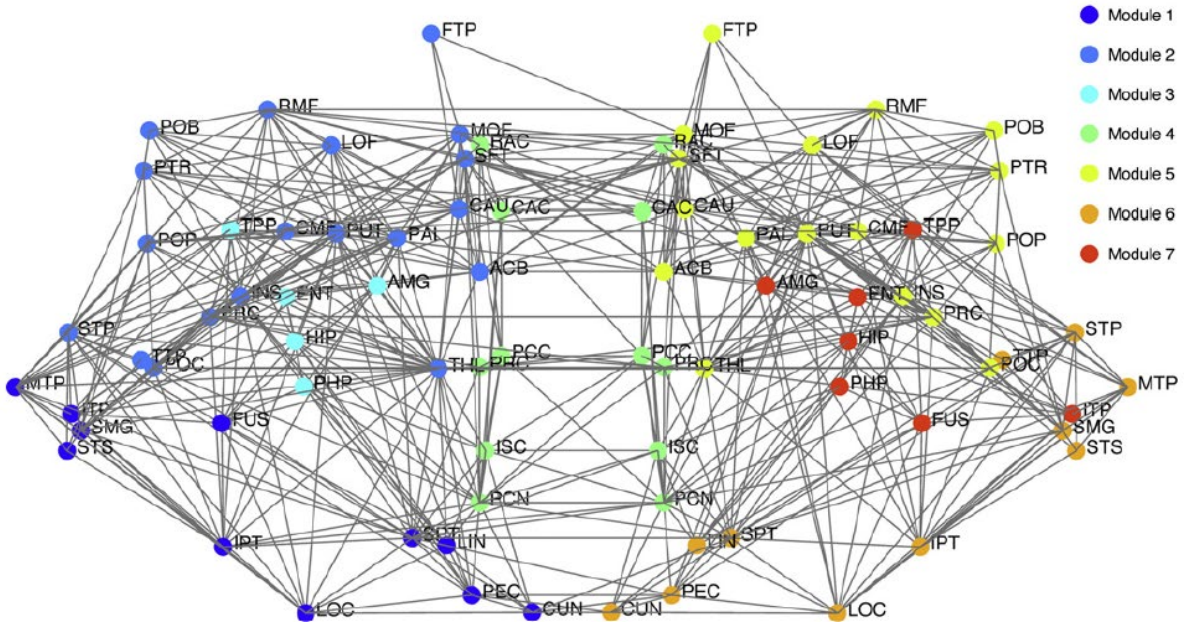
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journal homepage: www.elsevier.com/locate/ynimg

Edge density imaging: Mapping the anatomic embedding of the structural connectome within the white matter of the human brain

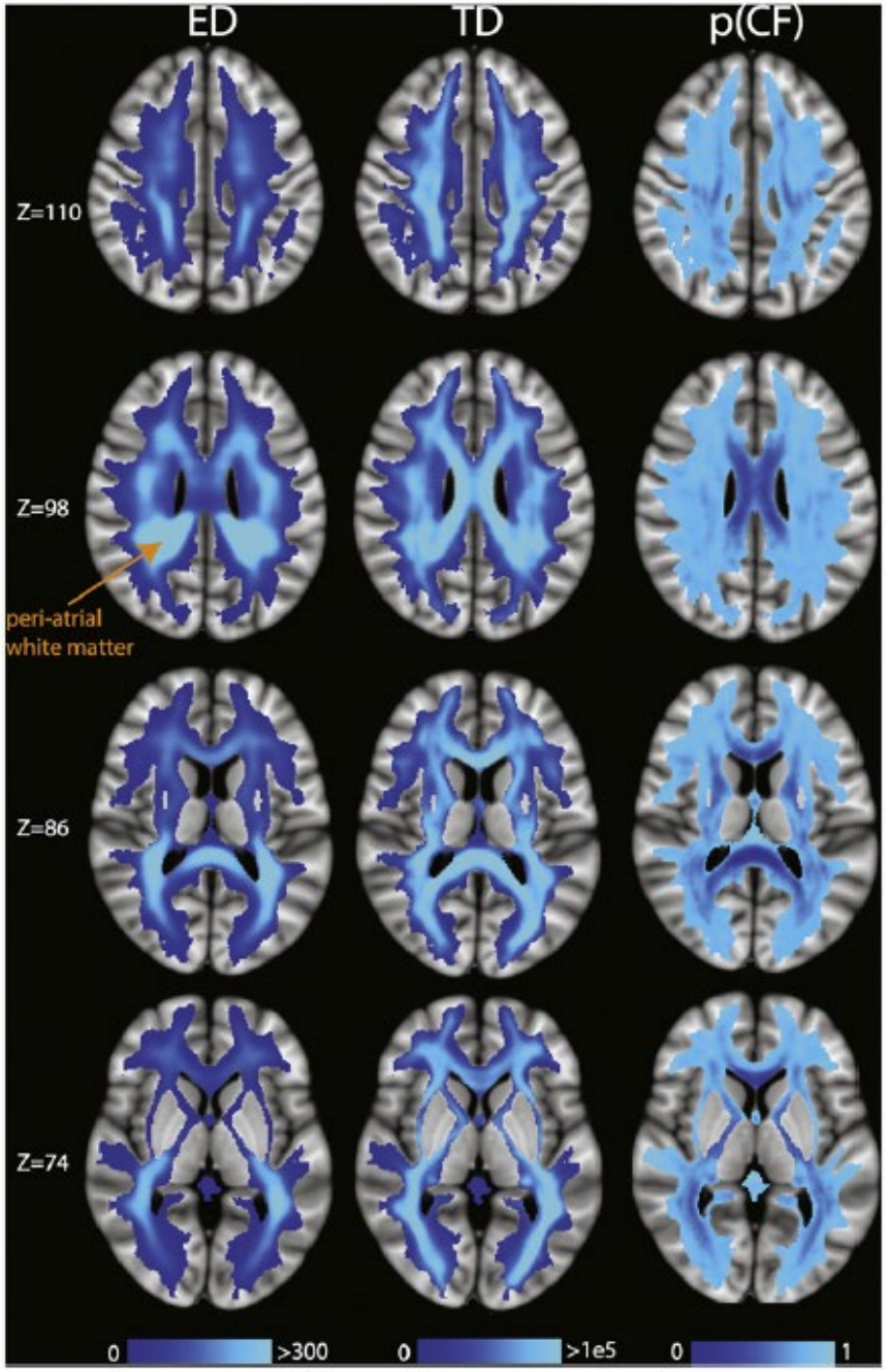
Julia P. Owen [a], Yi Shin Chang [a], Pratik Mukherjee [a,b,*]

[a] Department of Radiology & Biomedical Imaging, University of California, San Francisco, USA
[b] Department of Bioengineering & Therapeutic Sciences, University of California, San Francisco, USA



Periventricular WM:
"crossing fiber nexus"

Corpus Callosum:
"collimated fiber nexus"



"Periventricular Crossroads": Crossing Fiber Nexus Regions

Periventricular white matter contains crossing association, projection and commissural (callosal) pathways

Originally discovered by von Monakow in 1905 and further characterized by Judas et al. (2005)

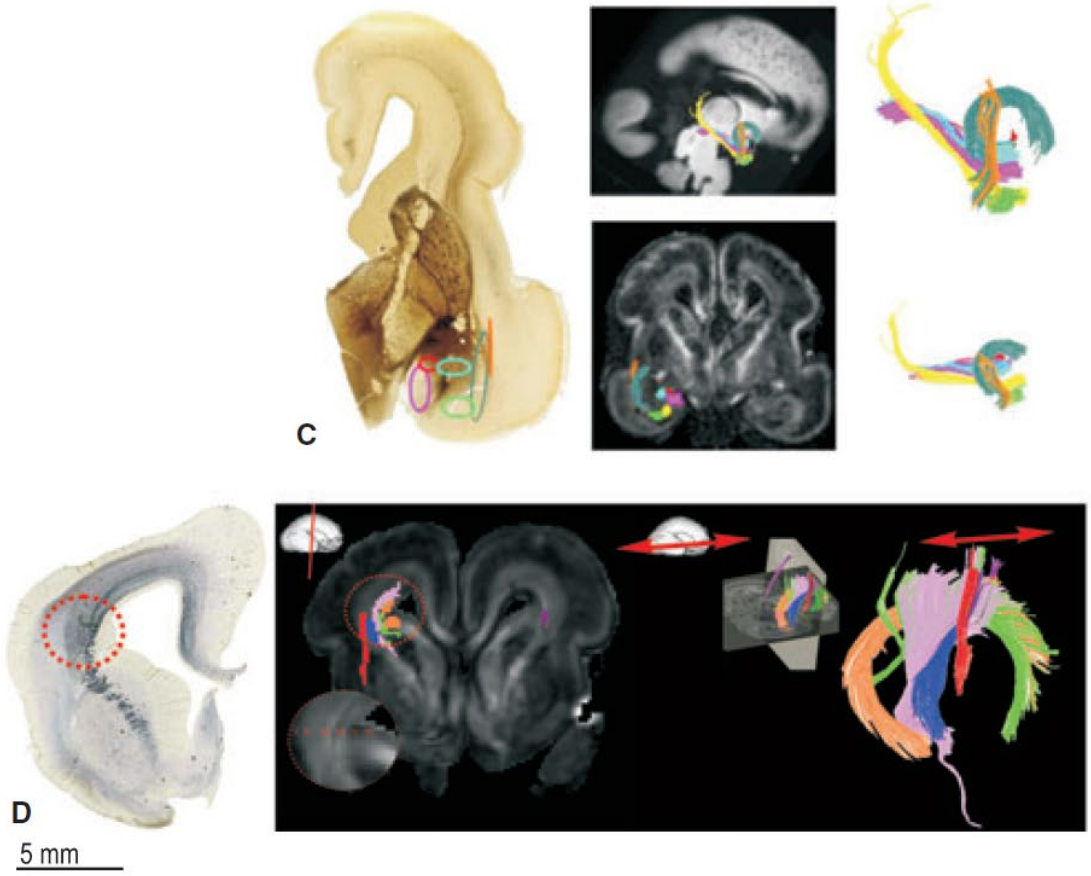


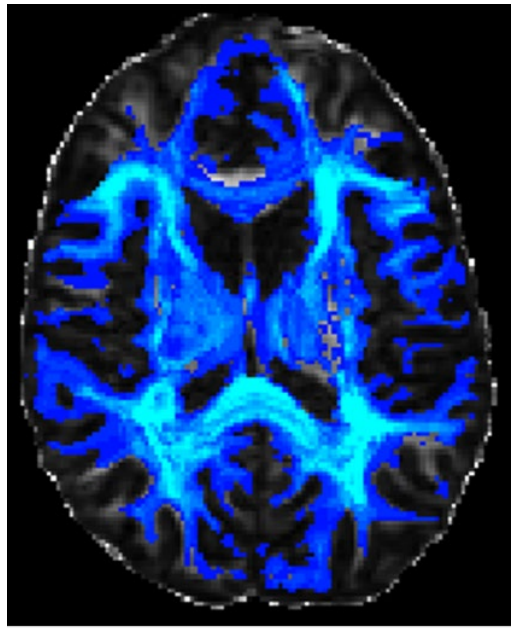
Fig. 8 Development of associative pathways and crossroad formation during mid fetal period. Formation of cingulum bundle at 17 PCW is shown by AChE staining and comparative DTI tractography (A, red colour). During 15 PCW (B) and 17 PCW (C) the amygdala connections and crossroad C6 becomes more complex- as revealed by DTI (C). During 19 PCW crossroad C1 formation can be show by SNAP staining and DTI tractography reconstruction (D). The crossroad area C1 is organized by axonal pathways that run in radial (thalamocortical), sagittal (associative) and transverse (callosal) direction (B, C). In D the different ROIs for the crossroad C1 can be seen (I-VI) and thus reconstructed with tractography (different colours represent different ROIs).

Vasung et al., *J Anat* (2010)

White Matter "Edge Density"

Why are Nexus Regions More Prominent Posteriorly in the Brain?

- **Cortical hubs have a preferentially posterior distribution, too** (Hagmann et al., 2008)
- The **posterior cerebral regions are phylogenetically older than prefrontal regions**, the latter of which underwent greater evolutionary expansion in primates and especially humans





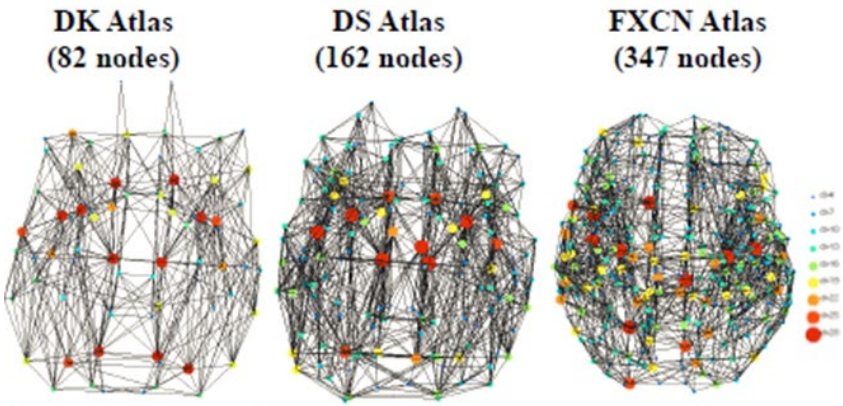
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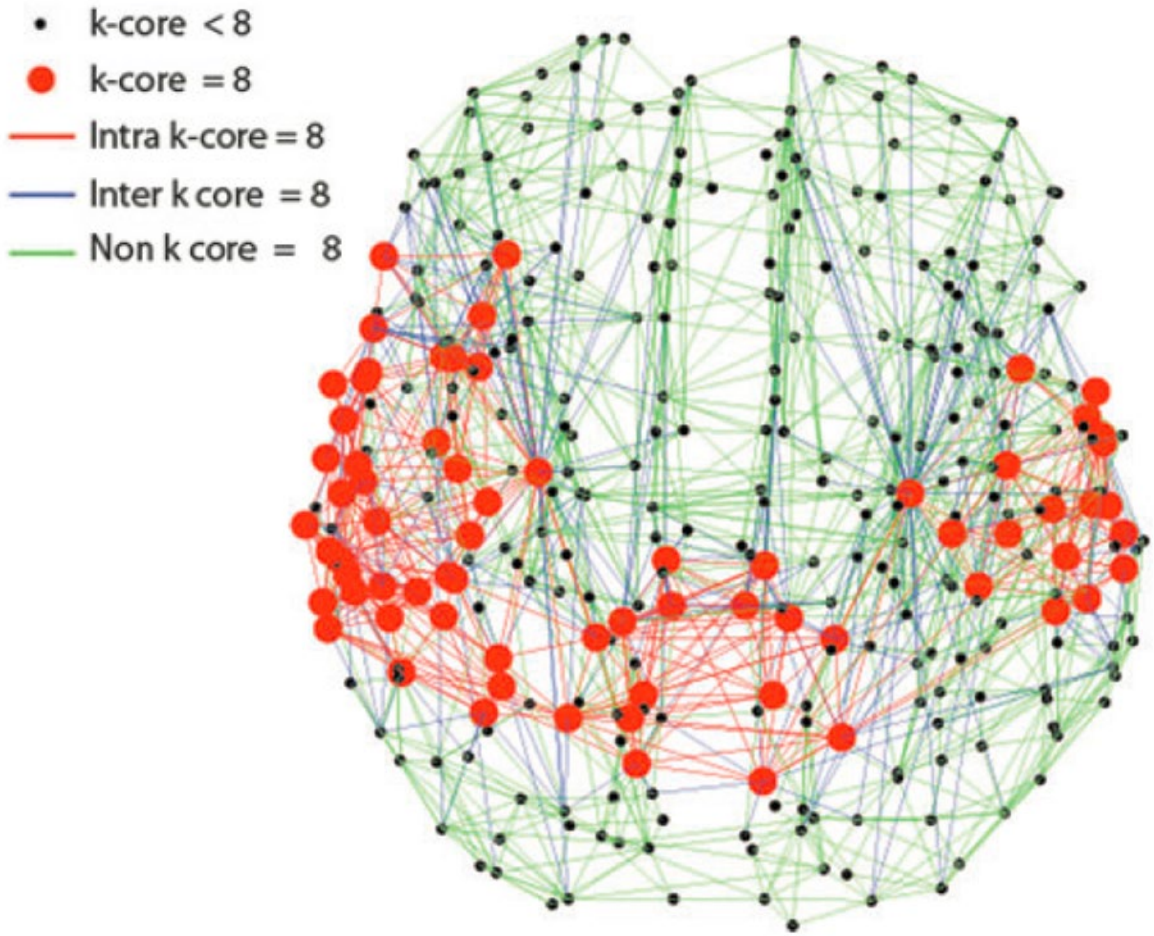
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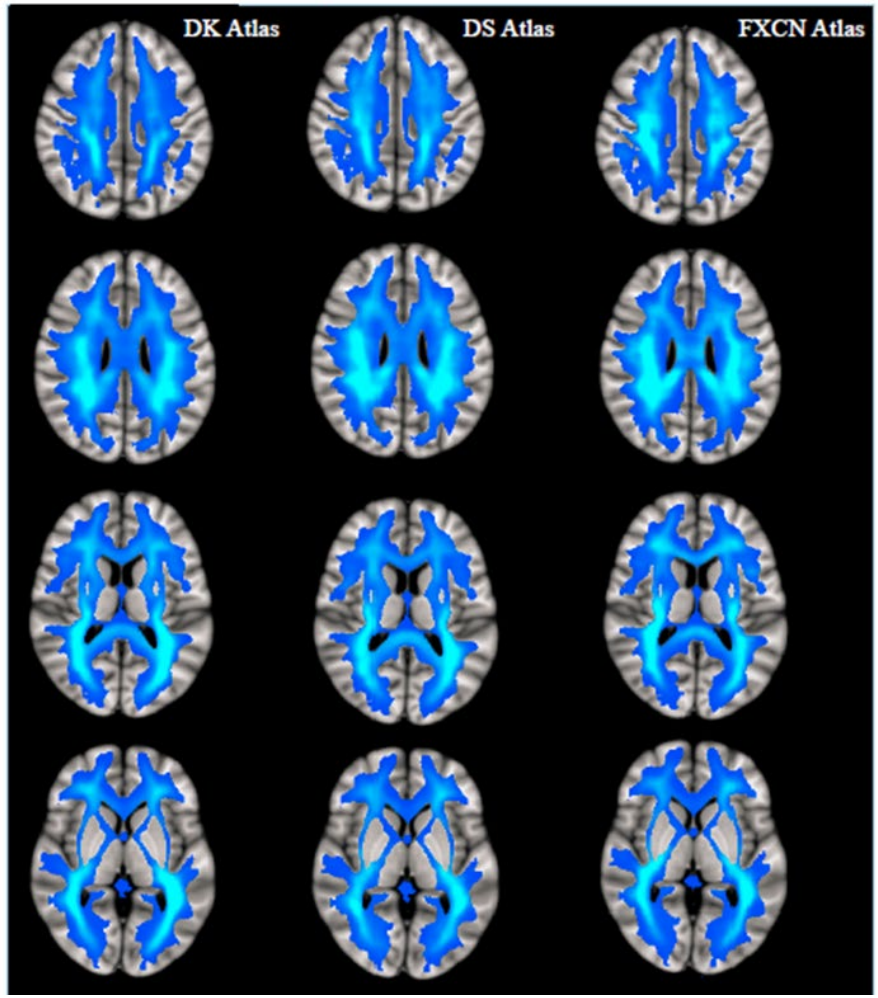
BRAIN CONNECTIVITY
Volume 6, Number 7, 2016
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DOI: 10.1089/brain.2016.0431

Periventricular White Matter Is a Nexus for Network Connectivity in the Human Brain

Julia P. Owen, Maxwell B. Wang, and Pratik Mukherjee

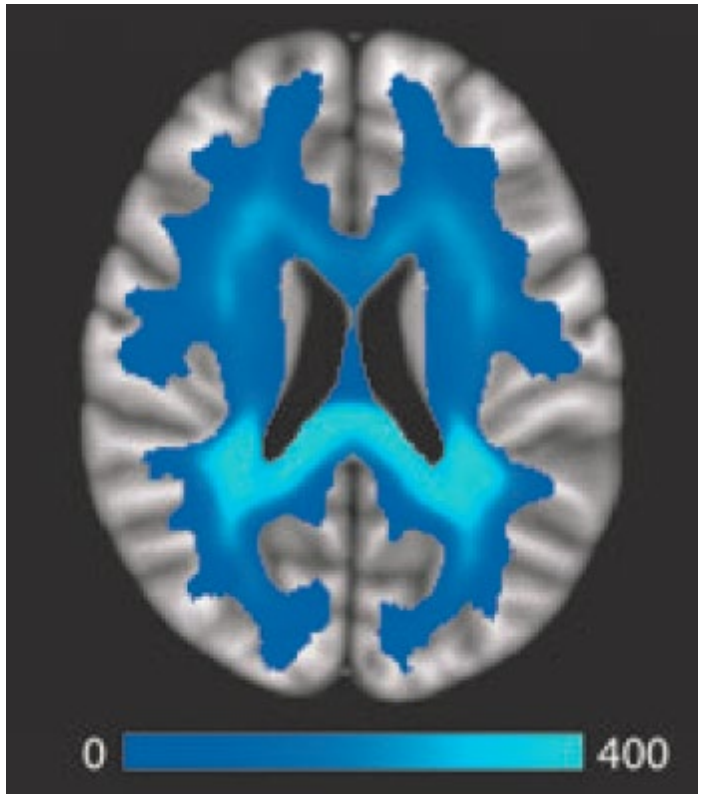




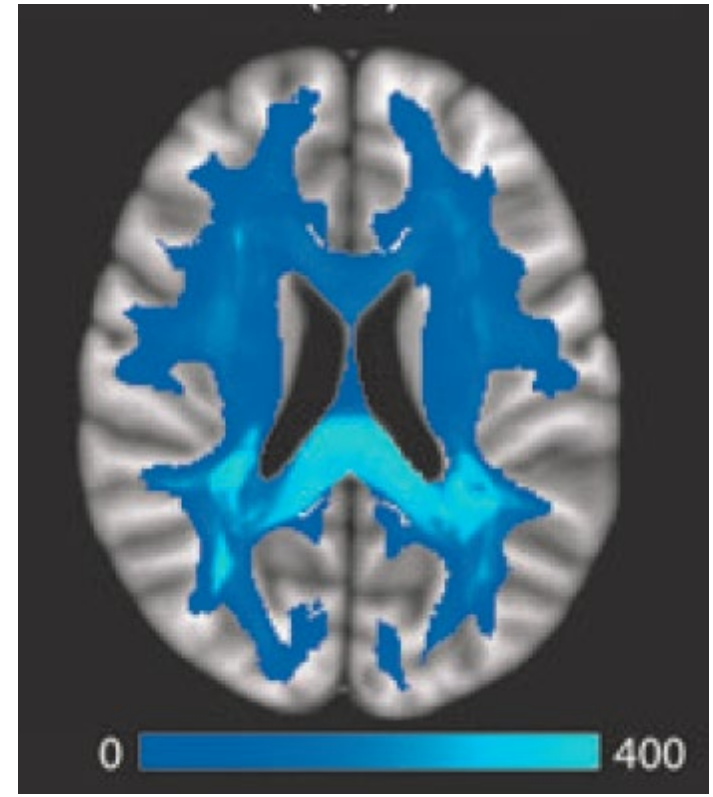


Edge Density Imaging:
Effect of Acquisition & Tractography

UCSF Tractography Results
Siemens 3T Tim Trio
ss-EPI acquisition
FSL MCMC probtrackx2



IIT Tractography Atlas
GE 3T Signa
Turboprop acquisition
MRTrix CSD tractography



Julia P. Owen PhD, Maxwell B. Wang BS, Pratik Mukherjee MD PhD
Brain Connectivity **(2016)**

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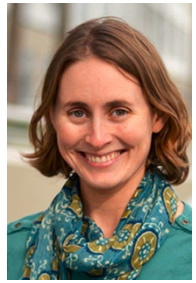
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Edge density imaging: Mapping the anatomic embedding of the structural connectome within the white matter of the human brain

Julia P. Owen [a], Yi Shin Chang [a], Pratik Mukherjee [a,b,*]

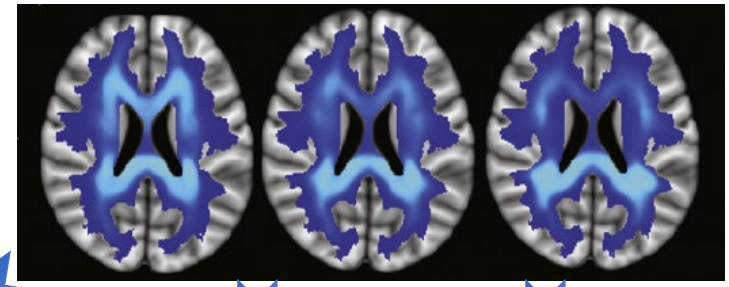
[a] Department of Radiology & Biomedical Imaging, University of California, San Francisco, USA
[b] Department of Bioengineering & Therapeutic Sciences, University of California, San Francisco, USA

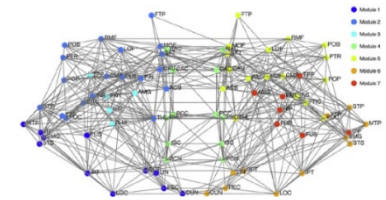


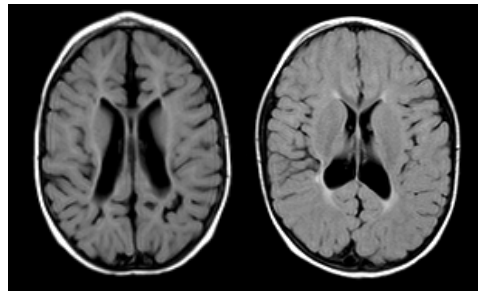
Julia P. Owen, PhD

Neuroskeptic @Neuro_Skeptic · Jan 12
Edge Density Imaging (EDI): Mapping the Anatomic Embedding of the Structural Connectome In the Brain's White Matter
sciencedirect.com/science/articl…

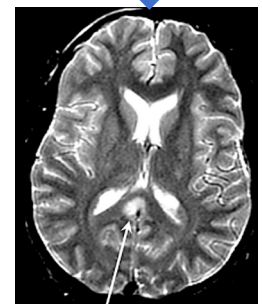
Olaf Sporns @spornslab · Jan 20
Edge Density Imaging - sciencedirect.com/science/articl…



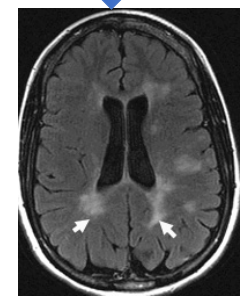




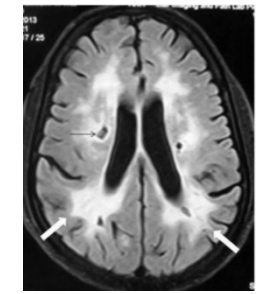
White Matter Injury of Prematurity



Traumatic Brain Injury (TBI)



Multiple Sclerosis (MS)



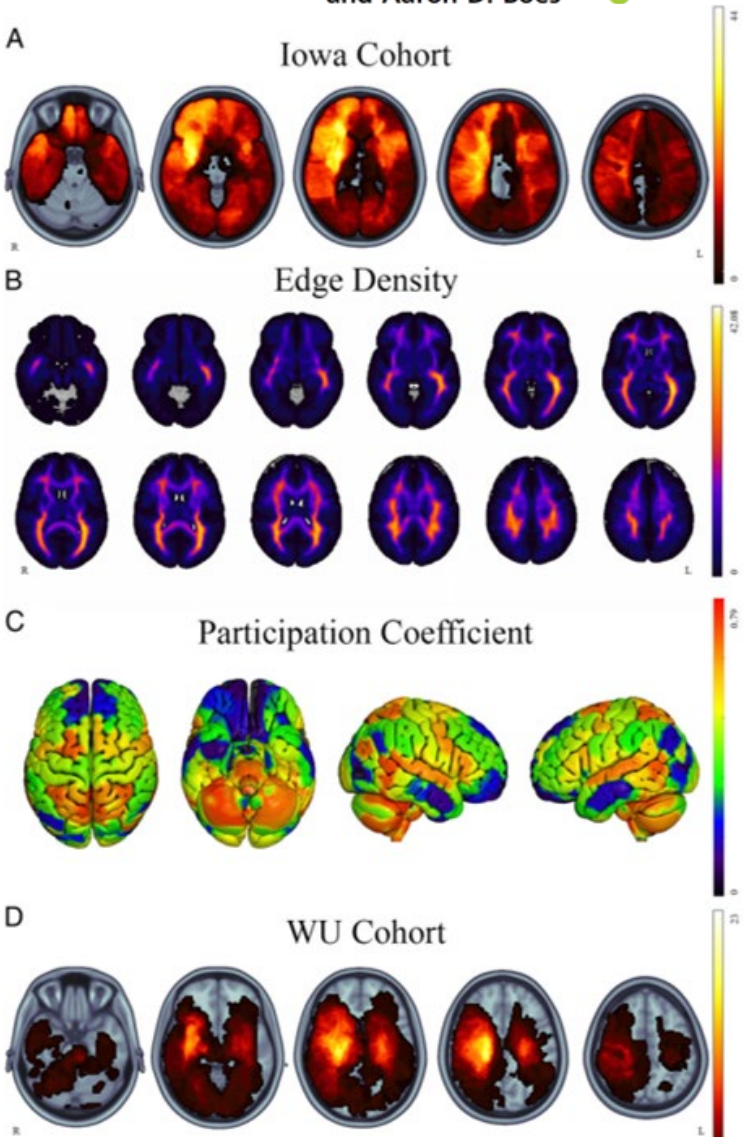
Vascular Dementia (SVID)

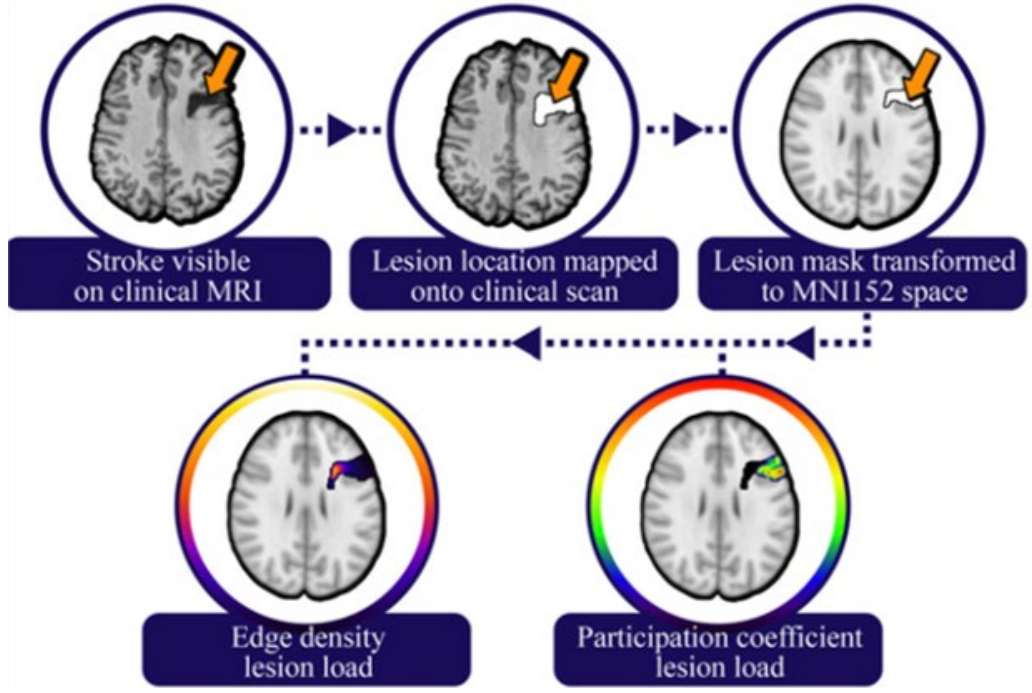
From a Clinical Perspective, Nexus Regions are More Like "Dark Matter" than White Matter

- **The function of white matter in nexus regions is not as well understood as other regions, perhaps due to their complexity**
- **The effects of damage to nexus white matter regions is typically not easily observed clinically, as they may entail only cognitive dysfunction and behavioral difficulties, rather than focal neurological deficits (paresis, aphasia, scotoma, etc.)**
- **Neurosurgeons consider nexus white matter regions to be "non-eloquent", and therefore resectable, as opposed to "eloquent" areas such as corticospinal tract and arcuate fasciculus**

Cognitive impairment after focal brain lesions is better predicted by damage to structural than functional network hubs

Justin Reber[a,b,1], Kai Hwang[c], Mark Bowren[b,c], Joel Bruss[b], Pratik Mukherjee[d], Daniel Tranel[b], and Aaron D. Boes[a,b,e]





"Lesions disrupting white matter regions with high edge density were associated with cognitive impairment, whereas lesions damaging gray matter regions with high participation coefficient had a weaker, less consistent association with cognitive outcomes. Similar results were observed with six other gray matter hubness measures. This suggests that damage to densely connected white matter regions is more cognitively impairing than similar damage to gray matter hubs, helping to explain interindividual differences in cognitive outcomes after brain damage."

Reber et al. **PNAS (2021)**

Network Eigenmodes of the Structural Connectome

Generative Models of the Connectome

Neural Mass Models (NMM)

Neural Field Theory (NFT)

Weakness: Lack of data on long-range information transmission in the human brain



Maxwell B. Wang

Rockford, IL

"These interactions will help me to explore the various fields of bioengineering and settle on a direction for graduate school and the rest of my career."

Host University: University of California, San Francisco (UCSF)
Home University: Washington University in St. Louis
Amgen Scholar Year: 2015
Major: Electrical Engineering
Expected Graduation: 2016

Amgen Scholars is an international program funded by the **Amgen Foundation** with direction and technical assistance provided by the **Massachusetts Institute of Technology** and the **University of Cambridge**.

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Spectral Graph Theory: a linear systems approach

$$\frac{dx}{dt} = \beta \left(\begin{cases} -\sum_{k \neq i,j} \mathcal{A}_{ki} & i = j \\ \mathcal{A}_{ij} & \text{otherwise} \end{cases} \right) x(t) = -\beta \mathcal{L} x(t)$$

Network Diffusion Equation

Laplacian Matrix — Diagonal Matrix — Adjacency Matrix — Network Eigenmodes — Network Eigenvalues

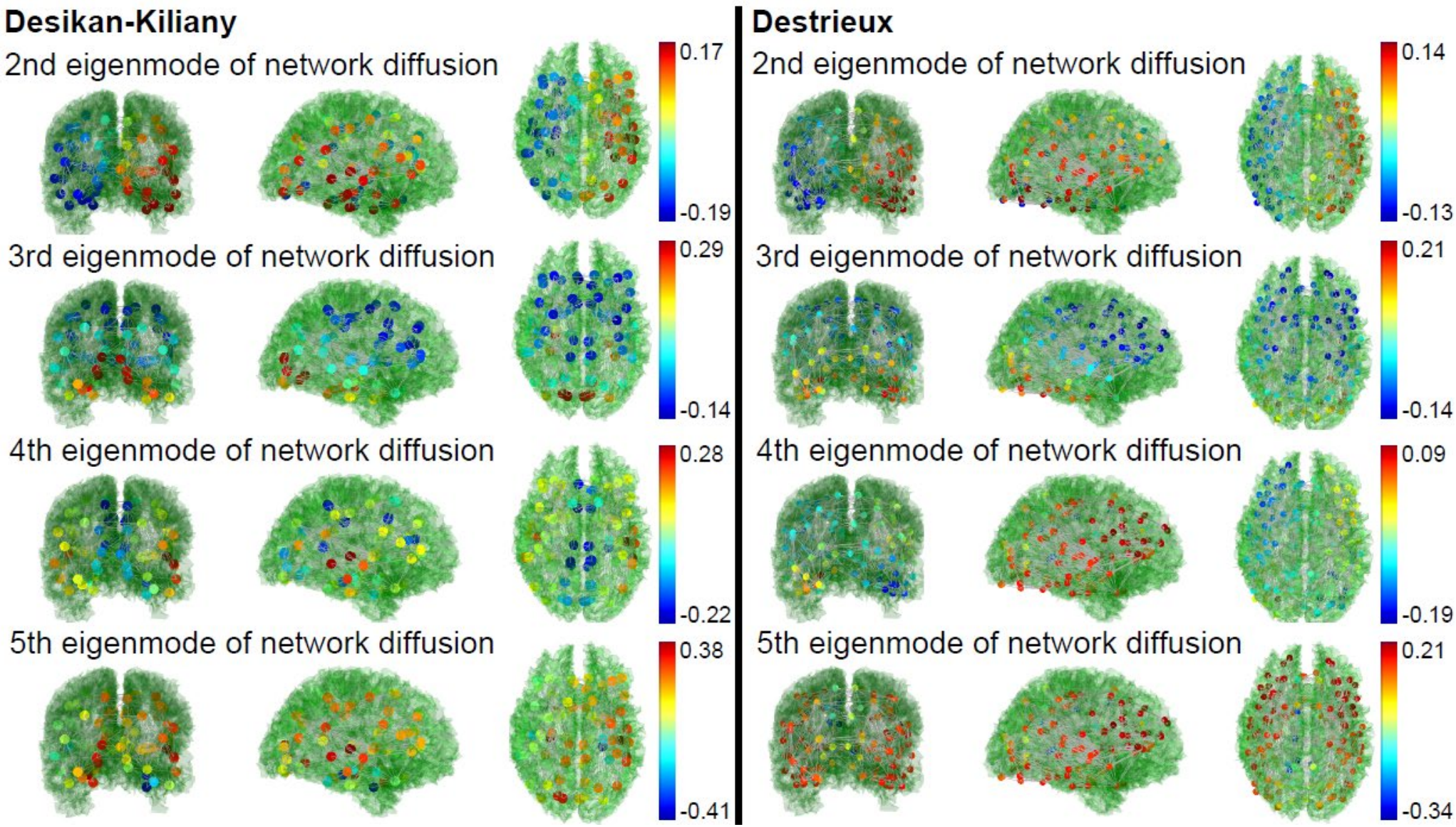
$$L = D - A = Q \Lambda Q^{-1}$$

Laplacian Eigendecomposition

Maxwell B. Wang BS, Julia P. Owen PhD, Pratik Mukherjee MD PhD, Ashish Raj PhD

***PLoS Comput Biol* (2017)**

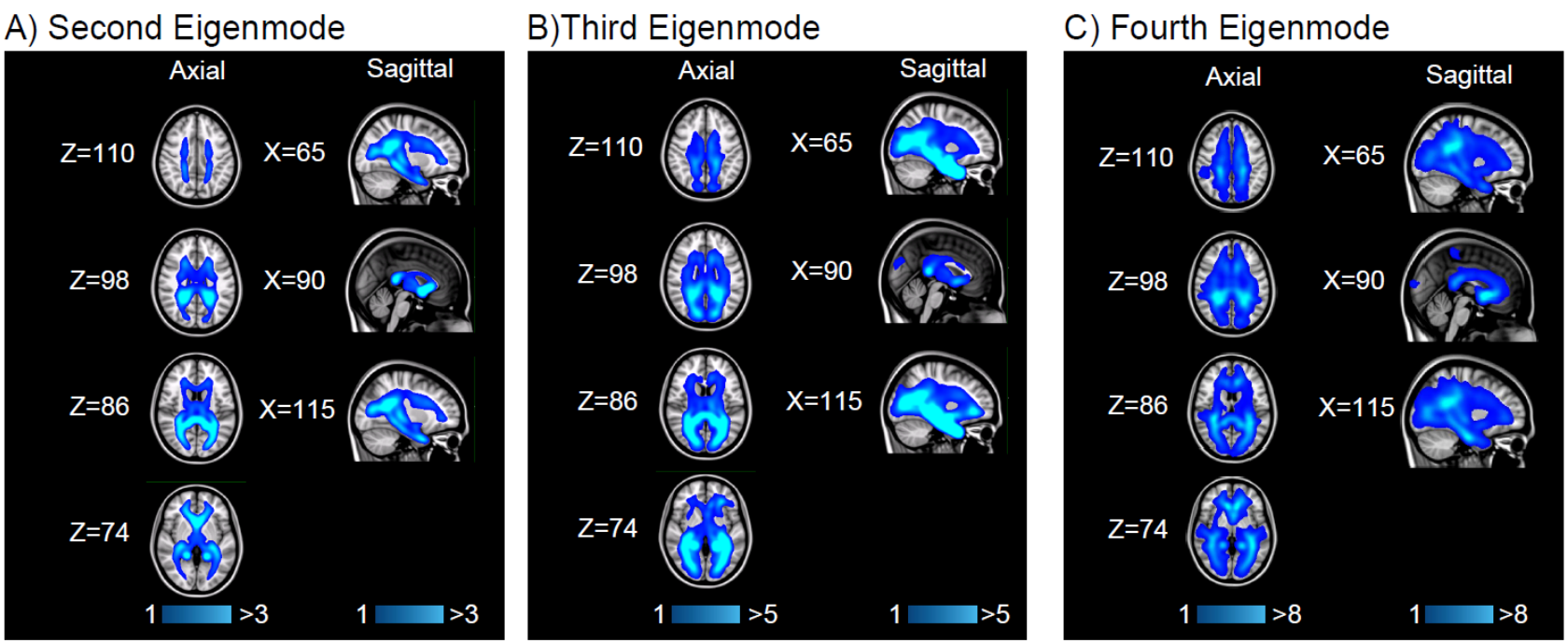
Network Eigenmodes of the Structural Connectome



Maxwell B. Wang BS, Julia P. Owen PhD, Pratik Mukherjee MD PhD, Ashish Raj PhD

***PLoS Comput Biol* (2017)**

Network Eigenmodes vs Edge Density





Maxwell B. Wang



Ashish Raj, PhD

PLOS | COMPUTATIONAL BIOLOGY

RESEARCH ARTICLE

Brain network eigenmodes provide a robust and compact representation of the structural connectome in health and disease

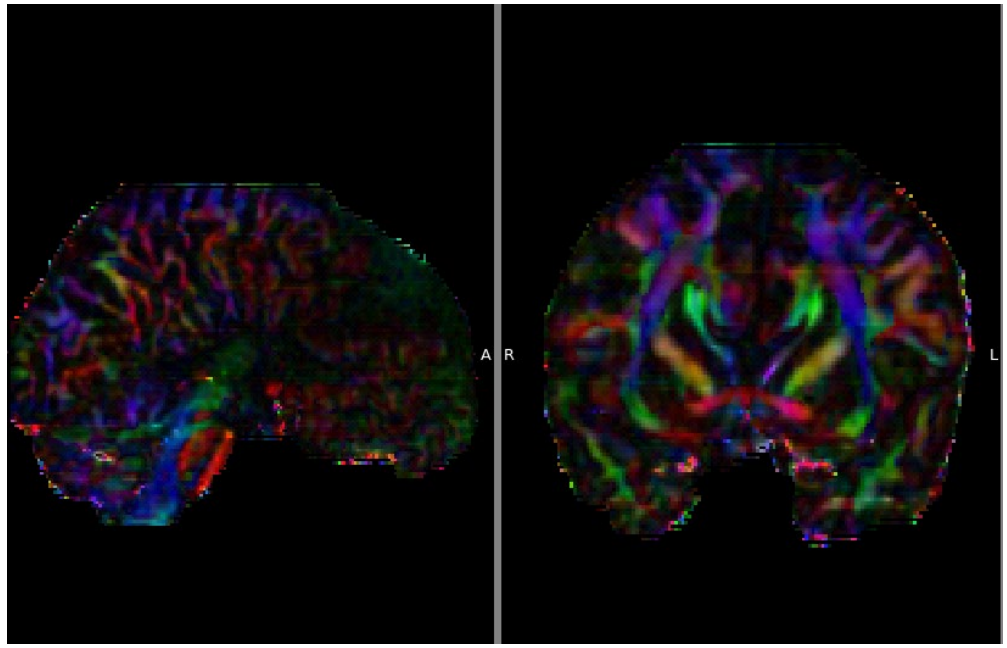
Maxwell B. Wang[1☯], Julia P. Owen[1☯], Pratik Mukherjee[1,2], Ashish Raj[3]*

1 Department of Radiology & Biomedical Imaging, University of California, San Francisco, California, United States of America, **2** Department of Bioengineering & Therapeutic Sciences, University of California, San Francisco, California, United States of America, **3** Department of Radiology, Weill Cornell Medical College, New York, New York, United States of America

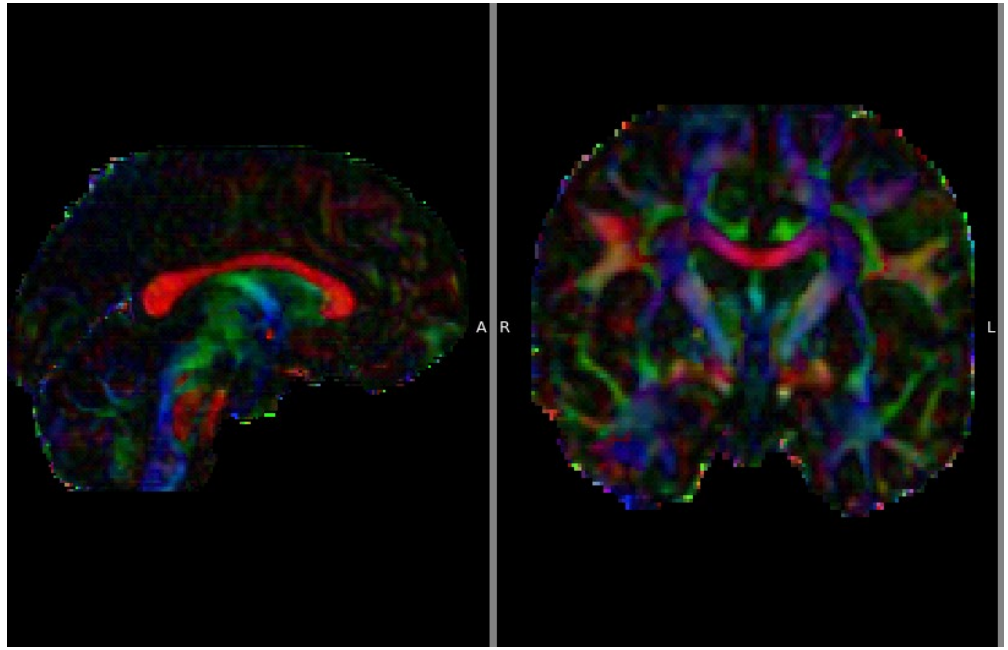
Network eigenmodes provide a better metric for mapping vulnerable regions of the connectome than traditional graph metrics, such as efficiency (global) and clustering (local).

Application to “Connectopathies”

Agenesis of the Corpus Callosum



Normal Brain



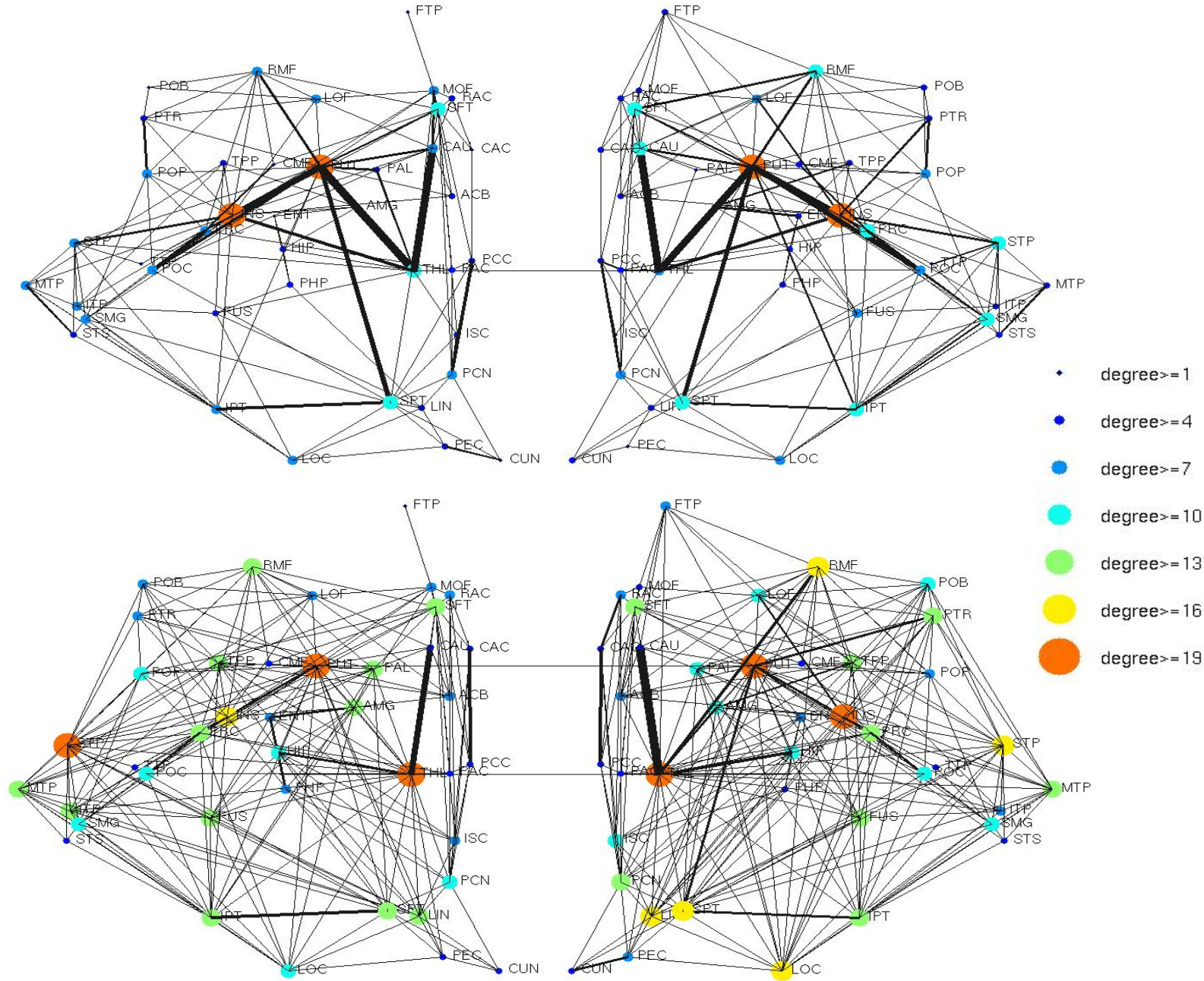
Owen et al. Neuroimage (2012)

Application to “Connectopathies”

Agenesis of the Corpus Callosum

Owen et al. Neuroimage (2012)

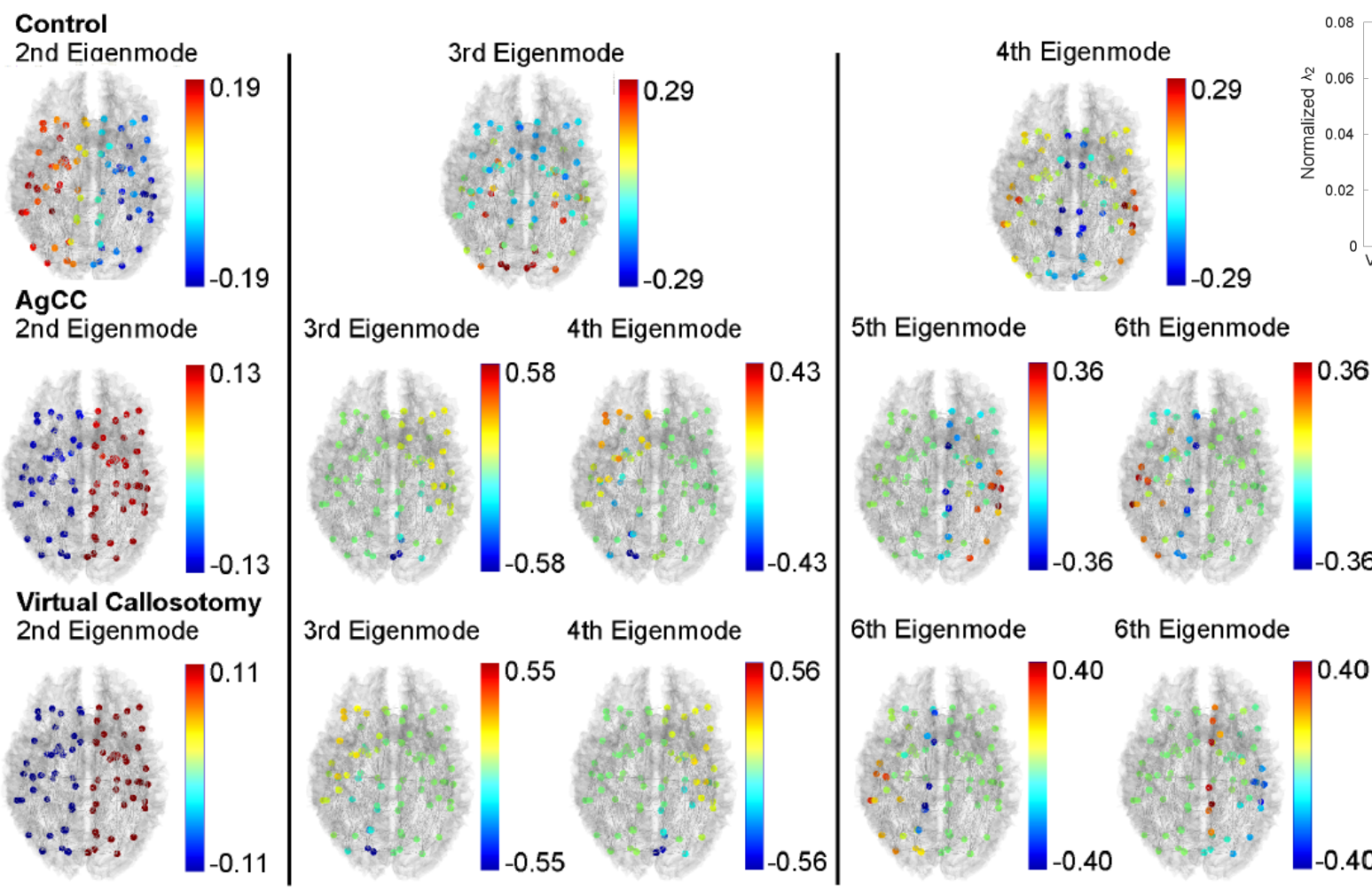
Virtual Callosotomy

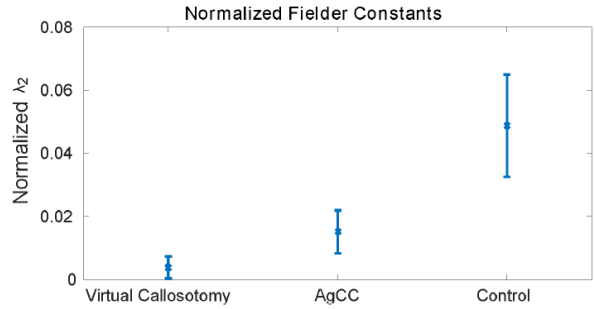


Network Eigenmodes in Agenesis of the Corpus Callosum

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Representing the structural brain connectome in health and disease

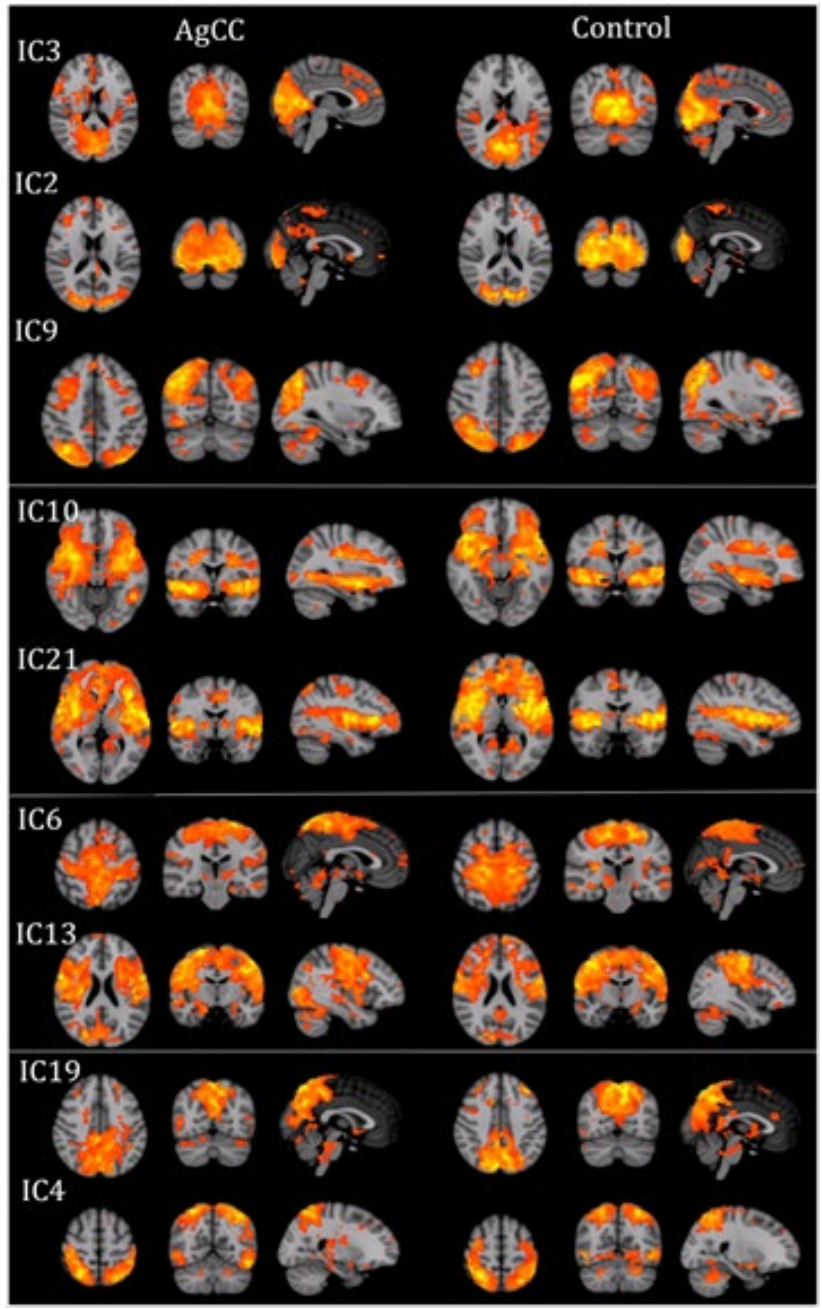


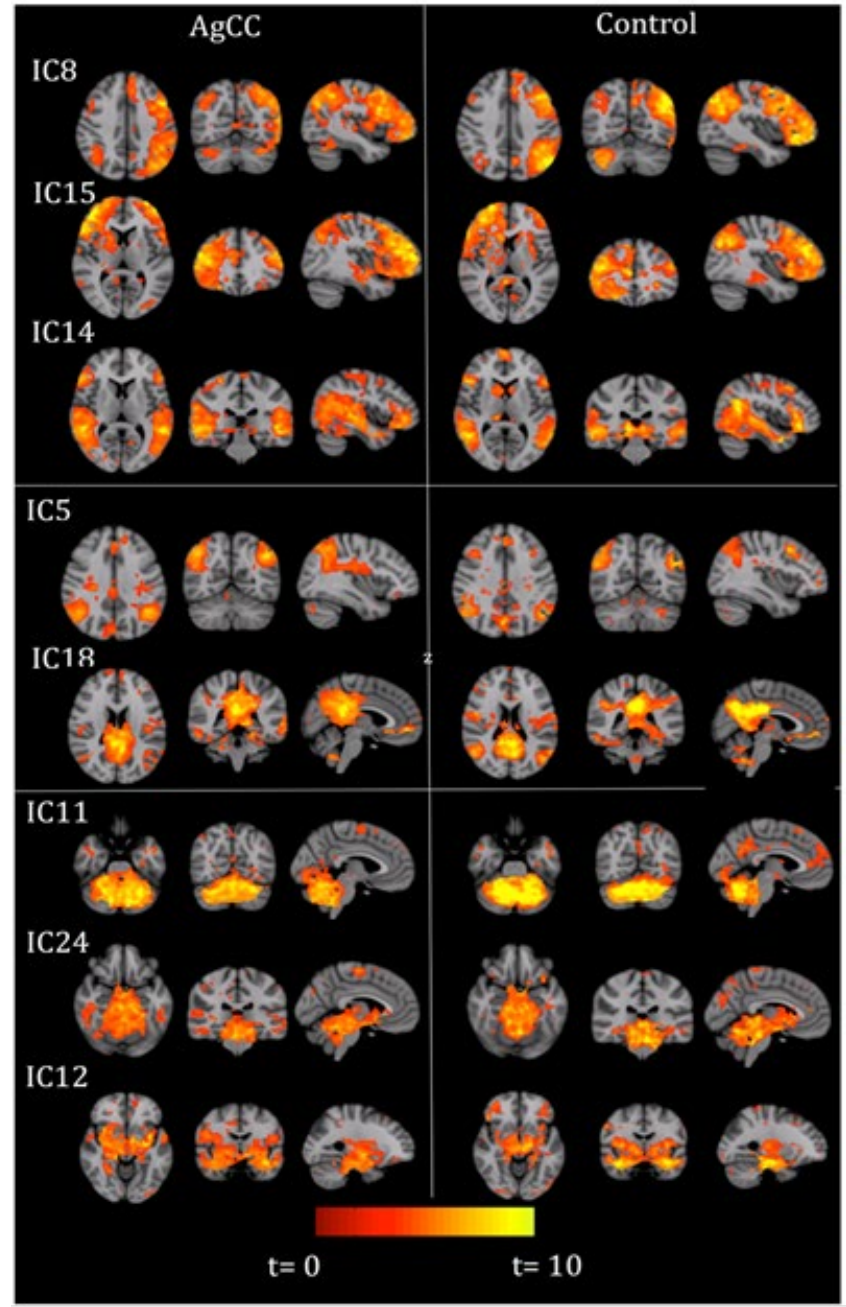


Maxwell B. Wang BS, Julia P. Owen PhD, Pratik Mukherjee MD PhD, Ashish Raj PhD

***PLoS Comput Biol* (2017)**

Resting State Functional Networks: AgCC vs Normal

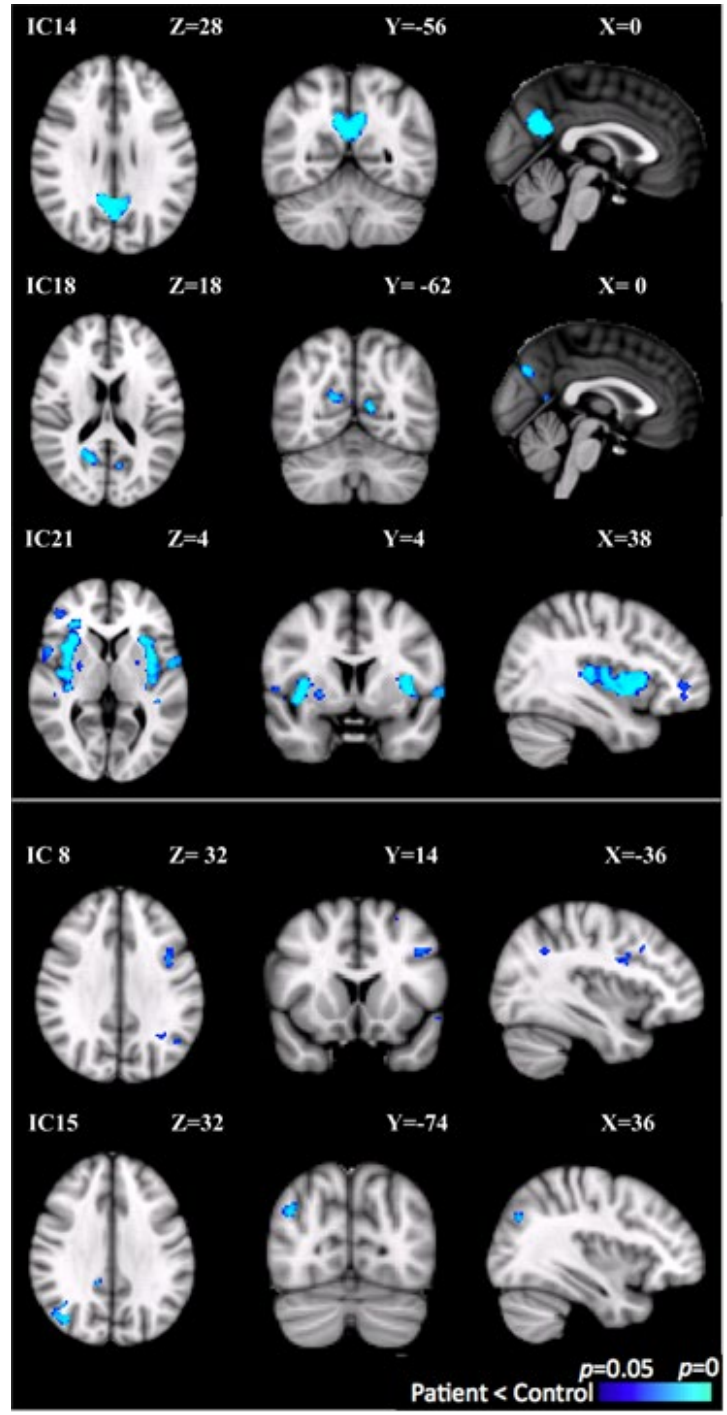




Bilaterally reduced FC in AgCC: precuneus, posterior cingulate, insula

Unilaterally reduced FC in AgCC: frontoparietal networks

Owen et al. *Brain Connectivity* (2013)



(HC<ACC)

P=0
(sign. Diff.)

P=1

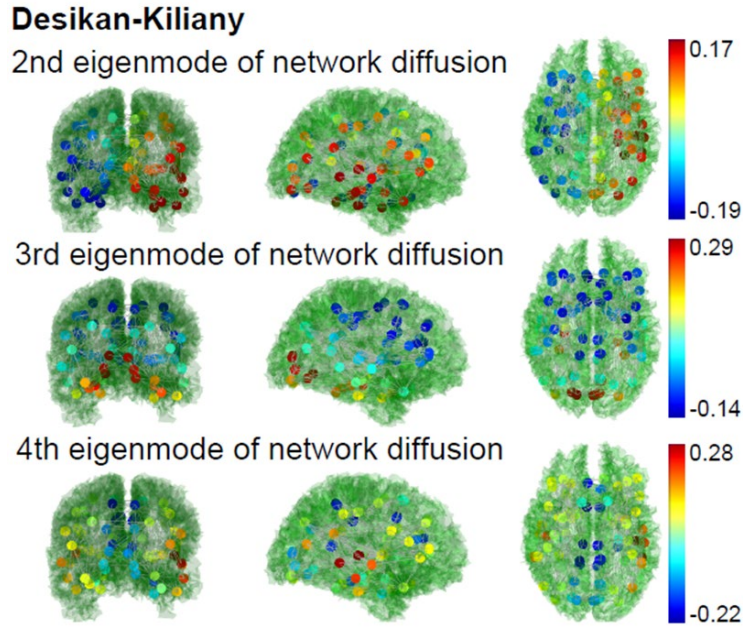
(HC>ACC)

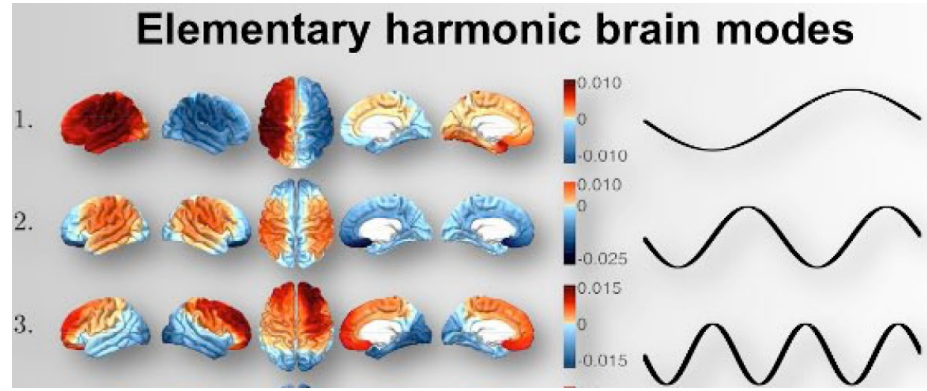
P=0
(sign. Diff.)

P=1

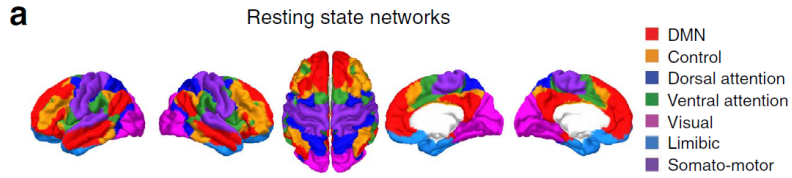
Structural Eigenmodes and Resting State fMRI Networks

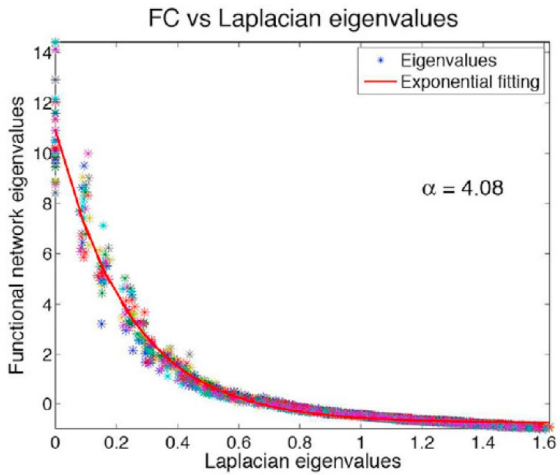
Wang et al., ***PLoS Comput Biol*** **(2017)**





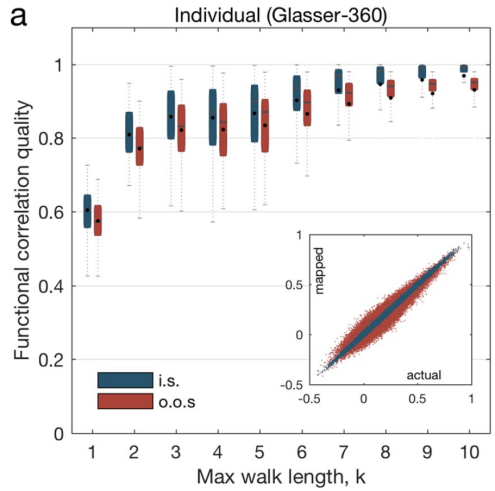
Atasoy et al., ***Neuroscientist*** **(2017)**





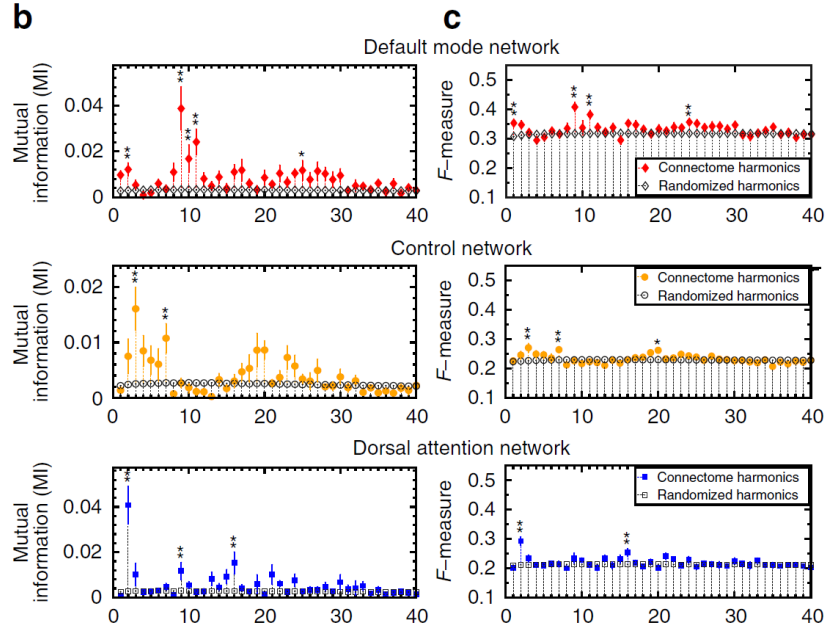
$$\frac{d\mathbf{x}(t)}{dt} = -\beta\mathscr{L}(\mathbf{x}(t) - \mathbf{x}^*), \quad \mathbf{C}_f^{eig} = ae^{-\beta\mathscr{L}t} + \mathbf{K}$$

Abdelnour et al., ***Neuroimage*** **(2018)**

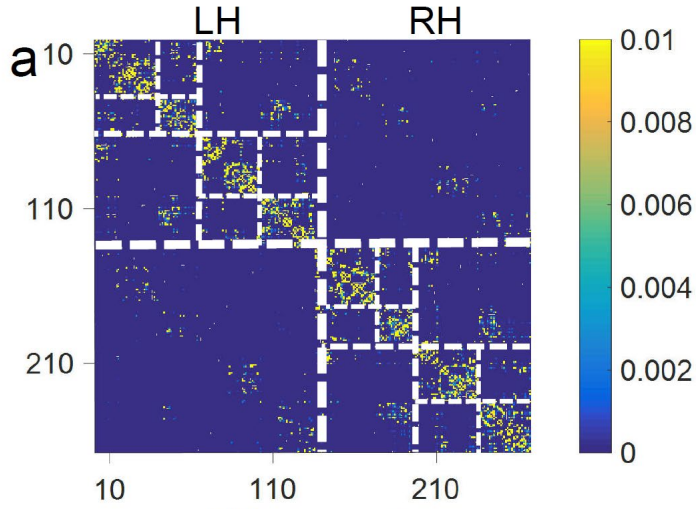


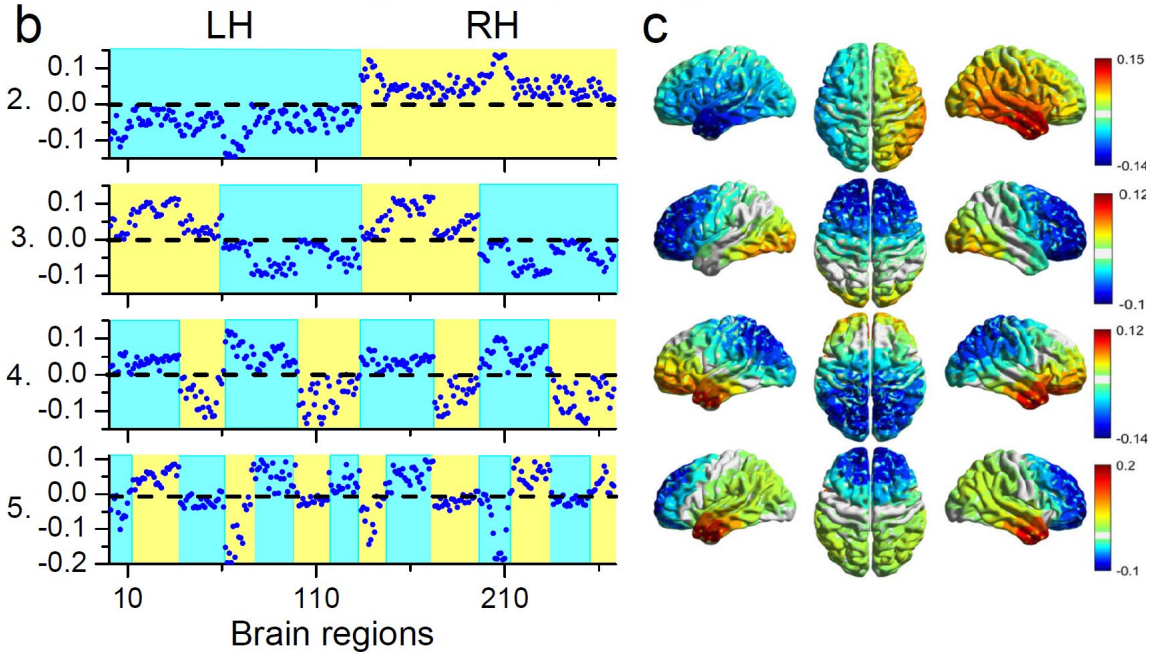
$$\hat{F} = R^{\star}\left(\sum_{i=0}^{k} a_i^{\star} S^i\right)(R^{\star})^{\mathsf{T}}$$

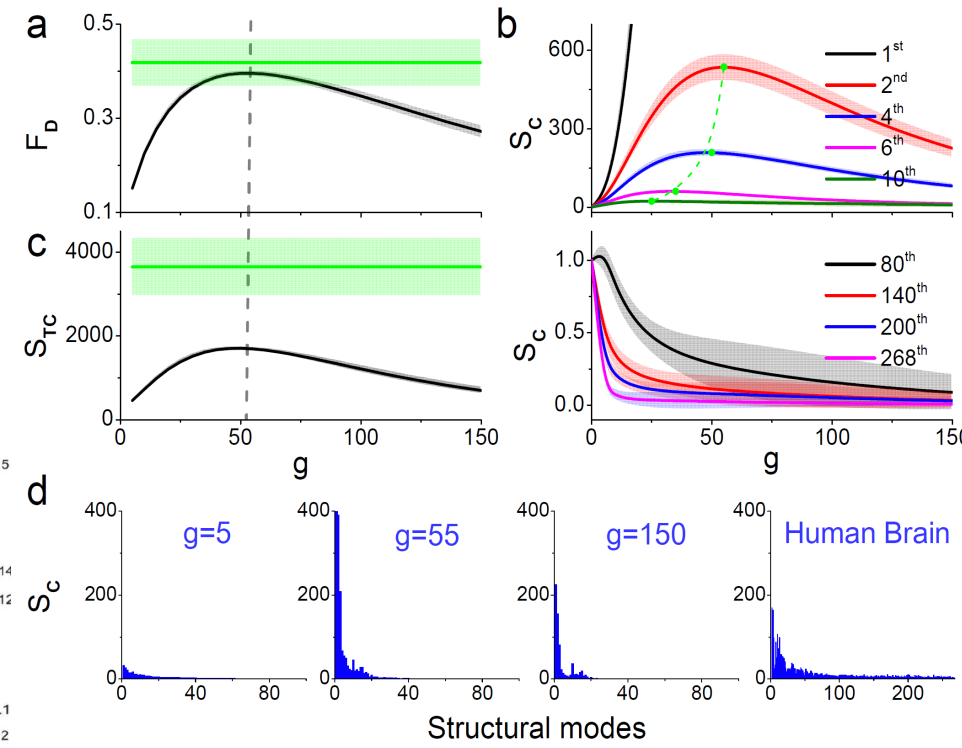
Becker et al., ***Sci Rep*** **(2018)**



Structural Eigenmodes and Resting State fMRI Networks







$$\frac{dx_i}{dt} = -x_i + g\sum_{j=1}^{N} A_{ij}(x_j - x_i) + \sqrt{2}\xi_i$$

Rong Wang, Pan Lin, Yanzin Liu, Ying Wu, Tao Zhou, Changsong Zhou

***Phys Rev Letters* (2019)**

Spectral Graph Models of the Connectome

Linking Across Scales: From Micro- to Meso- to Macro-scale

- Power spectrum of hierarchical modular connectivity

Linking Structural Connectivity to Functional Connectivity

- Noninvasive: fMRI, MEG, fNIRS, DOT, OCT

Parsimonious Description of Altered Connectivity in Disease

- neurodevelopmental
- psychiatric
- neurodegenerative

Linking Across Time: Longitudinal Trajectories of Connectivity

- human brain development and aging
- plasticity due to cognitive/behavioral training or neurostimulation
- treatment monitoring of neurological & psychiatric disorders

qb3 ucb·ucsc·ucsf

Challenges: fast dynamics and their latencies

UCSF University of California San Francisco

Human Brain Connectome: Centerpiece for Translational Neuroscience & Neuroengineering?

Wearable EEG



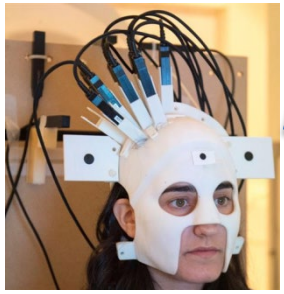
https://dansteer.wordpress.com/tag/eeg

Wearable fNIRS



www.artinis.com

Wearable MEG



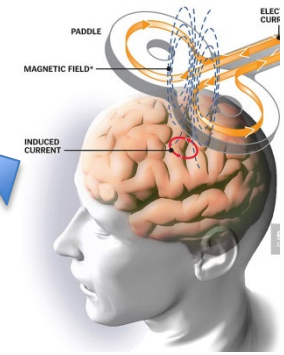
Boto et al. *Nature* (2018)

Connectome



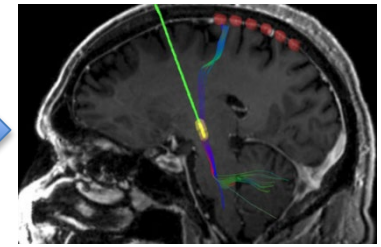
Human Connectome Project
https://thought.artsci.wustl.edu

TMS/TDCS/TACS



LM Oberman, BIDMC

DBS



ucsf.edu

Optogenetics



Boyden et al. *Nat Neurosci* (2005)

communications biology

A Nature Portfolio journal

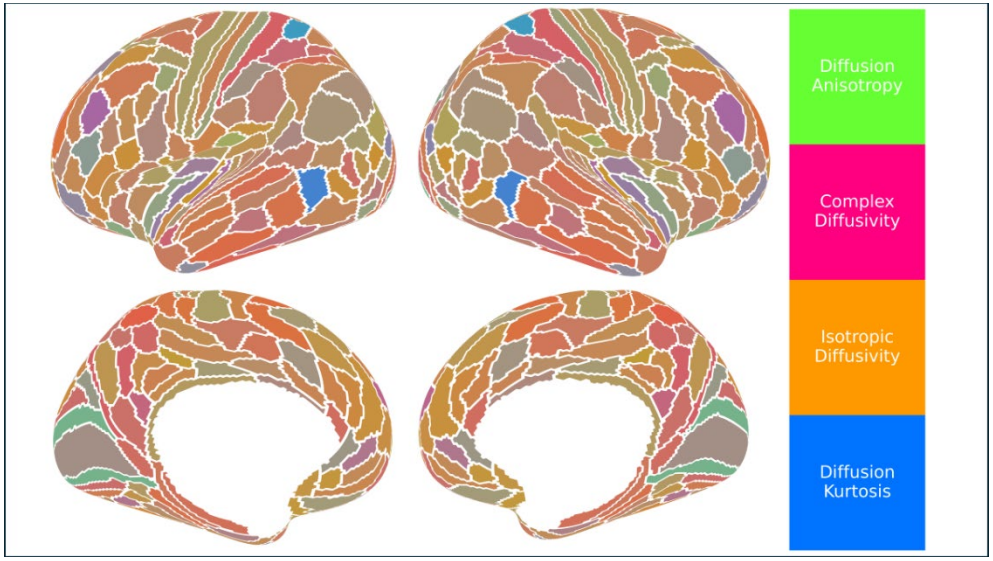
Article

https://doi.org/10.1038/s42003-025-08523-9

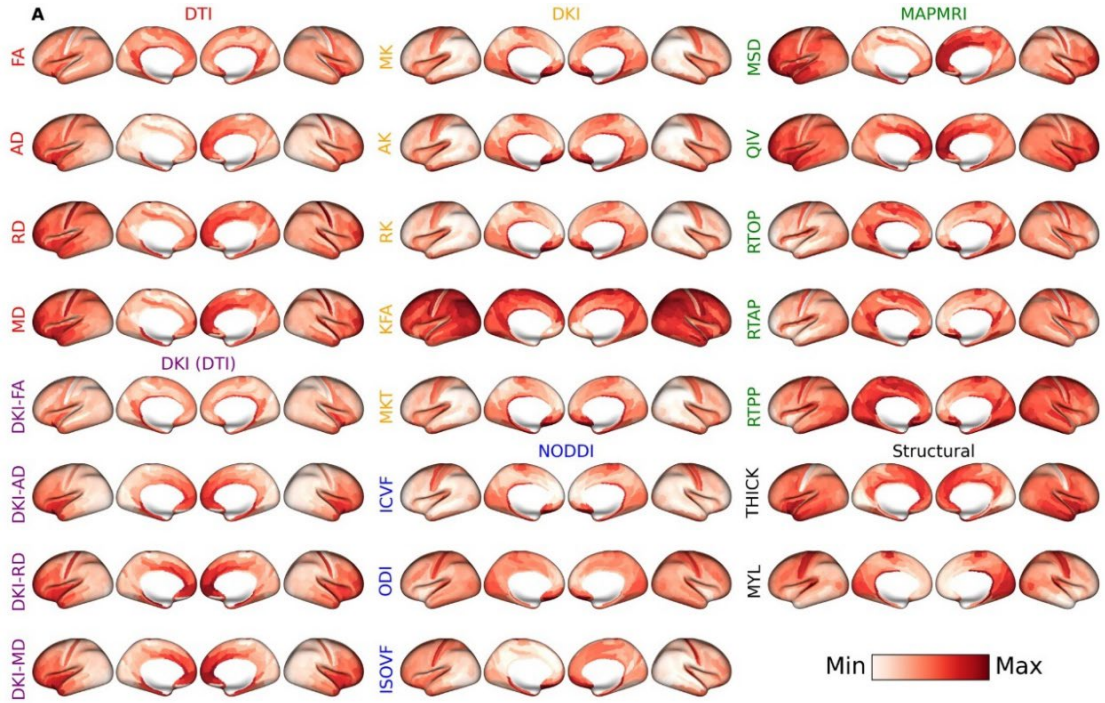
Mapping the microstructure of human cerebral cortex in vivo with diffusion MRI

Check for updates

Amir Sadikov[1,2], Hannah L. Choi[1], Jaclyn Xiao[1], Lanya T. Cai[1] & Pratik Mukherjee[1,2]

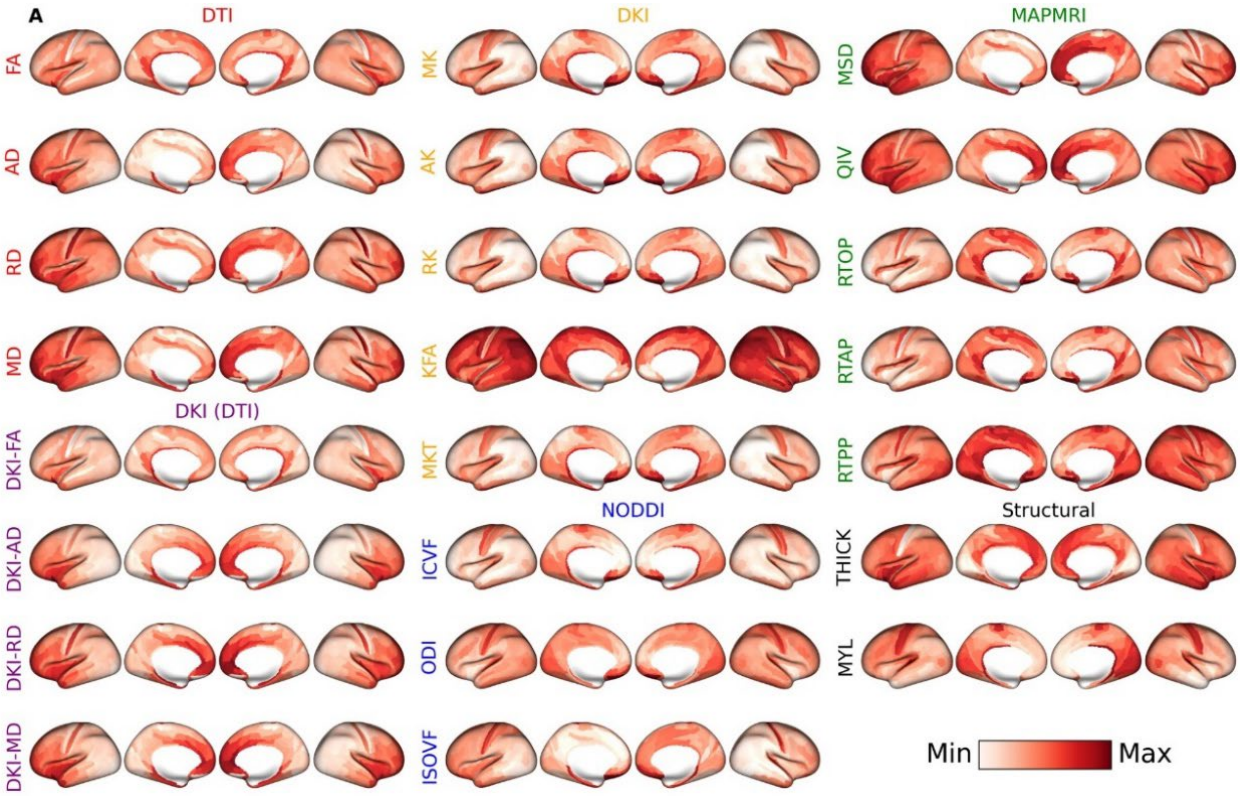


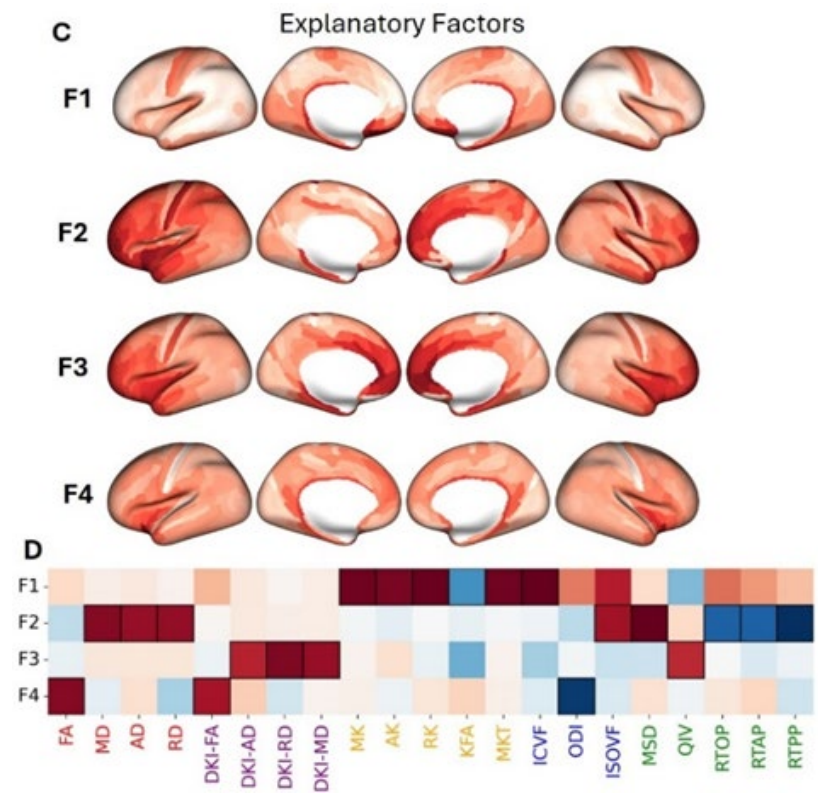
F1: diffusion kurtosis / intracellular volume fraction (ICVF)
F2: mean (homogeneous) diffusivity / free water fraction (ISOVF)
F3: complex (heterogeneous) diffusivity/ extracellular volume fraction
F4: diffusion anisotropy / neurite orientation dispersion index (ODI)



Diffusion Tensor Imaging: rank 2 tensor (Gaussian)
Diffusion Kurtosis Imaging: rank 4 tensor
NODDI: biophysical model of ICVF, ISOVF, & ODI
MAP-MRI: mean apparent propagator (q-space)

Human brain cortical microstructure *in vivo* from diffusion MRI: HCP-YA Data

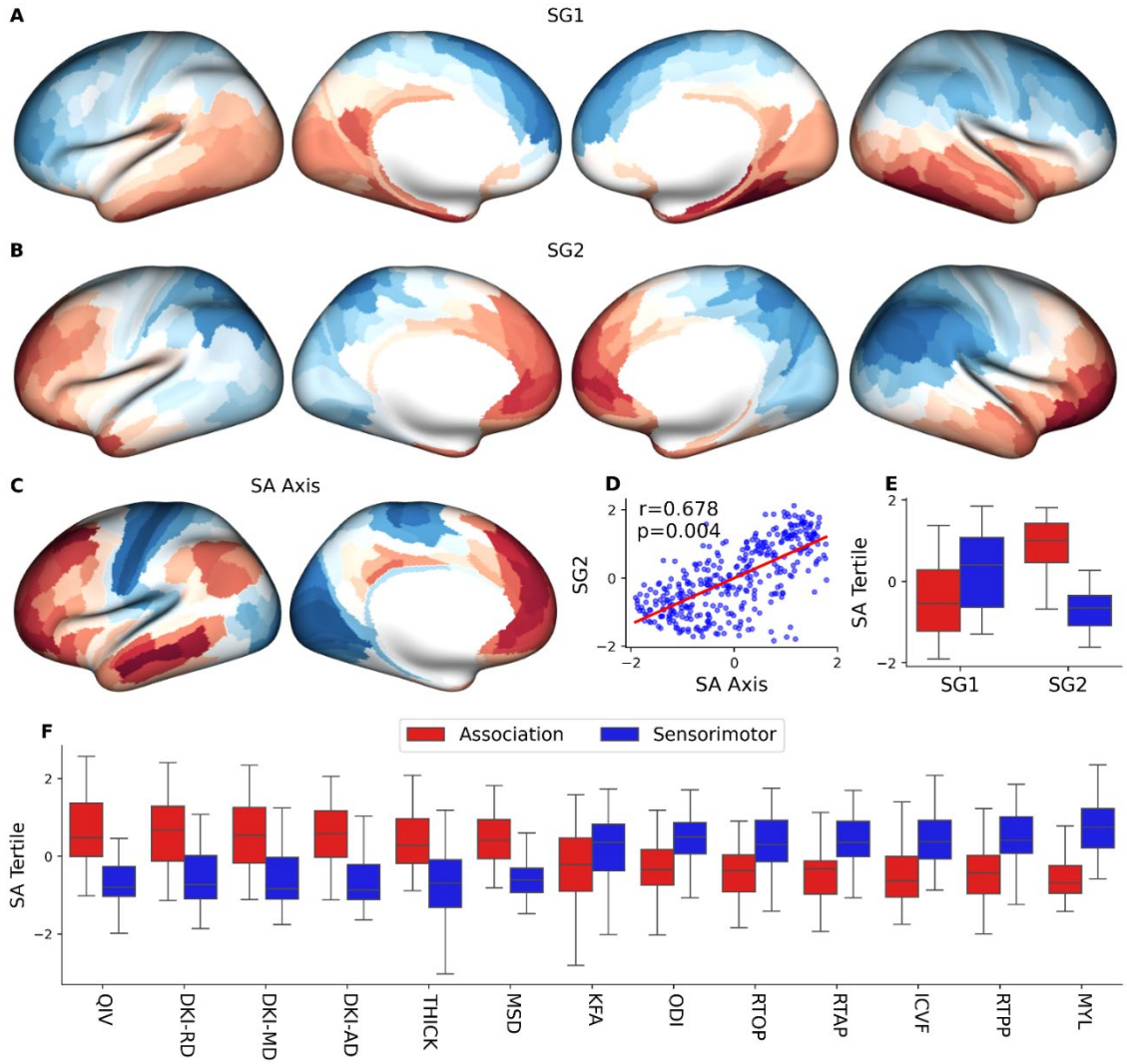




Diffusion Tensor Imaging: rank 2 tensor (Gaussian)
Diffusion Kurtosis Imaging: rank 4 tensor
NODDI: biophysical model of ICVF, ISOVF, & ODI
MAP-MRI: mean apparent propagator (q-space)

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Sadikov A, Choi HL, Xiao J, Cai LT, Mukherjee P. *Commun Biol* (2025)
ISMRM 2025: Abstract #1250



communications biology

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Article

https://doi.org/10.1038/s42003-025-08523-9

Mapping the microstructure of human cerebral cortex in vivo with diffusion MRI

Check for updates

Amir Sadikov[1,2], Hannah L. Choi[1], Jaclyn Xiao[1], Lanya T. Cai[1] & Pratik Mukherjee[1,2]

Cortical Diffusion Spatial Gradients

SG1: Rostro-Caudal Axis

SG2: Sensorimotor-Association (SA) Axis (r=0.68, p=0.004)

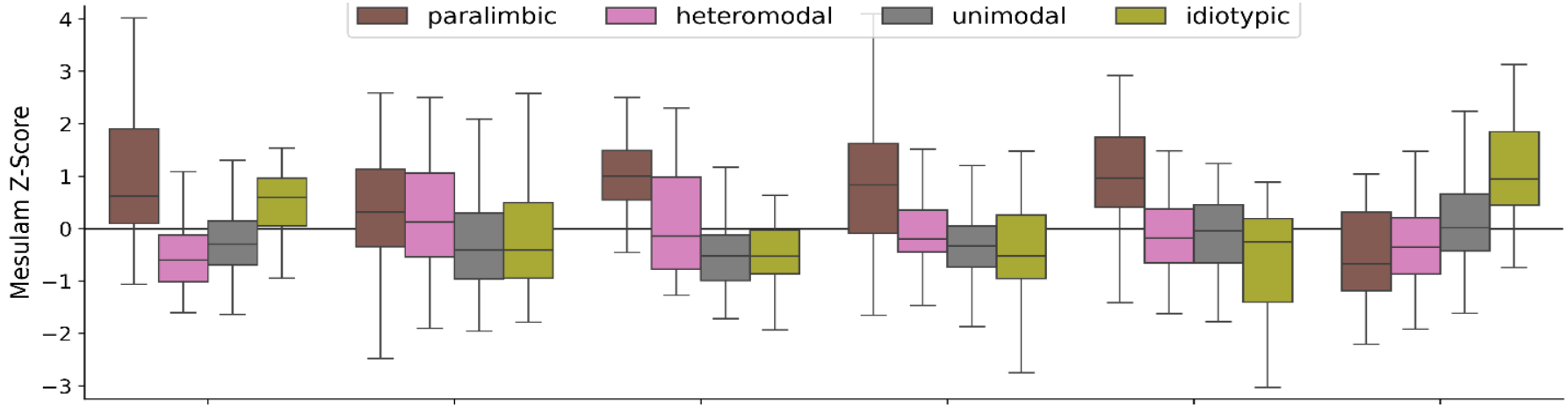
SG2 versus SA Axis Components

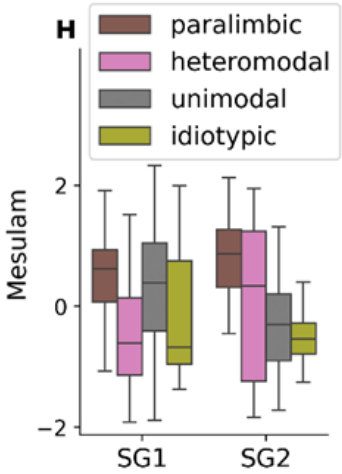
evolutionary areal scaling (r=0.46,p=0.012)

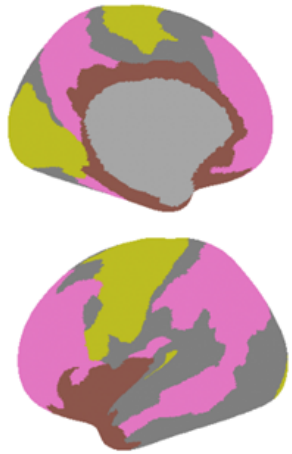
principal component of gene expression (r=-0.73, p=0.002)

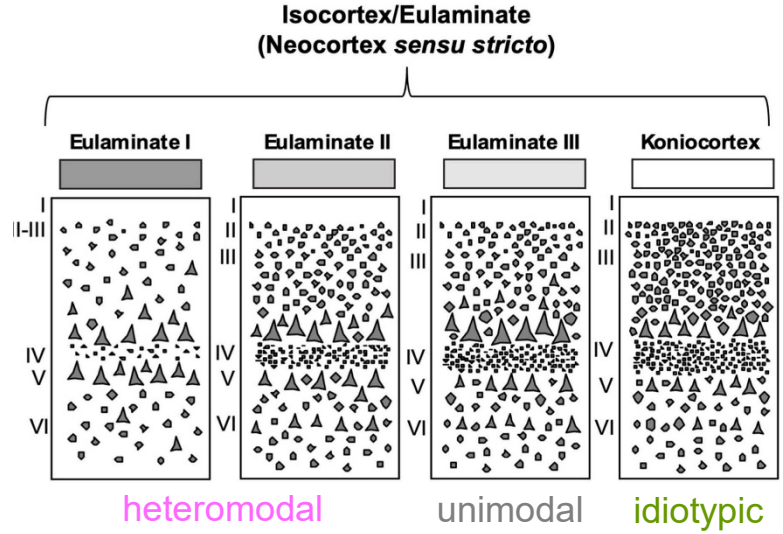
principal gradient of functional connectivity (r=0.50, p=0.023)

Cortical microstructure from dMRI reflects Mesulam's hierarchy of laminar differentiation



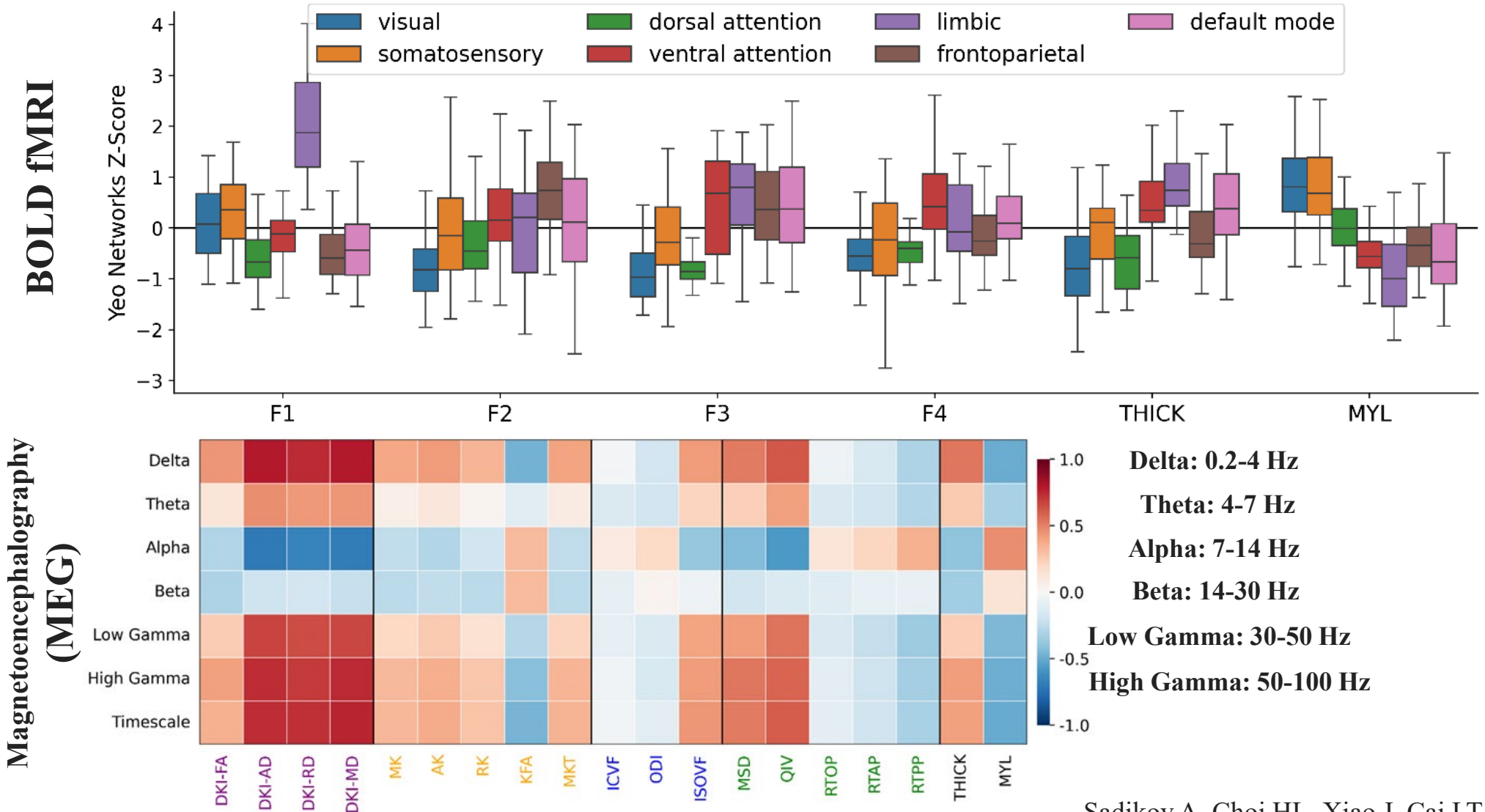






Sanchez-Velasco A et al.,
Front. Neuroanat (2023)
https://doi.org/10.3389/fnana.2023.1187280

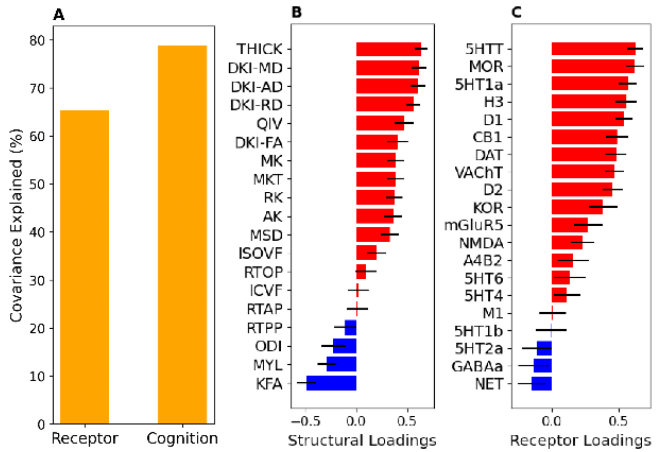
Cortical microstructure from dMRI reflects fMRI networks and MEG neural oscillations

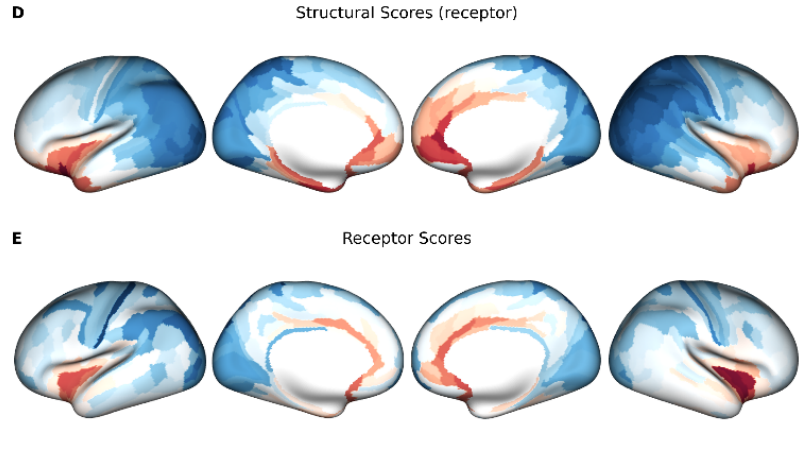


Sadikov A, Choi HL, Xiao J, Cai LT, Mukherjee P. *Commun Biol* (2025)

Cortical microstructure from dMRI reflects neurotransmitter receptor & transporter distributions and also an affective vs cognitive behavioral spatial gradient

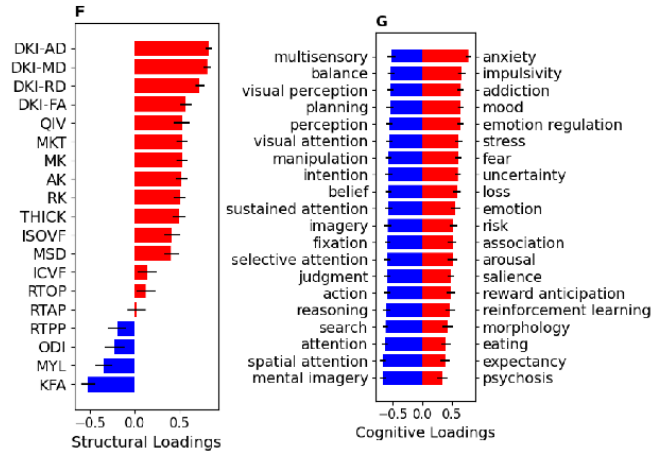
dMRI vs Neurotransmitters

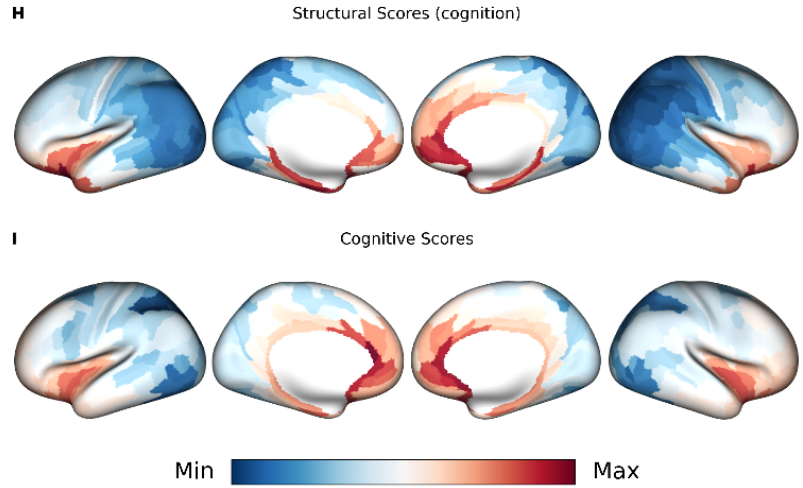




$R^2 = 65\%$
$(p=0.002)$

dMRI vs Cognition/Behavior

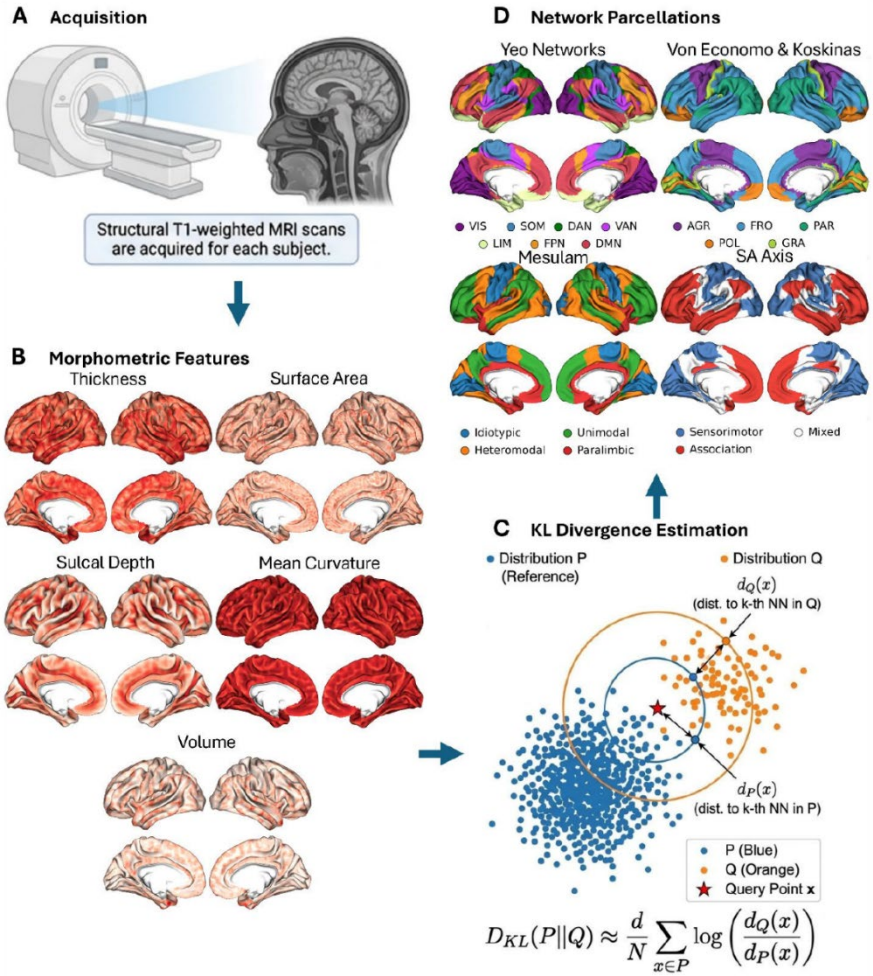


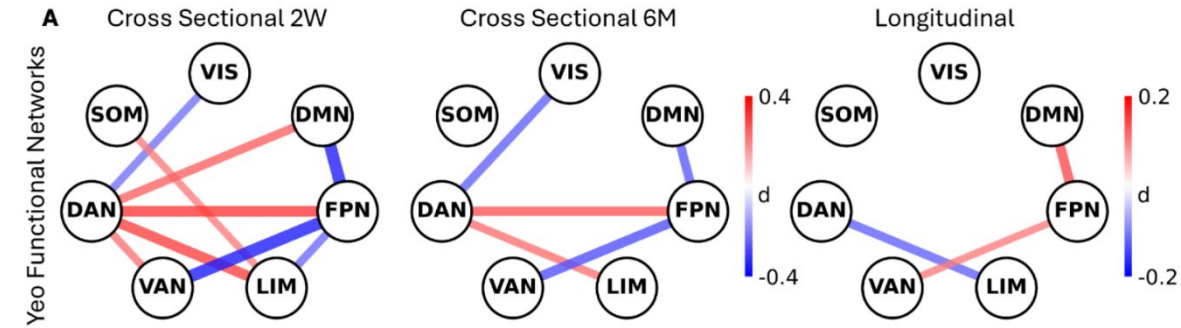


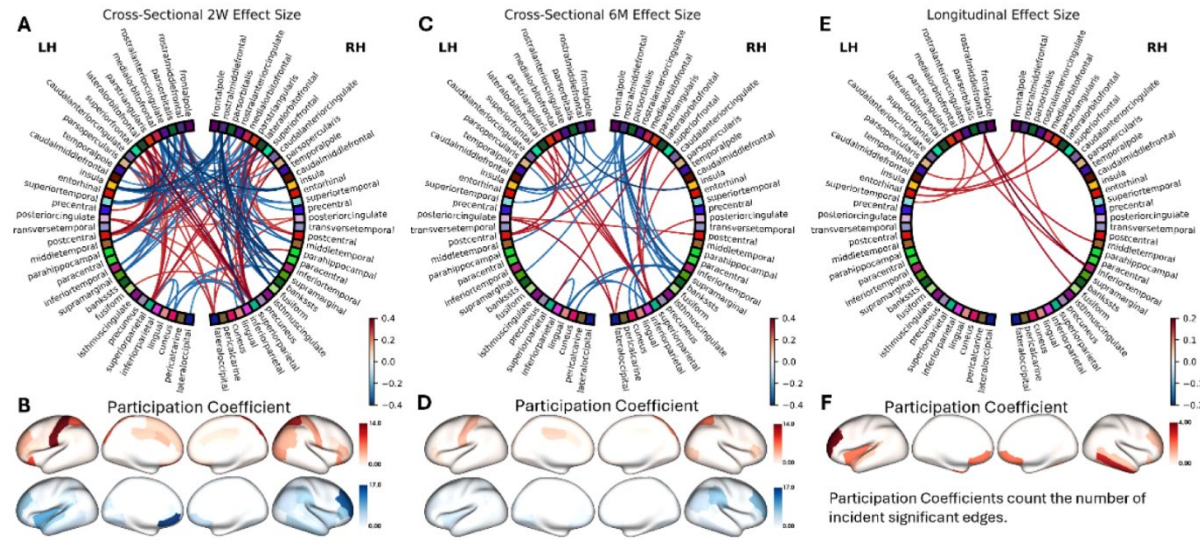
$R^2 = 79\%$
$(p=0.001)$

Sadikov A, Choi HL, Xiao J, Cai LT, Mukherjee P. *Commun Biol* (2025)

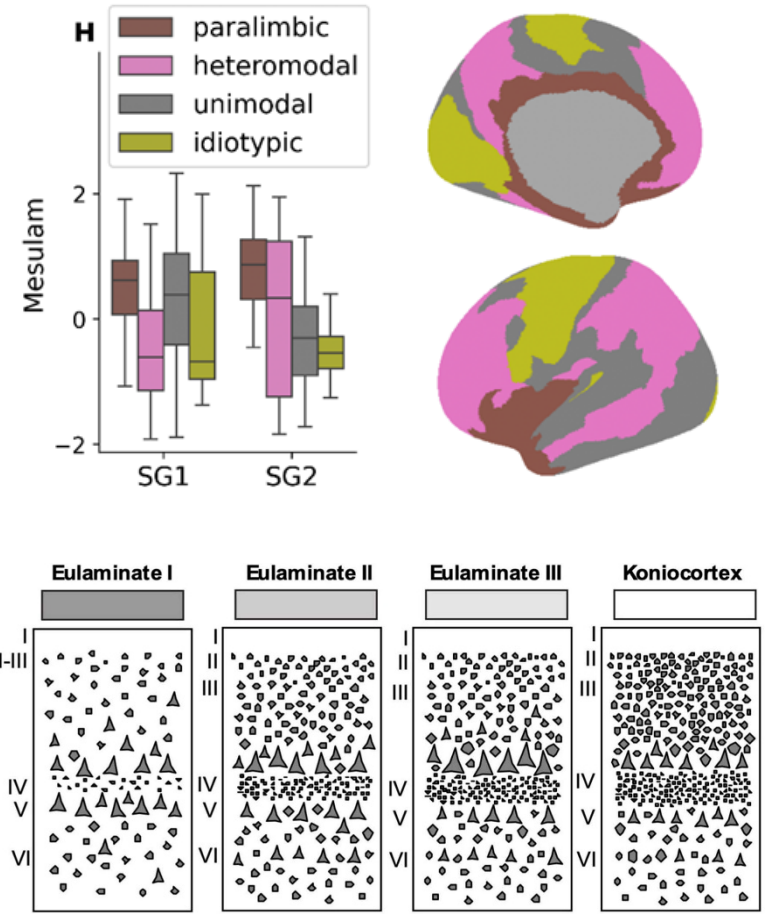
Cortical Gray Matter Morphological Networks from Machine Learning Analysis of 3D T1 MRI



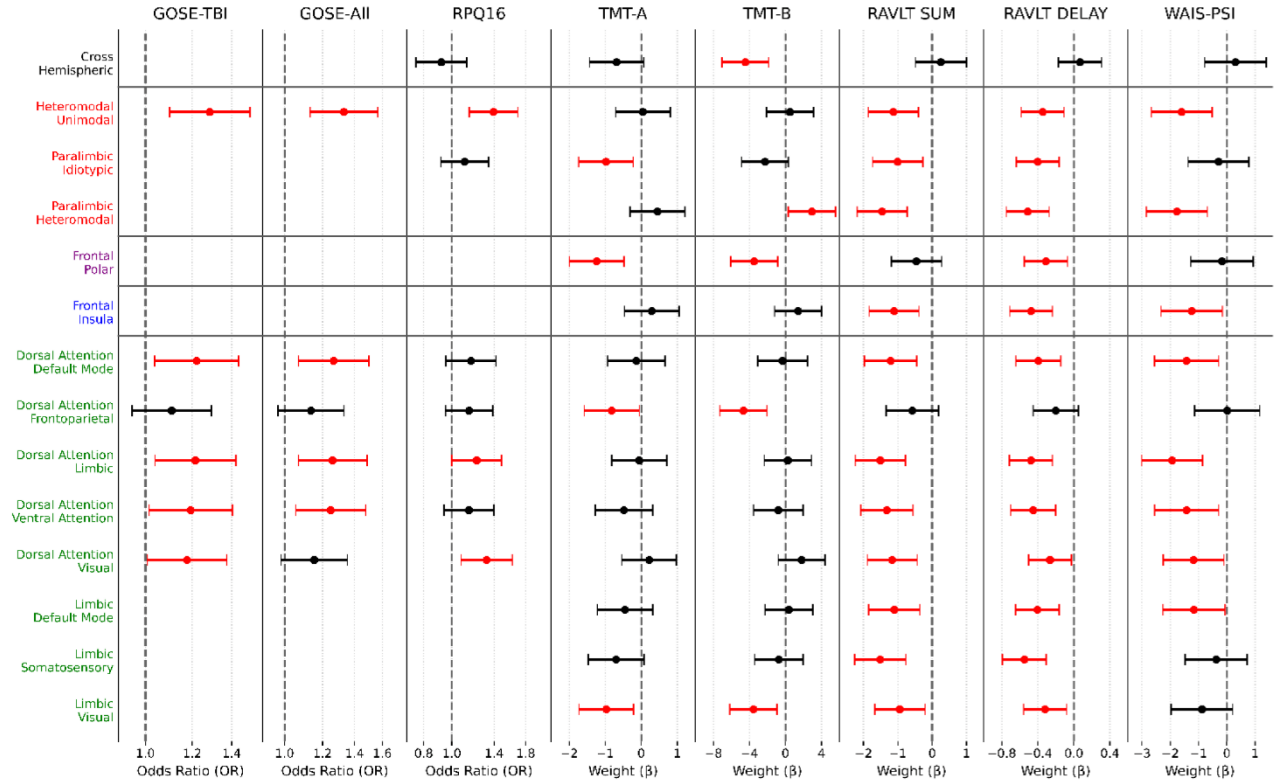




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Sanchez-Velasco A et al.,
Front. Neuroanat (2023)
https://doi.org/10.3389/fnana.2023.1187280



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Title

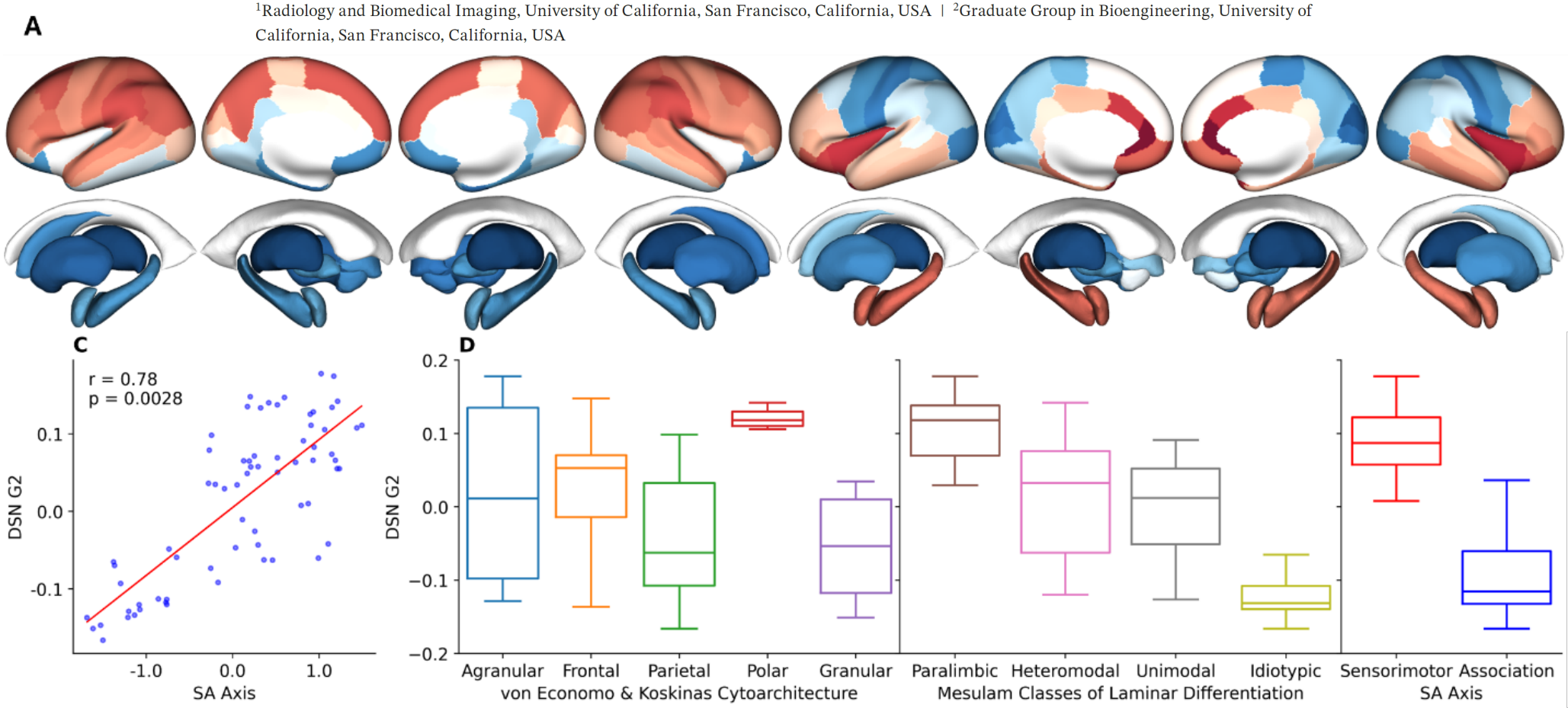
- Full title: **Gray Matter Morphological Networks are Associated with Neurobiological Features, Cognitive Status and Clinical Recovery in Traumatic Brain Injury**
- Short title: Gray Matter Morphological Networks After Trauma

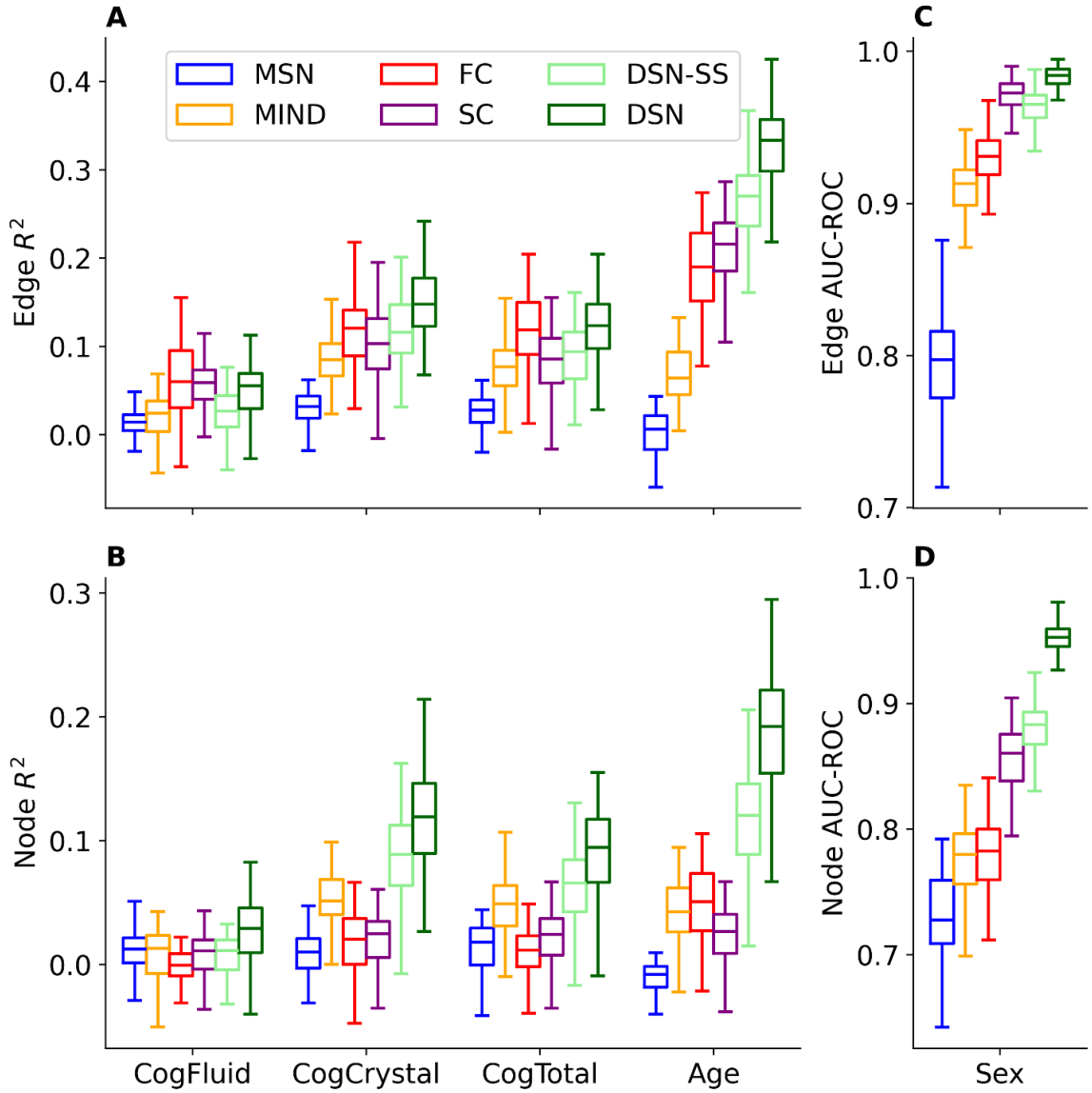
RESEARCH ARTICLE OPEN ACCESS

Estimating Brain Similarity Networks With Diffusion MRI

Amir Sadikov[1,2] | Hannah L. Choi[1] | Lanya T. Cai[1] | Pratik Mukherjee[1,2]

[1]Radiology and Biomedical Imaging, University of California, San Francisco, California, USA | [2]Graduate Group in Bioengineering, University of California, San Francisco, California, USA





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MSN: morphometric similarity network (sMRI)
MIND: morphometric inverse divergence (sMRI)
FC: functional connectome (fMRI)
SC: structural connectome (dMRI tractography)
DSN-SS: diffusion similarity network (single-shell)
DSN: diffusion similarity network (multi-shell)

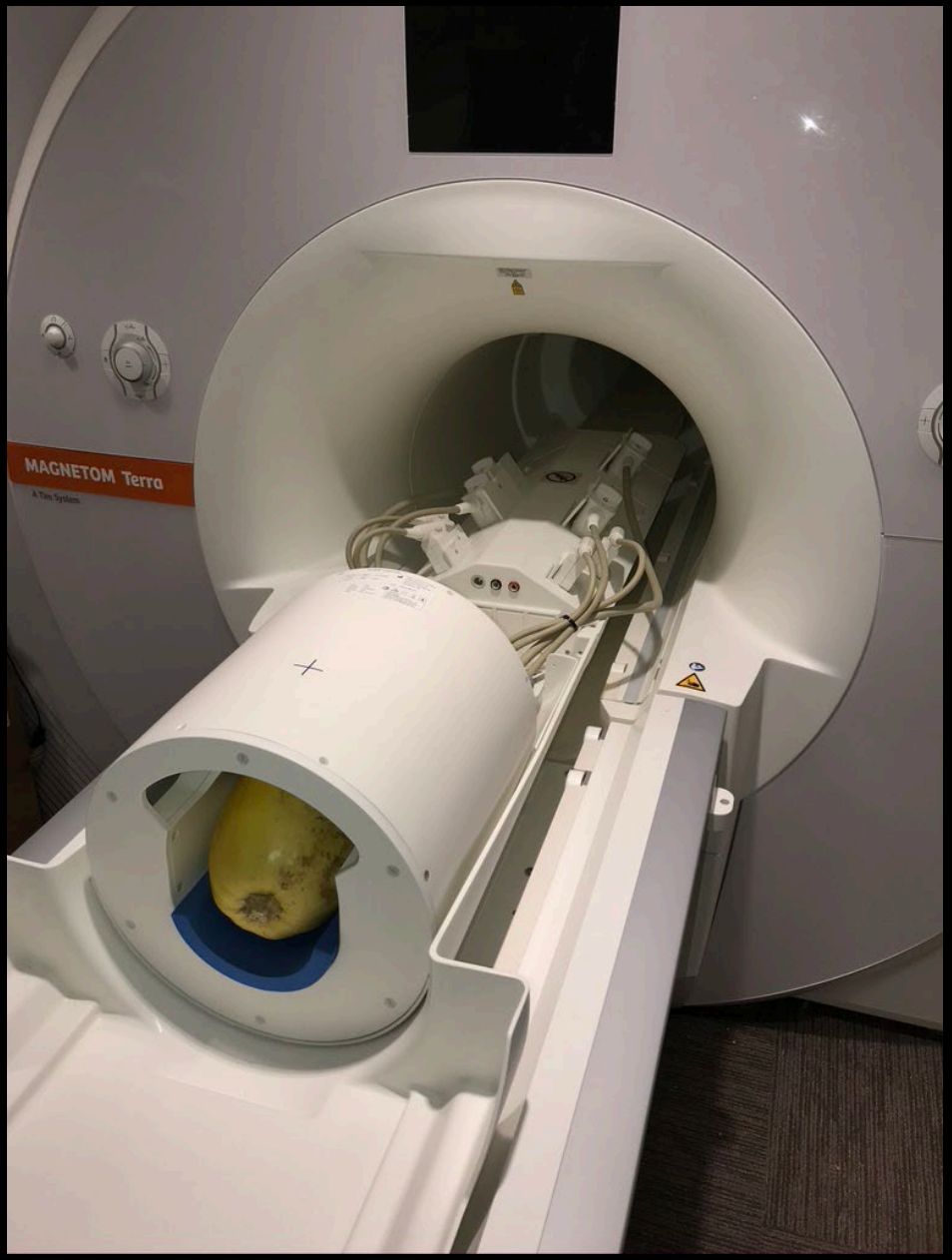
Sadikov A, Choi HL, Xiao J, Cai LT, Mukherjee P. *Human Brain Mapping* (2025)

NextGen 7T with Impulse Gradients

First 7T with 128 channel receiver,
16 channel transmit
and Impulse gradient system

	Standard 7T	NexGen 7T
G_{max}	80 mT/m	200 mT/m
G_{slew}	200 T/m/s	900 T/m/s
GP = $G_{max} * G_{max}$	16,000	180,000
Rx chs	32-64	128
Tx chs	1-8	16

Feinberg, Beckett, Vu et al *Nature Methods* 2023



Mesoscale Resolution (0.9mm isotropic) Diffusion MRI on the NextGen 7T

Wren-Jarvis *et al.*
Journal of Neurodevelopmental Disorders (2024) 16:1
https://doi.org/10.1186/s11689-023-09513-w

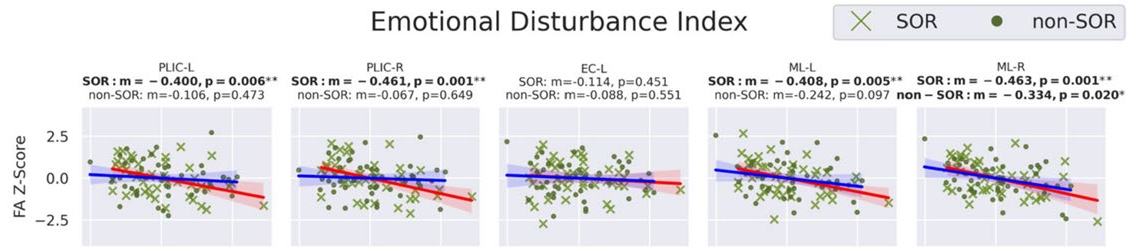
Journal of
Neurodevelopmental Disorders

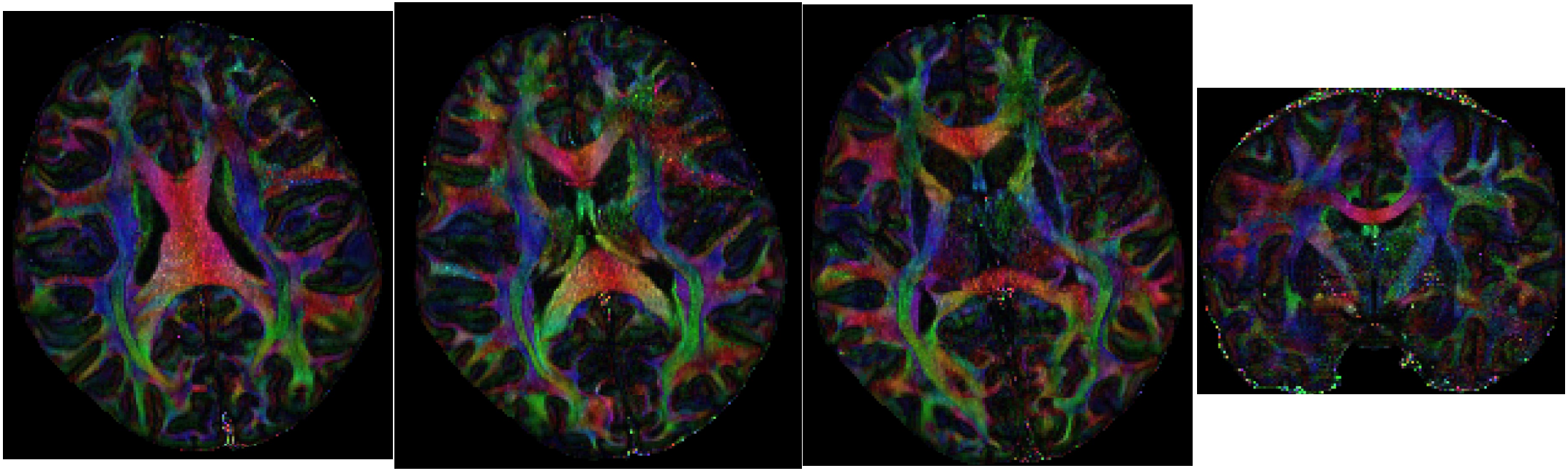
RESEARCH Open Access

White matter microstructure of children with sensory over-responsivity is associated with affective behavior

Jamie Wren-Jarvis[1], Rachel Powers[1,2], Maia C. Lazerwitz[2], Jaclyn Xiao[1], Lanya T. Cai[1], Hannah L. Choi[1], Annie Brandes-Aitken[2], Robyn Chu[2], Kaitlyn J. Trimarchi[2], Rafael D. Garcia[2], Mikaela A. Rowe[3], Mary C. Steele[4], Elysa J. Marco[2,4*] and Pratik Mukherjee[1*]

School-age children ages 8-15 years with sensory processing disorder (SPD)





Hiya Ghosh, Lanya Cai, Joseph An Vu, David Feinberg, Pratik Mukherjee

Sadikov, A., Pan, X., Choi, H., Cai, L.T., & Mukherjee, P. (2024). Generative AI for Rapid Diffusion MRI with Improved Image Quality, Reliability and Generalizability. *Imaging Neuroscience*, Advance Publication. https://doi.org/10.1162/imag_a_00193

Generative AI for Rapid Diffusion MRI with Improved Image Quality, Reliability and Generalizability

Amir Sadikov[1,2], Xinlei Pan[3], Hannah Choi[1], Lanya T. Cai[1], and Pratik Mukherjee[1,2]

[1] Radiology and Biomedical Imaging, University of California, San Francisco
[2] Graduate Group in Bioengineering, University of California, San Francisco
[3] University of California, Berkeley

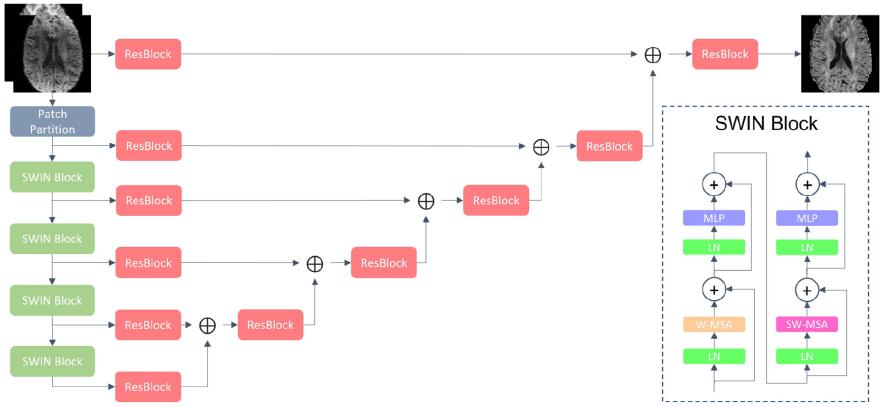
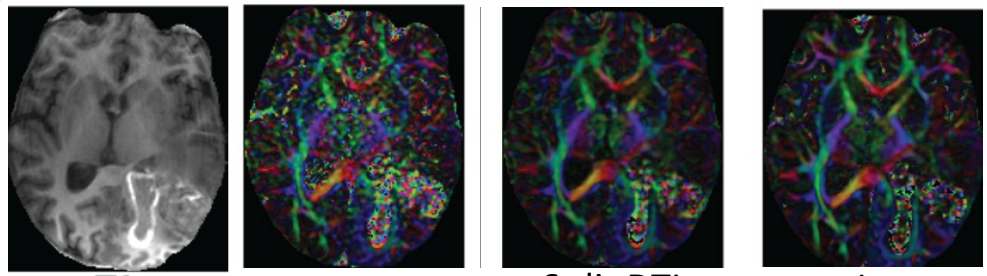


Fig. 1. A general overview of the SWIN architecture. The input is a concatenated 3D T1 and dMRI scan, which is encoded by a Swin transformer at multiple resolutions and fed into a residual convolutional neural net (CNN) decoder, consisting of residual CNN UNet blocks (ResBlocks), to reconstruct the ground truth dMRI scan. The SWIN Block contains LayerNorm (LN), MultiLayer Perceptron (MLP), regular multi-head self-attention (W-MSA), and partitioning multi-head self-attention (SW-MSA) modules.

	HCP	NextGen 7T
Field Strength	3T	7T
Gradients	100/250	200/1000
Receiver Coils	64	128
Transmit Coils	1	32

AI Denoising



Dataset	Tissue	Metric	RAW	P2S	TPCA	MPPCA	BM4D	UNET	SWIN	UNET-F1	SWIN-F1	P-Value
HCP	WM	AD	0.13	0.285	0.126	0.101	0.0848	0.0913	**0.0811**			**2.5e-08**
		FA	0.0935	0.249	0.0994	0.0672	0.0563	0.0556	**0.0496**			**2.2e-19**
		MD	0.0657	0.0695	0.0497	0.0556	0.0483	0.0526	**0.0452**			**7.8e-08**
		RD	0.0773	0.124	0.0635	0.0622	0.0541	0.0558	**0.0488**			**1.0e-13**
		V1	19.7	66.9	15.9	15.2	13.9	13.4	**12.6**			**2.4e-29**
	GM	AD	0.133	0.107	0.0873	0.0903	0.0931	0.0957	**0.0794**			**3.1e-12**
		FA	0.111	0.0793	0.0559	0.0542	0.0588	0.0569	**0.0484**			**8.53-14**
		MD	0.0723	0.0728	0.0655	0.07	0.0683	0.0725	**0.0597**			**8.8e-11**
		RD	0.0849	0.0814	0.0695	0.0731	0.0719	0.0754	**0.0626**			**2.0e-12**
		V1	33.6	64.1	30.1	28.7	28.1	28.4	**26.7**			**4.6e-21**
TBI	WM	AD	0.211	0.295	0.148	0.173	0.206	0.133	0.131	0.14	**0.13**	**1.8e-24**
		FA	0.145	0.229	0.0986	0.117	0.14	0.0866	0.0922	0.0864	**0.0808**	**3.5e-25**
		MD	0.0941	0.0966	0.0767	0.0886	0.0907	0.0743	0.073	0.0784	**0.0702**	**5.3e-16**
		RD	0.116	0.138	0.0865	0.103	0.111	0.0841	0.085	0.0848	**0.076**	**3.5e-21**
		V1	26.6	67.1	23.3	24.2	26.1	21.5	22.1	21.8	**21.0**	**7.0e-29**
	GM	AD	0.218	0.136	0.135	0.173	0.217	0.147	0.149	0.151	**0.127**	**4.6e-04**
		FA	0.181	0.0966	0.0955	0.139	0.175	0.102	0.123	0.102	**0.0949**	2.5e-01
		MD	0.0908	0.0897	0.0889	0.089	0.0893	0.0905	**0.0809**	0.0926	0.0817	**3.9e-08**
		RD	0.124	0.0982	0.0983	0.11	0.12	0.102	0.102	0.104	**0.0948**	**4.8e-02**
		V1	38.0	62.0	39.1	36.6	37.6	35.5	36.2	35.6	**35.0**	**4.5e-22**

AI Super-Resolution ("Upsampling")

