Machine learning and low-field MRI: unlocking a new class of portable scanners

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14 March 2025

Athinoula A. Martinos Center For Biomedical Imaging

Disclosures

Founder & equity holder:
- Hyperfine
- BlinkAI (acquired 2021)
- Vizma Life Sciences
- Intact Data Services
- Q4ML
- Greenlight Quantum
- YMRI

Scientific Advisory Board:
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Consulting:
- DeepSpin
- Chipiron
- Nudge Workbench

Machine learning and low-field MRI: unlocking a new class of portable scanners

"Bay Zero", Bldg 75, CNY

Athinoula A. Martinos Center For Biomedical Imaging

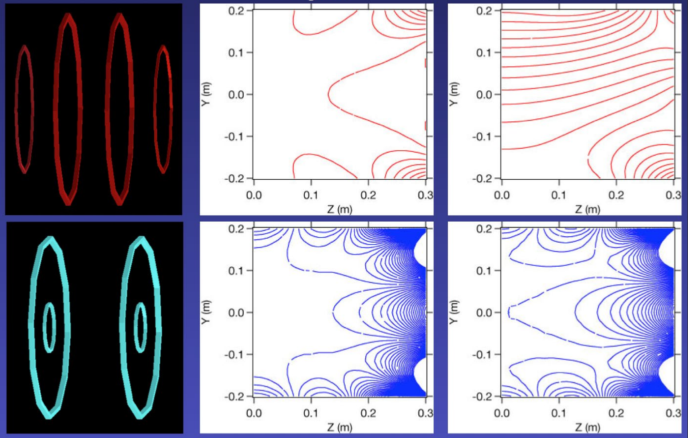
20 years ago: DIY 6.5 mT

Design of an optimized open-access human-scale MRI magnet for orientational lung study

ISMRM 2004

M. S. Rosen[1], L. L. Tsai[1,2], R. W. Mair[1], R. L. Walsworth[1]
[1]Harvard-Smithsonian Center for Astrophysics, Cambridge, MA, United States, [2]Harvard-MIT Division of Health Sciences and Technology, Cambridge, MA, United States


Leo Tsai



(20 ppm field lines)

Main flange


220 cm OD!


Anti-eddy-current slotting

Winding the big coils


163 turns ~ 1 km

Lofting the big coils…


Flying the first flange


Aligning & mounting

Bare Flange: 200 lbs
1 km of Gauge 6 Copper: 400 lbs

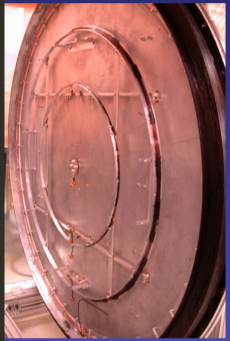
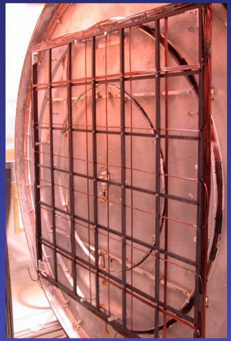
B0 power supply



Alpha supply, c. 1982. 110 A, 100 V, 20 ppm/day

2nd generation human low-field MRI system

(now awaiting B0 supply repair…)


Funding: NASA, NSF, and Smithsonian

^{3}He lung imaging at 6.5 mT

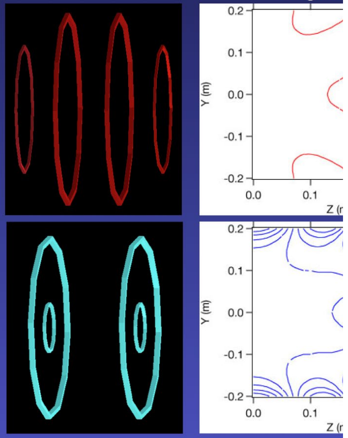
2008

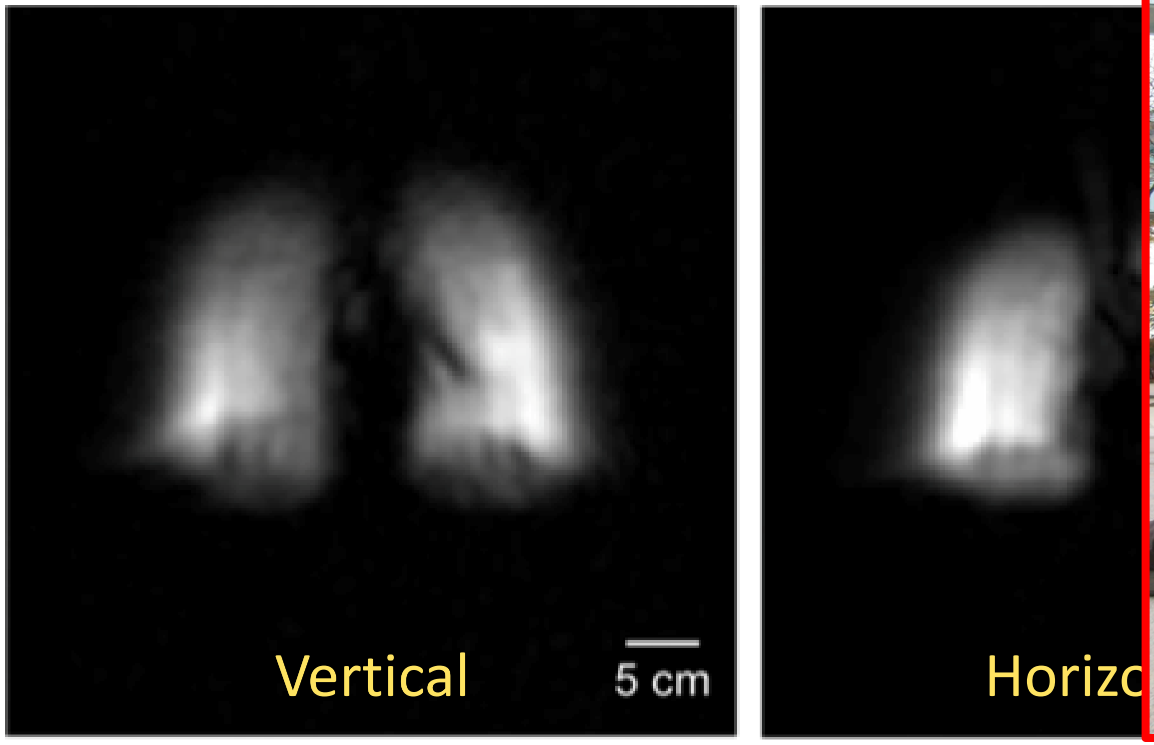
Contents lists available at ScienceDirect
Journal of Magnetic Resonance
journal homepage: www.elsevier.com/locate/jmr
ELSEVIER
JMR

An open-access, very-low-field MRI system for posture-dependent ^{3}He human lung imaging

L.L. Tsai [a,b,c], R.W. Mair [a,*], M.S. Rosen [a,d], S. Patz [c,e], R.L. Walsworth [a,d]

Aligne

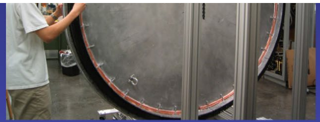




2009

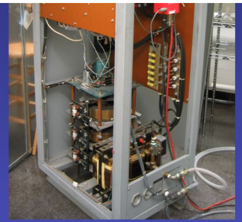
Lofting the big coils…

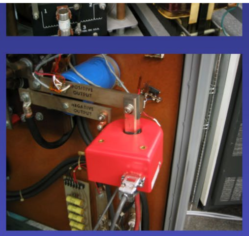
Flying the first flange



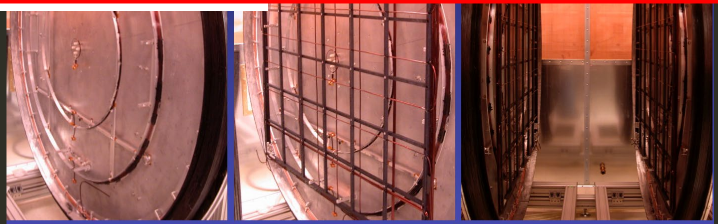
Aligning & mounting

Bare Flange: 200 lbs
1 km of Gauge 6 Copper: 400 lbs





Alpha supply, c. 1982. 110 A, 100 V, 20 ppm/day



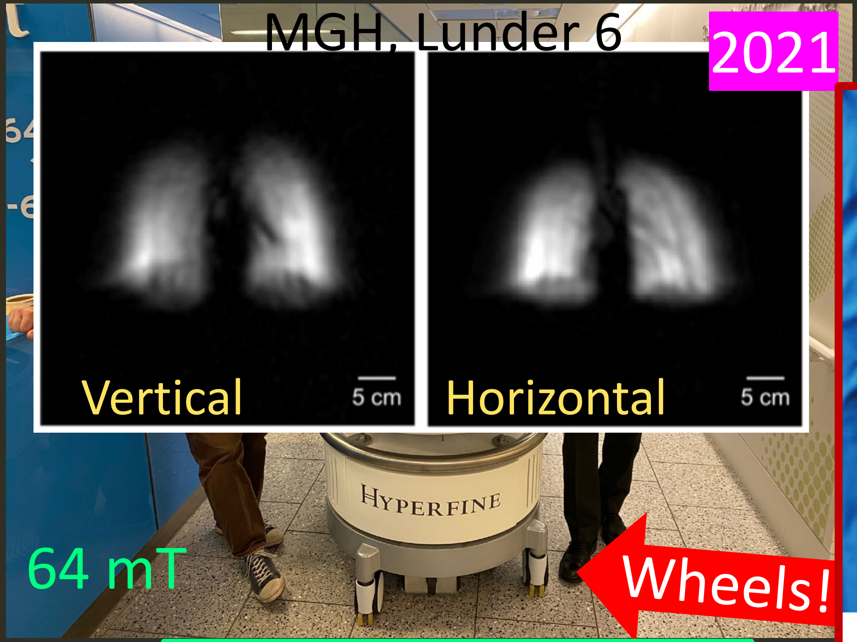
Funding: NASA, NSF, and Smithsonian

Low field: incidental vs intentional

“It enables MRI operation anywhere”

Hyperpolarized ^{3}He

“It was easier”



ISMRM Workshop on

Low Field MRI

17-18 March 2022

Online Virtual Workshop

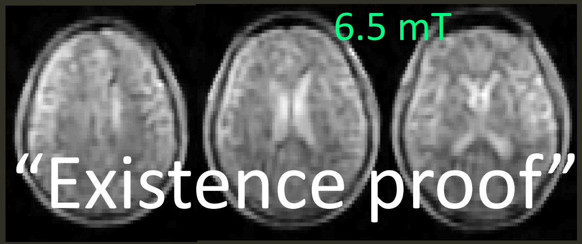

FEATURES

Hyperfine's Swoop, the first U.S. FDA–approved low-field brain scanner, can be wheeled to a patient's bedside.

2023

MRI FOR ALL

Portable low-field scanners could revolutionize medical imaging in nations rich and poor—if doctors embrace them *By* **Adrian Cho**




HEADLINES INVENTION OF THE MONTH

2010

THE DIY MRI

An MRI machine built in a basement is the first to show how we really breathe

STAND AND DELIVER Matthew Rosen's lung imager, shown here in his new lab, can scan standing patients to reveal airflow in normal upright conditions.

HOW TO LOOK AT A LUNG

In 2002, Matthew Rosen won a NASA grant to study how gravity affects the lungs. He soon found out what lung specialists already know: An MRI scanner reveals how well a lung moves air, but it only works ...

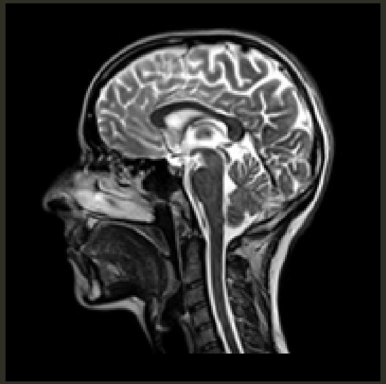
- Some applications honestly benefit from low field
- Exploit strategies that leverage compute

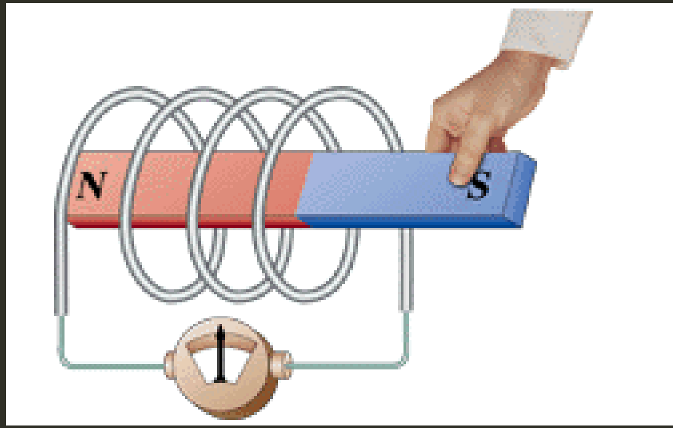
What do we measure in MRI?

3 T

VERY SMALL!

Nuclear polarization: $P \approx \mu B / k_B T$





Inductive detection

Ultra-low field MRI?

3 T

×460

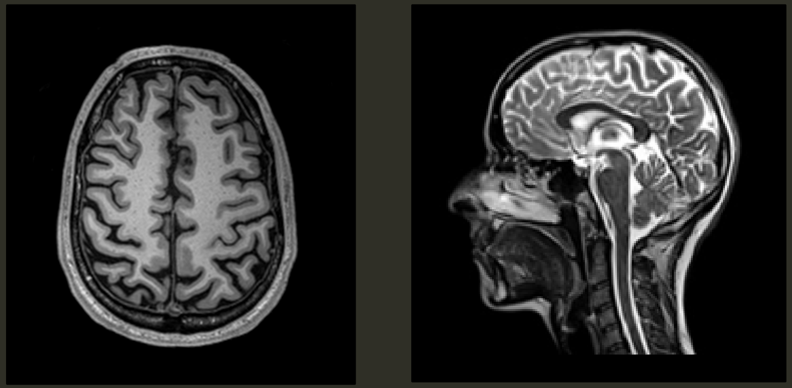
Magnetic field

×10,000

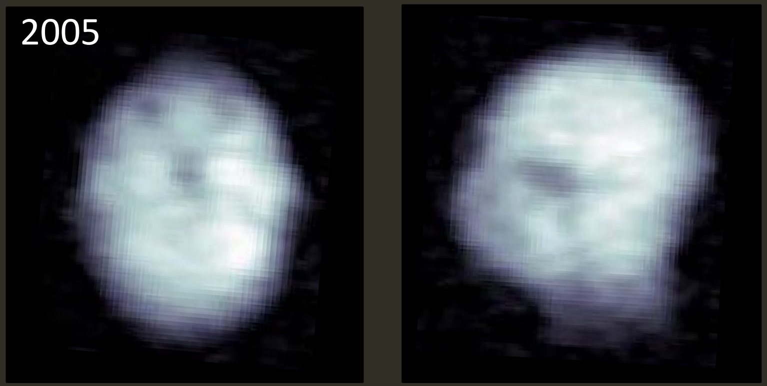
Signal-to-noise

VS

0.0065 T



Acquisition time: seconds, minutes…



2D Gradient echo – 1 slice – acquired at ULF

Acq. time = 52 min / Voxel size = (3.9 x 7.8 x 15) mm^3

How to solve a hard problem

Enabling MRI at ultra-low field

1. Physics
   - High-efficiency sampling strategies
   - Low-noise detectors

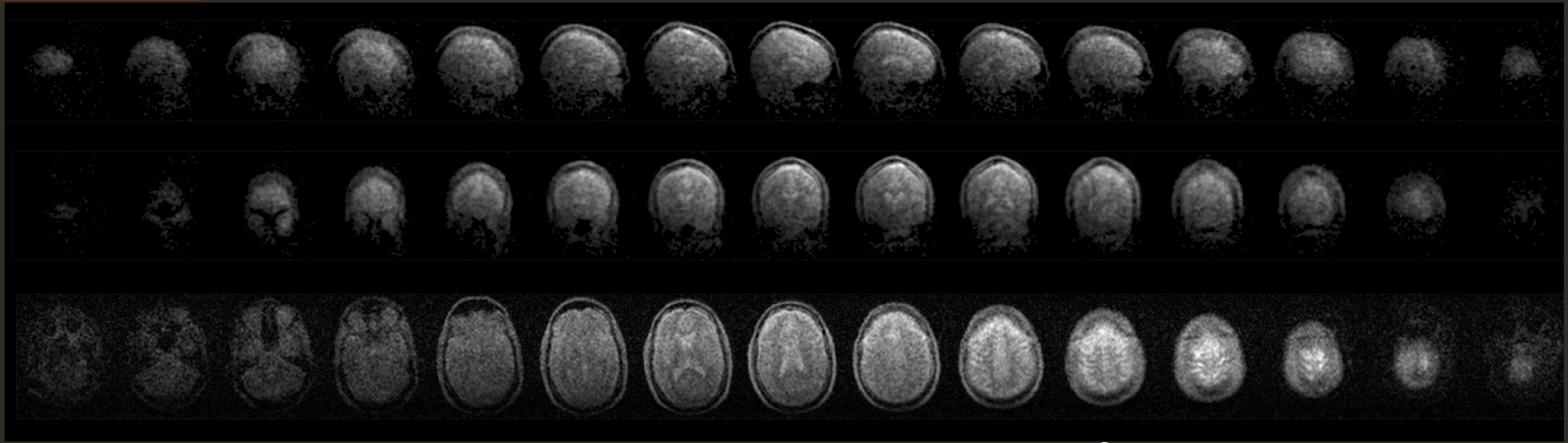
   } Maximize acquisition SNR

2. Compute
   - Magnetic resonance fingerprinting
   - Deep learning reconstruction

   } Reduce noise AKA “fix it in post”

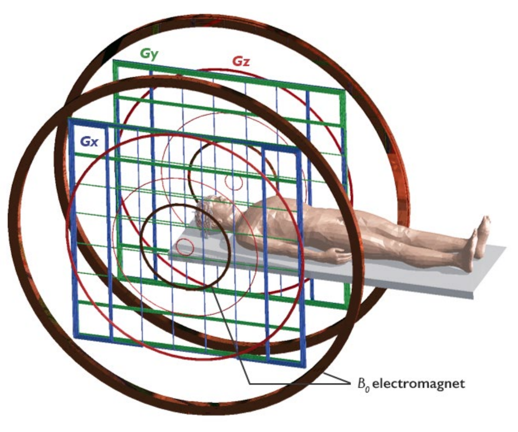

2015
www.nature.com/scientificreports
SCIENTIFIC REPORTS
OPEN
Low-Cost High-Performance MRI
Mathieu Sarracanie[1,2], Cristen D. LaPierre[1,2], Najat Salameh[1,2,3], David E. J. Waddington[1,2,4], Thomas Witzel[1] & Matthew S. Rosen[1,2,5]

Brain imaging at 6.5 mT



6 min, 3D b-SSFP, NA=30, 50% US, α=70°, 64x75x15

Sagittal, Coronal, Axial: 2.5 x 2.5 x 8 mm

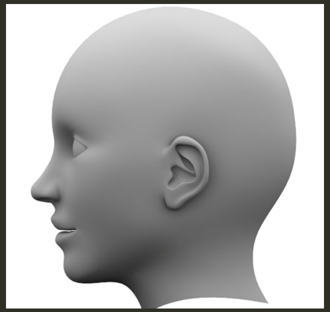


Single slice
2D GE
52 minutes

Image acquisition and reconstruction

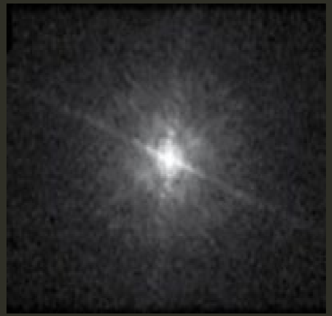
"Can't improve signal? Just reduce noise!"

Object



Acquisition Encoding

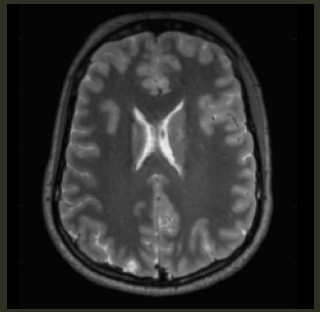
Sensor Domain



Ultras[illegible]space

Reconstruction

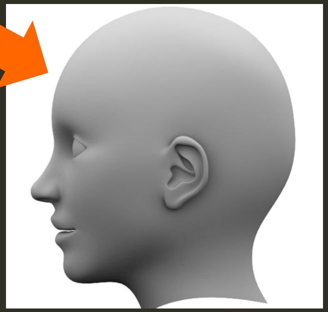
Image



MRI acquisition and reconstruction

1. NMR inductive detection
2. ϕ and ω modulated by magnetic gradient fields

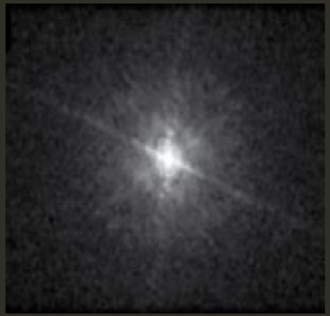
Object



“Signal”

Acquisition Encoding

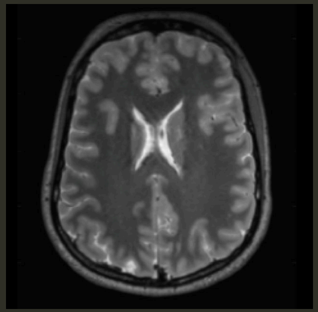
Sensor Domain



Fourier k-space

Reconstruction

Image



Fourier Transform

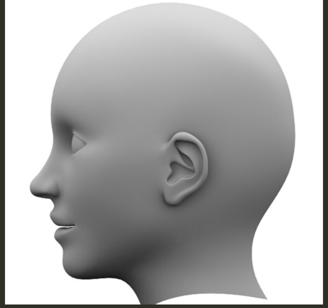
Inverse Fourier Transform

$$S(t) = \int_x \int_y m(x,y) e^{-i\omega_0} \qquad |dxdy$$

2D Cartesian MRI forward encoding model

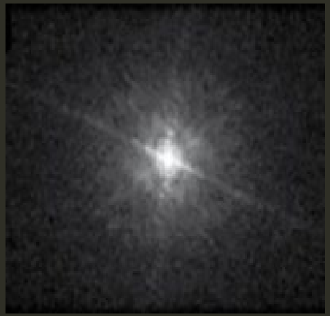
MRI acquisition and reconstruction

Object



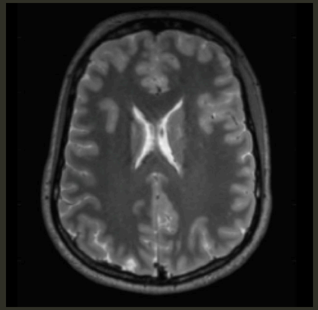
Acquisition Encoding

Sensor Domain



Reconstruction

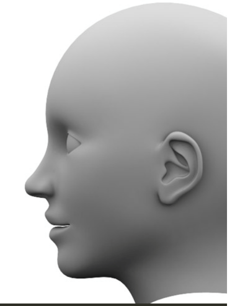
Image

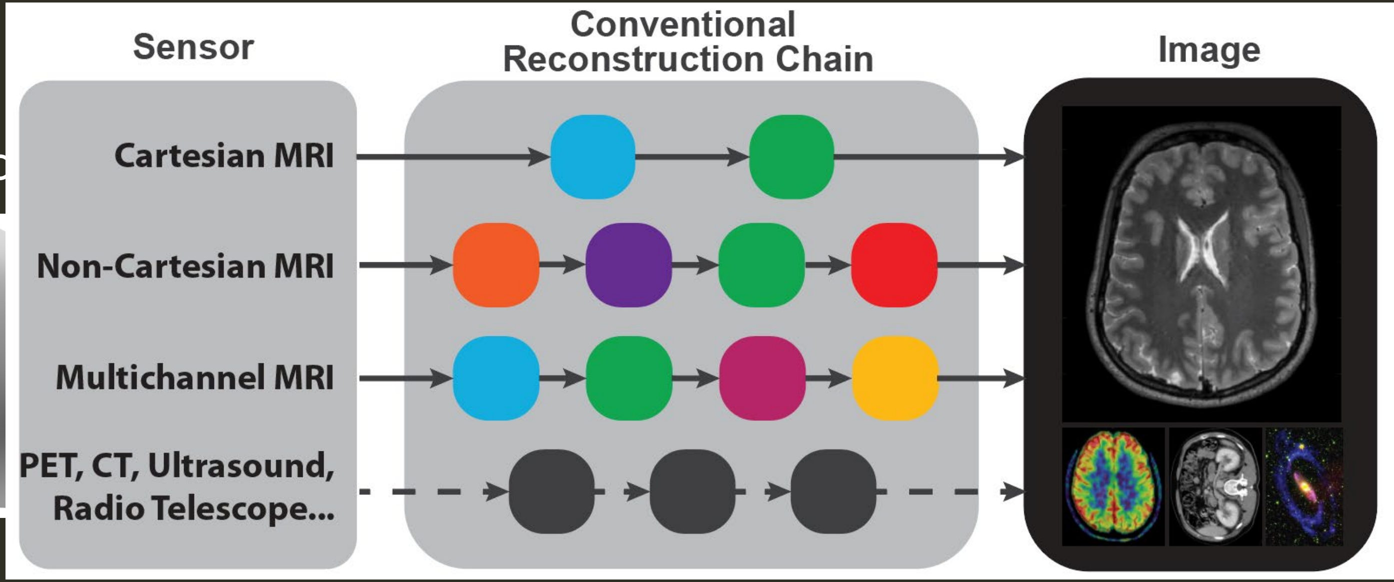


Fourier Transform	Inverse Fourier Transform
Non-Cartesian Sampling	Gridding, Density Compensation
Parallel/Multichannel Rx	Coil Compression, autocalibration, nonlinear optimization
Undersampling	Sparsifying transform, CG optimization, backtracking line search

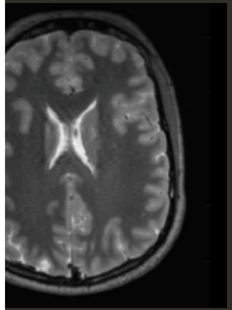
MRI acquisition and reconstruction

Objec





Image



Fourier Transform — Inverse Fourier Transform

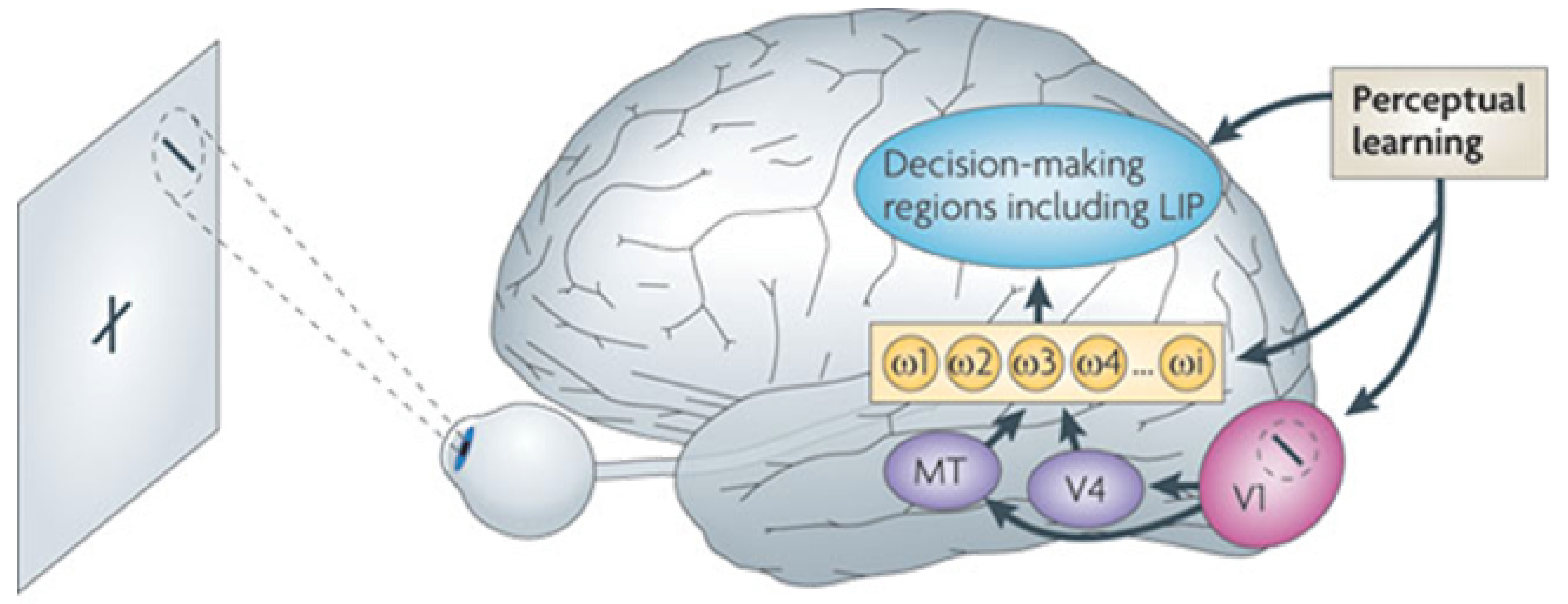
Non-Cartesian Sampling — Gridding, Density Compensation

Parallel/Multichannel Rx — Coil Compression, autocalibration, nonlinear optimization

Undersampling — Sparsifying transform, CG optimization, backtracking line search

Inspiration: biological perceptual vision

Refinement of perception based on exposure to and training on stimuli

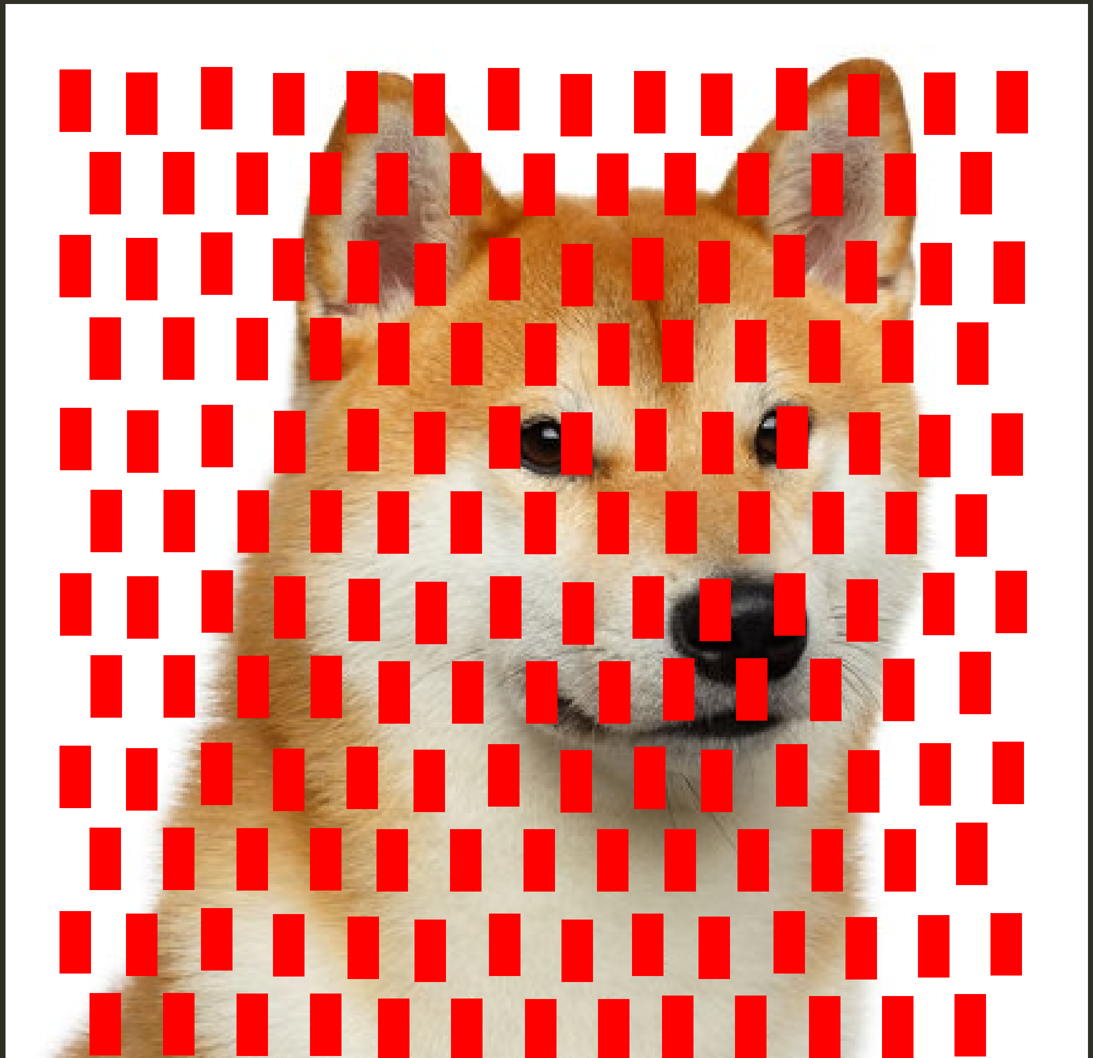


Sasaki, Yuka, Jose E. Nanez, and Takeo Watanabe. "Advances in visual perceptual learning and plasticity." *Nature Reviews Neuroscience* 11.1 (2010): 53-60.

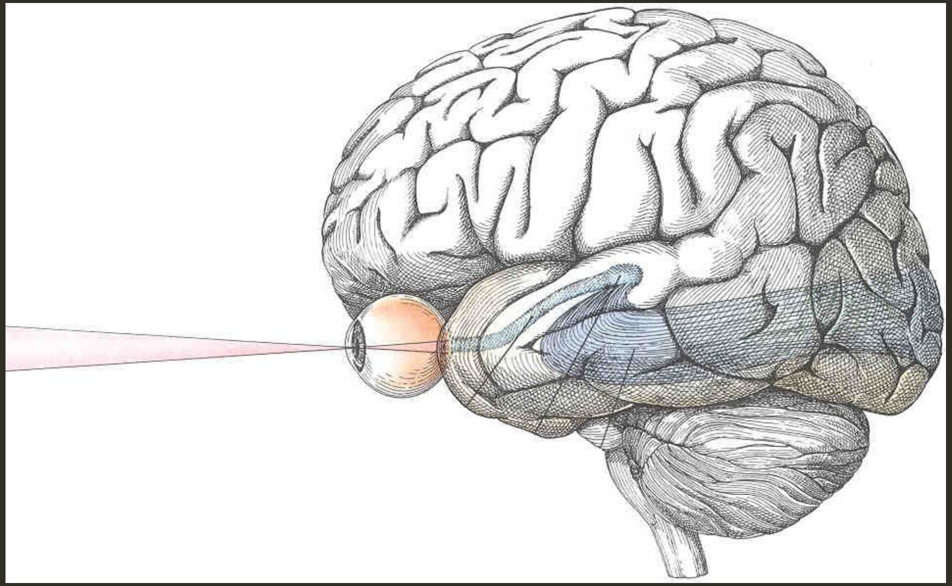
→ Perceptual learning is critical to robust performance in low-SNR settings

Lu, Z.-L., et al. Visual perceptual learning. *Neurobiology of Learning and Memory* **95,** 145–151 (2011)

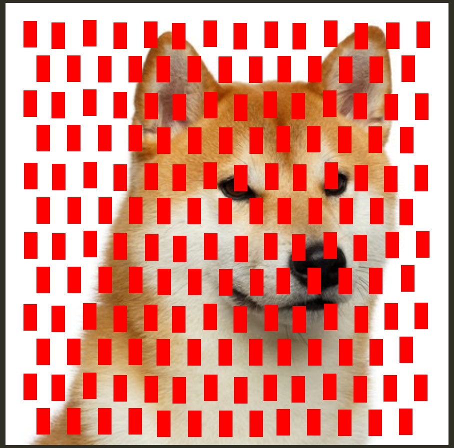
What animal is this?

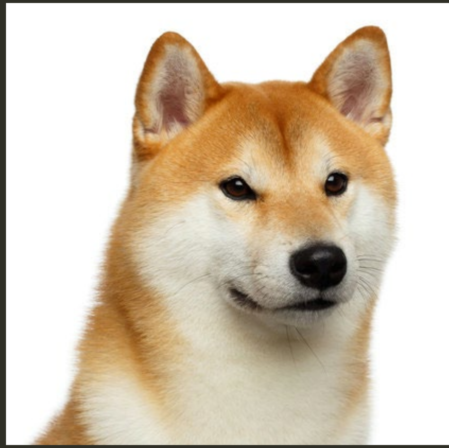


Your brain learns from seeing many examples



- Under-sampled
- Low SNR



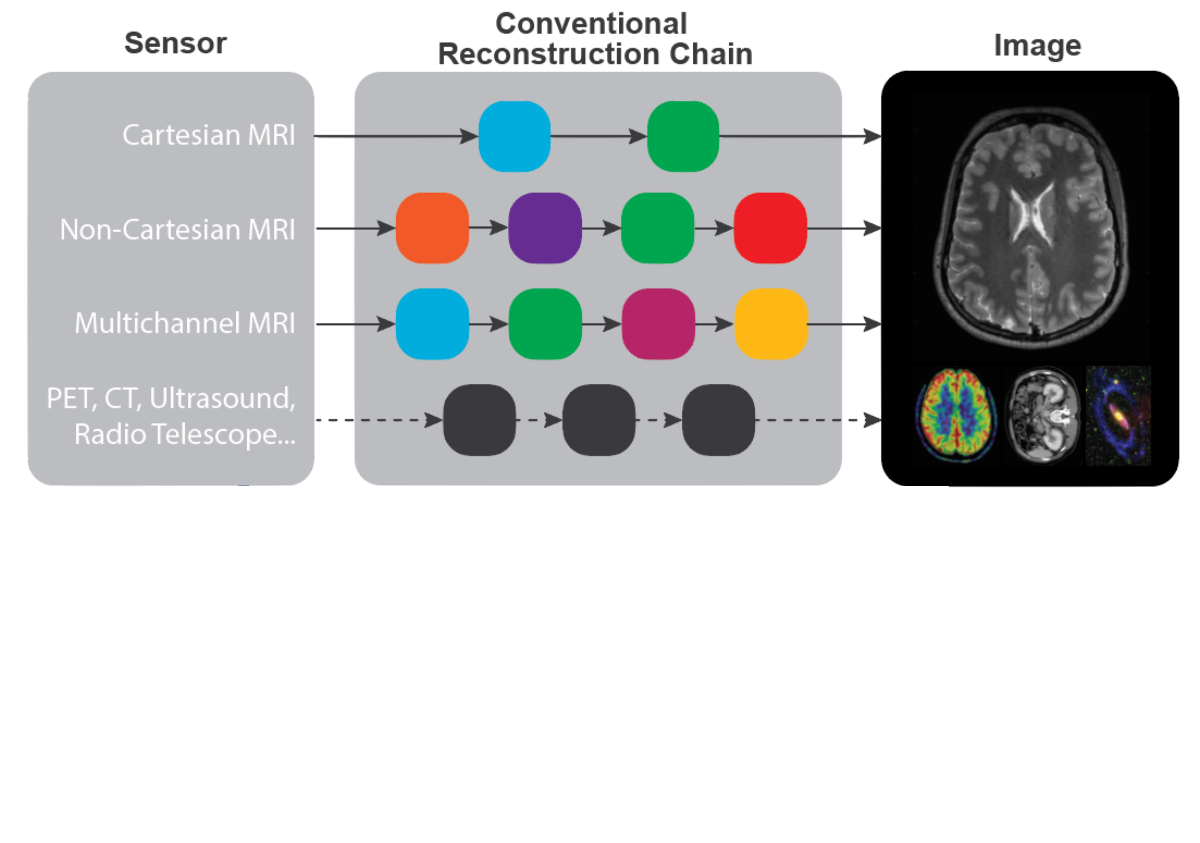


- Fully sampled
- High SNR

“Hallucination”

Deep learning for image reconstruction

AUTOMAP: Automated Transform by Manifold Approximation



LETTER nature 2018

doi:10.1038/nature25988

Image reconstruction by domain-transform manifold learning

Bo Zhu[1,2,3], Jeremiah Z. Liu[4], Stephen F. Cauley[1,2], Bruce R. Rosen[1,2] & Matthew S. Rosen[1,2,3]

Data driven approach:

1. Learns to invert an arbitrary encoding
2. Operates on a learned joint sparse manifold improving SNR & accuracy

→ Recast image reconstruction as a supervised learning task

Convolutional NN denoiser

AUTOMAP:
not noise training!

Noisy image

CNN

Learned mapping

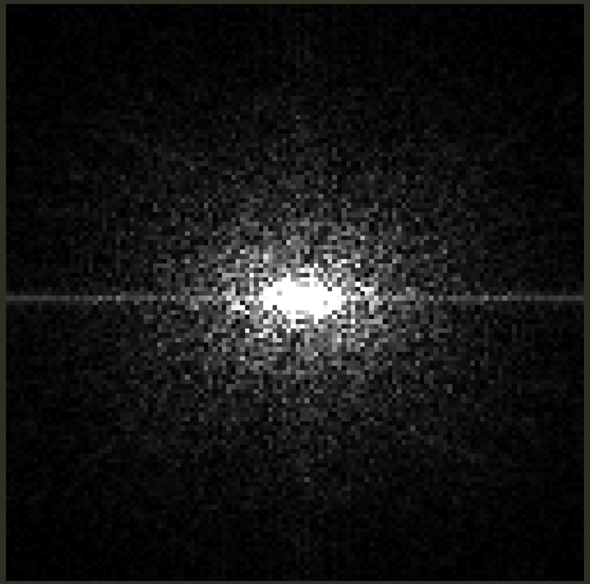
Clean image

Mapping from noisy to clean aka noise training learned from pairs of examples

Images: Jaakko Lehtinen

Deep learning for image reconstruction

In contrast: we train on clean pairs from forward encoding model

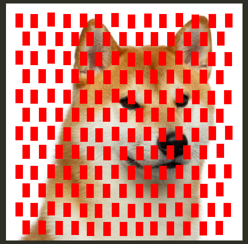


Sensor domain

Image domain

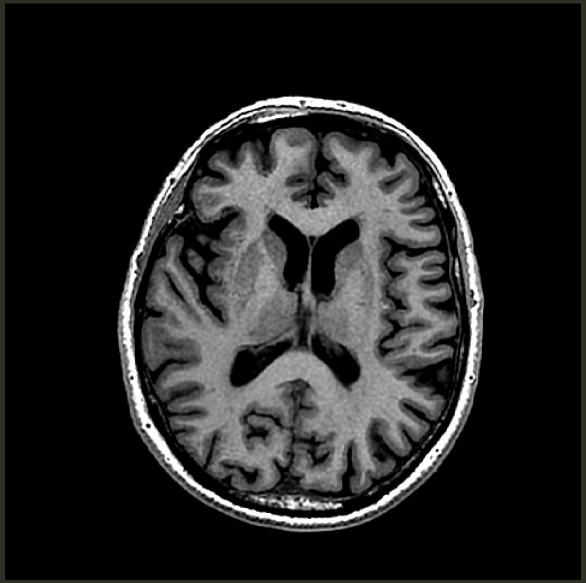
1. Identify sparsity in two domains
2. Learn to invert encoding

Noise immunity develops "naturally":
→ learned domain mapping between sparse manifolds
a la perceptual learning

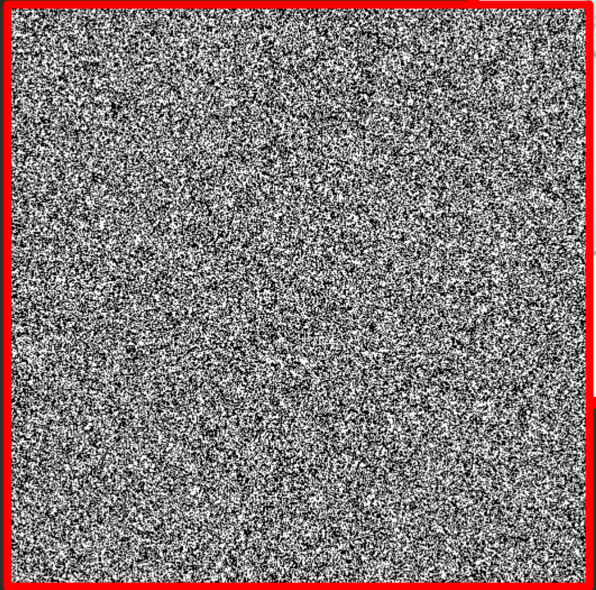


Sparsity: natural separation of signal and noise

Natural images are special Noise can be anything



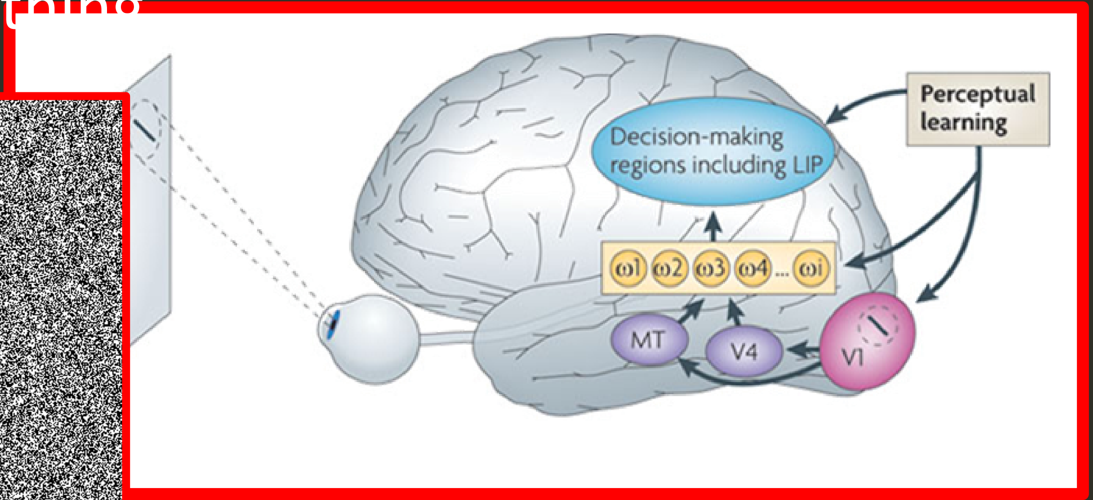
Not sparse

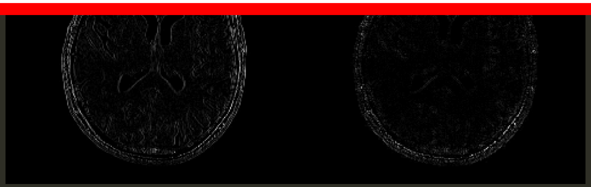


Possible images: $2^{128 \times 128}$

(4,933 digits!)

Fourier domain:
also not sparse





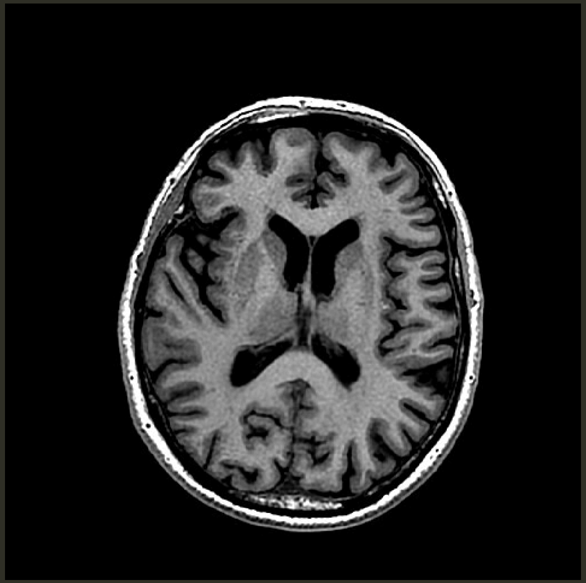
Wavelet domain:
→ sparse

"Brain hallucinates image using learned sparse features"

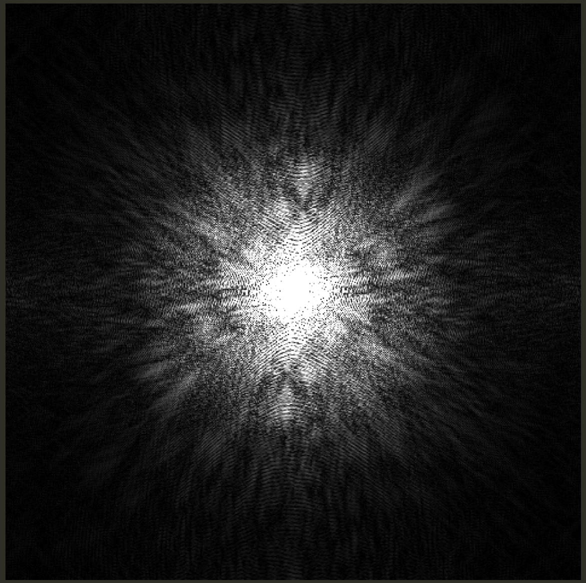
→ High dimensional data can be represented with fewer coefficients in a sparse domain

Sparsity: natural separation of signal and noise

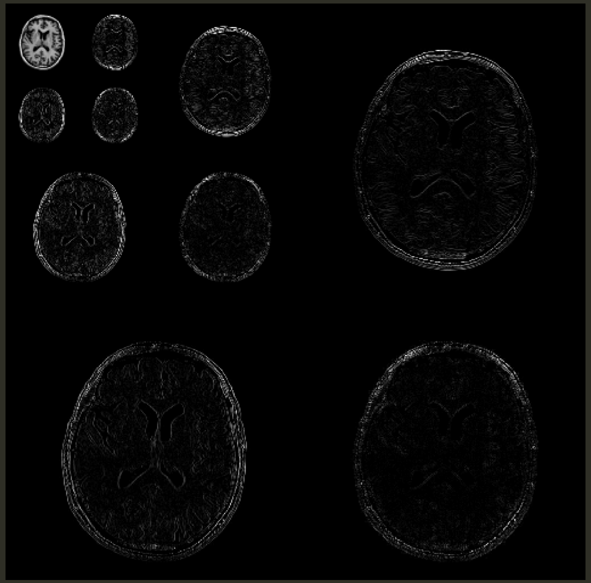
→ High dimensional data can be represented with fewer coefficients in a sparse domain



Not sparse



Fourier domain:
also not sparse



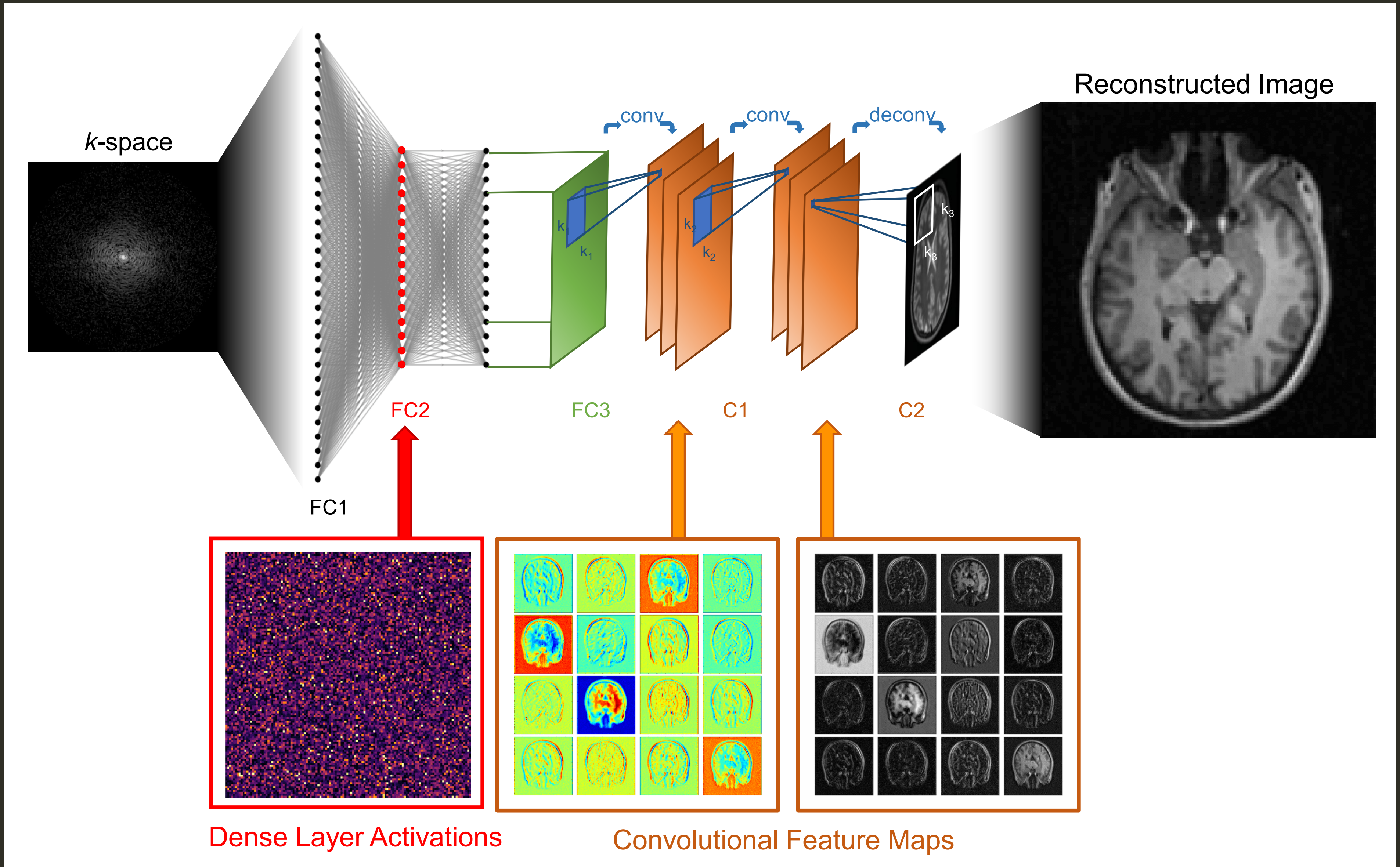
Wavelet domain:
→ sparse

- NN training can encourage efficient internal representation of learned mapping

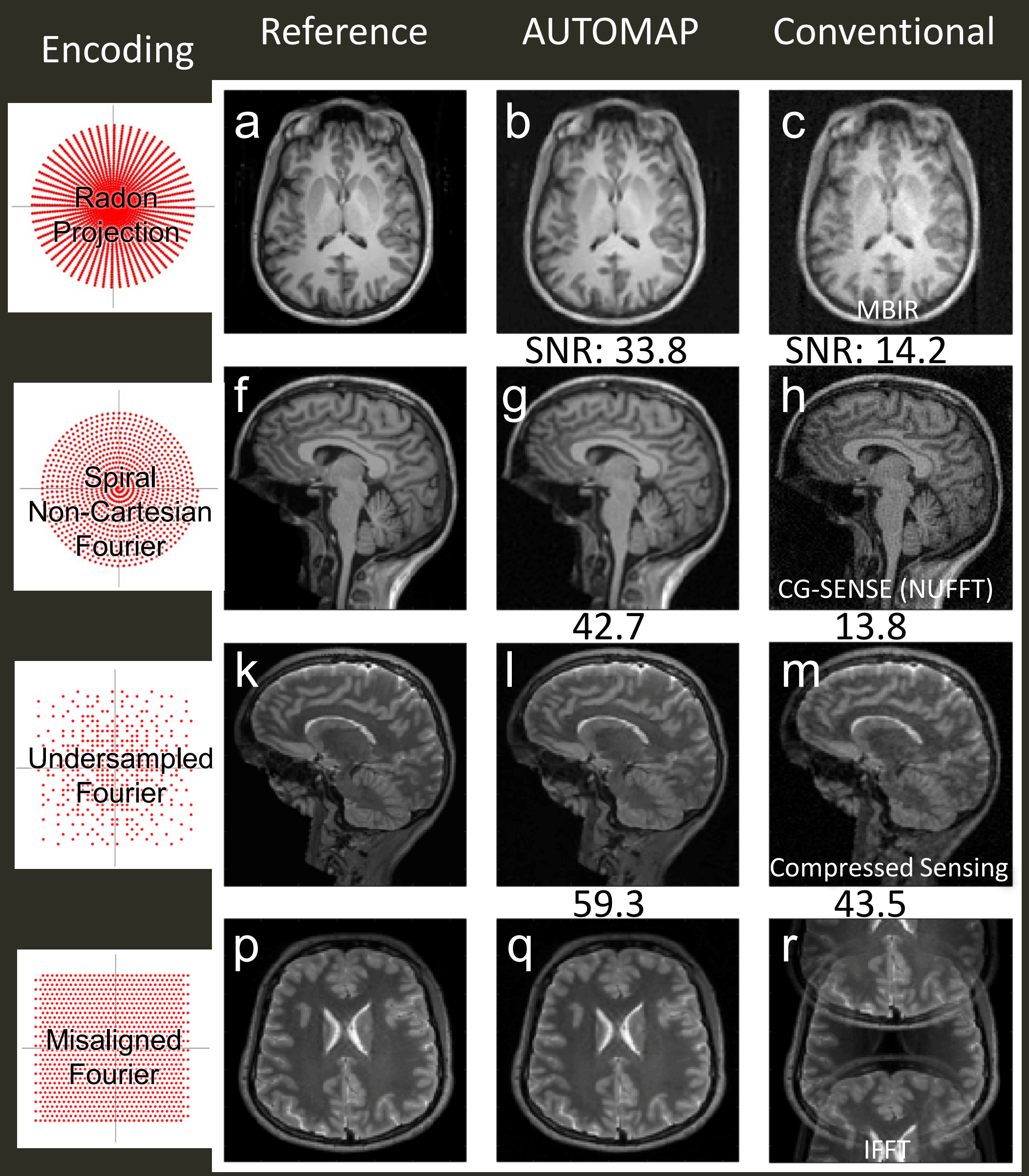
→ AUTOMAP transform operates between data-defined sparse domains

→ Image is hallucinated from the learned sparse convolutional feature maps

AUTOMAP feed-forward reconstruction



AUTOMAP reconstructs all encodings



LETTER nature 2018

doi:10.1038/nature25988

Image reconstruction by domain-transform manifold learning

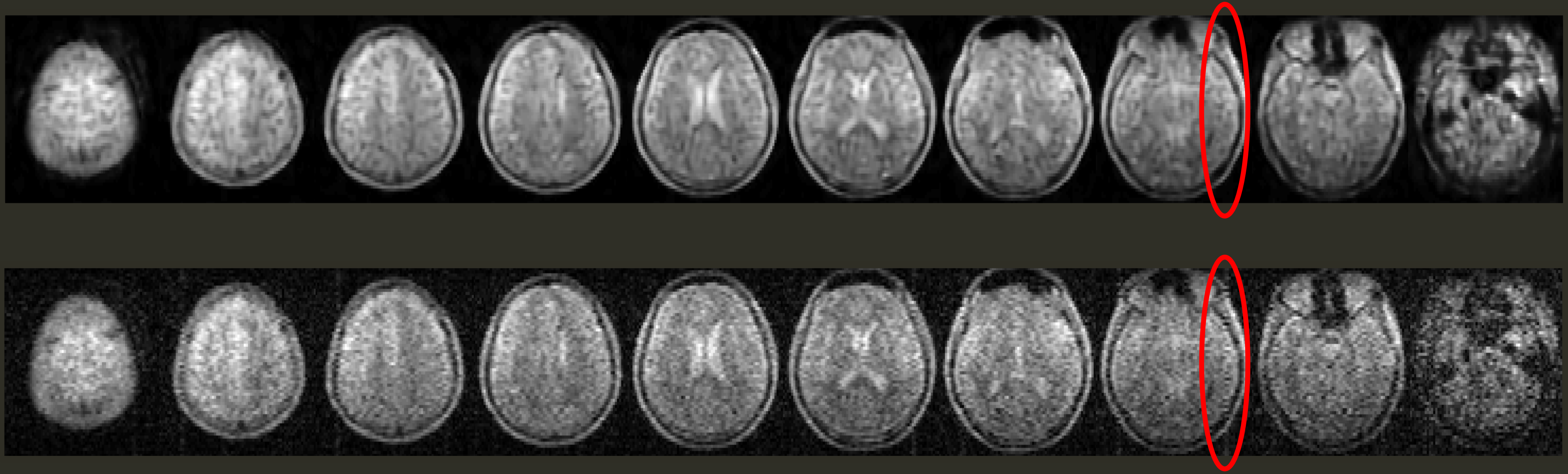
Bo Zhu[1,2,3], Jeremiah Z. Liu[4], Stephen F. Cauley[1,2], Bruce R. Rosen[1,2] & Matthew S. Rosen[1,2,3]

AUTOMAP reconstructs 6.5 mT brain imaging

- SNR increase: 1.5 – 2.6x
- Removal of zipper artifact

AUTOMAP

FFT



11 min acquisition, 10 of 15 slices shown

AUTOMAP learns a non-linear transform:

- Glitches in *k*-space attenuated by transform
- "Unnatural" image artifacts suppressed in reconstruction

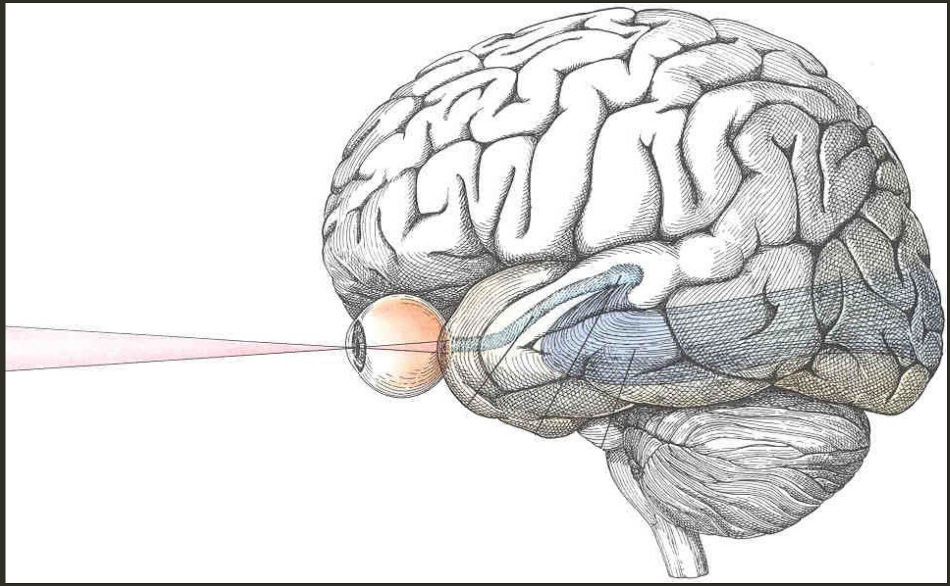
scientific reports 2021

Neha Koonjoo, Bo Zhu, Cody Bagnall, MSR

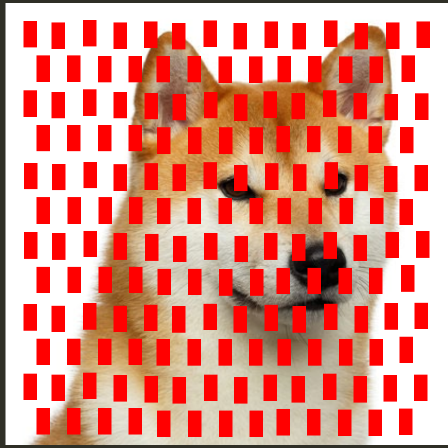
OPEN **Boosting the signal-to-noise of low-field MRI with deep learning image reconstruction**

N. Koonjoo[1,2], B. Zhu[1,2], G. Cody Bagnall[3], D. Bhutto[1,4] & M. S. Rosen[1,2,5]

Your ~~brain~~ learns from seeing many examples
AI network



- Under-sampled
- Low SNR



- Fully sampled
- High SNR

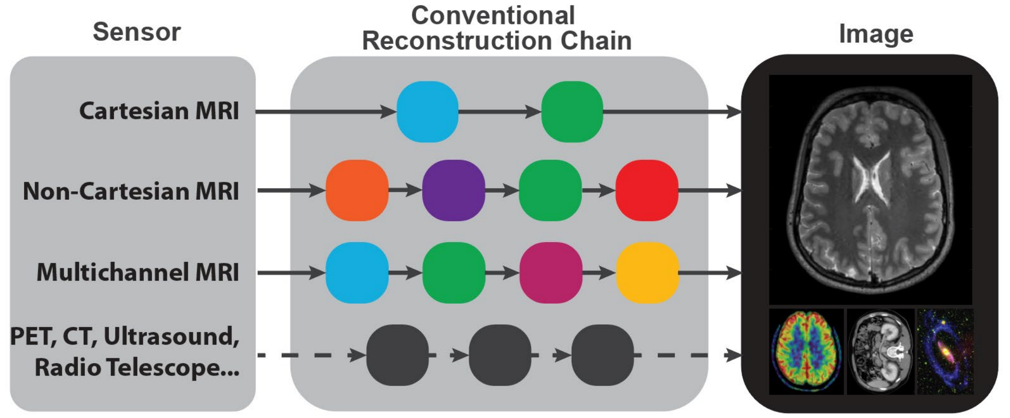
"Hallucination"

Hallucinations and reconstruction uncertainty

Fear: AI-based reconstruction methods might not “see” your tumor

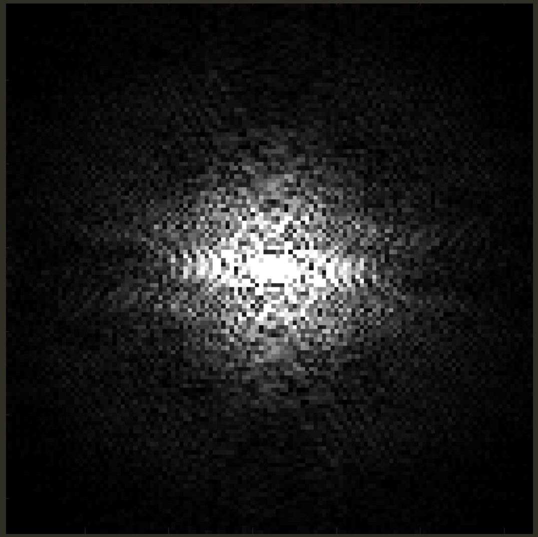
Reality: reconstruction solves a well-defined math problem

Chihuahua or muffin?



$$f(m,n) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} F(x,y) e^{j2\pi\left(x\frac{m}{M}+y\frac{n}{N}\right)}$$

AUTOMAP solves an inverse problem



k-space

Recon.

AUTOMAP

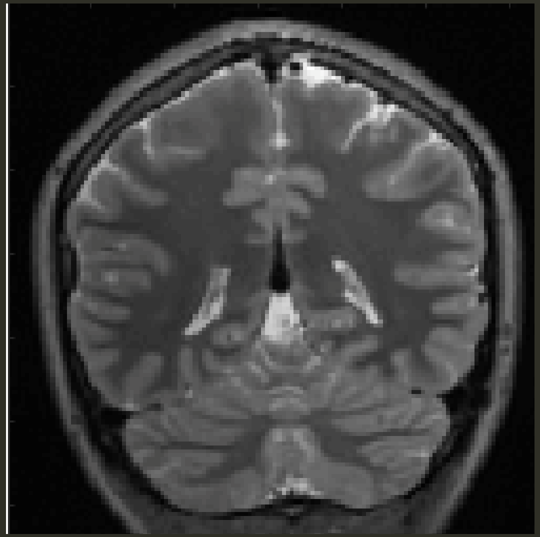
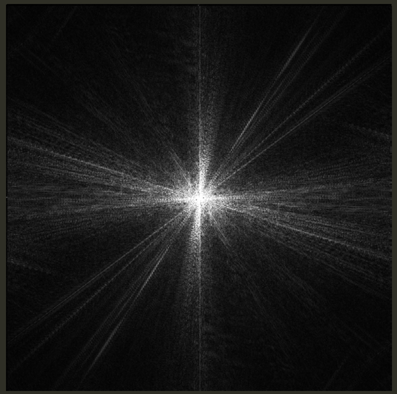


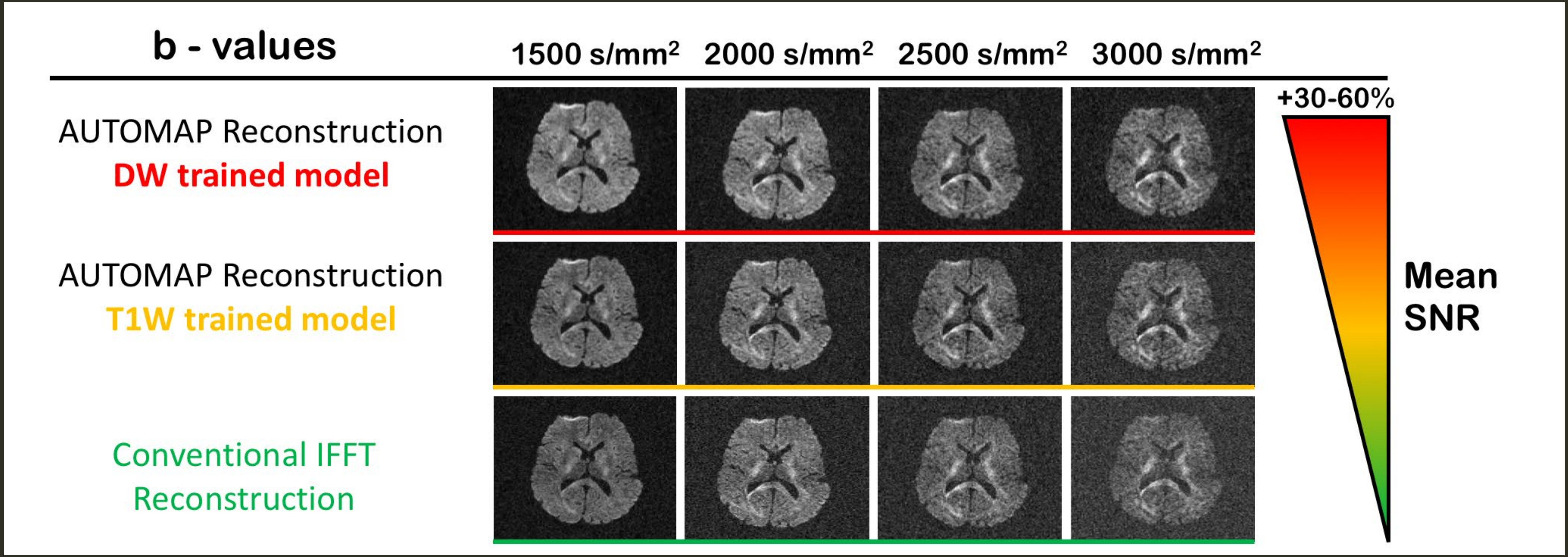
Image domain



$$f(m,n) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} F(x,y)e^{j2\pi\left(x\frac{m}{M}+y\frac{n}{N}\right)}$$

Trained on forward encoding

High-b DWI at 1.5 T: AUTOMAP vs. inverse FFT

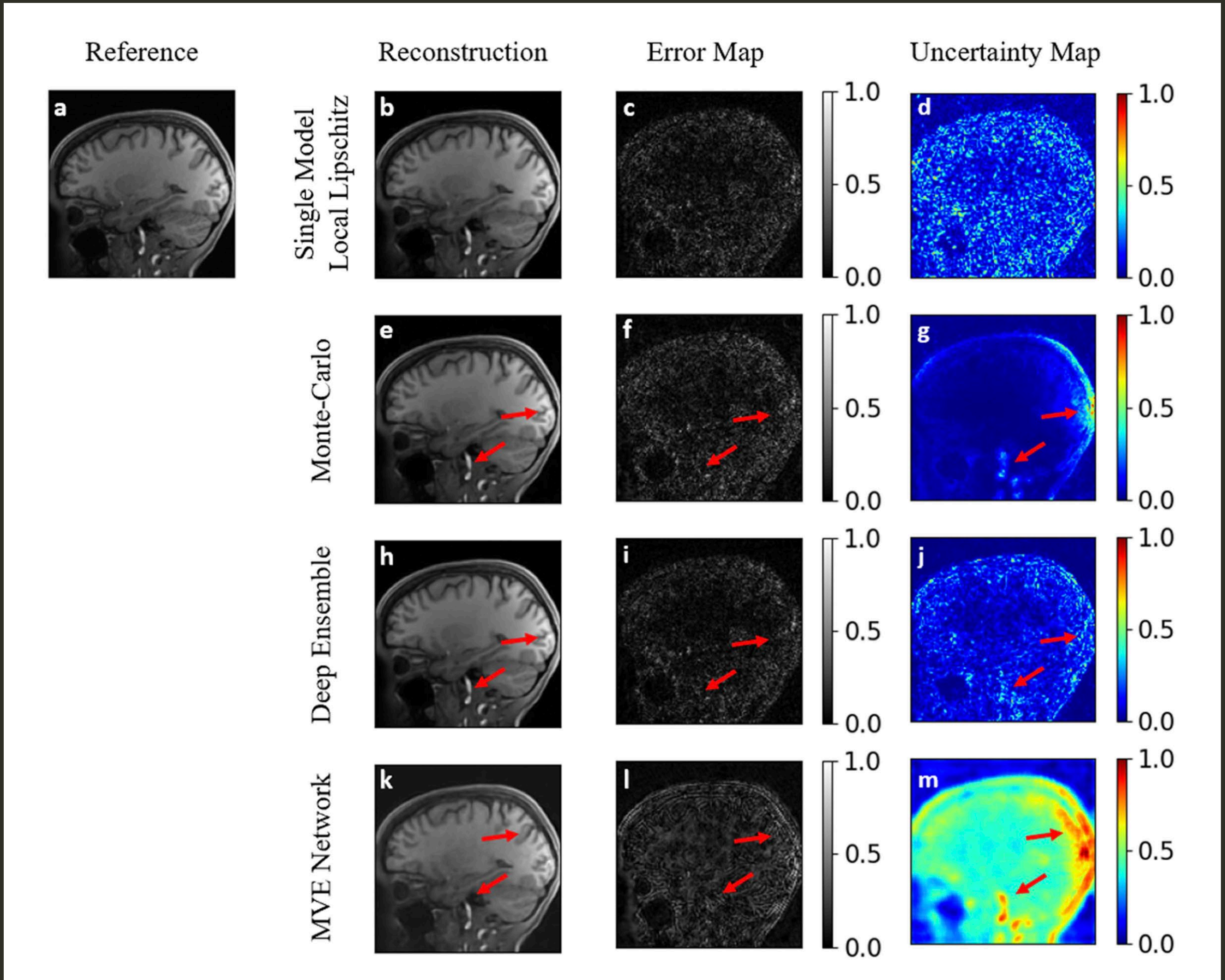


Diffusion-weighted brain MRI Reconstruction: AUTOMAP with different training sets

2019 ISMRM

Neha Koonjoo, Bo Zhu, Matthew Christensen, John E. Kirsch, and Matthew S. Rosen

Hallucinations and reconstruction uncertainty



IEEE J Biomed. and Health Informatics 2024

- Appropriate training corpus
- Parameterize network bias

MRI at the bedside

Study in <u>comatose</u> COVID19 patients

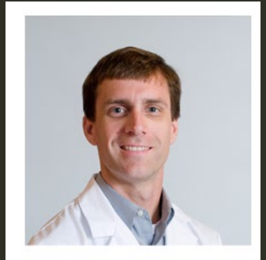
JAMA Neurology | Original Investigation 2020

Assessment of Brain Injury Using Portable, Low-Field Magnetic Resonance Imaging at the Bedside of Critically Ill Patients

Kevin N. Sheth, MD; Mercy H. Mazurek, BS; Matthew M. Yuen, BA; Bradley A. Cahn, BS; Jill T. Shah, BA; Adrienne Ward, RN; Jennifer A. Kim, MD, PhD; Emily J. Gilmore, MD; Guido J. Falcone, MD, ScD, MPH; Nils Petersen, MD, PhD; Kevin T. Gobeske, MD, PhD, MPH; Firas Kaddouh, MD; David Y. Hwang, MD; Joseph Schindler, MD; Lauren Sansing, MD, MS; Charles Matouk, MD; Jonathan Rothberg, PhD; Gordon Sze, MD; Jonathan Siner, MD; Matthew S. Rosen, PhD; Serena Spudich, MD, MA; W. Taylor Kimberly, MD, PhD


Kevin Sheth

Yale

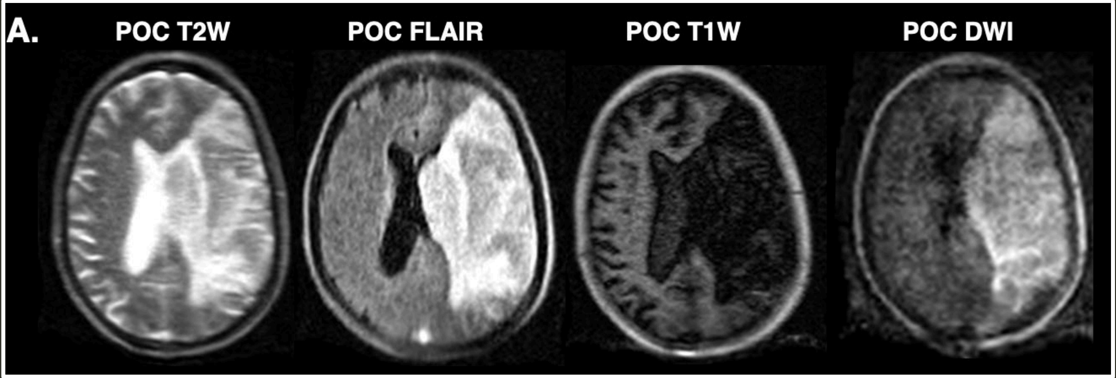

Taylor Kimberly

MGH

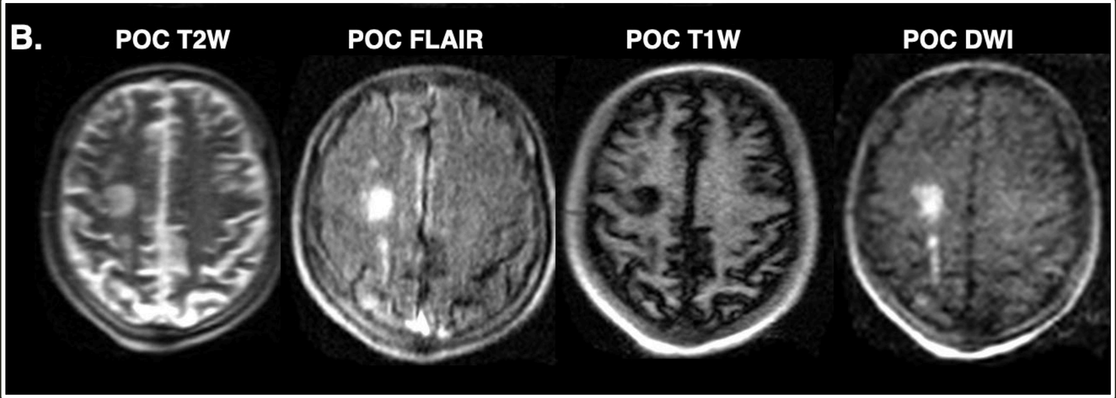
64 mT Hyperfine

Yale New Haven Hospital

IRB protocol with FDA clearance



Left MCA stroke w/ hemorrhagic transformation



Right ACA-MCA watershed infarction

- Comatose, ventilated
- Imaged at bedside
- Neuro-exam unavailable
- Significant neuro findings
- No patient transport

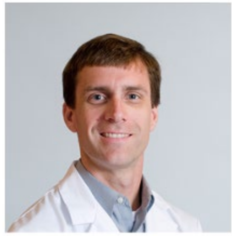
Collaborative Science Award

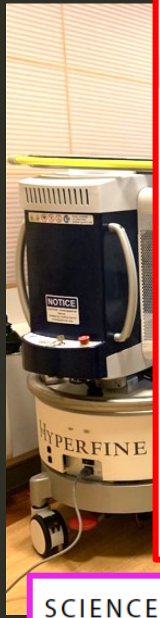
Co-PIs: Sheth, Kimberly, Rosen

MRI at the bedside

Emerging clinical use cases


Kevin Sheth


Taylor Kimberly



JAMA Neurology | Original Investigation 2020

Assessment of Brain Injury Using Portable, Low-Field Magnetic Resonance Imaging at the Bedside of Critically Ill Patients

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nature COMMUNICATIONS 2021

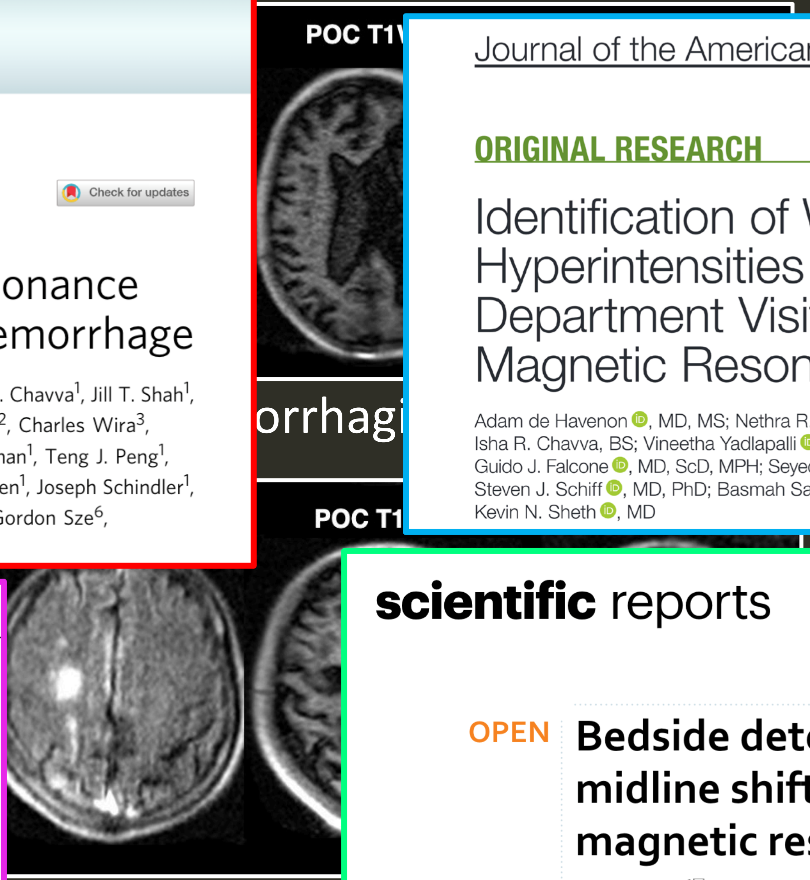
ARTICLE

Check for updates

https://doi.org/10.1038/s41467-021-25441-6 OPEN

Portable, bedside, low-field magnetic resonance imaging for evaluation of intracerebral hemorrhage

Mercy H. Mazurek[1,9], Bradley A. Cahn[1,9], Matthew M. Yuen[1], Anjali M. Prabhat[1], Isha R. Chavva[1], Jill T. Shah[1], Anna L. Crawford[1], E. Brian Welch[2], Jonathan Rothberg[2], Laura Sacolick[2], Michael Poole[2], Charles Wira[3], Charles C. Matouk[4], Adrienne Ward[5], Nona Timario[5], Audrey Leasure[1], Rachel Beekman[1], Teng J. Peng[1], Jens Witsch[1], Joseph P. Antonios[4], Guido J. Falcone[1], Kevin T. Gobeske[1], Nils Petersen[1], Joseph Schindler[1], Lauren Sansing[1], Emily J. Gilmore[1], David Y. Hwang[1], Jennifer A. Kim[1], Ajay Malhotra[6], Gordon Sze[6], Matthew S. Rosen[7], W. Taylor Kimberly[8✉] & Kevin N. Sheth[1✉]



Journal of the American Heart Association

ORIGINAL RESEARCH 2023

Identification of White Matter Hyperintensities in Routine Emergency Department Visits Using Portable Bedside Magnetic Resonance Imaging

Adam de Havenon, MD, MS; Nethra R. Parasuram, BS; Anna L. Crawford, BS, MS; Mercy H. Mazurek, BS; Isha R. Chavva, BS; Vineetha Yadlapalli, BS; Juan E. Iglesias, PhD; Matthew S. Rosen, PhD; Guido J. Falcone, MD, ScD, MPH; Seyedmehdi Payabvash, MD; Gordon Sze, MD; Richa Sharma, MD, MPH; Steven J. Schiff, MD, PhD; Basmah Safdar, MD; Charles Wira, MD; William T. Kimberly, MD, PhD; Kevin N. Sheth, MD

SCIENCE ADVANCES | RESEARCH ARTICLE

APPLIED SCIENCES AND ENGINEERING 2022

Portable, low-field magnetic resonance imaging enables highly accessible and dynamic bedside evaluation of ischemic stroke

Matthew M. Yuen[1], Anjali M. Prabhat[1], Mercy H. Mazurek[1], Isha R. Chavva[1], Anna Crawford[1], Bradley A. Cahn[1], Rachel Beekman[1], Jennifer A. Kim[1], Kevin T. Gobeske[1], Nils H. Petersen[1], Guido J. Falcone[1], Emily J. Gilmore[1], David Y. Hwang[1], Adam S. Jasne[1], Hardik Amin[1], Richa Sharma[1], Charles Matouk[2], Adrienne Ward[3], Joseph Schindler[1], Lauren Sansing[1], Adam de Havenon[1], Ani Aydin[4], Charles Wira[4], Gordon Sze[5], Matthew S. Rosen[6], W. Taylor Kimberly[7]*, Kevin N. Sheth[1]*

scientific reports 2022

Check for updates

OPEN **Bedside detection of intracranial midline shift using portable magnetic resonance imaging**

Kevin N. Sheth[1✉], Matthew M. Yuen[1], Mercy H. Mazurek[1], Bradley A. Cahn[1], Anjali M. Prabhat[1], Sadegh Salehi[2], Jill T. Shah[1], Samantha By[2], E. Brian Welch[2], Michal Sofka[2], Laura I. Sacolick[2], Jennifer A. Kim[1], Seyedmehdi Payabvash[3], Guido J. Falcone[1], Emily J. Gilmore[1], David Y. Hwang[1], Charles Matouk[4], Barbara Gordon-Kundu[1], Adrienne Ward RN[5], Nils Petersen[1], Joseph Schindler[1], Kevin T. Gobeske[1], Lauren H. Sansing[1], Gordon Sze[3], Matthew S. Rosen[6], W. Taylor Kimberly[7] & Prantik Kundu[2]

s

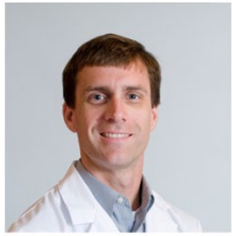
, Rosen

MRI at the bedside

...and emerging locations!

Kevin Sheth

Yale



Taylor Kimberly

MGH

ICU

Interventional suite

Emergency department

Photos courtesy of Dr. Kevin Sheth
Yale New Haven Hospital

Collaborative
Science Award

Co-PIs: Sheth, Kimberly, Rosen

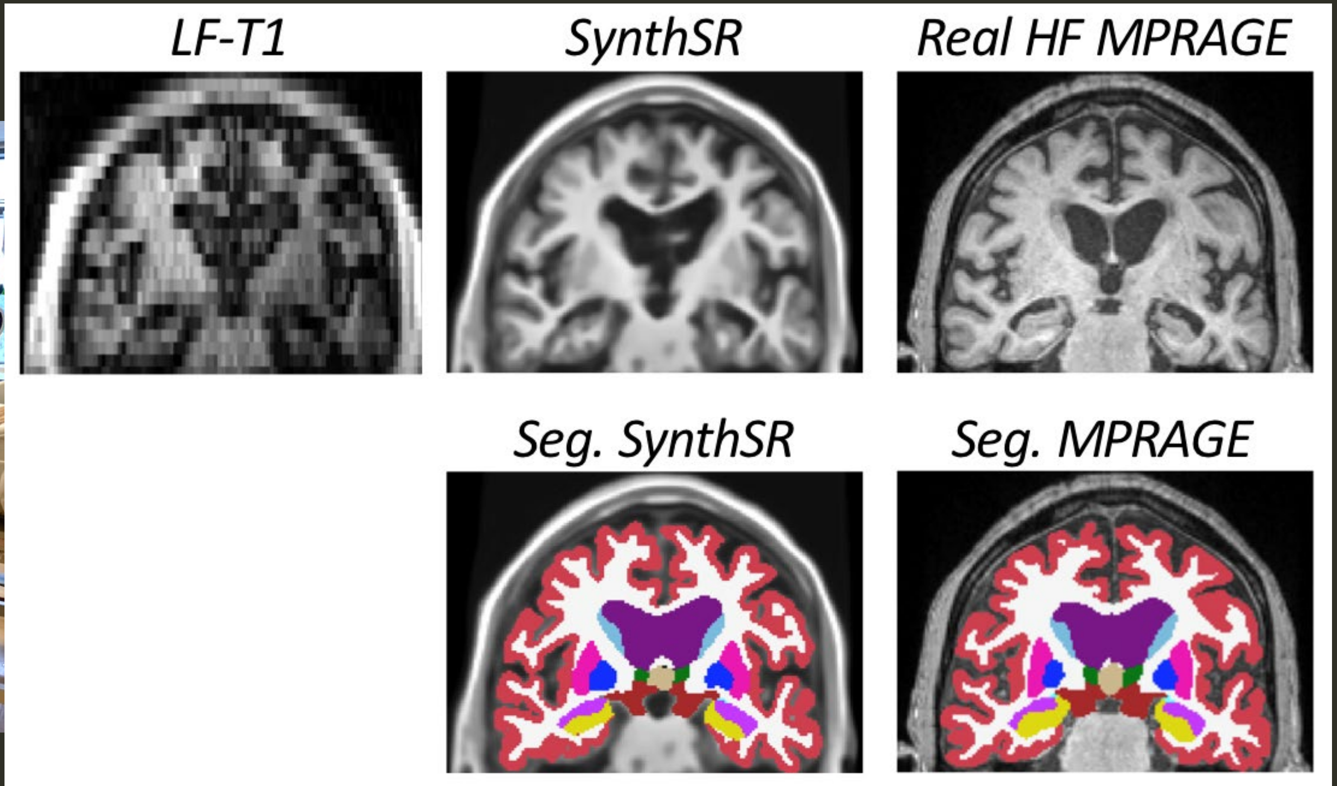
MRI at the bedside

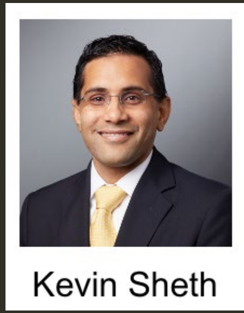
Super resolution + segmentation

64 mT Hyperfine

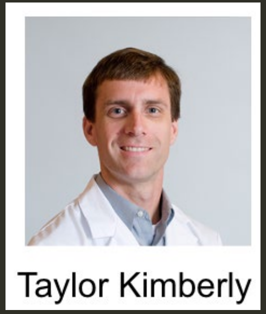
Yale New Haven Hospital

IRB protocol with FDA clearance





Yale



MGH

Eugenio Iglesias

Radiology

ORIGINAL RESEARCH • NEURORADIOLOGY

2022

Quantitative Brain Morphometry of Portable Low-Field-Strength MRI Using Super-Resolution Machine Learning

Juan Eugenio Iglesias, PhD • Riana Schleicher, BS • Sonia Laguna, MSc • Benjamin Billot, PhD • Pamela Schaefer, MD • Brenna McKaig, BS • Joshua N. Goldstein, MD, PhD • Kevin N. Sheth, MD, PhD • Matthew S. Rosen, PhD • W. Taylor Kimberly, MD, PhD**

Collaborative Science Award

Co-PIs: Sheth, Kimberly, Rosen

Hallucinations and pathology

Fear: SR-based methods might not “see” your tumor

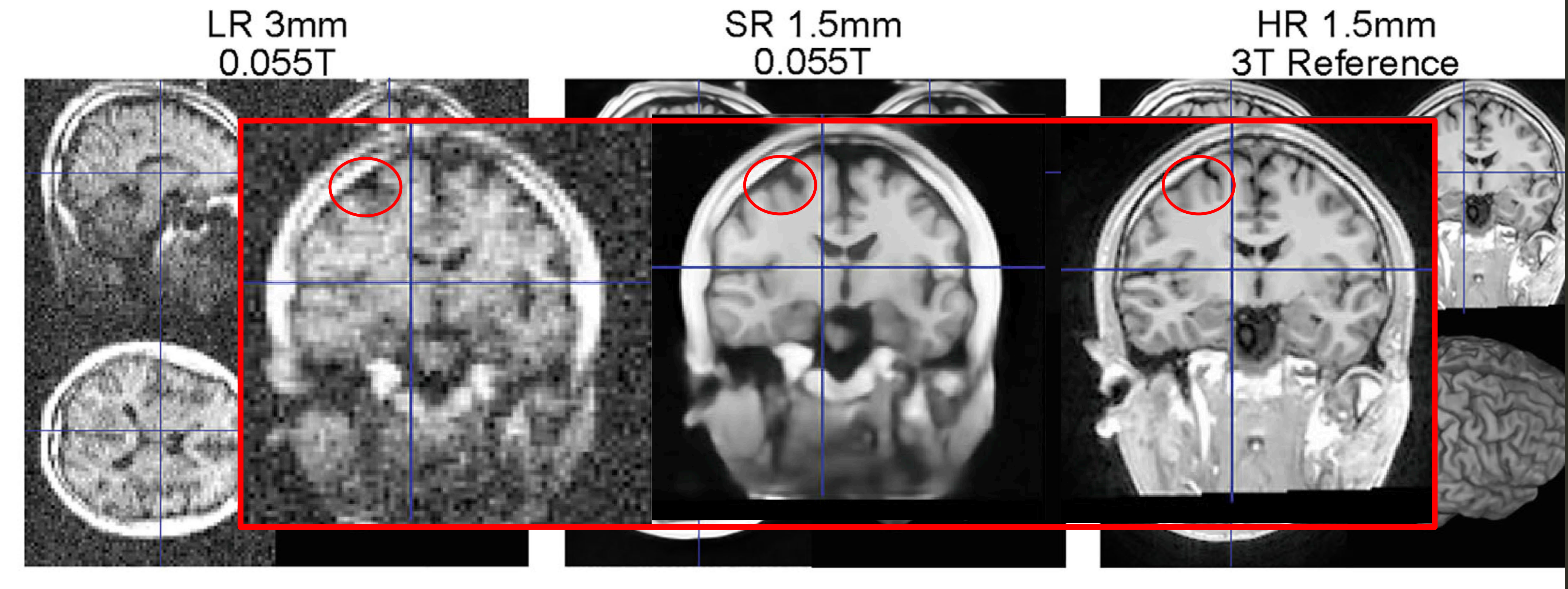
Corollary: SR-based methods might create abnormal pathology

Artificial intelligence

The deep route to low-field MRI with high potential

Patricia M. Johnson & Yvonne W. Lui

A type of magnetic resonance imaging, known as low-field MRI, could make the technique more widely accessible, but only if the image quality can be improved. A deep-learning protocol might hold the key.



SCIENCE ADVANCES | RESEARCH ARTICLE

2023

APPLIED SCIENCES AND ENGINEERING

Deep learning enabled fast 3D brain MRI at 0.055 tesla

Christopher Man[1,2]†, Vick Lau[1,2]†, Shi Su[1,2], Yujiao Zhao[1,2], Linfang Xiao[1,2], Ye Ding[1,2], Gilberto K. K. Leung[3], Alex T. L. Leong[1,2], Ed X. Wu[1,2]*

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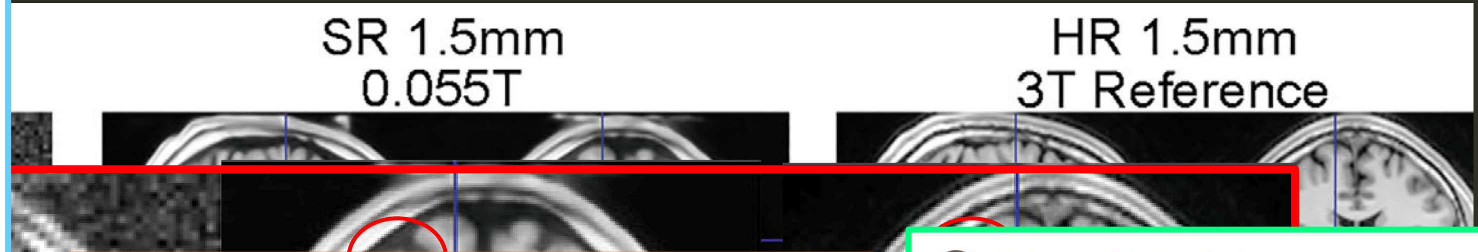


Francesco Santini
@MriFranz

Why I don't trust AI "super resolution" for medical imaging. This tool "enhances" a plant into a completely different plant.

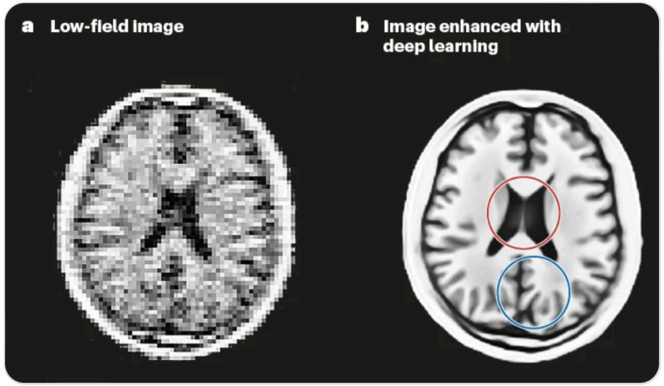
Chase Lean @chaseleantj · Nov 23
Just got early access to Magnific AI, and it's easily the best AI image upscaler I've ever seen.

The detail that it adds to images is SERIOUSLY impressive!
...
Show more

7:44 AM · Nov 23, 2023 · **5,707** Views

Francesco Santini @MriFranz · Nov 23
Yes, data consistency. Which means that if your data is garbage, your output will be consistent with that garbage. Would you trust this image to make a diagnosis of MS? This scares me, but it's been touted as a great result.

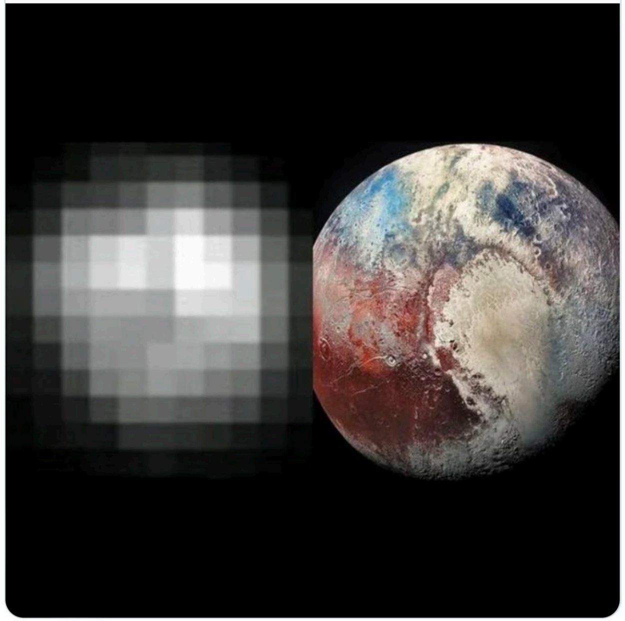
Ref: nature.com/articles/d4158...



2 10 431

Moritz Zaiss @altustro · Dec 2
they should try pluto!

World of Engineering @engineers_feed · Dec 2
Pluto: 1994 vs 2019



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2023

SCIENCE ADVANCES | RESEARCH ARTICLE

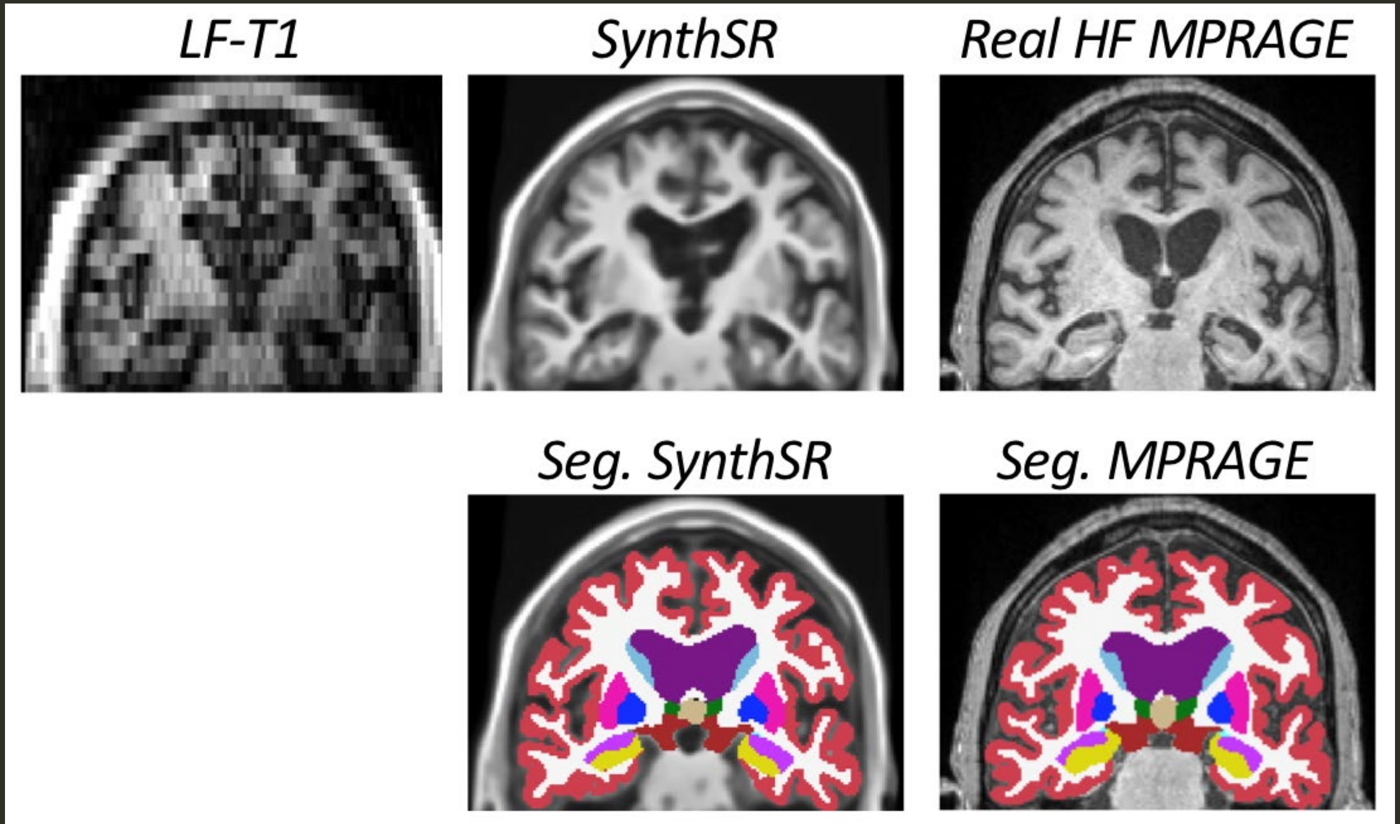
APPLIED SCIENCES AND ENGINEERING

Deep learning enabled fast 3D brain MRI at 0.055 tesla

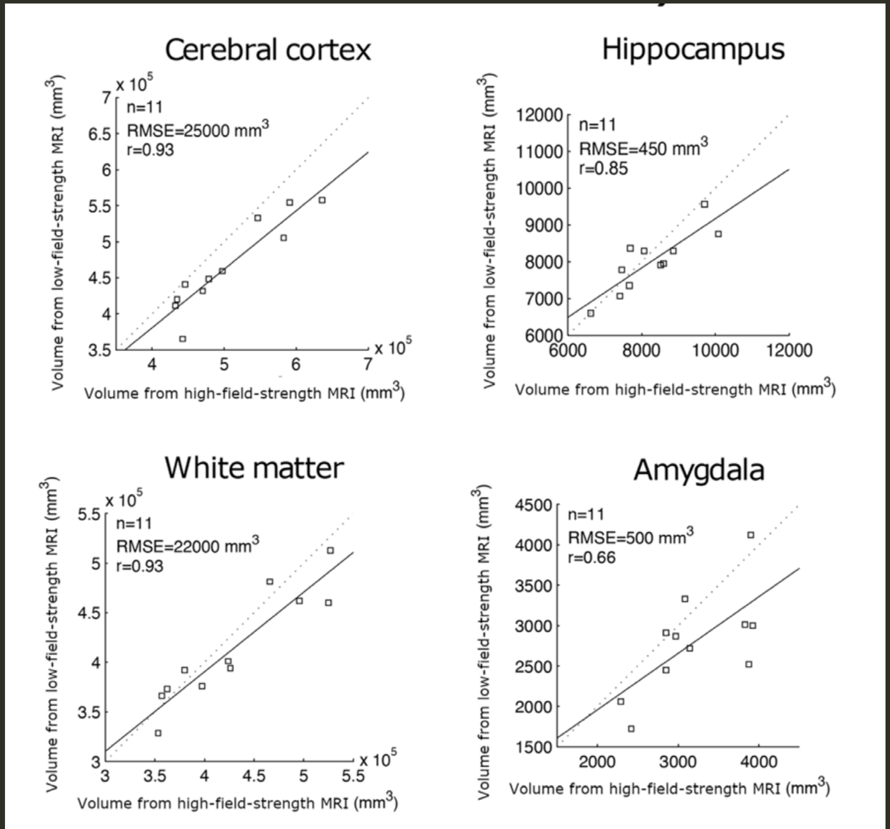
Christopher Man[1,2]†, Vick Lau[1,2]†, Shi Su[1,2], Yujiao Zhao[1,2], Linfang Xiao[1,2], Ye Ding[1,2], Gilberto K. K. Leung[3], Alex T. L. Leong[1,2], Ed X. Wu[1,2]*

Accurate quantitative morphology

These tools have their place!



Super resolution + segmentation



Comparable accuracy to ground truth

Radiology

ORIGINAL RESEARCH • NEURORADIOLOGY

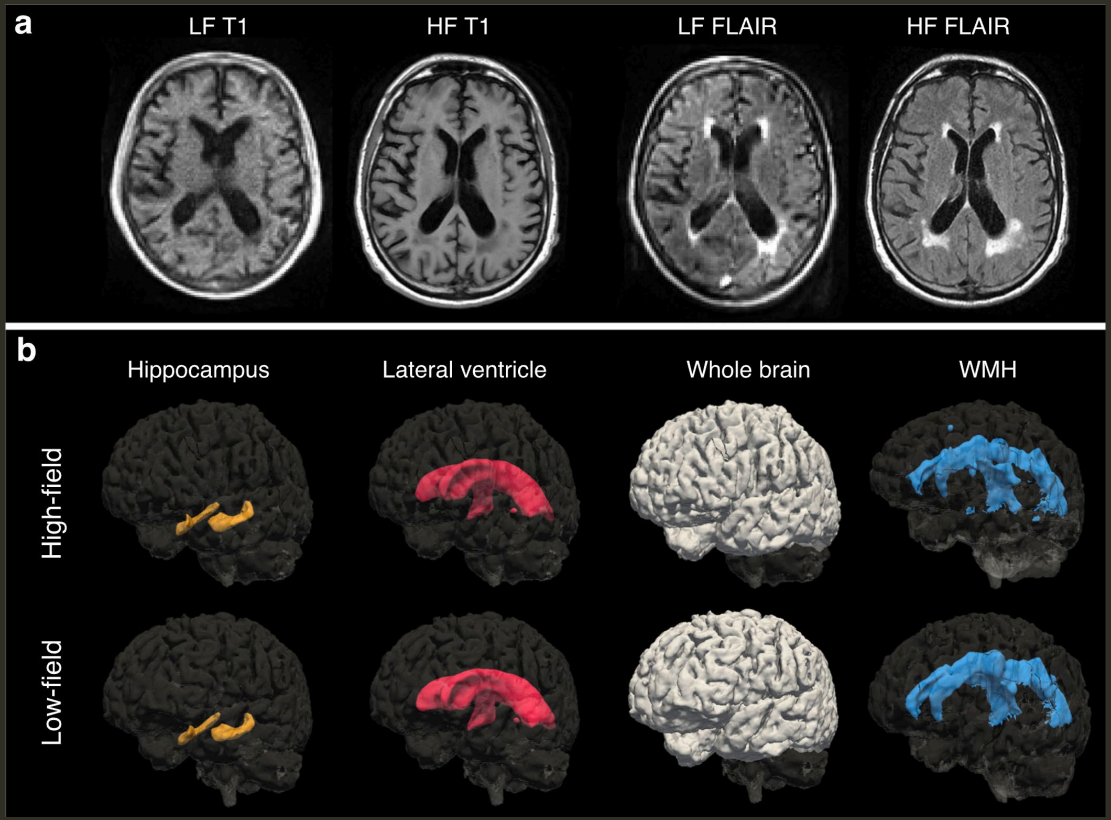
Quantitative Brain Morphometry of Portable Low-Field-Strength MRI Using Super-Resolution Machine Learning

2022

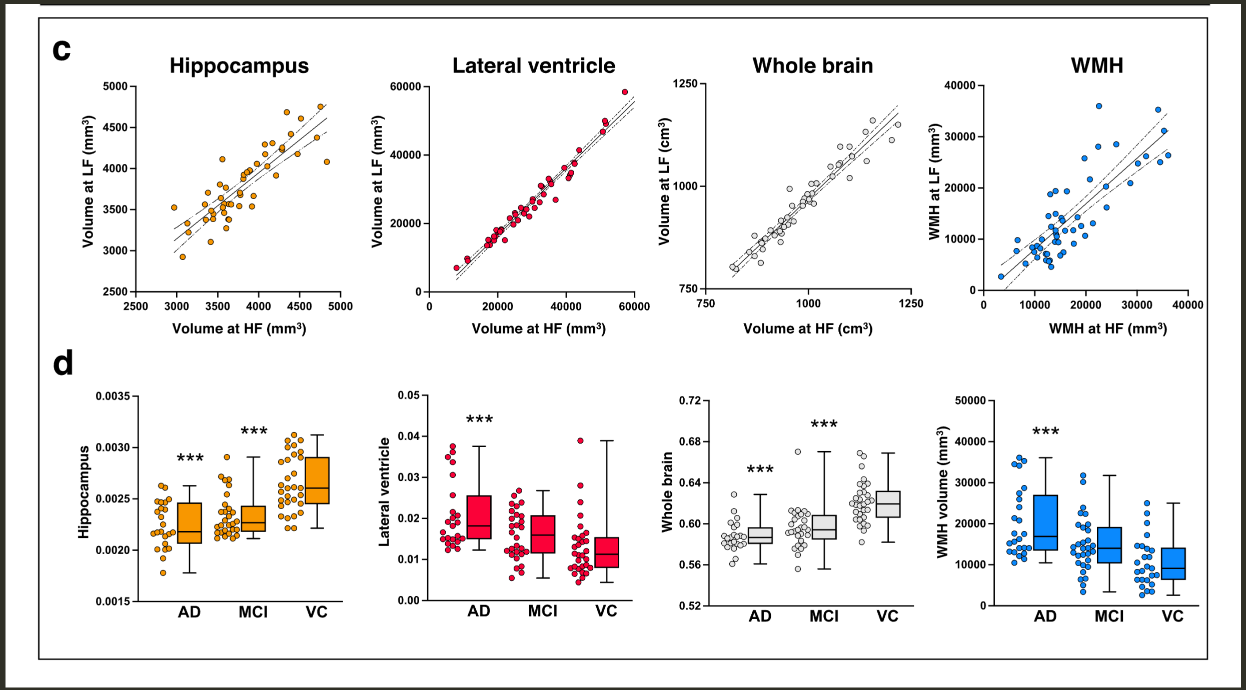
Juan Eugenio Iglesias, PhD • Riana Schleicher, BS • Sonia Laguna, MSc • Benjamin Billot, PhD • Pamela Schaefer, MD • Brenna McKaig, BS • Joshua N. Goldstein, MD, PhD • Kevin N. Sheth, MD, PhD • Matthew S. Rosen, PhD • W. Taylor Kimberly, MD, PhD**

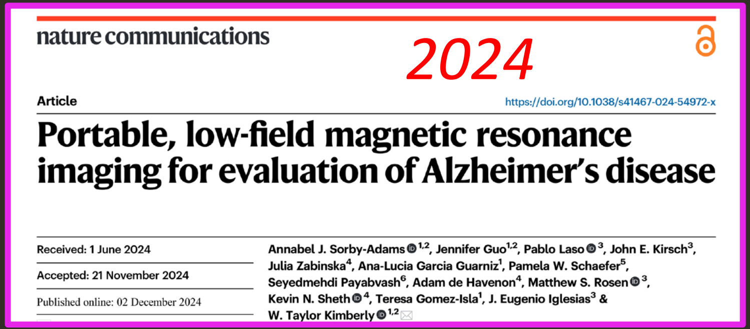
Quantitative evaluation in Alzheimer's disease

These tools have their place!



Cohort: memory disorders outpatient neurology clinic





nature communications

2024

Article

https://doi.org/10.1038/s41467-024-54972-x

Portable, low-field magnetic resonance imaging for evaluation of Alzheimer's disease

Received: 1 June 2024

Accepted: 21 November 2024

Published online: 02 December 2024

Annabel J. Sorby-Adams[1,2], Jennifer Guo[1,2], Pablo Laso[3], John E. Kirsch[3], Julia Zabinska[4], Ana-Lucia Garcia Guarniz[1], Pamela W. Schaefer[5], Seyedmehdi Payabvash[6], Adam de Havenon[4], Matthew S. Rosen[3], Kevin N. Sheth[4], Teresa Gomez-Isla[1], J. Eugenio Iglesias[3] & W. Taylor Kimberly[1,2]

AD: n = 24

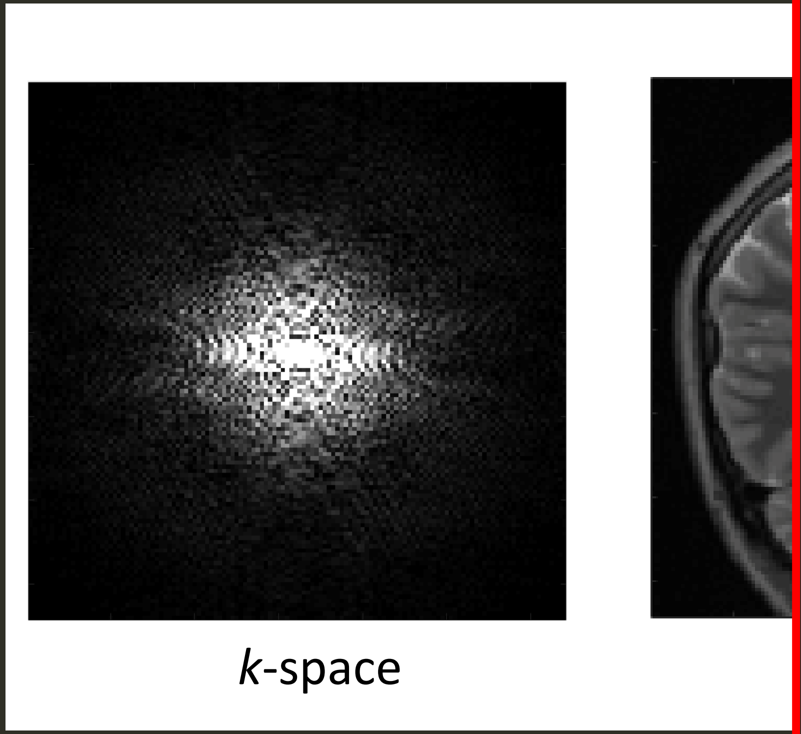
MCI: Mild cognitive impairment n = 30

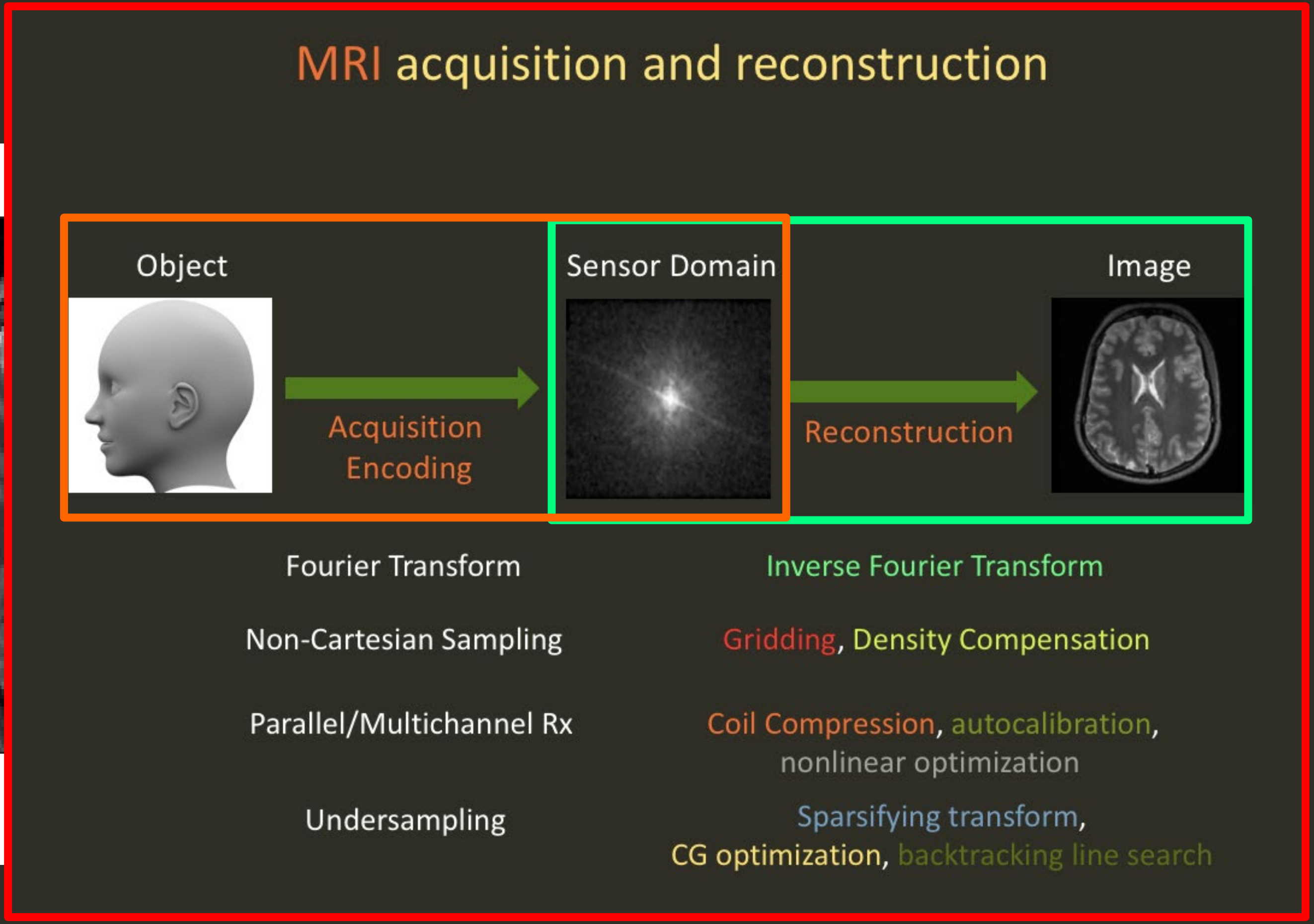
VC Vascular cohort presenting w/o memory complaints: n = 23

Annabele Sorby-Adams

AUTOMAP deduces the reconstruction

“B





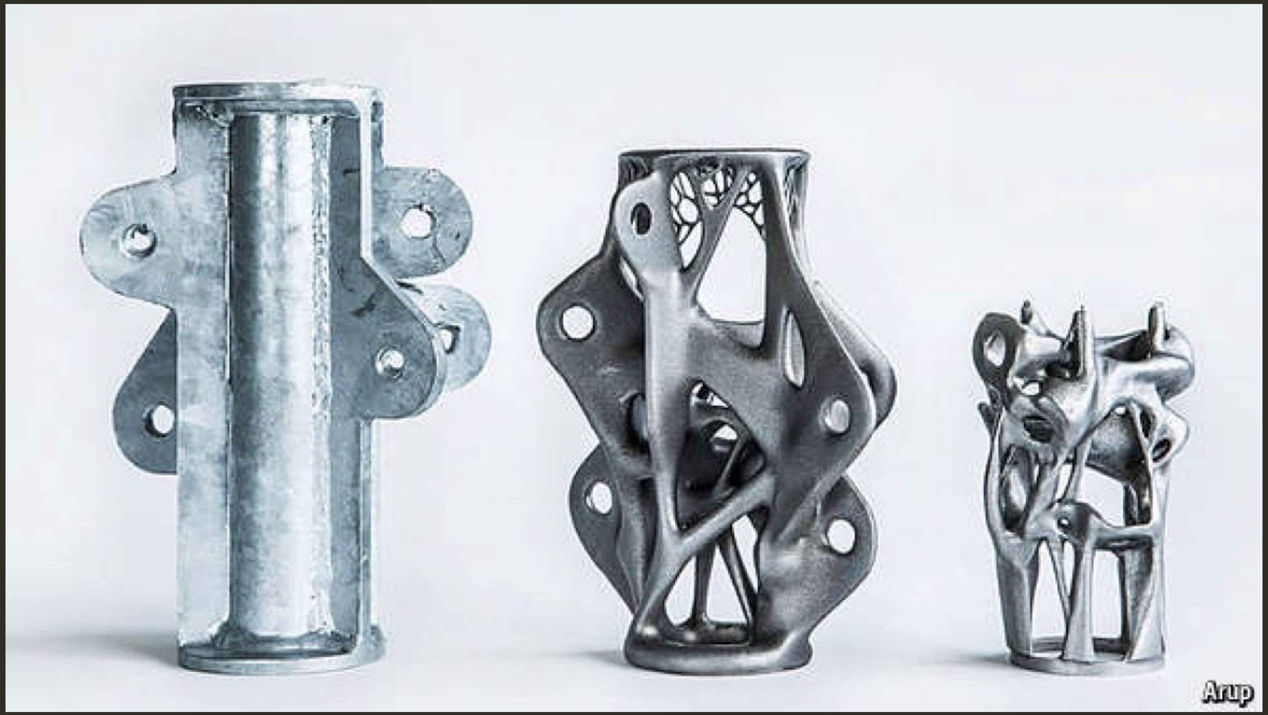
Opens the space for learning arbitrary encoding schemes!

Non-intuitive evolutionary optimized designs

Weird!

Cable support system

Original 60% weight 25% weight



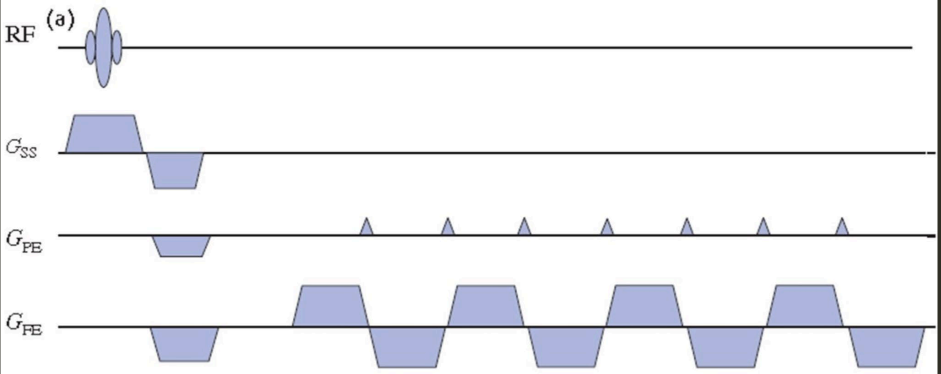
http://www.economist.com/news/technology-quarterly/21662653-components-become-more-elegant-software-produces-most-efficient

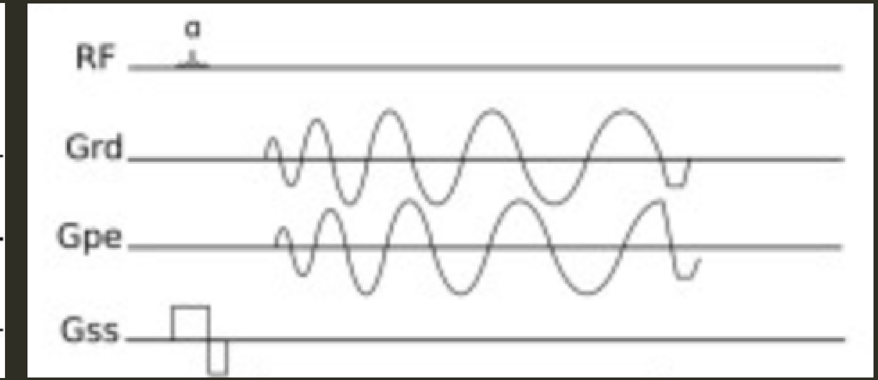
NASA ST5
spacecraft antenna

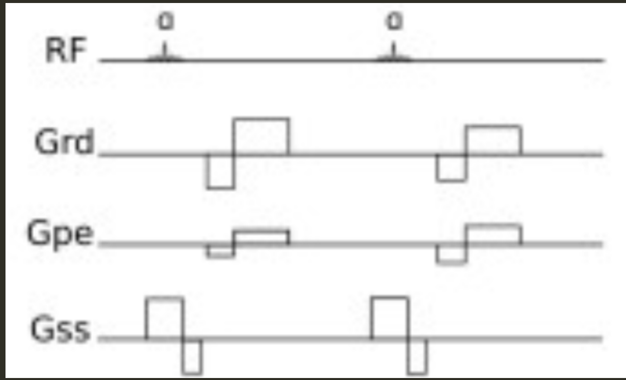
https://ti.arc.nasa.gov/m/pub-archive/1244h/1244%20(Hornby).pdf

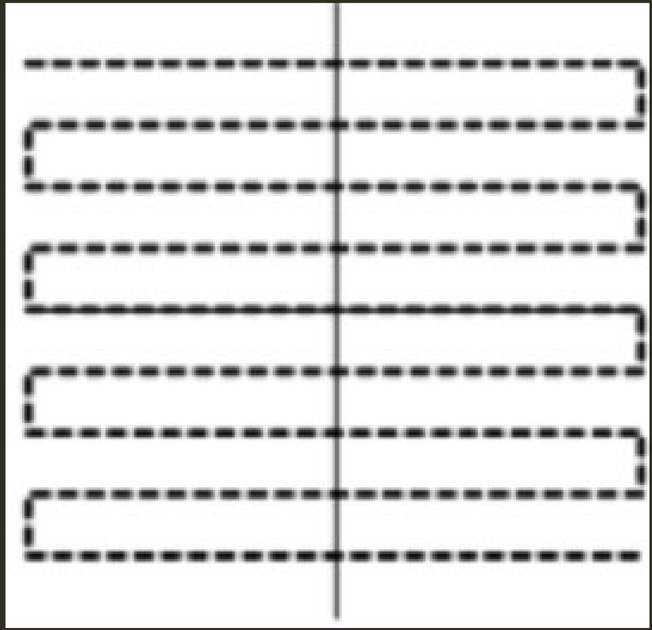
MRI spatial encoding schemes

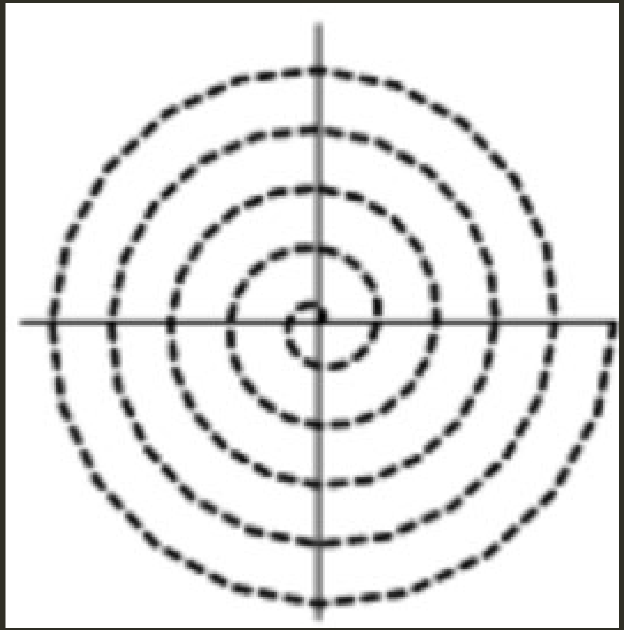
Can we do better?

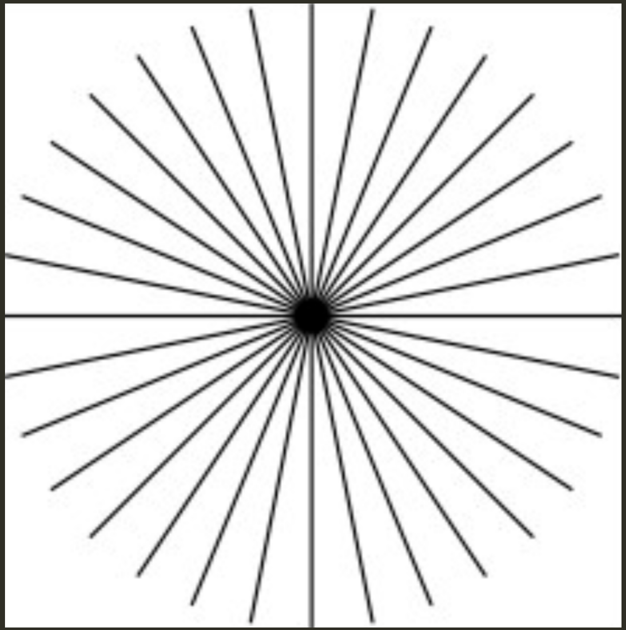








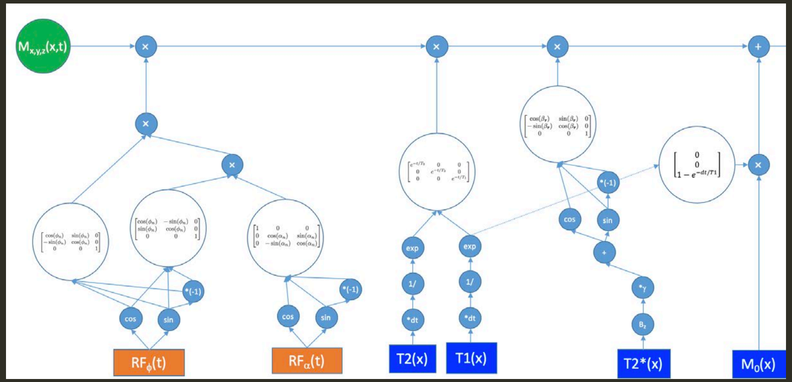


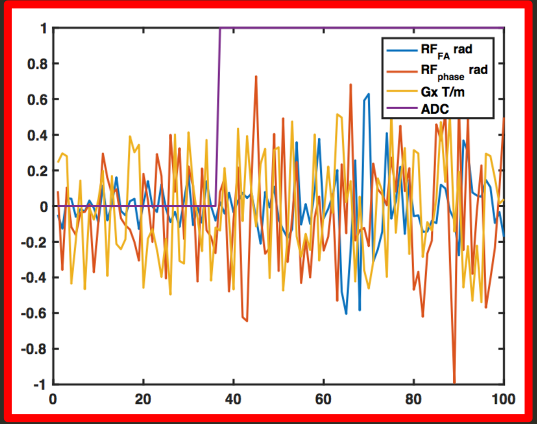


Machine learning for MRI encoding:
Automated pulse sequence discovery (AUTOSEQ)

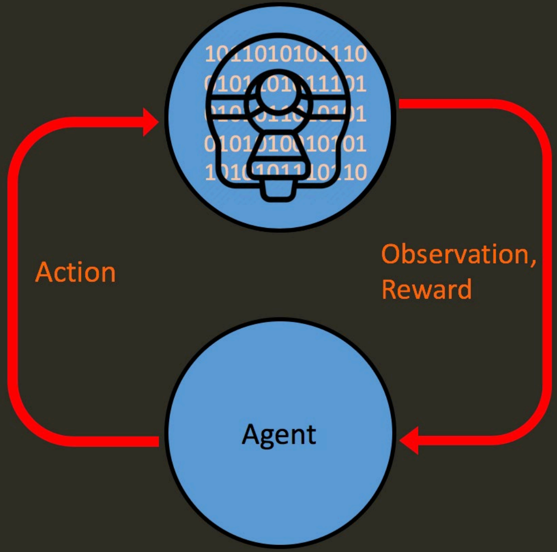
1. Model-based computational graph

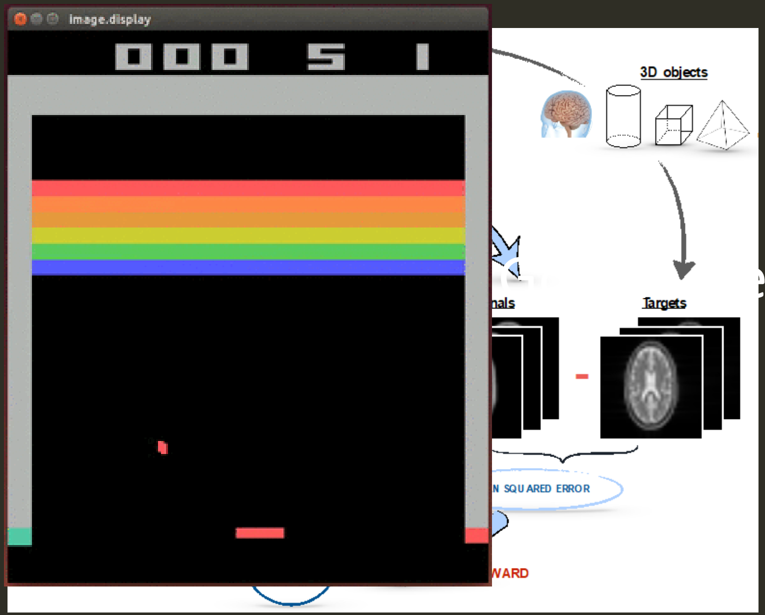
$$\frac{dM_x(t)}{dt} = \gamma(\mathbf{M}(t) \times \mathbf{B}(t))_x - \frac{M_x(t)}{T_2}$$
$$\frac{dM_y(t)}{dt} = \gamma(\mathbf{M}(t) \times \mathbf{B}(t))_y - \frac{M_y(t)}{T_2}$$
$$\frac{dM_z(t)}{dt} = \gamma(\mathbf{M}(t) \times \mathbf{B}(t))_z - \frac{M_z(t) - M_0}{T_1}$$

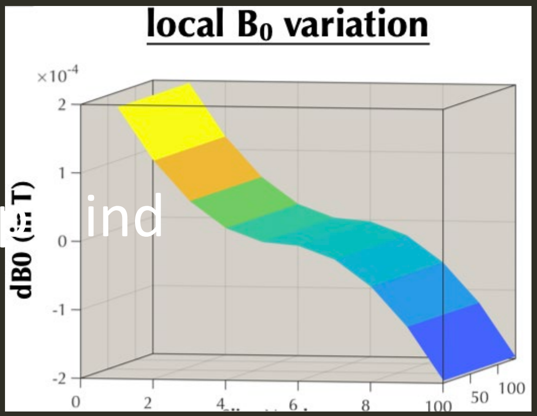


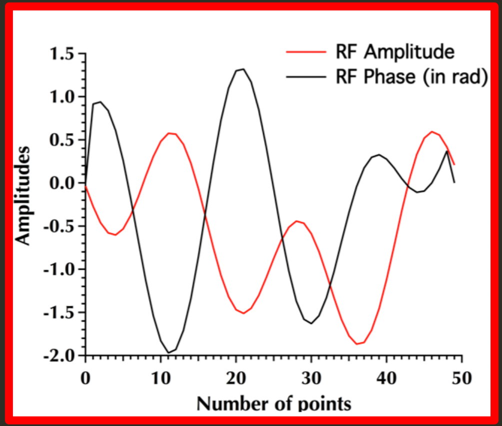


2. Model-free reinforcement-learning





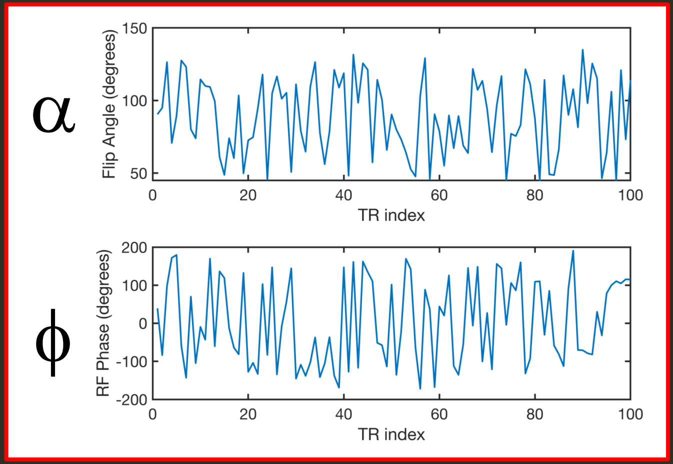




Zhu, et al. ISMRM ML Workshop 2018
Zhu, et al. ISMRM 2019 Power Pitch

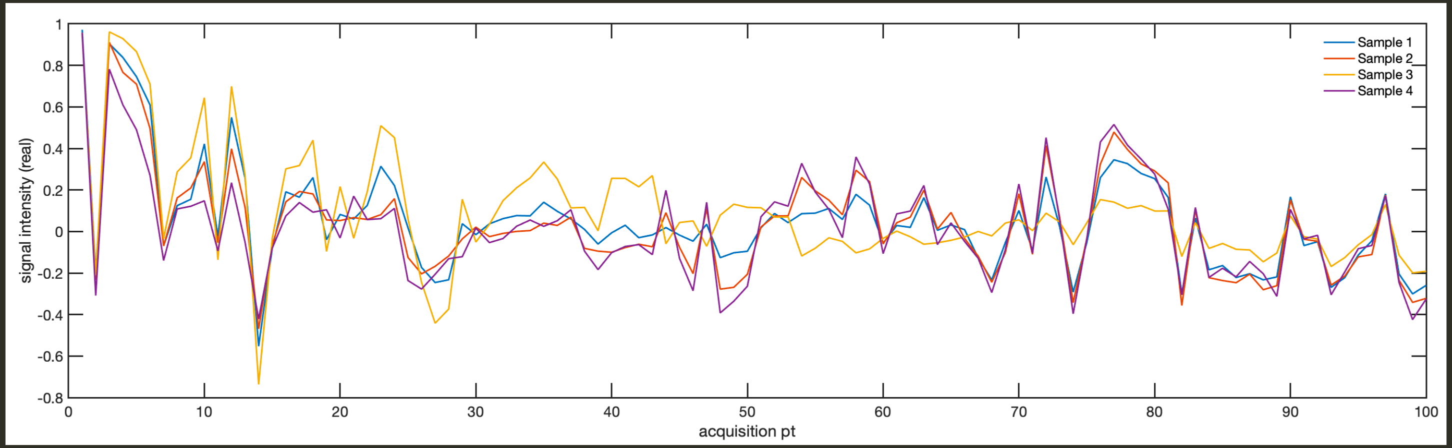
AUTOSEQ at 6.5 mT

“The fastest way to measure T_1 and T_2”



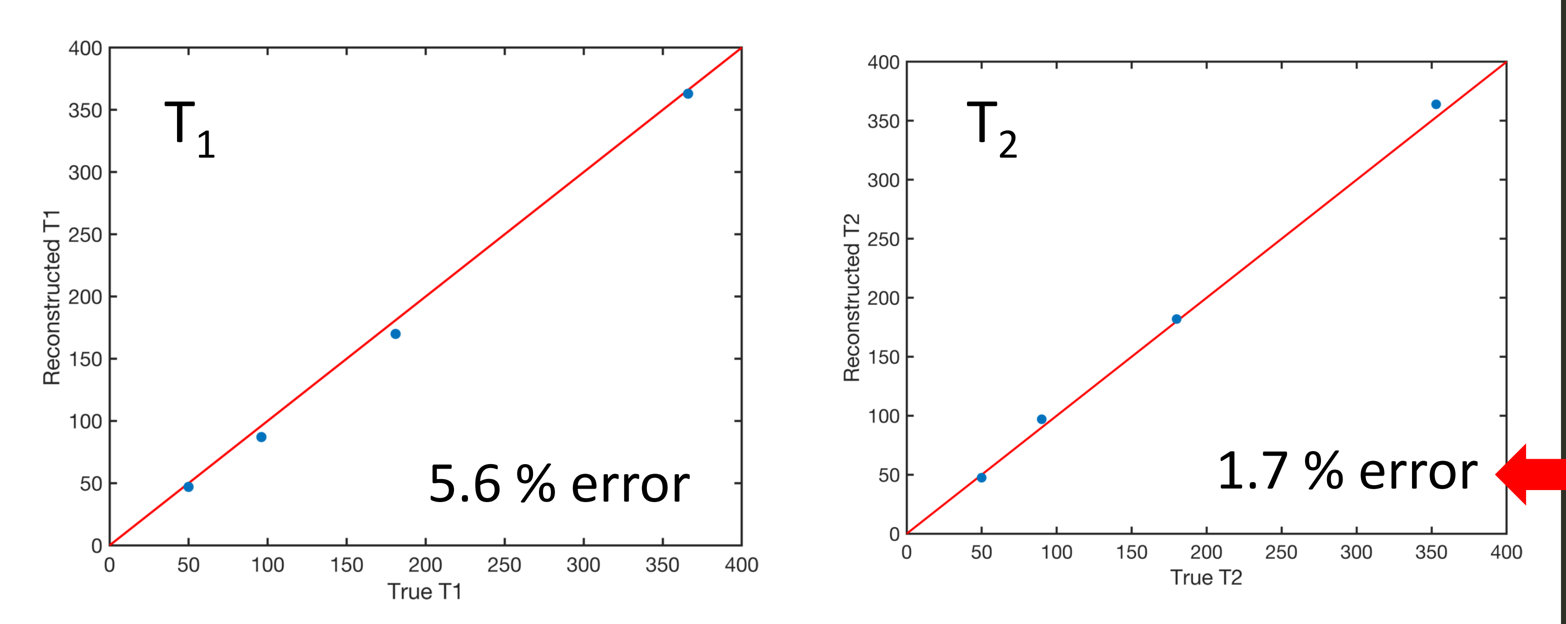
Discovered 1 sec pulse sequence

- 100 RF pulses
- 10 ms fixed TR
- Acquire signal at each TR



AUTOSEQ at 6.5 mT

“The fastest way to measure T_1 and T_2”



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RAPID COMMUNICATION
Magnetic Resonance in Medicine

MR fingerprinting Deep RecOnstruction NEtwork (DRONE)

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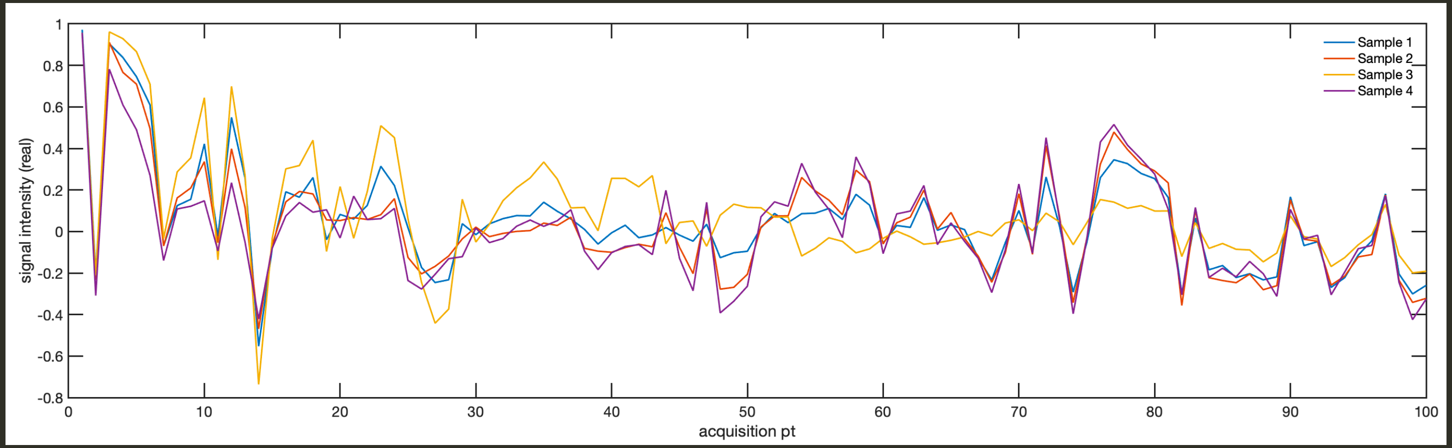

Conclusions

- MRI is possible in the mT regime

  Physics + Compute + Deep Learning

  AUTOMAP: unified reconstruction framework

  - Manifold learning with deep neural networks

  → Effectively boosts SNR and image quality

  → Uncertainty estimation

  Super resolution + segmentation

  - Accurate quantitative morphological measurement

  → Volumetric measurements more robust than planar images

  AI-discovered pulse sequences for quantitative magnetic resonance

CURE Children's Hospital
Mbale, Uganda

"Low-cost MRI could revolutionize medical care" –Steve Schiff

> All I ever wanted was to pick apart the [scanner]
> and put the pieces back together my way –Aesop Rock

Some applications honestly benefit from ML

How will you use these tools in 21^{st} Century?

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