Learning to See: perceptual learning and MRI image reconstruction

Matt Rosen
MGH/A.A. Martinos Center

AAPM
San Antonio, TX
16 July 2019

Commercial Disclosures

Founder and SAB member:

HYPERFINE
blink · AI

SAB member:

Sponsored research: GE Healthcare
Image acquisition and reconstruction

Object > Acquisition > Encoding > Image

Sensor Domain

Ultrasound: element - time space

MRI: Fourier k-space

PET/CT: radon sinogram

MRI acquisition and reconstruction

1. NMR inductive detection
2. $\mathbf{\phi}$ and $\mathbf{w}$ modulated by magnetic gradient fields

Object > Fourier Transform > Image

Signal

$S(t) = \mathbf{m}(x, y)e^{-i\omega_0 t}\exp(-ig\int\mathbf{g}_x(t)x + \mathbf{g}_y(t)y)dt)dx dy$

2D Cartesian MRI forward encoding model

MRI acquisition and reconstruction

Object > Fourier Transform > Image

Non-Cartesian Sampling

Parallel/Multichannel Rx

Undersampling

Gridding, Density Compensation

Coil Compression, autocalibration, nonlinear optimization

Sparsity promoting, CG-optimization, backtracking line search
MRI acquisition and reconstruction

- Fourier Transform
- Non-Cartesian Sampling
- Parallel/Multichannel Rx
- Undersampling
- Gridding
- Density Compensation
- Cartesian
- Non-Cartesian Sampling
- Parallel/Multichannel Rx
- Undersampling

Speech recognition before 2010:
hand-crafted expert feature extraction

- Expert-coded methods to represent vowels, consonants, phoneme transitions...

Supervised learning:
- Deep Recurrent Neural Network

Deep learning revolutionized speech recognition
Supervised learning: Training refines network weights w/o external theory of language

- Highly expressive architecture
- Large number of degrees of freedom
- Data defines its own internal representation
Automated feature extraction: Solving difficult problems

Previously reliant on expert feature engineering:
- Speech Recognition
- Natural Language Processing
- AI Gaming (Chess, Go, ATARI)
- Image Classification
- Medical Image Segmentation
- Scene analysis (autonomous vehicles)

Enabled by a technological convergence:
- Algorithms/architectures (Deep+Convolutional Neural Networks)
- Accessibility to training data (Big Data)
- Advanced parallel computing hardware (Multi-GPU)

Perceptual Learning

Refinement of perception based on exposure to and training on stimuli

Perceptual learning is critical to robust performance in low SNR settings.

What animal is this?
Your brain learns from seeing many examples

- Under-sampled
- Low SNR

- Fully sampled
- High SNR

"Hallucination"

MRI acquisition & reconstruction is different!

Data acquisition is slow!
(and slower at ULF!)

Data Acquisition

Image Reconstruction

20 minutes

10 minutes

Optic nerve neural signaling

Reconstructed image

Perceptual Learning for MRI
Recast image reconstruction as a supervised learning task

1. Data-driven supervised learning replaces hand-crafted pipelines
2. Perceptual learning biologically-inspired approach improves SNR of noisy data

Deep learning for image reconstruction

• Reconstruction relationship emerges from raw sensor and image data
• Forward model is inverted by learning pairs of examples

Convolutional NN denoiser

Mapping from noisy to clean aka noise training learned from pairs of examples
Deep learning for image reconstruction

In contrast, we train on clean pairs from forward encoding model.

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
- 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

Pixel space

“Circle space”

(\(x_0, y_0, r_0\))

→ a sparse domain for circles
Sparsity: natural separation of signal and noise

Noise can be anything... except sparse!

Possible images: \(2^{128} \times 128\)

...we need all those coefficients!

**Sparsity: natural separation of signal and noise**

Noise is not sparse in any domain!

- Not sparse
- Fourier domain: also not sparse
- Wavelet domain: no sparsity here

\(\Rightarrow\) High dimensional data can be represented with fewer coefficients in a sparse domain

Not surprising given the data dimensionality:

\(2^{128} \times 128 \gg 10^{80}\) atoms in the universe

**Sparsity: natural separation of signal and noise**

Natural images are special

- Not sparse
- Fourier domain: also not sparse
- Wavelet domain: \(\Rightarrow\) sparse

"Brain hallucinates image using learned sparse features"
Sparsity: natural separation of signal and noise

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

- 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.

Deep learning for image reconstruction

- Reconstruction relationship emerges from raw sensor and image data.
- Training conditions joint manifold for sparsity & learns to invert encoding.

Neuromorphic approach: AUTOMAP

- Mathematical transform: sparse properties of natural images.
AUTOMAP feed-forward reconstruction

Dense Layer Activations

Convolutional Feature Maps

Reconstructed Image

AUTOMAP: Automated Transform by Manifold Approximation

Mathematical transform + sparse properties of natural images

Neuromorphic approach: AUTOMAP

Fully connected layers: universal function approximators that can represent any function on compact set

Neuromorphic approach: AUTOMAP

Mathematical transform + sparse properties of natural images

AUTOMAP: Automated Transform by Manifold Approximation
Neuromorphic approach: AUTOMAP

AUTOMAP: Automated transform by Manifold Approximation

- Specifying domain (inverse)
- Not assumed to be wavelet
- Hallucinate final image

Very similar to the receptive fields of our visual cortices (Gabor filters)

Mathematical transform - Sparse properties of natural images

Training AUTOMAP

- Image domain: 10,000 natural scene images from ImageNet
- Sensor domain: Fourier Transform of each image

AUTOMAP learns the inverse FT

Training Corpus: pairs of sensor and image domain data

- Manifold assumption - natural high-dim data concentrates close to a low-dimensional manifold

→ Low dim representations are stable & robust to input corruption
AUTOMAP deduces the reconstruction

"Brain agnostic"

Opens the space for learning arbitrary encoding schemes!
MRI spatial encoding schemes

Can we do better?

Non-intuitive evolutionary optimized designs

Weird!

Cable support system

Original  60% weight  25% weight

NASA ST5 spacecraft antenna


https://ti.arc.nasa.gov/na卯d PUB/monthly/1244h/1244%20(Hornby).pdf

AUTOMAP deduces the reconstruction

Opens the space for learning arbitrary encoding schemes!
Testing AUTOMAP

Reconstruction shoot-out in the presence of noise

Ground Truth

Additive noise (finite SNR)

Sensor domain representation

in vivo image

AUTOMAP
Conventional

RMSE: 5.0%
SNR: 13.8

AUTOMAP: spiral k-space sampling

Sensor: Variable-density 10-interleave spiral k-space
  • Generated by NUFFT on reference image (2x resolution)
  • Gaussian noise added to 25 dB SNR

Reference

Conventional

Recon: Conjugate-gradient SENSE (single-coil) with NUFFT
regridding; 30 iterations
**AUTOMAP: spiral k-space sampling**

- **Sensor:** Variable-density 1D interleave spiral k-space
- **Generated by NUFFT on reference image (2x resolution)
- **Gaussian noise added to 25 dB SNR**
- **Recon:** Conjugate gradient SENSE (single-coil) with NUFFT regridding; 30 iterations

**Reference**

**AUTOMAP**

**Conventional**

RMSE: 3.7%
SNR: 42.7

RMSE: 5.0%
SNR: 13.8

---

**AUTOMAP reconstructs all encodings**

<table>
<thead>
<tr>
<th>Encoding</th>
<th>Reference</th>
<th>AUTOMAP</th>
<th>Conventional</th>
<th>AUTOMAP</th>
<th>Conventional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spiral</td>
<td></td>
<td>![Image]</td>
<td></td>
<td>![Image]</td>
<td></td>
</tr>
<tr>
<td>Radon Projection</td>
<td></td>
<td>![Image]</td>
<td></td>
<td>![Image]</td>
<td></td>
</tr>
</tbody>
</table>

**RMSE (single-coil, 30 iterations):**

- Spiral: 1.7%
- Radon Projection: 2.4%

**SNR:**

- Spiral: 42.7
- Radon Projection: 14.2

---

**AUTOMAP reconstructs very noisy data**

<table>
<thead>
<tr>
<th>Encoding</th>
<th>Reference</th>
<th>AUTOMAP</th>
<th>Conventional</th>
<th>AUTOMAP</th>
<th>Conventional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spiral</td>
<td></td>
<td>![Image]</td>
<td></td>
<td>![Image]</td>
<td></td>
</tr>
<tr>
<td>Radon Projection</td>
<td></td>
<td>![Image]</td>
<td></td>
<td>![Image]</td>
<td></td>
</tr>
</tbody>
</table>

**Robustness to noise:**

1. Low-dim internal representation of domain transfer function
2. Reconstruction hallucinated from sparse convolutional feature maps

**Error:**

- Spiral: 13.8
- Radon Projection: 23.9
AUTOMAP reconstructs (real) noisy ULF data

**Fig. 2:** AUTOMAP reconstruction vs. inverse FFT.

**Overall SNR enhancement:**
- AUTOMAP: 34.3%
- Conventional: 36.2%
- Noise reduction (STD):
  - AUTOMAP: 15%
  - Conventional: 26%

**Sorghum root image reconstruction: AUTOMAP vs. inverse FFT**

**AUtomap reconstructs (real) noisy ULF data**

**Conventional**

**AUTOMAP**

**Automap Reconstruction gives 60% increase in SNR**

**Conventional IFFT Reconstruction**

**Ultra-Low Field brain MRI Reconstruction:**
- AUTOMAP at 6.5T
- 2019 ISMRM

**Note:** Image by the lab of Matthew A. Movs.
Sorgham root image reconstruction: AUTOMAP vs. inverse FFT

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall SNR enhancement</th>
<th>Noise reduction (STD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUTOMAP</td>
<td>34.3%</td>
<td>15%</td>
</tr>
<tr>
<td>IFFT</td>
<td>36.2%</td>
<td>26%</td>
</tr>
<tr>
<td>(Dual UN hidden)</td>
<td>31.2%</td>
<td>17%</td>
</tr>
<tr>
<td>(Dual UN hidden)</td>
<td>37.3%</td>
<td>26%</td>
</tr>
<tr>
<td>(Dual UN hidden)</td>
<td>61.2%</td>
<td>37%</td>
</tr>
</tbody>
</table>

AUTOMAP hidden layer activation

- Trained on ImageNet images
- Activation with k-space of brain

Superior immunity to noise and artifacts: Sparse internal representation

Sparsity of hidden layer activation

- Gaussian noise
- Cartesian FT
Domain-specific training

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

Mean SNR

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

Domain-specific training:
from brain images to synthetic vasculature

Software and data: http://vascusynth.cs.sfu.ca
Conclusions
AUTOMAP: unified reconstruction framework
- Universal function approximation
- Manifold learning with deep neural networks
  Automatically learn optimal reconstruction for arbitrary encodings
  No imposed expert knowledge
AUTOMAP changes the game:
- Robust immunity to noise
- Faster scan times with less signal averaging (or dose)
- Rapid reconstruction (~1 ms), non-iterative feed-forward computation
  Generalized reconstruction: brand new acquisition strategies

Brandon Armstrong
Tom Boelle
Matt Christiansen
Dan Cohen
David Colby
Lei Cao
Stephen DeVreese
Sheng Ding
Aviash Kalpathy-Cramer
Nishant Kongini
Jeremiah Li
Gyu Kang
Najat Salameh
Matthew Satterfield
Sheng Shen
Joseph Stitt
Bragi Sveinsson
Bo Zhu

Brandon Armstrong
Tom Boelle
Matt Christiansen
Dan Cohen
David Colby
Lei Cao
Stephen DeVreese
Sheng Ding
Aviash Kalpathy-Cramer
Nishant Kongini
Jeremiah Li
Gyu Kang
Najat Salameh
Matthew Satterfield
Sheng Shen
Joseph Stitt
Bragi Sveinsson
Bo Zhu