Enhance Multi-contrast MRI Reconstruction For Improved Diagnosis with Deep Learning powered by NVIDIA GPU

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Acknowledgements

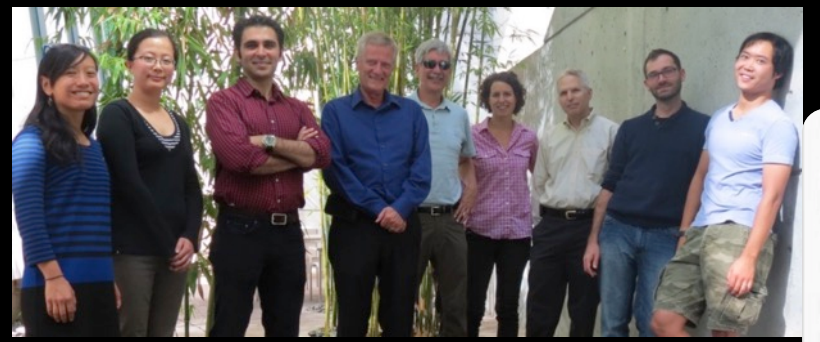
- Collaborators: Professor John Pauly, Prof. Greg Zaharchuk, Dr. Jia Guo, Dr. Morteza Mardani, …
- Additional helps: MRSRL@Stanford, CAFN@Stanford, Dr. Song Han, Prof. Bill Dally
- More collaboration is welcomed

Prof. John Pauly

Dr. Morteza Mardani

Prof. Greg Zaharchuk

Dr. Jia Guo

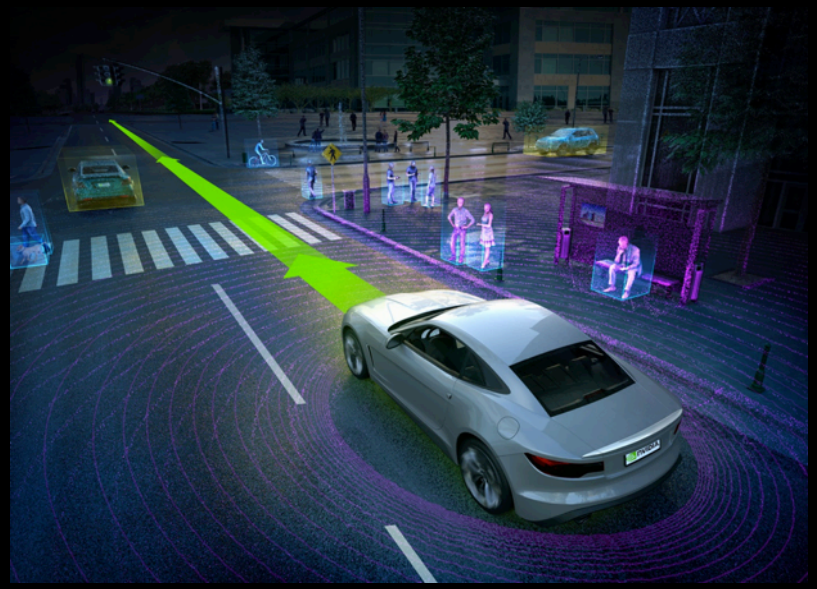


Agenda

- **Background:**
  - Deep Learning in Medical Imaging
  - MRI & Multi-contrast MRI Reconstruction
- **Example Cases:**
  - Improve Joint Multi-contrast MRI reconstruction
  - Improve Perfusion MRI in clinical settings
- **Discussion: Acceleration with NVIDIA GPU and CUDA**
  - 400x speed up in pre-processing
  - 100x faster in inference and entire reconstruction
- **Discussion: Apply DL algorithm in Medical Imaging**
  - Generative Adversarial Network (GAN) in CS-MRI

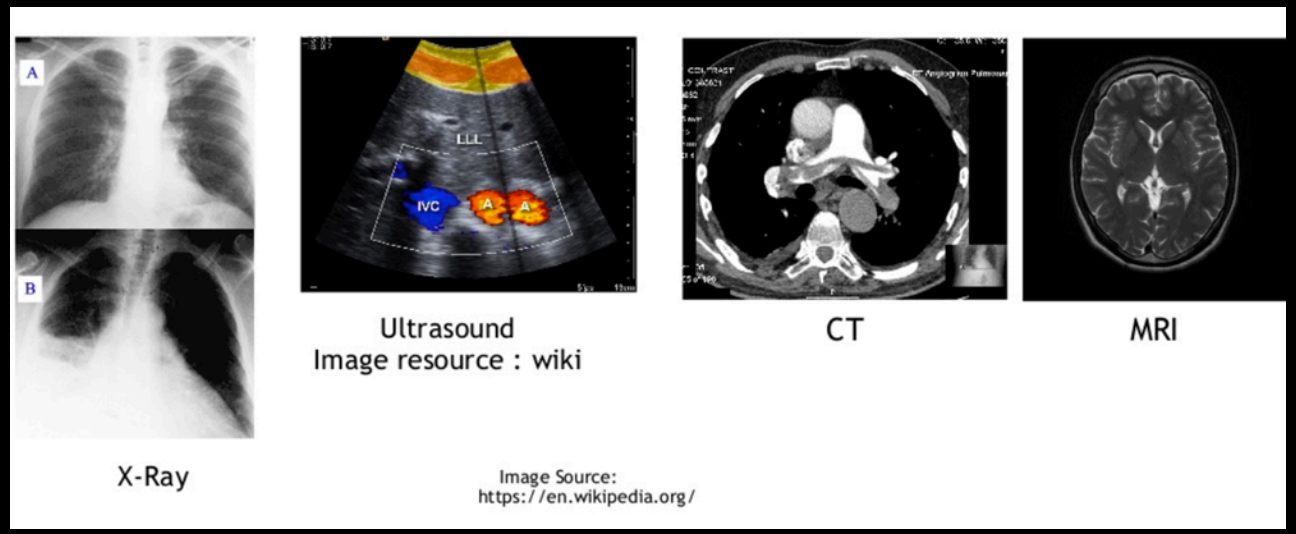
Trend of Deep Learning

- Deep Learning is changing the world
- Increasing attention and acceptance from radiology industry
  - Our talk in *Deep Learning MRI reconstruction* received great attention at ISMRM 2017

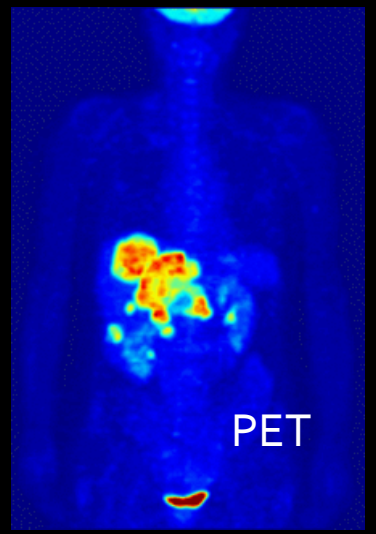


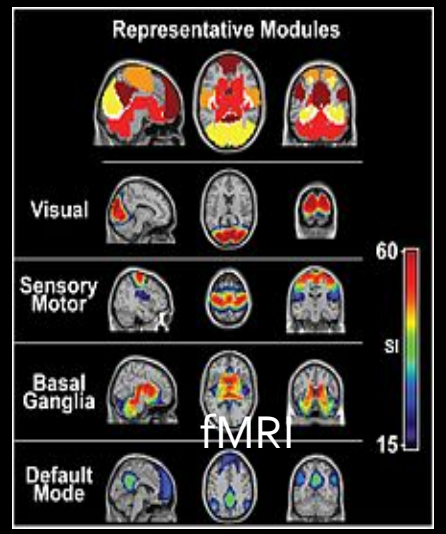
Background: Medical Imaging

- **Medical imaging** is the technique and process of creating visual representations of the **interior** of a body for **clinical analysis and medical intervention**, as well as **visual representation** of the function of organs or tissues



Structural Imaging





Functional Imaging

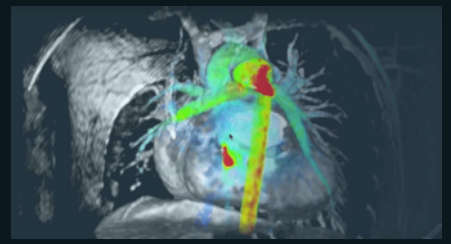
Image source: Wikipedia, NIVIDA

Background: Deep Learning for Medical Imaging

- Where and how deep learning can help

Scanner

Images



Enhancement & Augmentation

Image Reconstruction
- From anatomy to image
- Reconstruction and Restoration
- Denoising and Super-resolution

Pathology Detection
- From image to labels
- Tumor Segmentation
- Pathology Detection

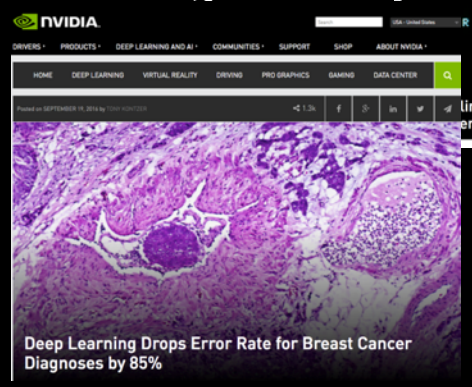
Diagnosis Assistance
- From pathology to diagnosis
- Prescription and Treatment
- Prognostic Prediction

Prognosis

Analytics

Pathology

Diagnosis



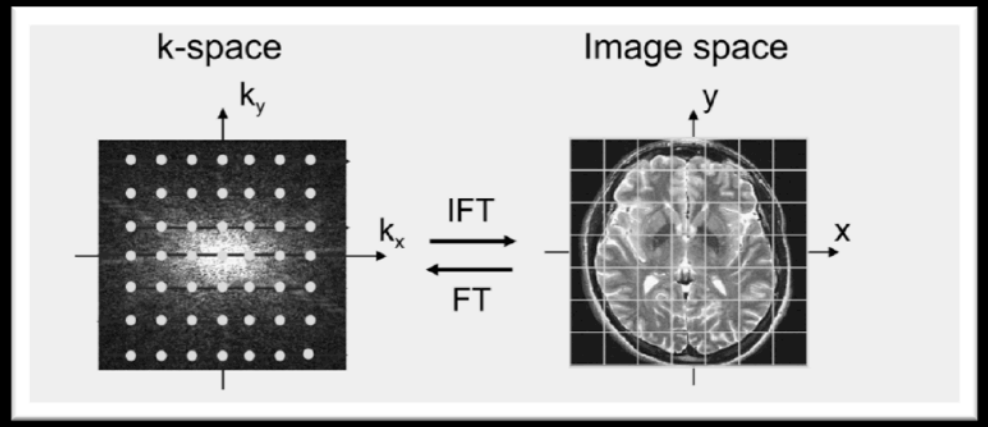
Treatment

Image source: blogs.nvidia.com

Background: MRI

- Magnetic Resonance Imaging
  - ✓Great tissue contrast for distinguish normal tissue vs pathology
  - ✓No exposure to ionizing radiation
- ❑Samples in Fourier domain (*k*-space)
  - Need some "magic" transform to convert to image domain

Scanner

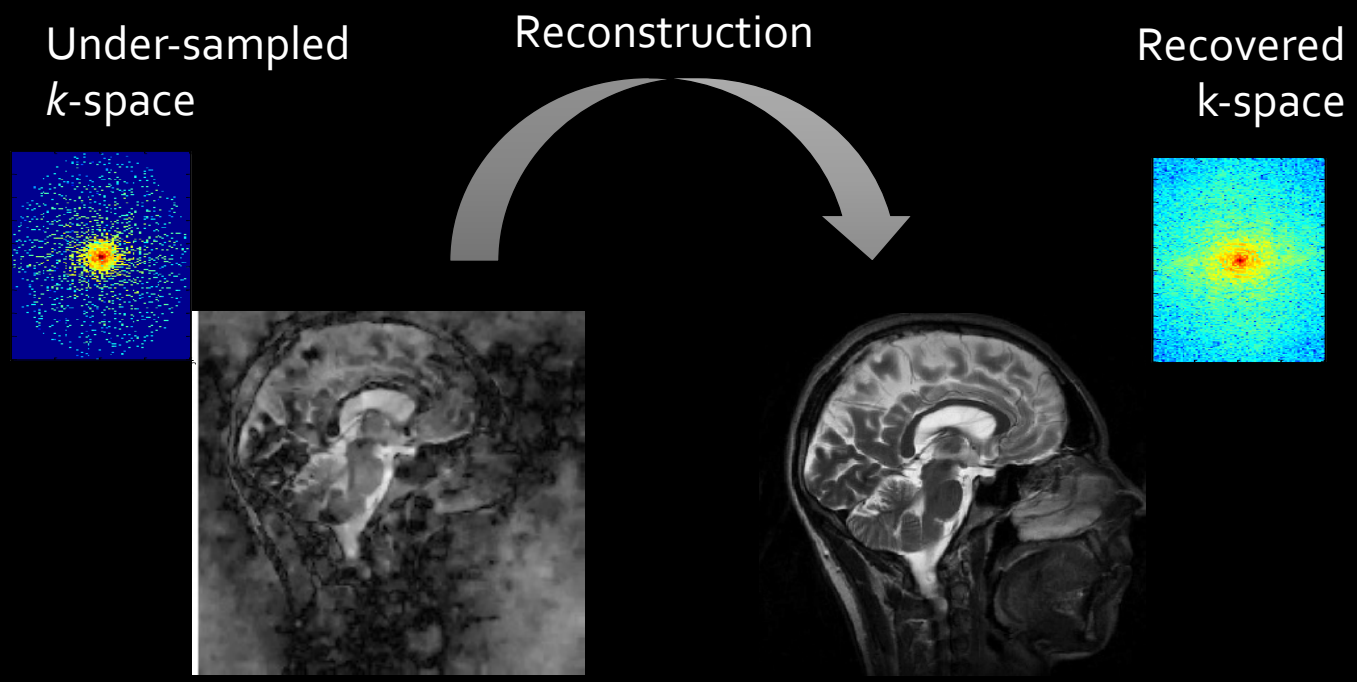


Signal

Image

Background: MRI Reconstruction

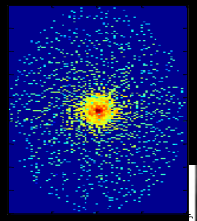
- Reconstruction of sparse sampled complex signal in Fourier domain (*k*-space) of images
- Much harder image restoration tasks



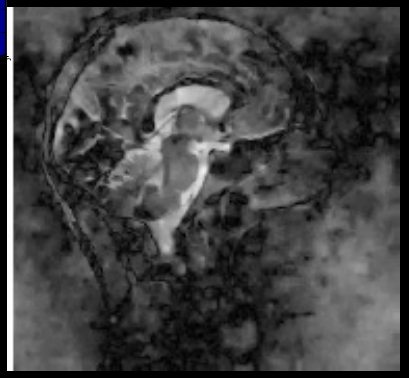
Background: MRI Reconstruction

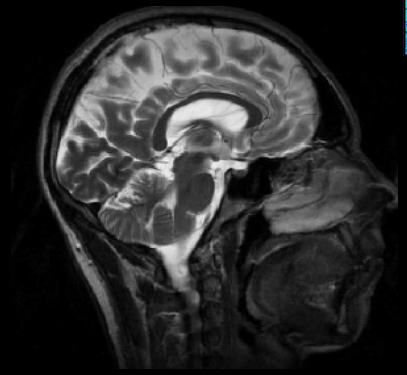
- Reconstruction of sparse sampled complex signal in Fourier domain (*k*-space) of images
- Harder image restoration tasks

Under-sampled *k*-space



Reconstruction





Recovered k-space

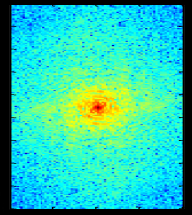


Image Super-resolution

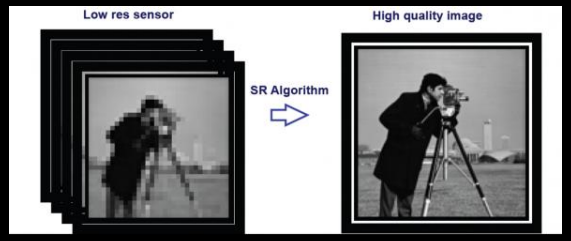
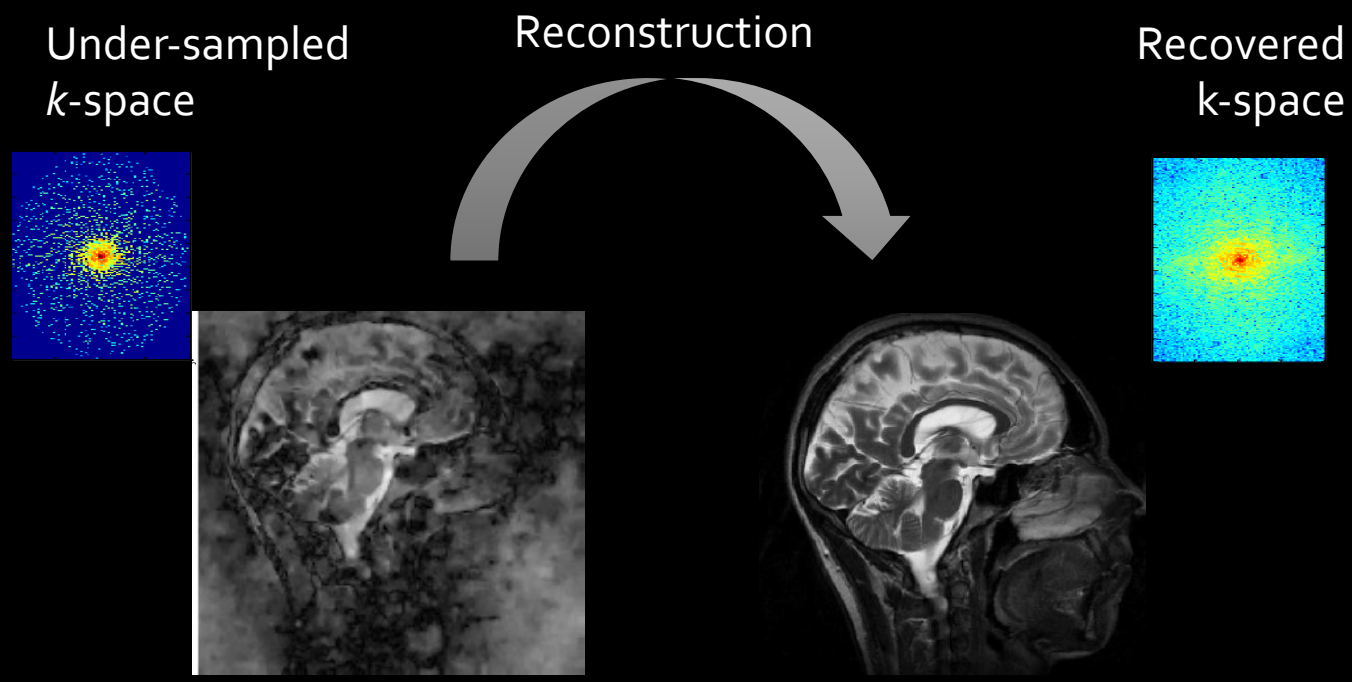


Image Restoration

Background: MRI Reconstruction

- Reconstruction of sparse sampled complex signal in Fourier domain (*k*-space) of images
- Solved with constrained optimization



- Reconstruction Model
  - Image: X
  - Acquisition Model: E
  - Measured Signal: Y=EX
- Solve inverse problem with optimization

$$X_{recon} = argmin_x \|Y - EX\|^2 + R(X)$$

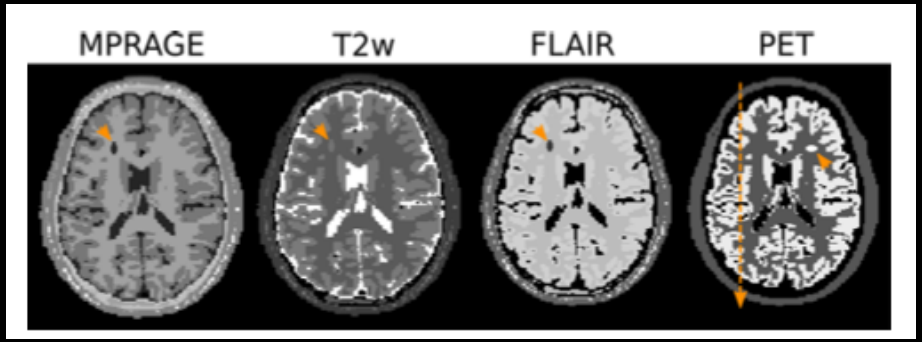
Consistent with Signal Model

Regularizations (Sparsity, Low-rank, Dictionary)

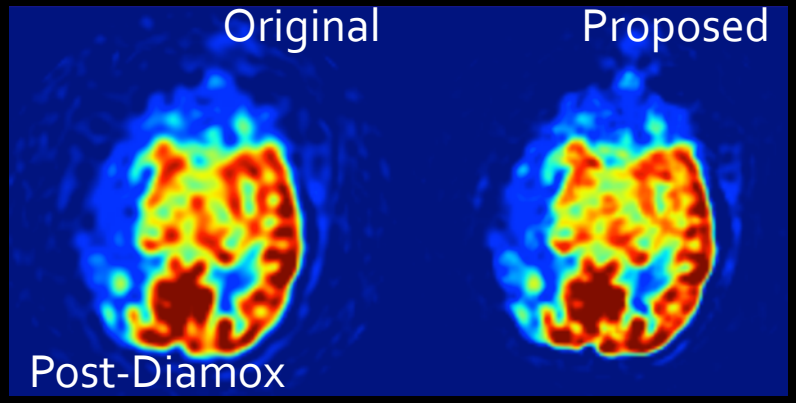
- Solving using Iterative Optimization

Case Study: Deep Learning based MRI Reconstruction

- **Case #1 Multi-contrast (structure) MRI reconstruction**

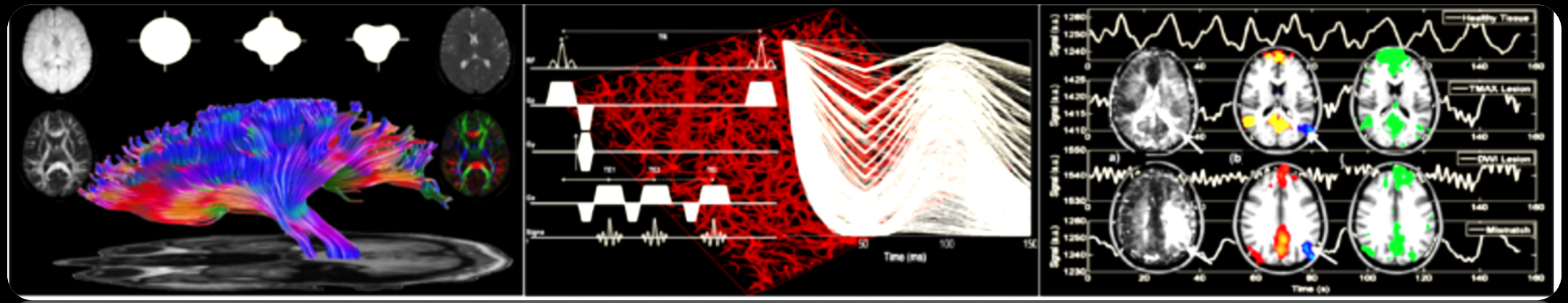


- Case #2 Perfusion MRI reconstruction



Background: Multi-contrast MRI Reconstruction

- Multi-contrast MRI for diagnosis
  - Tissue contrast to distinguish pathology
- Improving multi-contrast MRI Reconstruction
  - Existing Algorithms: Parallel Imaging (Sensor Fusion), Compressed Sensing (Sparsity Regularization)
  - Existing Approaches: Sequential approaches, Joint approaches



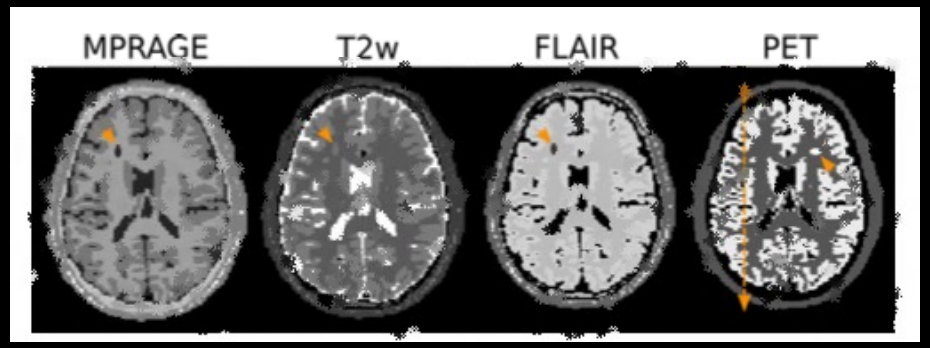
By Courtesy, Center for Advanced Functional Neuroimaging, Stanford

Case #1: Multi-contrast MRI reconstruction

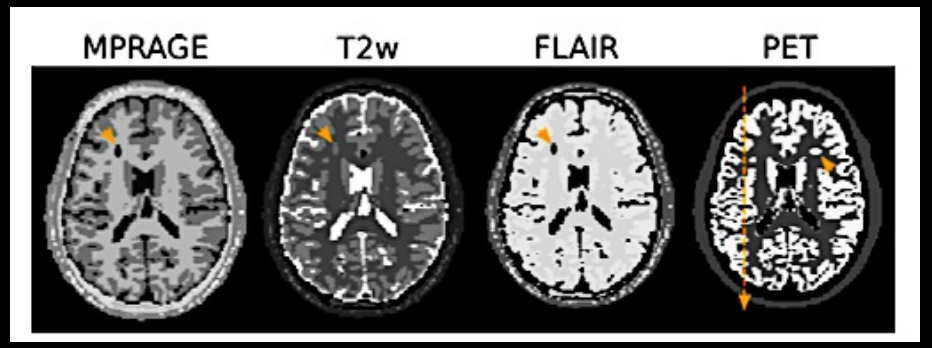
Sequential+Joint+Local approach based on deep Learning

Solve multi-contrast image reconstruction from image restoration direction:

Initial Recon



Ground-truth Recon



Sequential → **Jointly+Local** → **Patch→Image**

- Intermediate reconstruction
- Sequential and independent

- Train Local deep network for patch-patch regression
- Jointly improve multi-contrast local patch

- Image synthesis
- Generate Improved reconstruction

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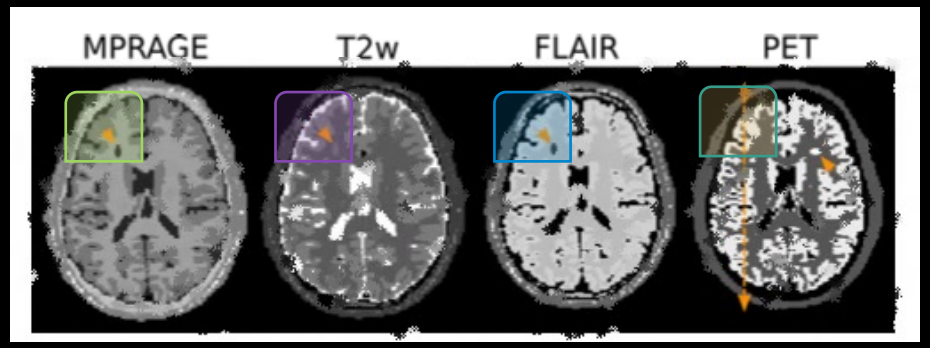
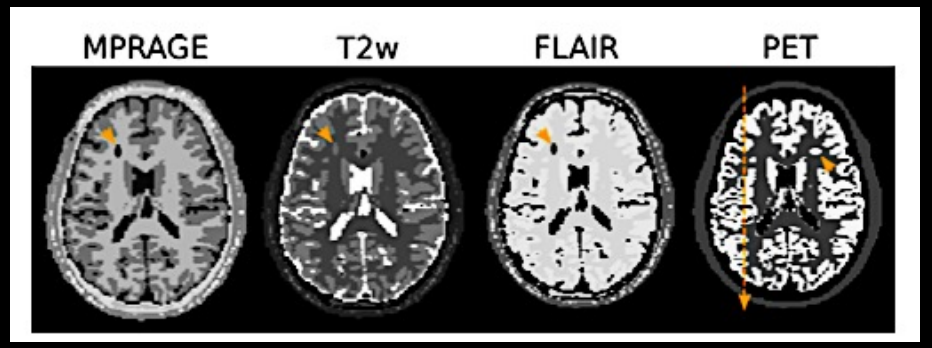


Ground-truth Recon



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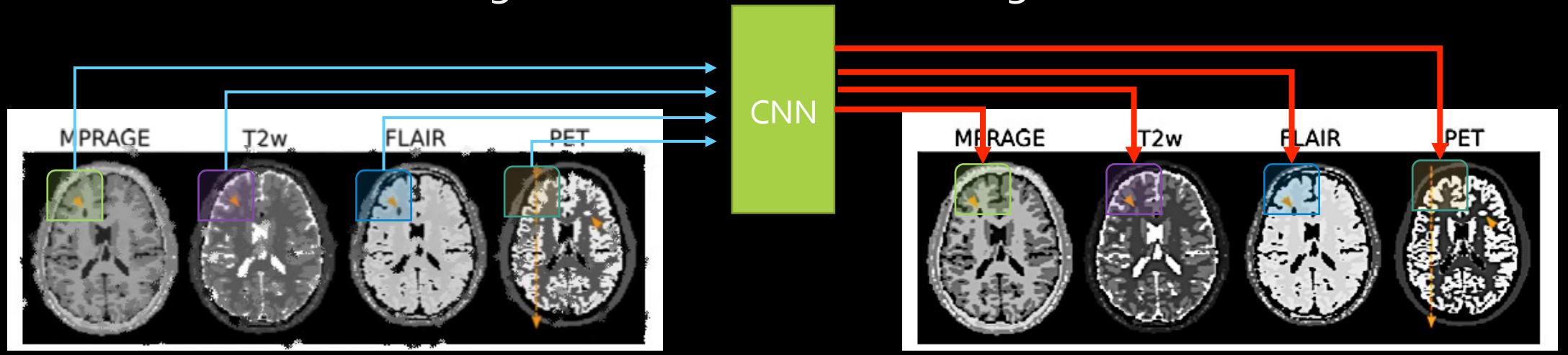

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Patch→Image

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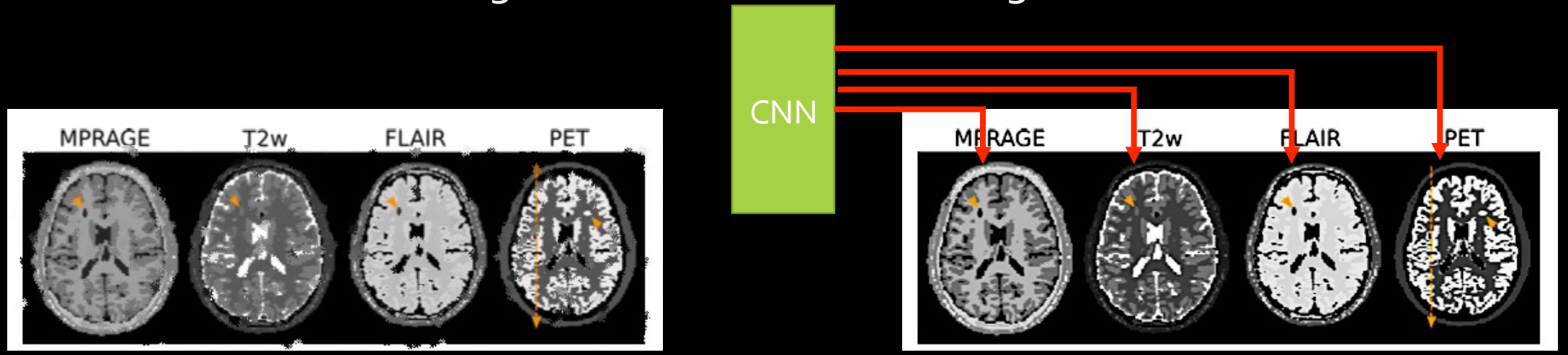

Sequential

- Intermediate reconstruction
- Sequential and independent

Jointly+Local

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Patch→Image

- Image synthesis
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Case #1: Multi-contrast MRI reconstruction

Sequential+Joint+Local approach based on deep Learning

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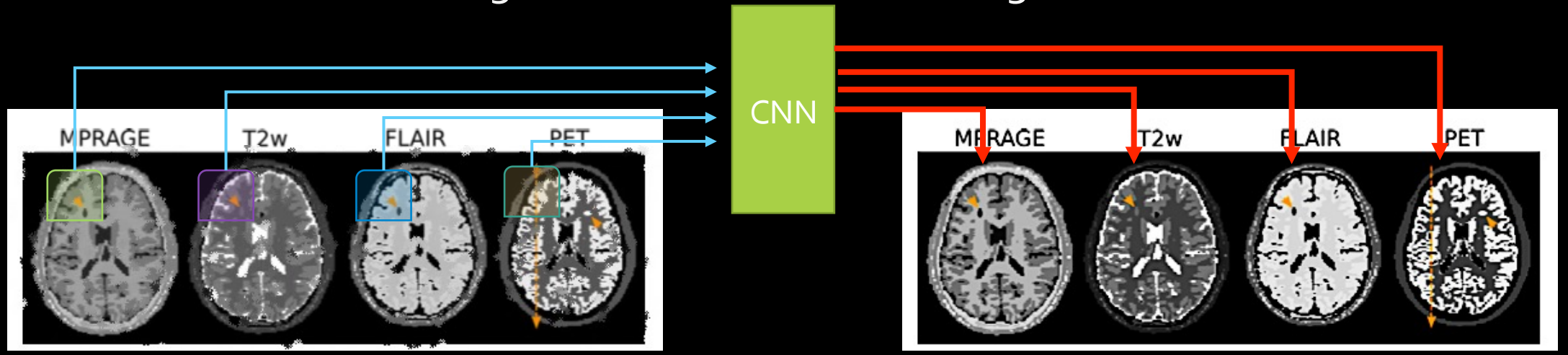


Convention Methods

- Intermediate reconstruction
- Sequential and independent

Using Deep Learning

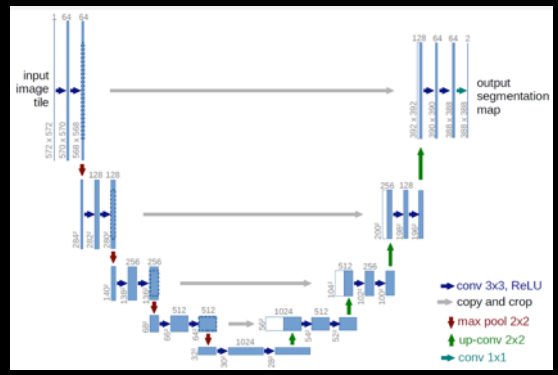
- Train Local deep network for patch-patch regression
- Jointly improve multi-contrast local patch

Data Augmentation

- Image synthesis
- Generate Improved reconstruction

Case #1: Multi-contrast MRI reconstruction
method details

- **Clinical multi-contrast protocol**
  - T1w, T2w, FLAIR, etc.
  - Goal: 30min→5min
- **Reconstruction from highly undersampled data**
  - 6x speed up → 1/6 samples
  - Ground-truth: fully-sampled images
  - Under-sampling: With different incoherent artifacts
- **Initial Reconstruction**
  - Parallel Imaging + Compressed Sensing [1,2]
- **Residual Encoder-Decoder Network**
  - Convolution/Pooling→Unpooling/Deconvolution
  - By-passes, Residual Learning
  - Similar models used in semantic segmentation, super-resolution, style transfer



Convolutional Encoder-Decoder with bypasses
O. Ronneberger, et al. 2015

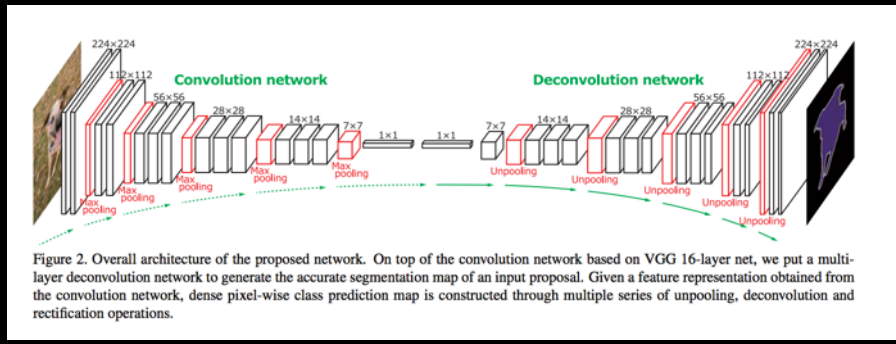


Figure 2. Overall architecture of the proposed network. On top of the convolution network based on VGG 16-layer net, we put a multi-layer deconvolution network to generate the accurate segmentation map of an input proposal. Given a feature representation obtained from the convolution network, dense pixel-wise class prediction map is constructed through multiple series of unpooling, deconvolution and rectification operations.

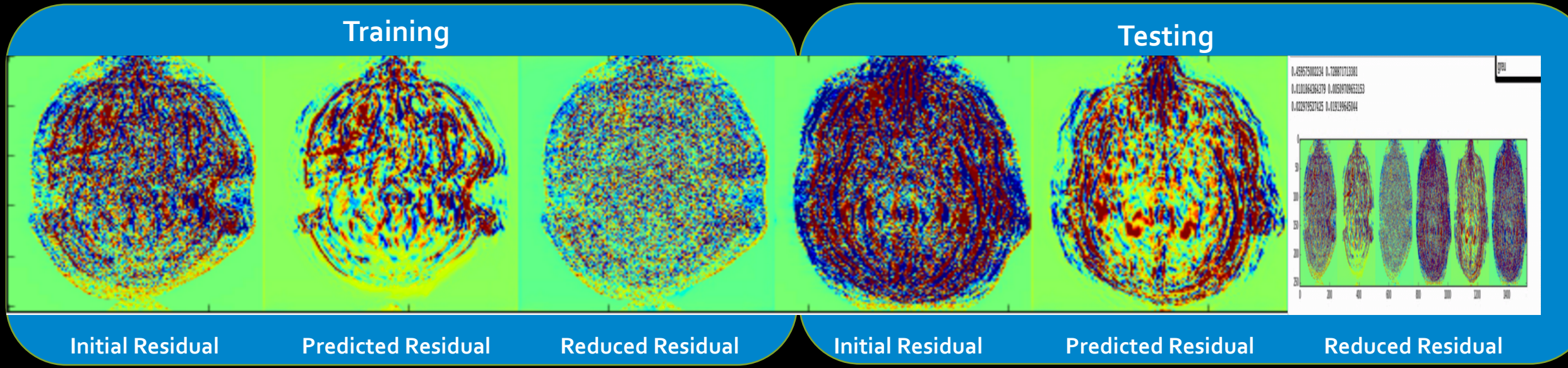
Convolutional Encoder-Decoder with downsample poolings
H. Noh, et al. ICCV2015

1. *M. Uecker et al. MRM 2014 2.M. Uecker, et al. BART*

Case #1: Multi-contrast MRI reconstruction

residual learning results

- How well we can predict the residual from under-sampled multi-contrast image patches
- How much of the residual we can reduce

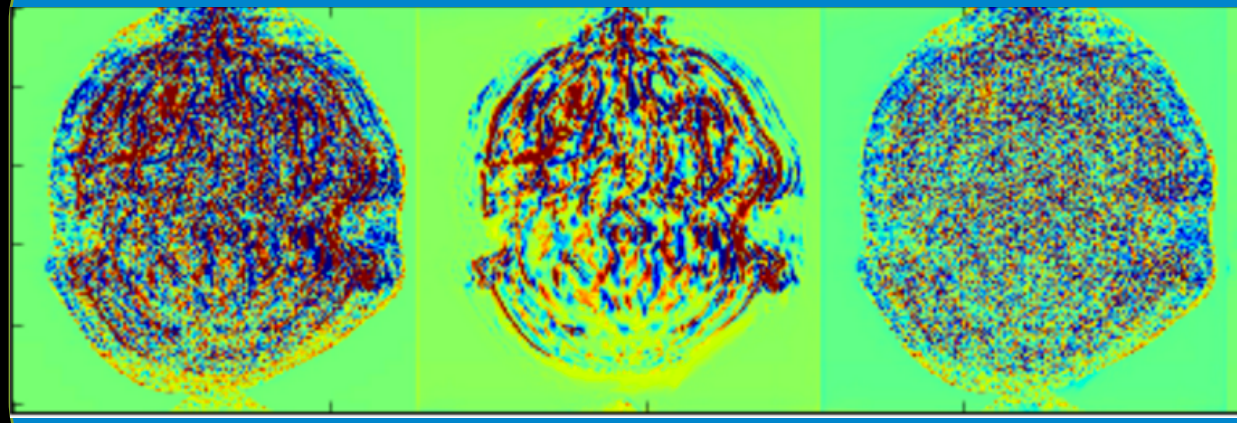


Case #1: Multi-contrast MRI reconstruction

residual learning results

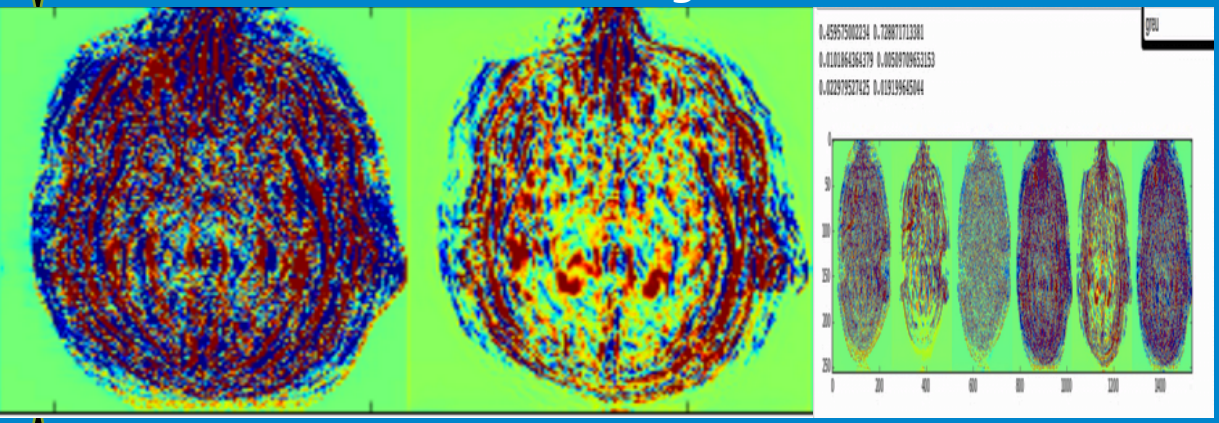
	Residual Fitting RMSE	Residual R2 Norm (Before)	Residual R2 Norm (After)	Artifact Reduction (%)
Train	0.460	0.0102	0.0051	50%
Test	0.729	0.0230	0.0192	17%

Training



Initial Residual | Predicted Residual | Reduced Residual

Testing



Initial Residual | Predicted Residual | Reduced Residual

Case #1: Multi-contrast MRI reconstruction

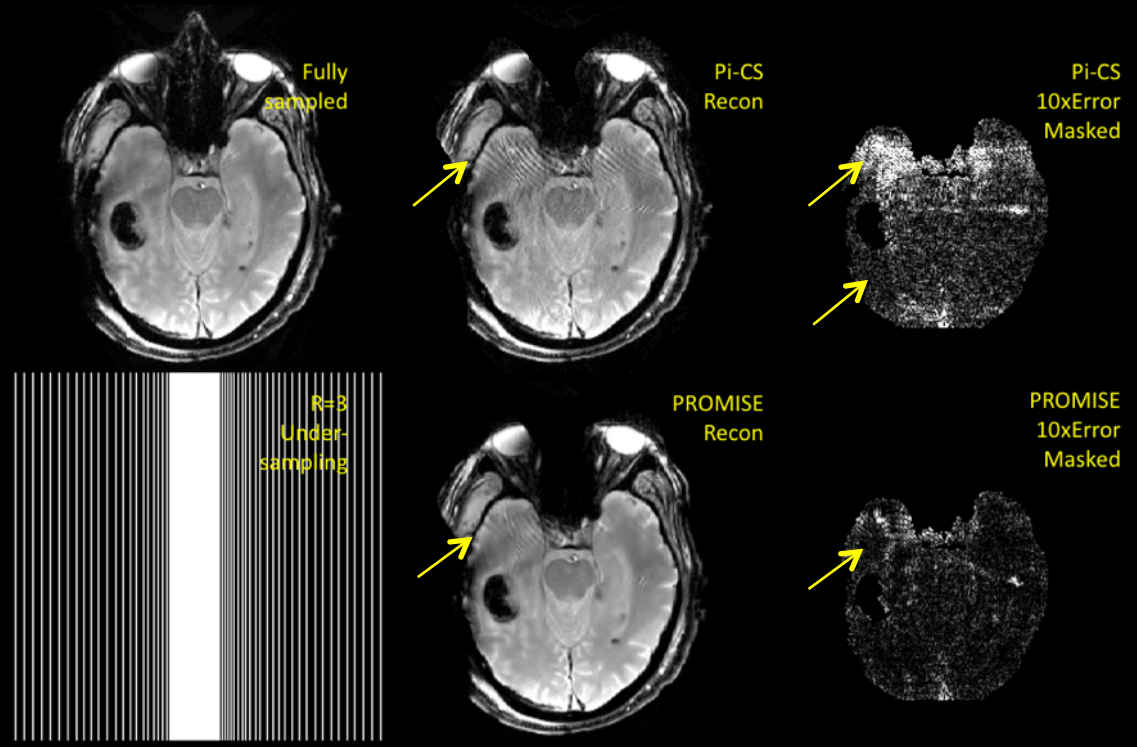
clinical results in routine multi-contrast neuro-imaging protocol

- ✓ Faster scan with less artifacts
- ✓ Accelerate FLAIR/GRE with T1w/T2w scan
- ✓ Reconstruction with sharable information
- ✓ Acceleration with preserved pathology

Example of proposed acceleration to multi-contrast neuro-imaging protocol

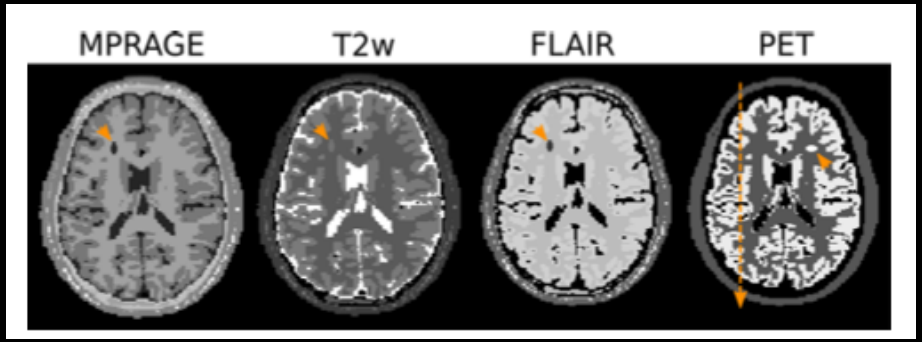
Contrast	Acquisition	Time cost	Acceleration Proposed
Ax T1 Bravo	Ax 3D	3:31	1x
Ax T2 FSE	2D	2:16	1x
Ax T2 FLAIR	2D	5:01	4x
Ax GRE	2D	3:45	4x
product ASL	Stack of Spiral	4:41	Nex3→Nex1

Improved GRE reconstruction on a hemorrhage subject

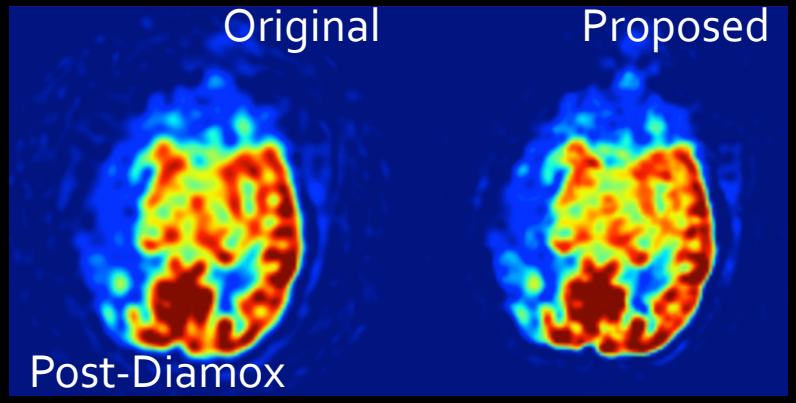


Case Study: Deep Learning based MRI Reconstruction

- Case #1 Multi-contrast (structure) MRI reconstruction

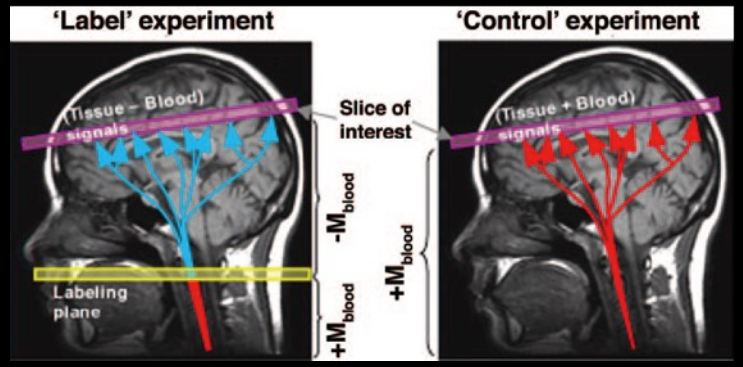


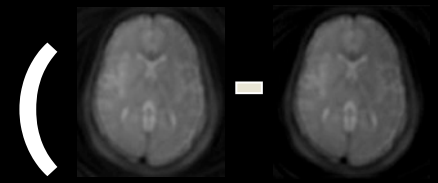
- **Case #2 Perfusion MRI reconstruction**

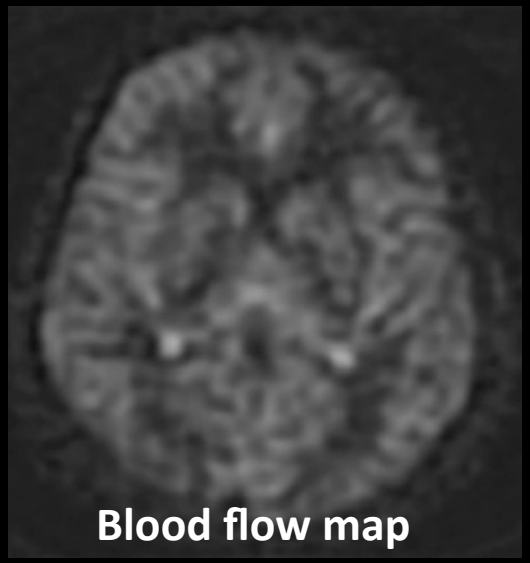


Case #2 Improve Perfusion (ASL) MRI
Background

- *Arterial Spin Labeling(ASL)* is a powerful neuro imaging tool
  - ASL quantifies perfusion maps (Cerebral Blood Flow) and evaluates perfusion function
  - High clinical values for neurological diseases (Alzheimer's, stroke, etc.)
  - Low SNR/Resolution limits many applications
    - Worse image quality for clinical scans
    - Worse quality for image with pathology







Case #2 Improve Perfusion (ASL) MRI

Detail Methods and innovations

- **Extend conventional spatial-frequency Denoising**
  - *Non-Local-Mean (NLM) Filtering*
  - *Extend with multi-contrast information*

NLM Denoising

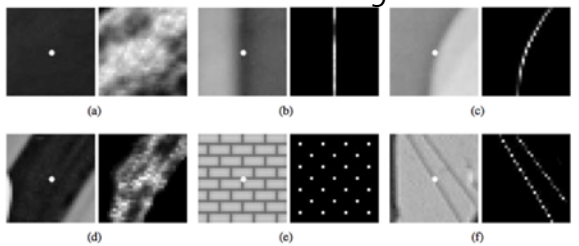


Figure 2. Display of the NL-means weight distribution used to estimate the central pixel of every image. The weights go from 1(white) to zero(black).

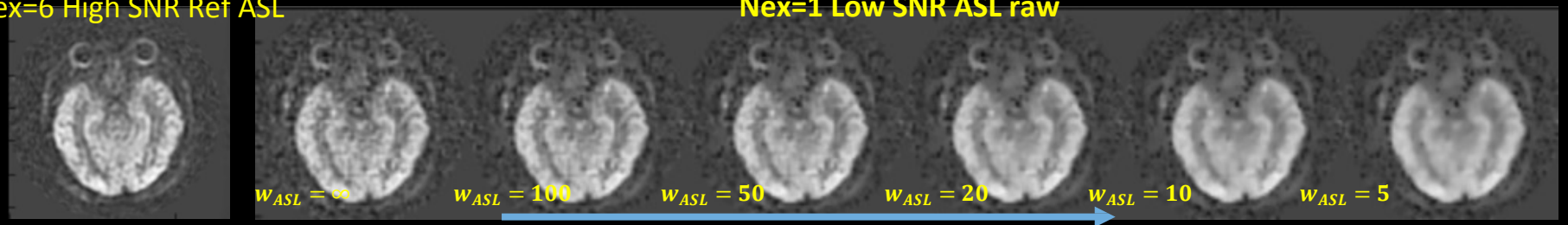
- **Train deep network models for image-to-image regression tasks**
  - *Ground-truth with higher resolution and SNR*
  - *End-to-end Denoising and super-resolution*

- **Use multi-contrast images/patches as inputs**
  - *More robustness, accuracy and avoid overfitting*

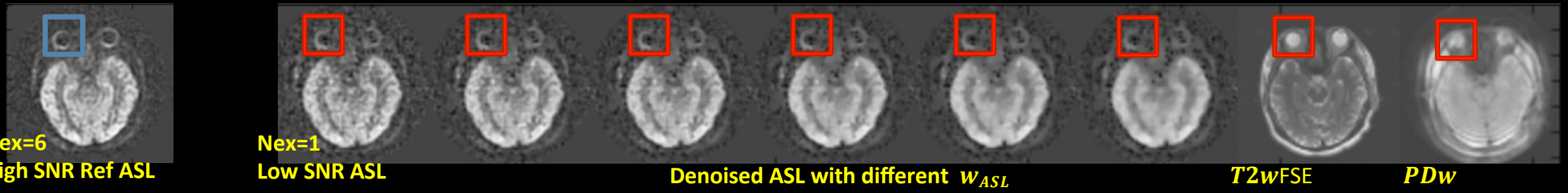
A. Buades, et.al. CVPR 2005

Training

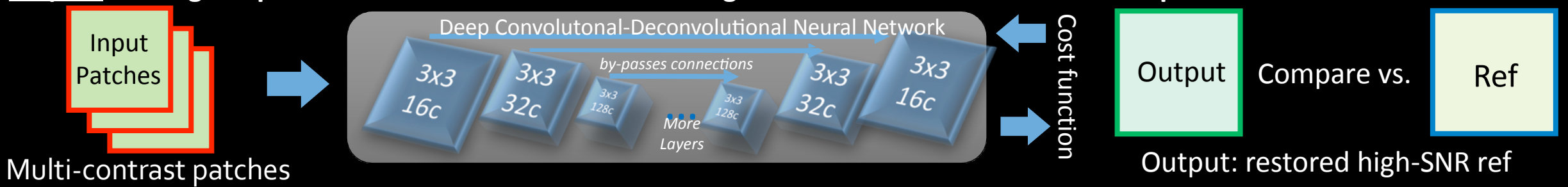
Step 1: Nonlinear ASL signal denoising using Non-Local (NLM) and Multi-contrast Guided Filter



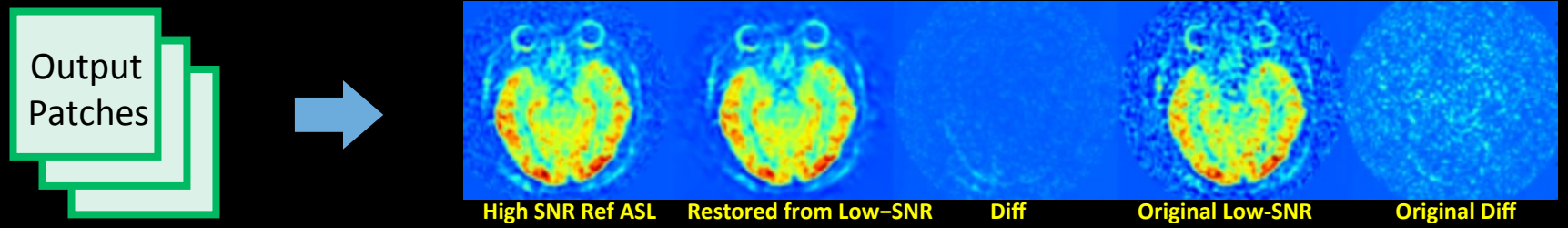
Step 2: Generate patches from High-SNR Ref. ASL, Low-SNR raw ASL, multi-level denoised ASL and anatomical MR images



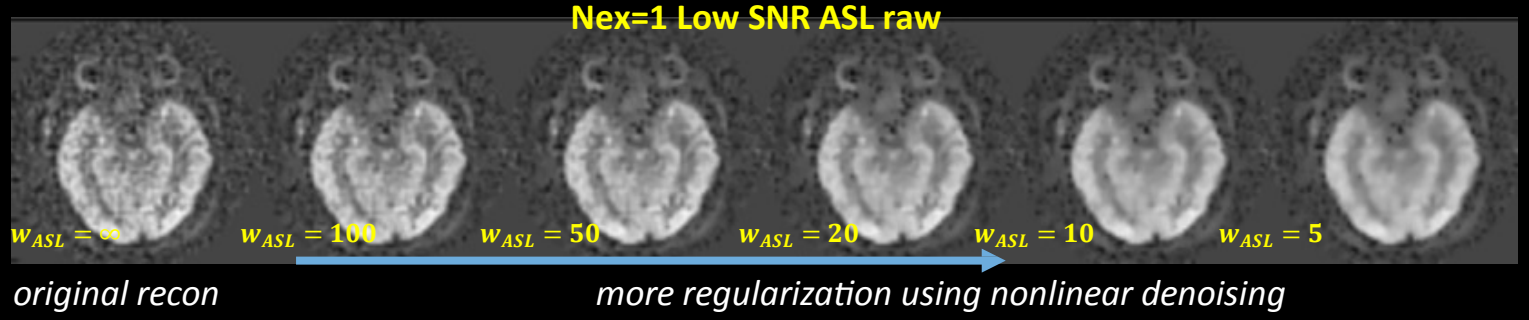
Step 3: Training deep network to learn the nonlinear image restoration from multi-contrast patches



Step 4: Generate the restored image from stored patches

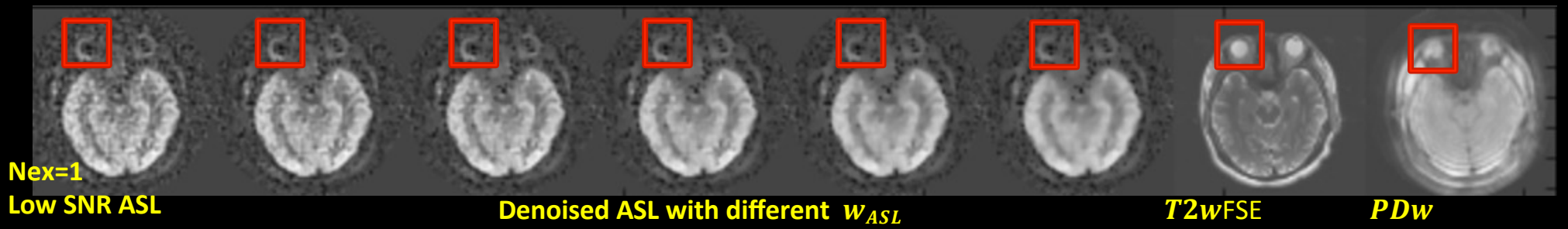


Step 1: Nonlinear ASL signal denoising using Non-Local (NLM) and Multi-contrast Guided Filter

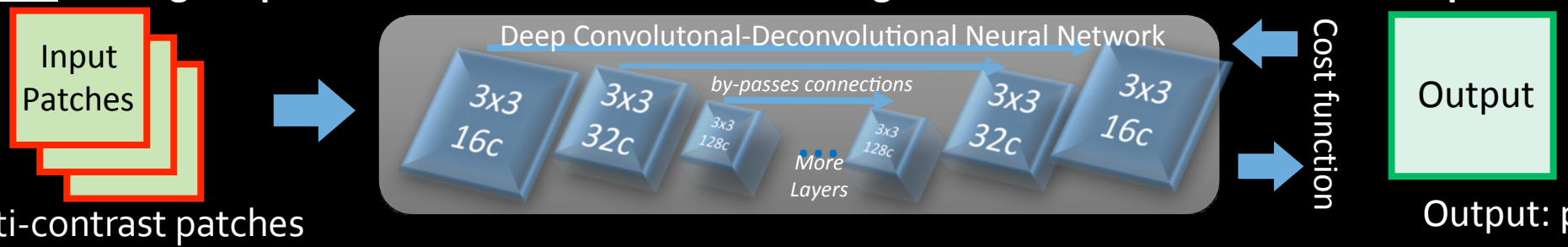


Applying

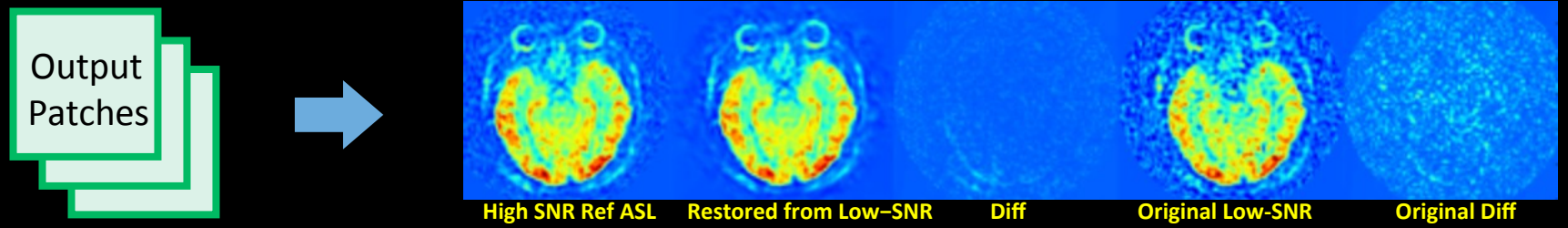
Step 2: Generate patches from High-SNR Ref. ASL, Low-SNR raw ASL, multi-level denoised ASL and anatomical MR images



Step 3: Training deep network to learn the nonlinear image restoration from multi-contrast patches



Step 4: Generate the restored image from stored patches

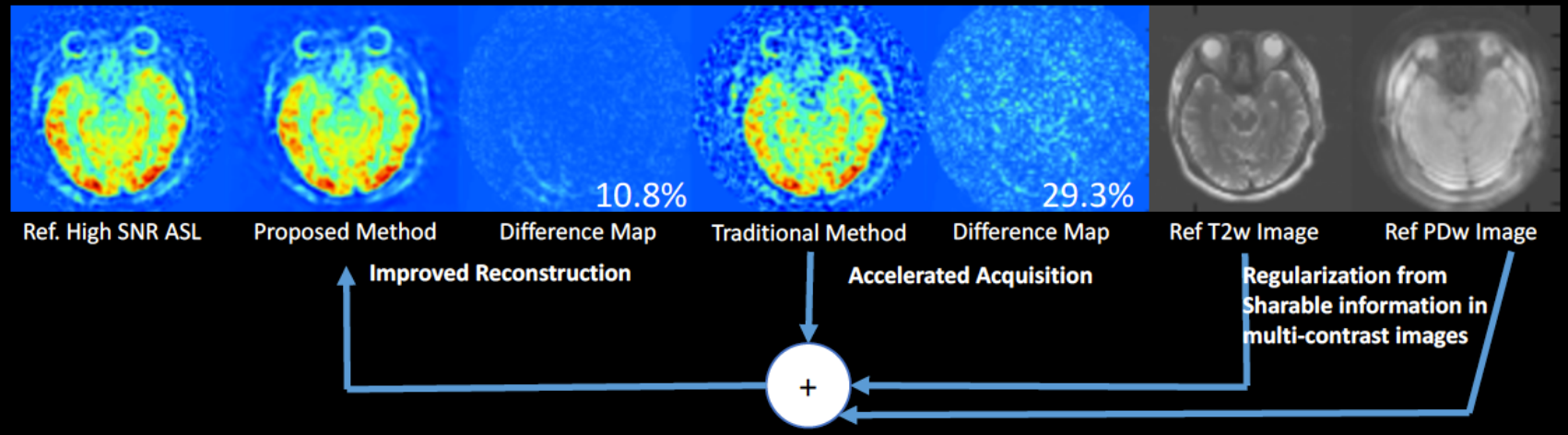


Case #2 Improve Perfusion (ASL) MRI

Results

4x faster acquisition with 7.78dB better SNR

ASL reconstruction comparison using multi-contrast sharable information

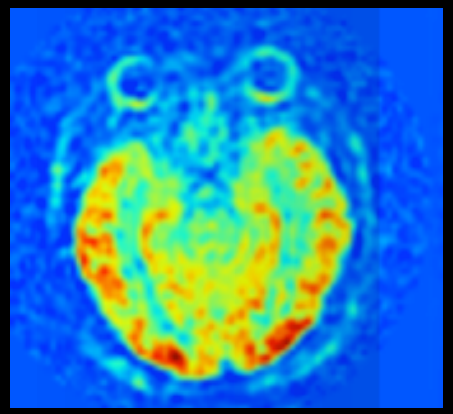


Product ASL	Reference High-SNR Result	Proposed	Traditional Low-SNR Result
Nex (Repetition, determine SNR)	6	1	1
Arm (Sampling Density, determine Resolution)	8	8	8
Time(min)	8:31	2:06 (~4 fold)	2:06
Res(mm)	3.64	3.64	3.64
SNR	7.78dB better	~7.78dB better	-

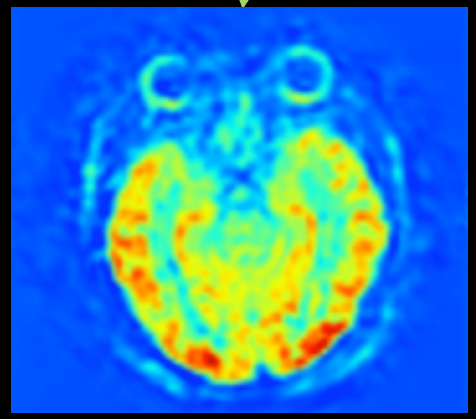
Case #2 Improve Perfusion (ASL) MRI

Results

Deep Learning Model

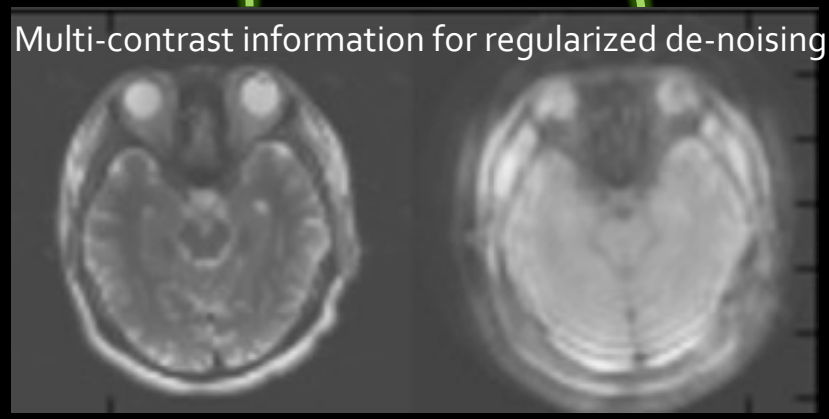


High SNR ASL

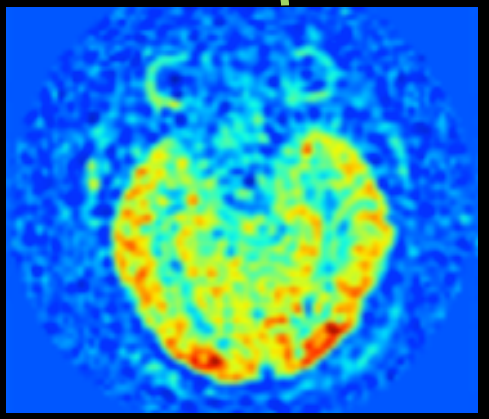


Synthetic ASL

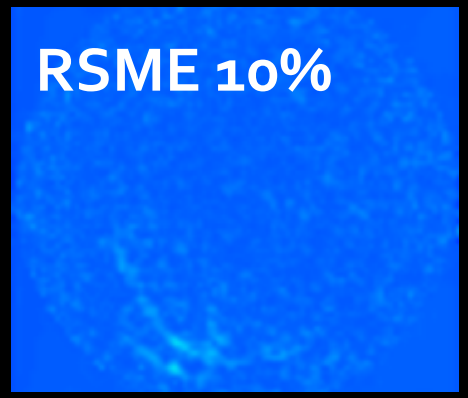
Multi-contrast information for regularized de-noising



T2 weighted Proton density

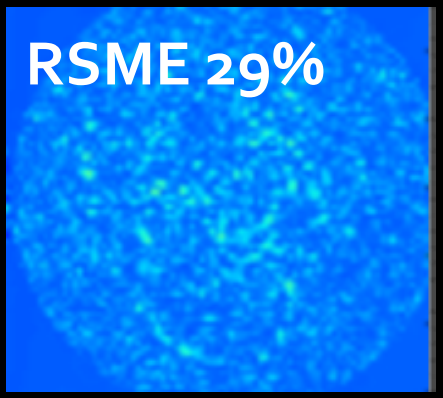


Low SNR ASL



Diff map vs High SNR

4-fold time reduction
3-fold RSME improvement



Diff map vs High SNR

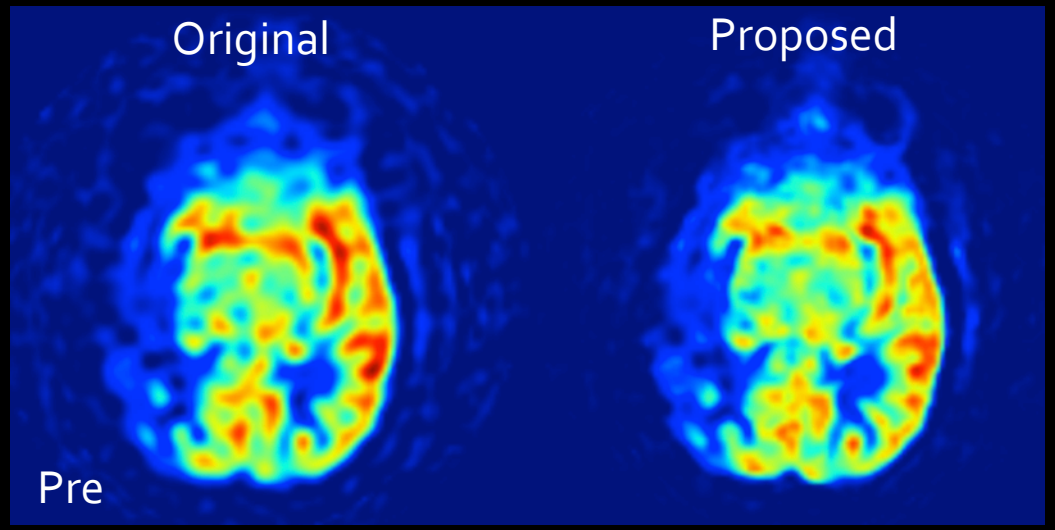
Note: RMSE=Root-Mean-Squared-Error (normalized)

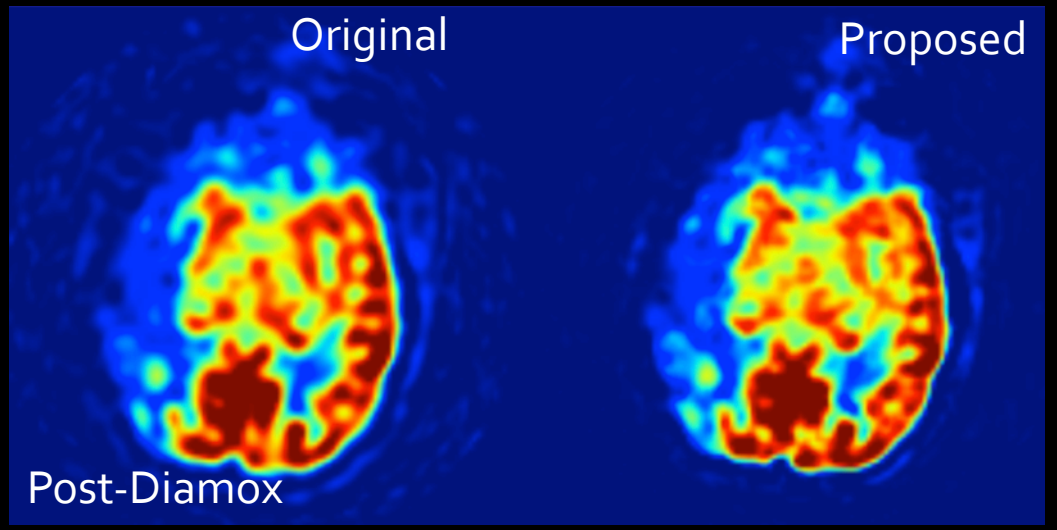
Case #2 Improve Perfusion (ASL) MRI

Clinical results

- ✓ Improved SNR and resolution in perfusion image and transit-delay image
- ✓ Pathology is well preserved for patients
- ✓ More patients datasets and human ratings are in progress

Moyamoya, pre and post Diamox

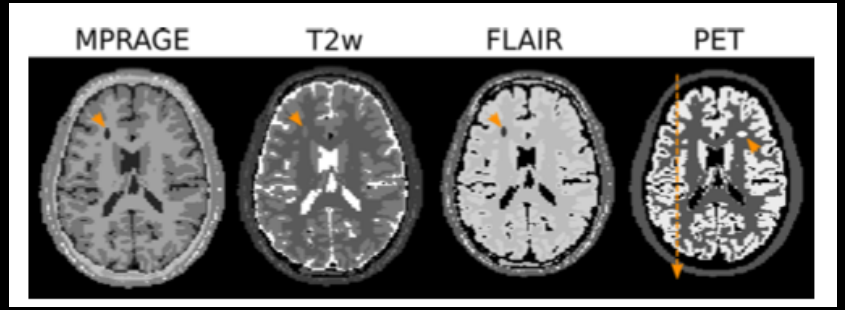




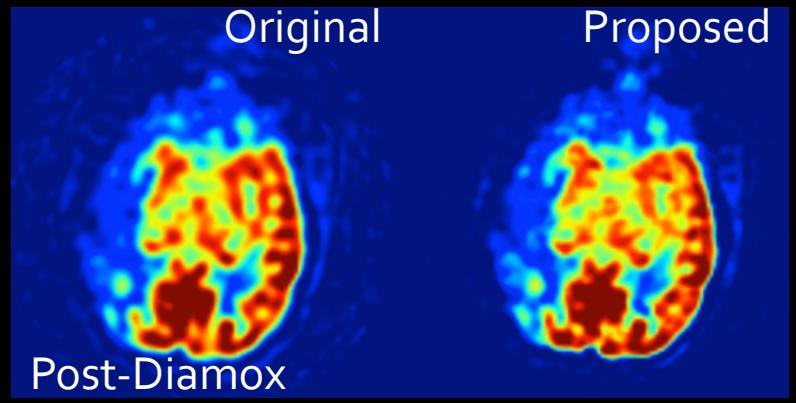
Case Study: Enhanced MRI Recon with Deep Learning

Summary: Improved Efficiency and Accuracy for clinical applications

- **Case #1 Multi-contrast (structure) MRI reconstruction**
  - 4x~6x acceleration
  - Preserved pathology in clinical scans
  - More efficient reconstruction for clinical applications



- **Case #2 Perfusion MRI reconstruction**
  - 4x~6x acceleration
  - Preserved pathology in clinical scans
  - Better SNR and resolution for clinical settings



Discussion: How to avoid overfitting?

- Lack of medical image datasets
- Network acts on local patches
  - More data, smaller network
- Data augmentations
  - Patch cropping and shifting
  - Transformations (rotations, flips)
  - Distortion and co-registration
- Patch-to-Image Synthesis
  - Averaging overlapping patches
  - Stable with different kernel used
- Transfer Learning

Augmentation with image transform:
Cropping + Rotation + Shifting + Flipping

Augmentation with image distortion:
co-registration + distortion with motion field

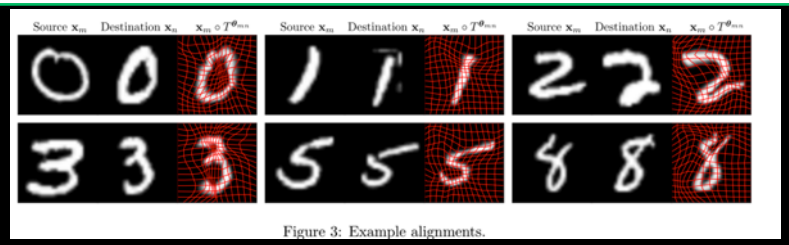


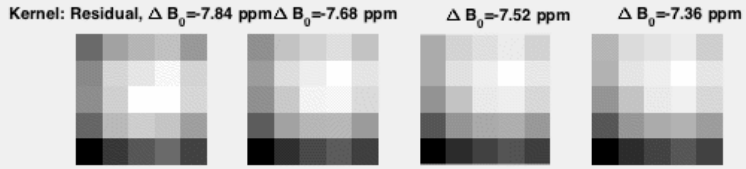
Figure 3: Example alignments.

A. Krizhevsky, et al. NIPS 2012
S. Hauberg, et al. Arxiv 2015

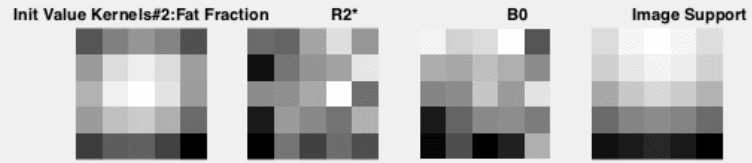
Discussion: Visualize network parameters

- **How network works**
  - Local CNN learns the consistencies and in-consistencies in multi-contrast structures
  - Distinguish contrast differences V.S. in-coherent aliasing artifacts
  - Learn the manifold of signal/patches
- **Potential Improvements**
  - Joint estimation of motions

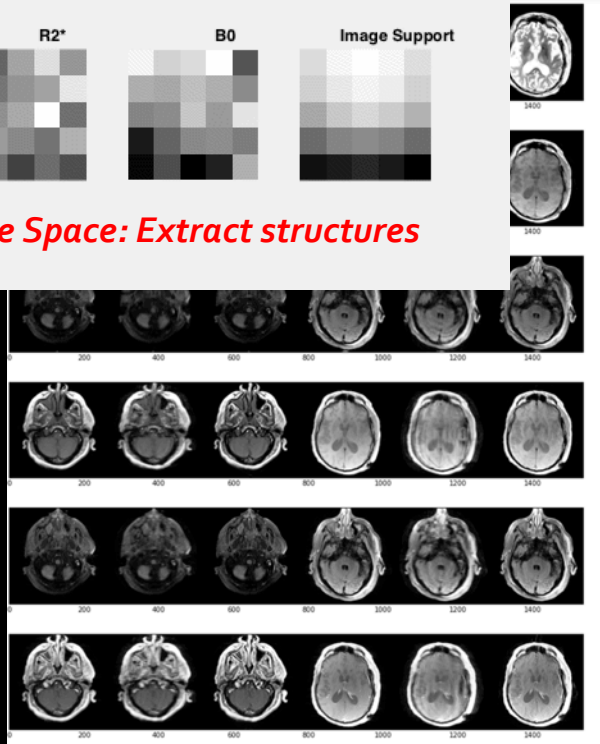
Example Kernels:



- ***For 3D Residual Space: Extract smoothness***



- ***For 2D Structure Space: Extract structures***



Discussion: Speed-up with NVIDIA GPUs and CUDA

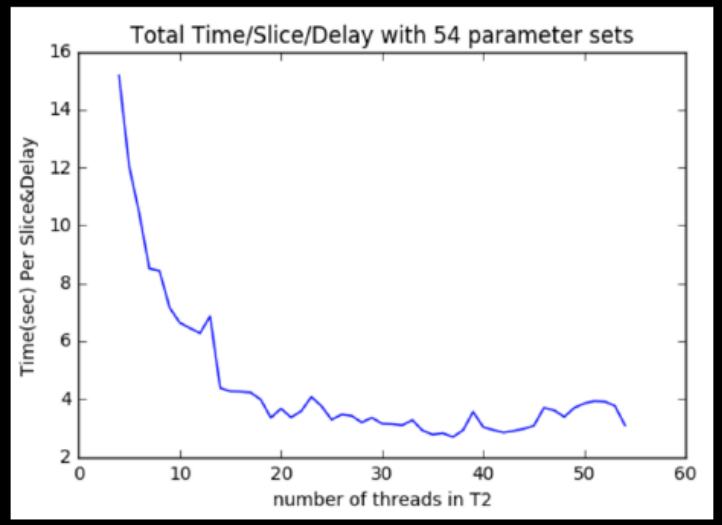
- Hardware of the server used
  - 2 NVIDIA GPUs: GTX 1080s
  - 2 CPUs: Xeon v4s
  - 512GB RAM
- Software
  - CUDA 8, CuDNN 5, Tensorflow, Keras
- We used two new GTX 1080s for acceleration.
- Compared with the performance only using CPU, the significant acceleration shows the unreplaceable advantage by using NVIDIA GPUs.

NVIDIA GTX 1080

Discussion: Speed-up with NVIDIA GPUs and CUDA

400x Acceleration applying spatial-frequency filtering (NLM)

- **By accelerating using CUDA, we achieve 400x speed-up in NLM step.**
- This acceleration makes the algorithm speed up enough to be clinically feasible instead of just for research only.



0	Acceleration Approaches		
Dataset	CPU Single Thread	CPU Multi-threading (10)	GPU CUDA
Entire 36 slice MRI data	~40min	~4min	~6sec
Per slice, for all (54) NLM parameter sets	65sec	6.5sec	0.16sec
Per slice, for one NLM parameter set	1.2sec	0.12sec	0.003sec

***Reconstruction Speed**: 1~10min→1sec/slice; big advantage over iterative methods!*

Discussion: Network Design in MRI Reconstruction

- Cost function designs
  - Comparison between L2 cost and Similarity Metrics (SSIM) [1]
- Generative Adversarial Network (GAN) based strategy[2,3,4,5]
  - Existing works in In-painting, Super-resolution, Random Matrix Compressed-Sensing
  - Extend to Compressed-Sensing MRI[5]

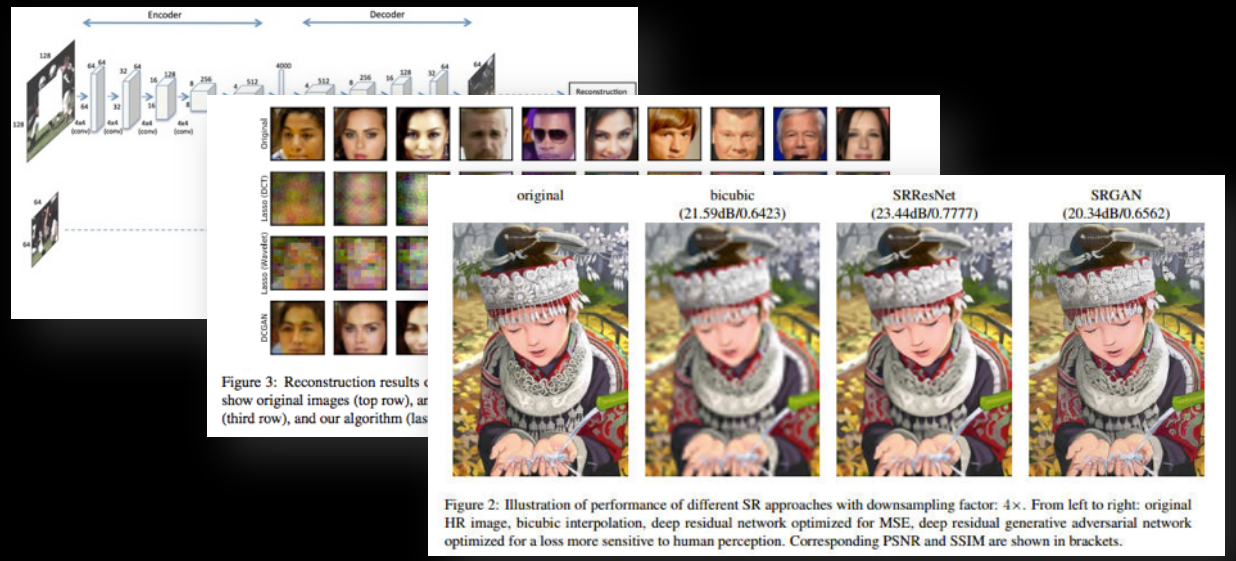
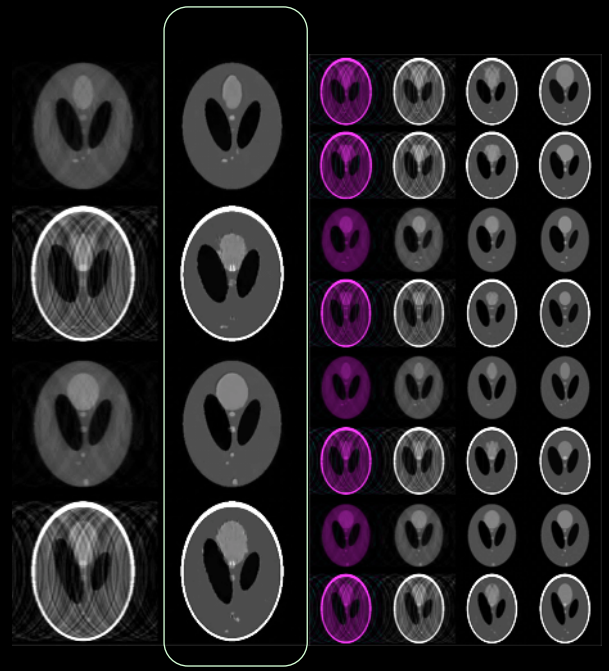


Figure 3: Reconstruction results c
show original images (top row), ar
(third row), and our algorithm (las

Figure 2: Illustration of performance of different SR approaches with downsampling factor: 4×. From left to right: original HR image, bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception. Corresponding PSNR and SSIM are shown in brackets.

Results on GAN based CS-MRI on MR Phantom (submitted to NIPS2017)



[1] K. Hammernik, et al. ISMRM 2017 *[2] I. Goodfellow, et al. NIPS 2014* *[3] D. Pathak, et al. CVPR 2016*
[4] A. Bola, et al. Arxiv 2017 *[5] M. Mardani, et al. Arxiv 2017*

Conclusion: Enhance multi-contrast MRI reconstruction with Deep Learning and NVIDIA GPUs

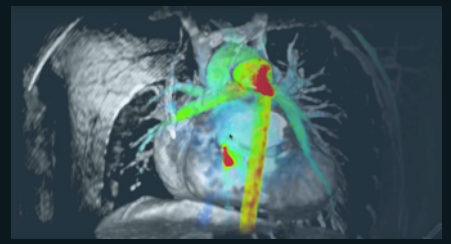
- **Deep Learning approach to solve medical imaging reconstruction**
  - Deep Learning model learns to remove artifact and fusing multi-contrast information
  - Better efficiency and accuracy for clinical applications and diagnosis
- **NVIDIA GPUs are key for computational acceleration**
  - 400x acceleration for Non-Local-Mean Denoising using CUDA
  - 100x acceleration for Model Inference using CUDA, CuDNN
- **Benefit to medical diagnosis**
  - Multi-contrast scans: 4x faster acquisition, preserve pathology
  - Single-delay Perfusion (ASL) MRI: 4x faster acquisition, 7.78dB SNR gain
  - Multi-delay Perfusion (ASL) MRI: 6x faster acquisition, 50% better resolution
  - Examples shown in clinical exams for hemorrhage and stroke diagnosis.

Conclusion: Deep Learning will be quickly adopted in medical imaging reconstruction and enhancement

- **Showcase of work in the direct big win in the content generation and augmentation**

Scanner

Images



Enhancement & Augmentation

Image Reconstruction
- From anatomy to image
- Reconstruction and Restoration
- Denoising and Super-resolution

Pathology Detection
- From image to labels
- Tumor Segmentation
- Pathology Detection

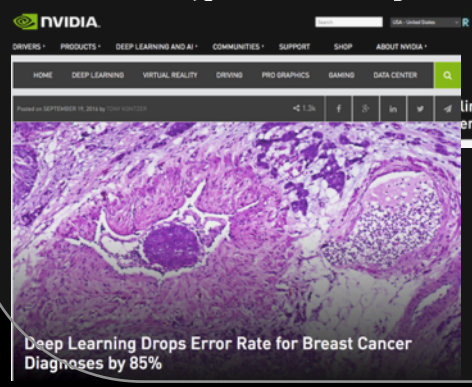
Diagnosis Assistance
- From pathology to diagnosis
- Prescription and Treatment
- Prognostic Prediction

Prognosis

Analytics

Pathology

Diagnosis



Treatment

Image source: blogs.nvidia.com

Conclusion: Deep Learning will be quickly adopted in medical imaging reconstruction and enhancement

- Applications in medical imaging
  - Image reconstruction/restoration
  - Lesion Detection
  - Diagnosis Assistance

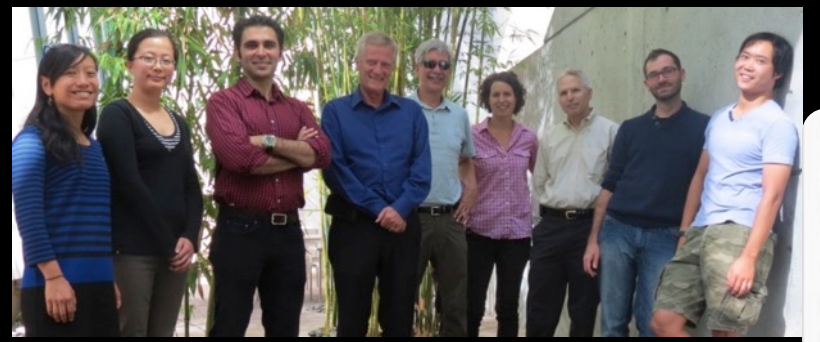
- Deep Learning in Radiology
  - Great attention from radiology community
    - ISMRM 2017: 5 sessions, 600 submissions
  - Some products already got FDA clearance
  - Compared with CS (10 years)

Acknowledgements

- Collaborators: Professor John Pauly, Prof. Greg Zaharchuk, Dr. Jia Guo, Dr. Morteza Mardani, …
- Additional helps: MRSRL@Stanford, CAFN@Stanford, Dr. Song Han, Prof. Bill Dally
- More collaboration is welcomed

Prof. John Pauly

Dr. Morteza Mardani

Prof. Greg Zaharchuk

Dr. Jia Guo