



Deep Learning in Medical Image Analysis

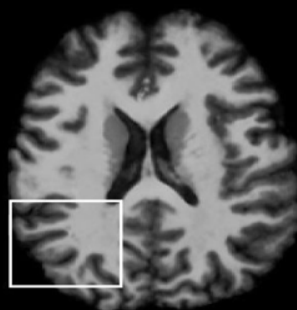
Dinggang Shen, Ph.D.

IDEA Lab, Department of Radiology, and Biomedical Research Imaging Center (BRIC)
University of North Carolina at Chapel Hill

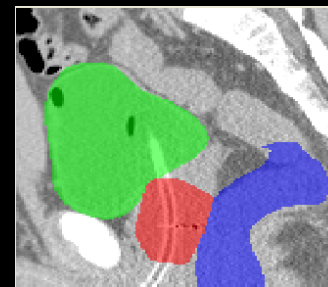
Outline



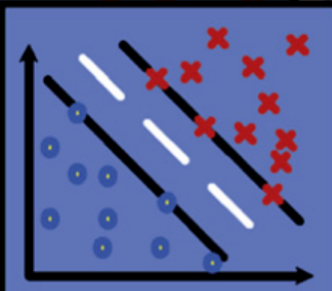
Segmentation /
Registration



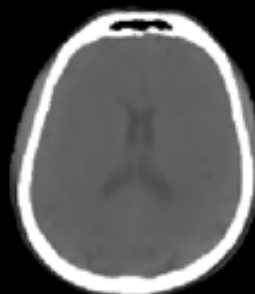
MRI
Enhancement



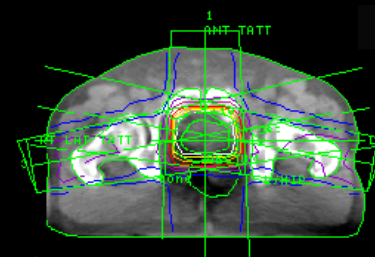
Planning CT
Segmentation



Disease Diagnosis



CT Estimation from MRI



Dose Planning

Neuroimaging Analysis

Image Synthesis

Cancer Radiotherapy



Neuroimaging Analysis

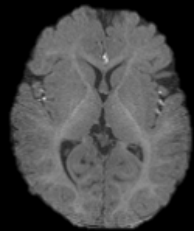
- Segmentation
- Registration
- Diagnosis

Overall Goal

Baby Connectome Project (BCP)

6 M

3~4 Y



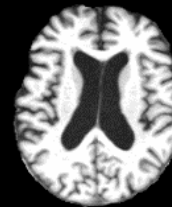
Genetics

Autism ?

Alzheimer's Disease Neuroimaging Initiative (ADNI)

70 Y (MCI)

75 Y



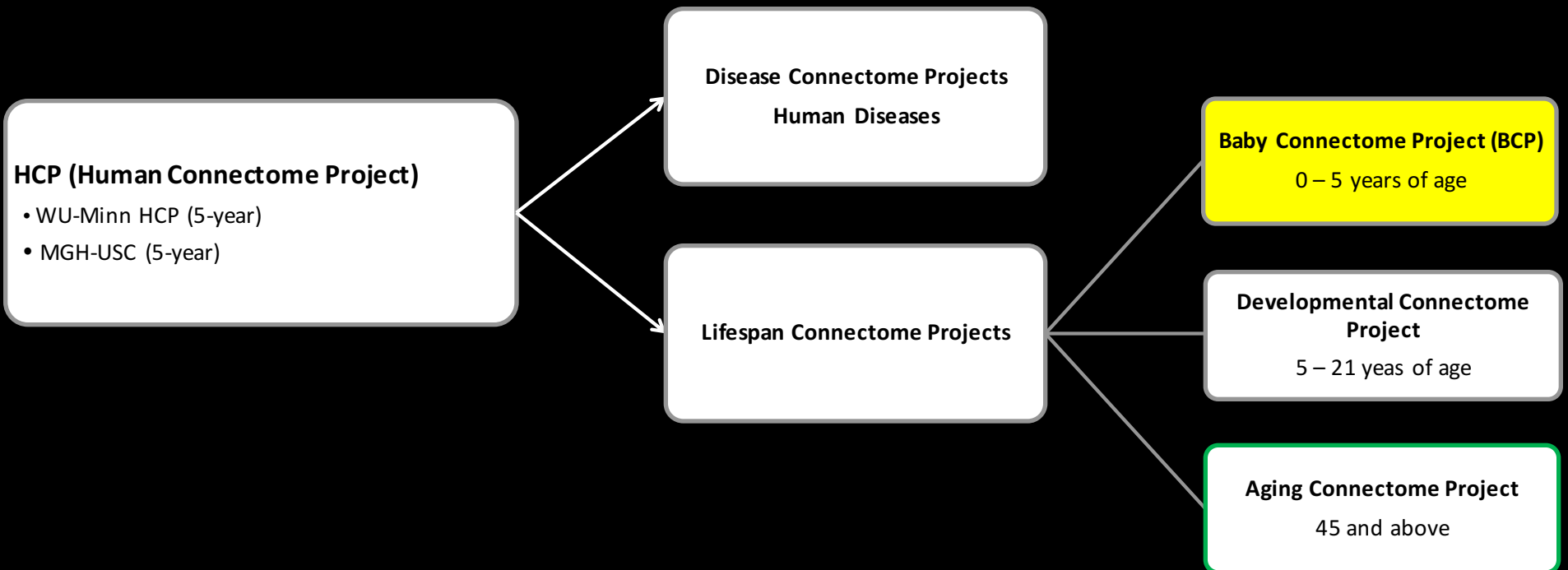
Genetics

Alzheimer's
Disease (AD)

Segmentation

Distinguishing White Matter, Gray Matter, and Cerebrospinal Fluid (CSF)

NIH Lifespan Human Connectome Projects



Co-PIs:

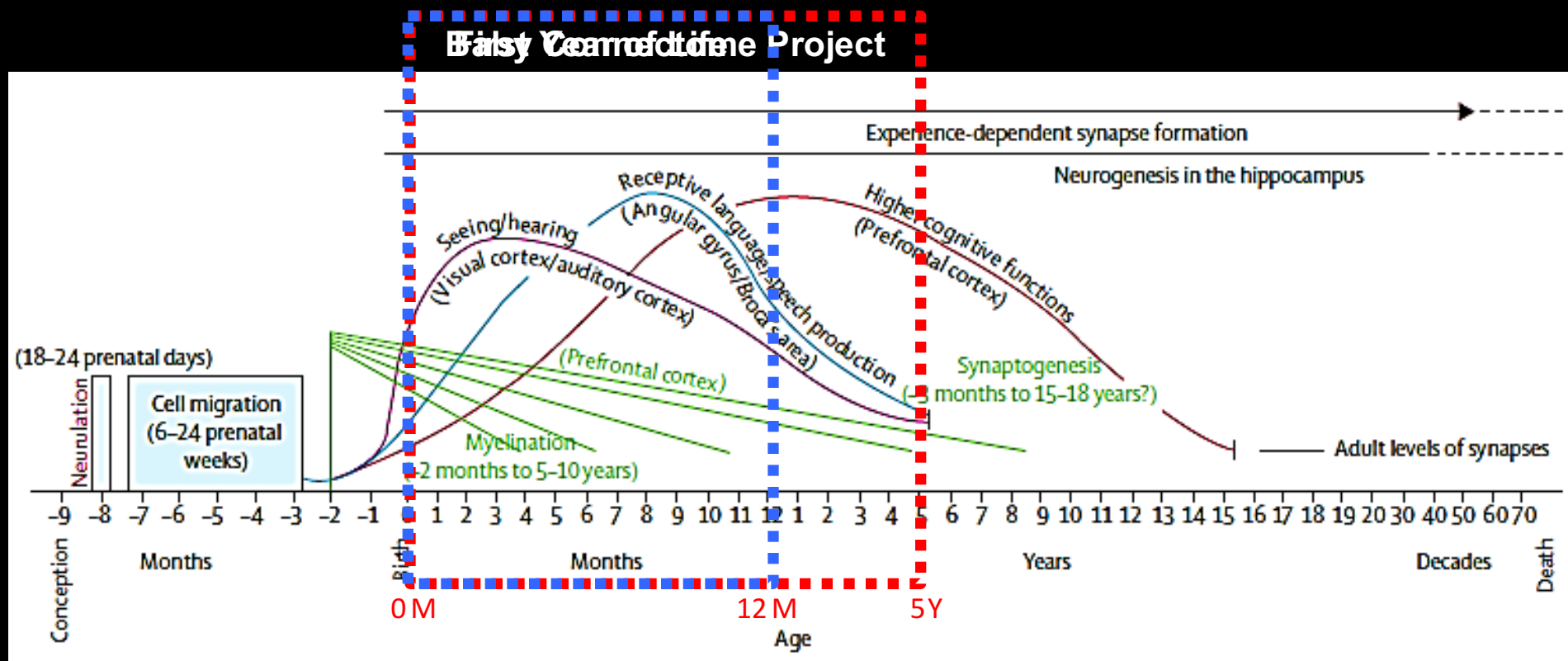
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Brain Functional Maturation

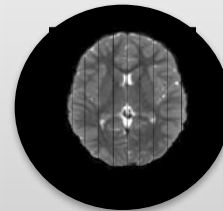


Thompson RA, Nelson CA. Developmental science and the media. Early brain development. *Am Psychol.* 2001; 56:5-15.

Baby Connectome Project (BCP)

- The first comprehensive imaging study focuses on early brain functional and structural development.
- A joint effort between University of North Carolina at Chapel Hill and University of Minnesota
- A total of **500 normally developing** children will be imaged

Brain Images



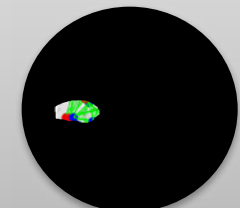
- Anatomical images
- Diffusion tensor images
- Functional connectivity (BOLD)

Behavior/Cognition



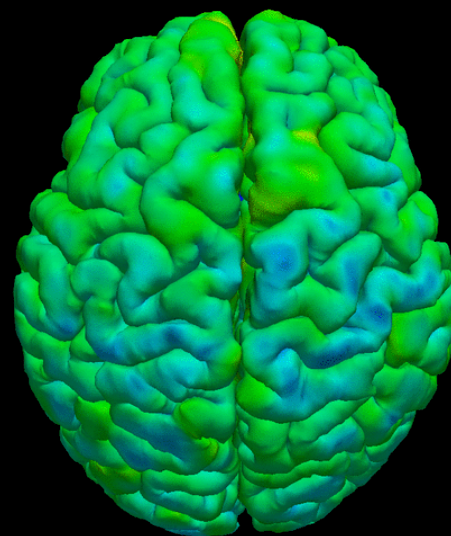
- Age-appropriate behavioral / cognitive assessments

Brain/Cognitive



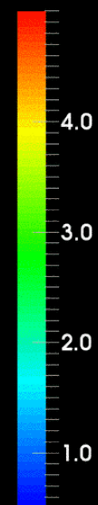


00 Months



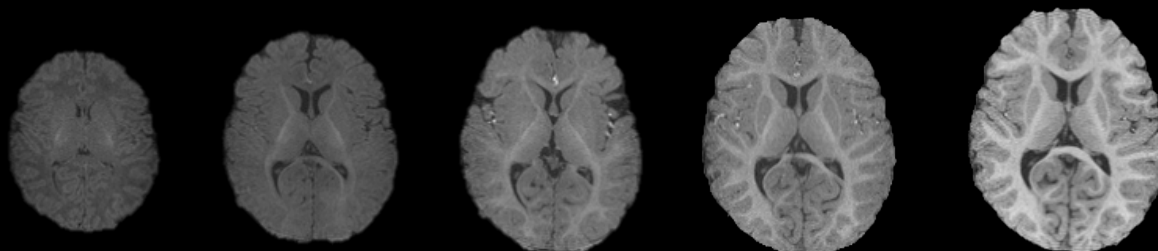
00 Months

Thickness

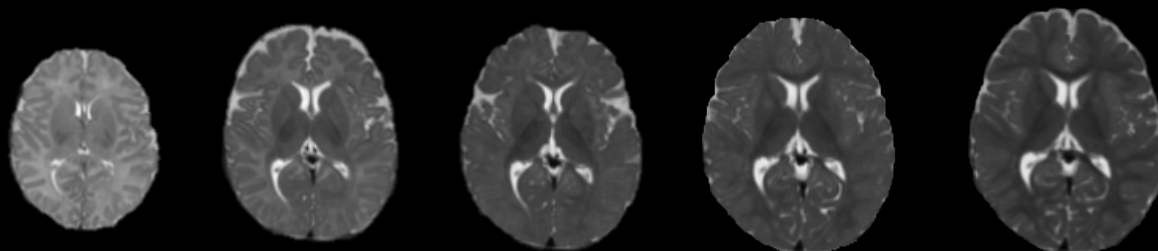


The Human Brain in the First Year of Life

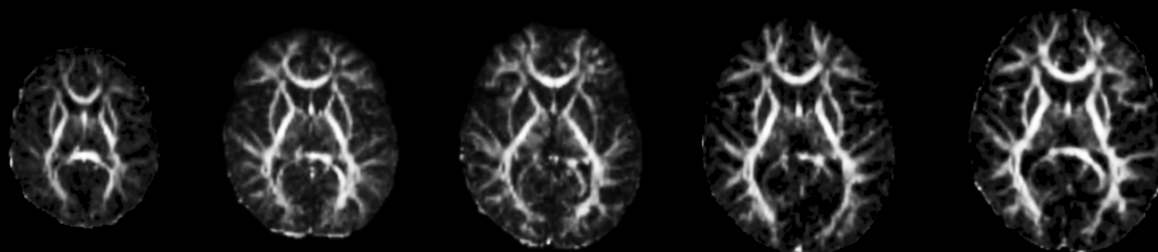
T1



T2



FA



2 weeks

3 months

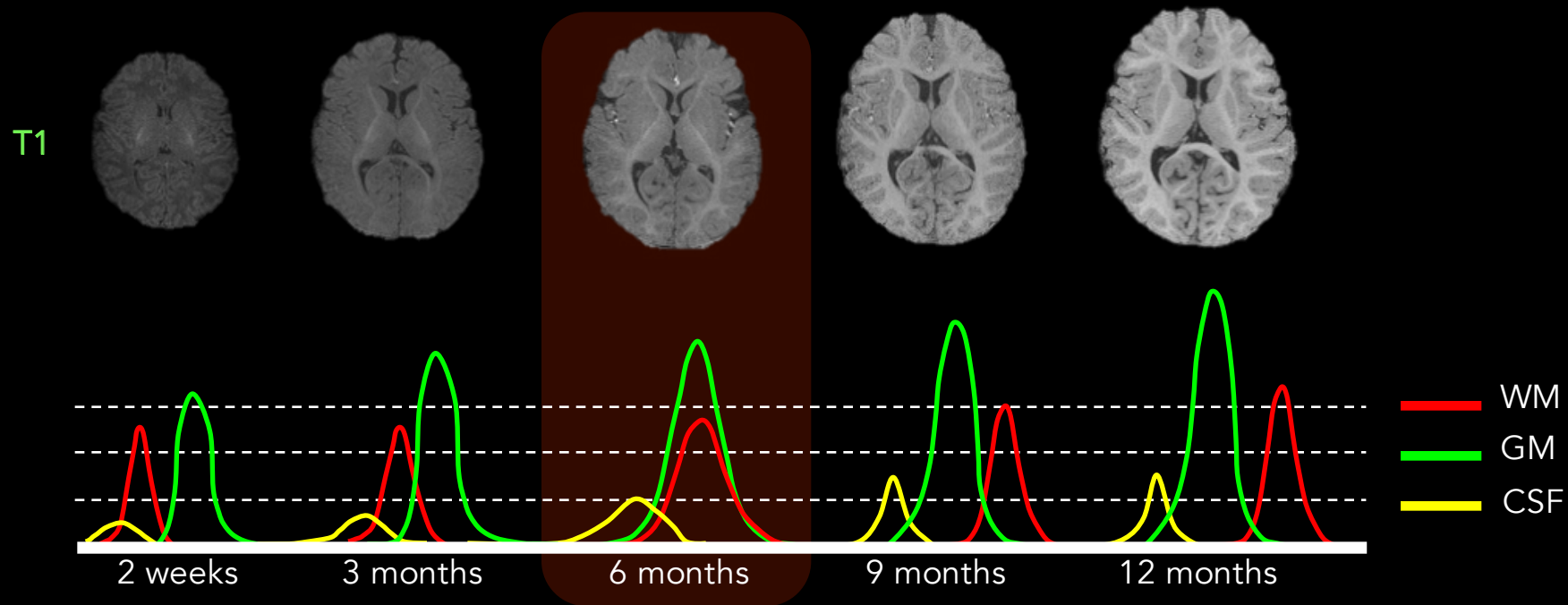
6 months

9 months

12 months

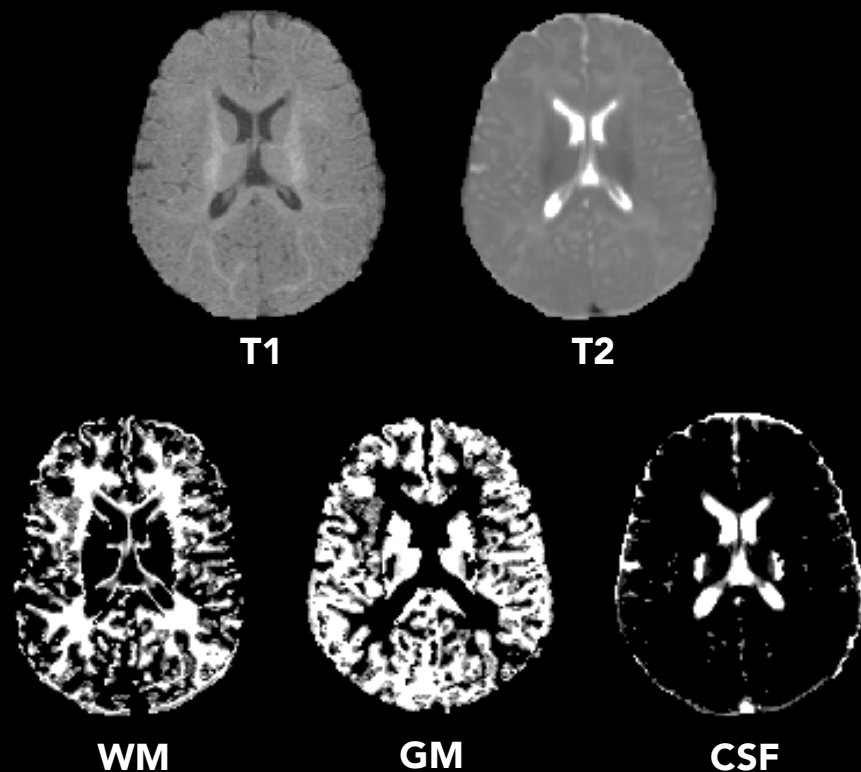
A Longitudinally-scanned Subject

The Human Brain in the First Year of Life



Challenges: Low tissue contrast (especially ~6 months of age) and low spatial resolution

Challenges

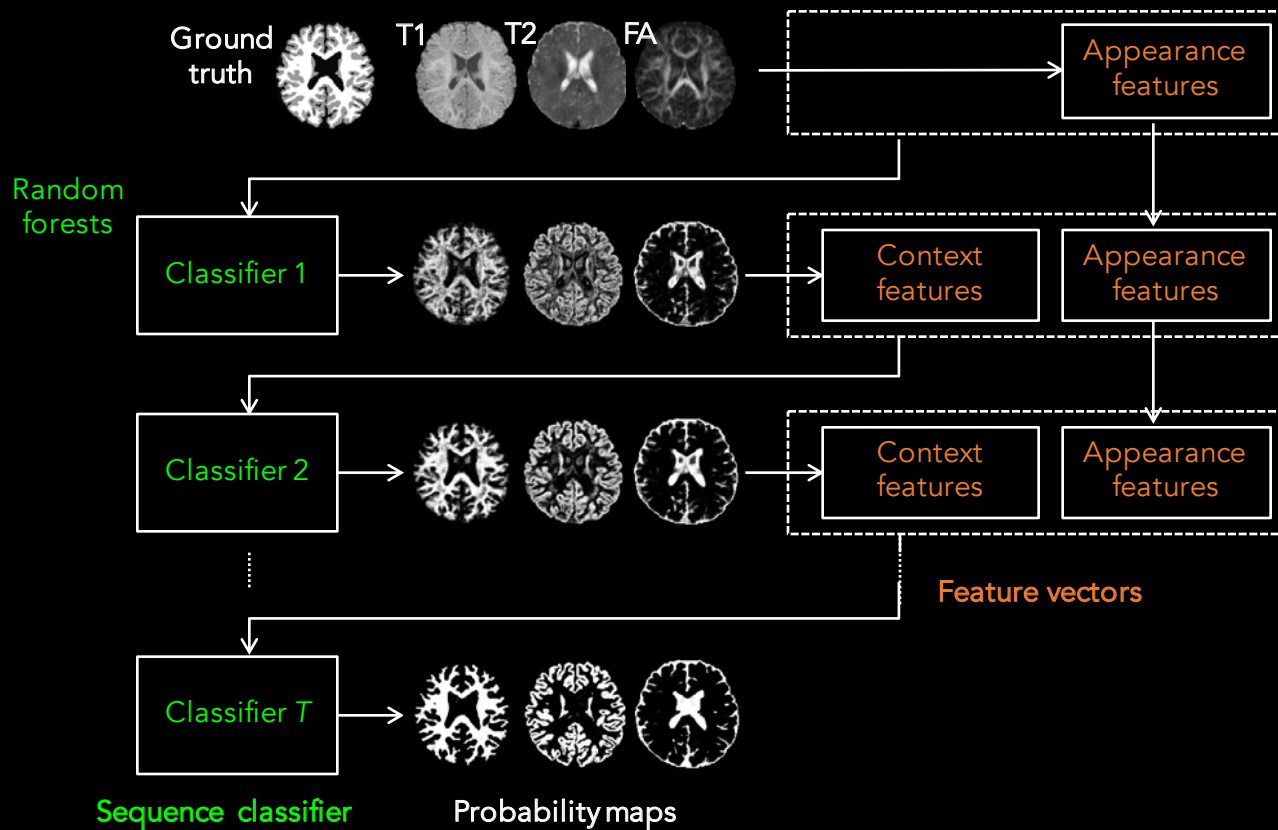


- Low tissue contrast
- Low SNR
- Partial volume effect
- On-going white matter myelination

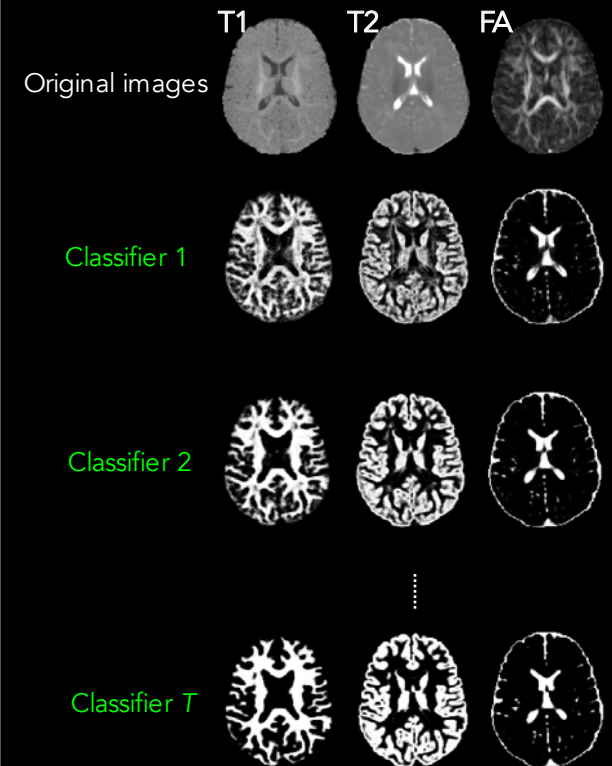
Typical FSL-FAST results for a *6-month-old* infant

LINKS

Training Stage



Testing Stage



L. Wang, Y. Gao, F. Shi, G. Li, J. H. Gilmore, W. Lin, D. Shen, "LINKS: Learning-based multi-source Integration framework for Segmentation of infant brain images," *NeuroImage*, 108:160-172, 2015.

MICCAI Grand Challenge on 6-month Infant Brain Segmentation (iSeg)

- Data
 - Training: 10 subjects (each with T1- and T2-weighted MRI)
 - Testing: 13 subjects
- Evaluation Metrics
 - Dice Ratio (DR)
 - Modified Hausdorff Distance (MHD)
 - 95th Percentile Hausdorff Distance
 - Average Surface Distance (ASD)
- Teams
 - 21 teams

Ranking – DR

			WM
RANK	TEAM	DATE	DR
1	MSL_SKKU	08/05/2017	0.901
2	LIVIA	07/12/2014	0.897
3	Bern_IPMI	07/24/2017	0.896
4	TU/e IMAG/e	06/25/2017	0.890
5	UPF_simbiosys	05/24/2017	0.885
6	NeuroMTL	08/01/2017	0.885
7	nic_vicorob	07/24/2017	0.885
8	UPC_DLMI	07/31/2017	0.882
9	CAMP_TUM	08/06/2017	0.880
10	QuILL	08/07/2017	0.877
11	Cumed	08/08/2017	0.876
12	STH	08/01/2017	0.870
13	BIGS2	08/07/2017	0.867
14	UofL-Biolmaging	08/07/2017	0.867
15	LRDE	07/25/2017	0.861
16	BUUA_braintech	08/06/2017	0.855
17	Authman	08/08/2017	0.838
18	CatholicU	07/18/2017	0.827
19	Xidian	08/08/2017	0.765
20	ASU-BNI	08/05/2017	0.739
21	BuzzLightDay	08/02/2017	0.686

			GM
RANK	TEAM	DATE	DR
1	MSL_SKKU	08/05/2017	0.919
2	LIVIA	07/12/2014	0.919
3	Bern_IPMI	07/24/2017	0.916
4	nic_vicorob	07/24/2017	0.910
5	UPC_DLMI	07/31/2017	0.907
6	TU/e IMAG/e	06/25/2017	0.904
7	UPF_simbiosys	05/24/2017	0.903
8	NeuroMTL	08/01/2017	0.902
9	CAMP_TUM	08/06/2017	0.901
10	Cumed	08/08/2017	0.896
11	UofL-Biolmaging	08/07/2017	0.895
12	QuILL	08/07/2017	0.894
13	STH	08/01/2017	0.892
14	BIGS2	08/07/2017	0.892
15	LRDE	07/25/2017	0.887
16	BUUA_braintech	08/06/2017	0.887
17	Authman	08/08/2017	0.872
18	CatholicU	07/18/2017	0.868
19	ASU-BNI	08/05/2017	0.781
20	BuzzLightDay	08/02/2017	0.768
21	Xidian	08/08/2017	0.767

			CSF
RANK	TEAM	DATE	DR
1	MSL_SKKU	08/05/2017	0.958
2	LIVIA	07/12/2014	0.957
3	Bern_IPMI	07/24/2017	0.954
4	nic_vicorob	07/24/2017	0.951
5	BIGS2	08/07/2017	0.948
6	TU/e IMAG/e	06/25/2017	0.947
7	UPC_DLMI	07/31/2017	0.945
8	UofL-Biolmaging	08/07/2017	0.942
9	CAMP_TUM	08/06/2017	0.940
10	STH	08/01/2017	0.936
11	NeuroMTL	08/01/2017	0.935
12	Cumed	08/08/2017	0.935
13	UPF_simbiosys	05/24/2017	0.929
14	QuILL	08/07/2017	0.929
15	LRDE	07/25/2017	0.928
16	BUUA_braintech	08/06/2017	0.922
17	Authman	08/08/2017	0.917
18	CatholicU	07/18/2017	0.915
19	Xidian	08/08/2017	0.876
20	ASU-BNI	08/05/2017	0.876
21	BuzzLightDay	08/02/2017	0.781

Popular Methods: Deep Learning

Only 1 team used conventional method:

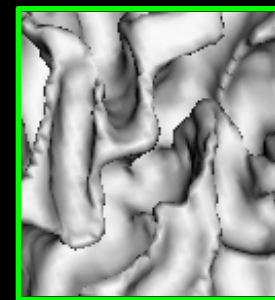
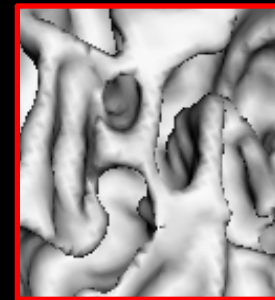
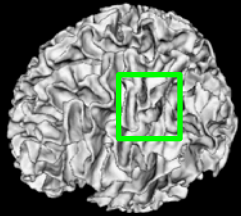
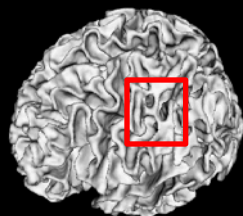
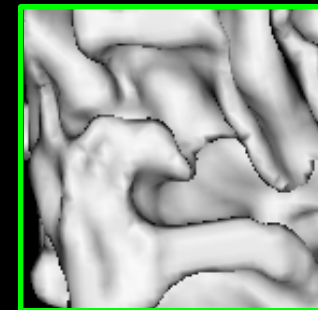
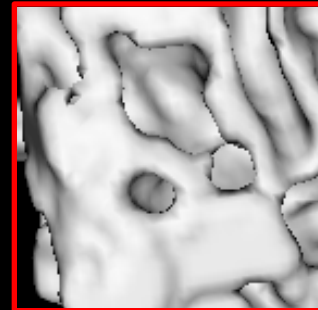
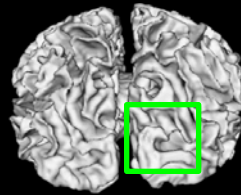
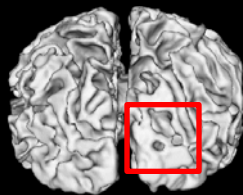
Other 20 teams used deep learning:

- U-Net: 9 teams
- CNN: 4 teams
- FCN: 4 teams
- DenseNet: 3 teams

RANK	TEAM	METHOD
1	MSL_SKKU	DenseNet
2	Bern_IPMI	U-Net
3	LIVA	Ensemble CNN
4	TU/e IMAG/e	Dilated CNN
5	UPC_DLMI	U-Net
6	UPF_simbiosys	Ensemble label fusion
7	NeuroMTL	U-Net
8	LRDE	FCN
9	Cumed	DenseNet
10	QuILL	ResNet+U-Net
11	nic_vicorob	FCN
12	BIGS2	CNN
13	STH	U-Net
14	CAMP_TUM	FCN
15	UofL-Biolmaging	CNN
16	BUUA_braintech	DenseNet
17	Authman	U-Net
18	CatholicU	U-Net
19	ASU-BNI	FCN
20	Xidian	U-Net
21	BuzzLightDay	U-Net

Limitations

Dice Ratio (DR): 0.901



Submitted result
(Team: MSL_SKKU)

Manual result

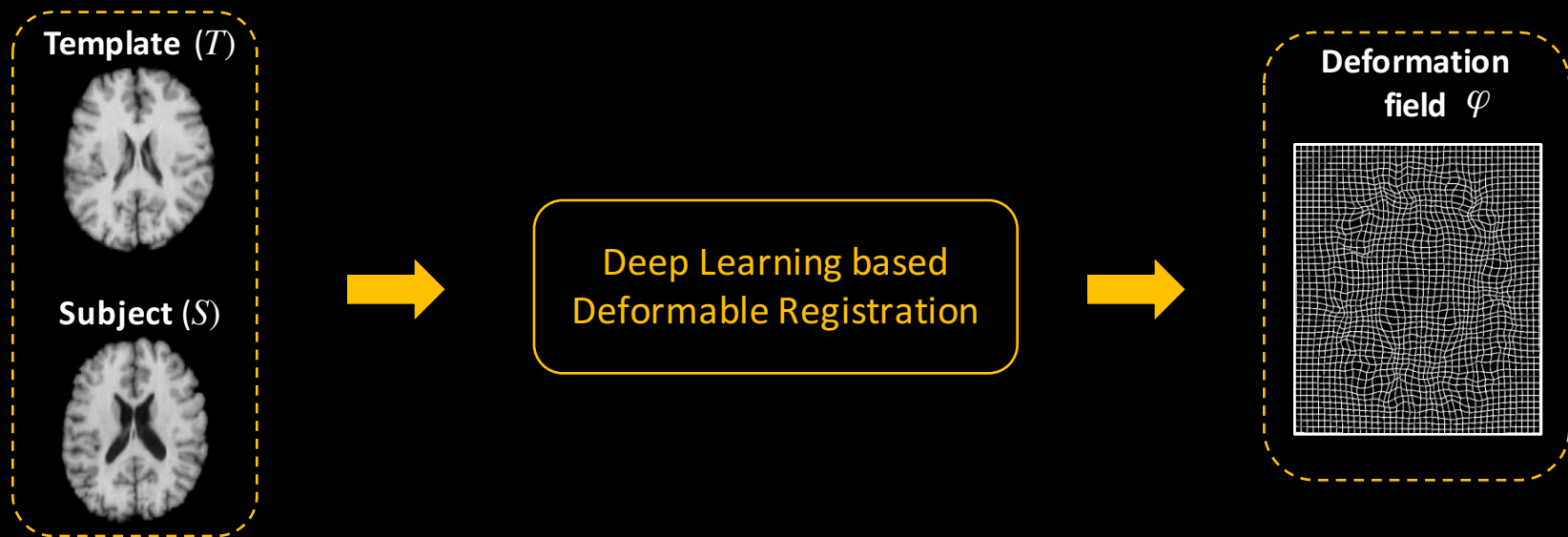


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Registration

Deep Learning-based Image Registration

Deep Learning Based Deformable Registration – Current Methods



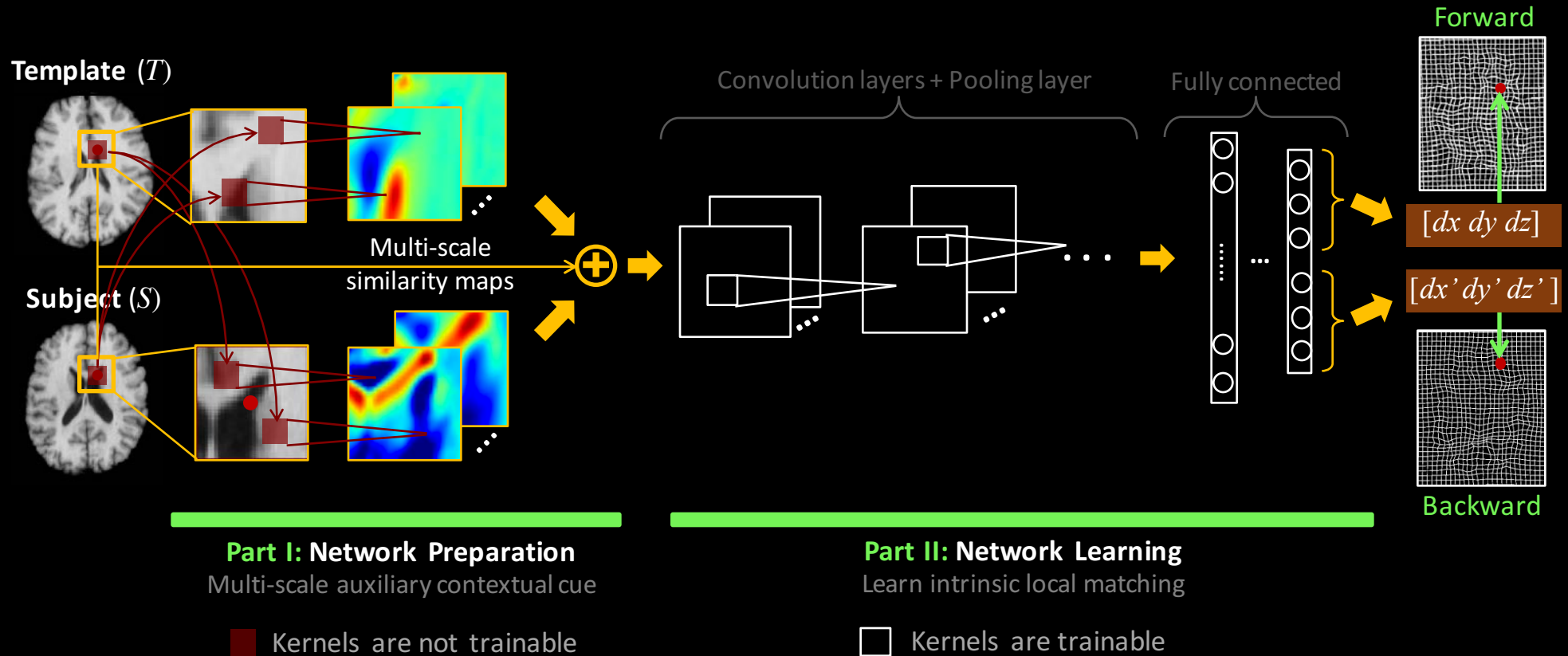
Limitations:

- Ignore intrinsic matching process
- Not symmetric

Improvements:

- Learn intrinsic matching process
- Symmetric registration framework

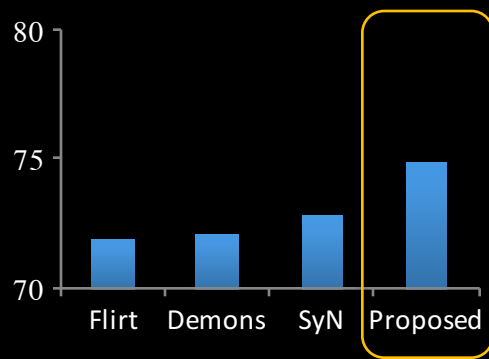
Deep Learning Based Deformable Registration – Our Proposed Method



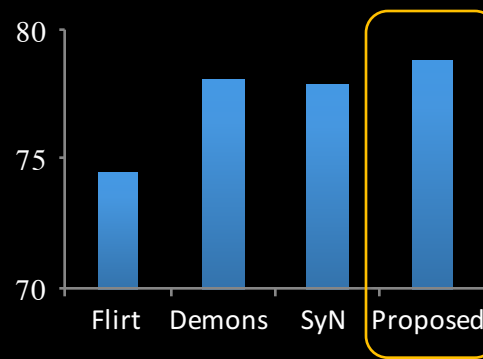
X. Cao, J. Yang, J. Zhang, D. Nie, M. Kim, Q. Wang, D. Shen, "Deformable Image Registration based on Similarity-Steered CNN Regression", MICCAI 2017.

Registration Results

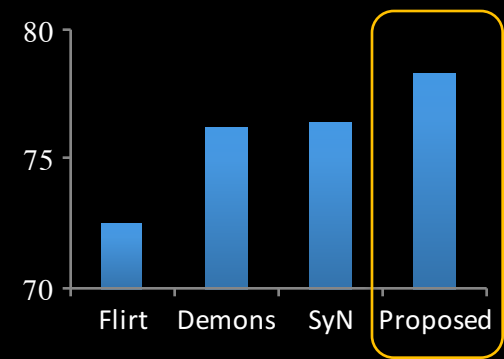
- On **three** datasets: Overall (GM+WM) Dice Ratio (%)



ADNI dataset



LONI dataset



IXI dataset

Advantages:

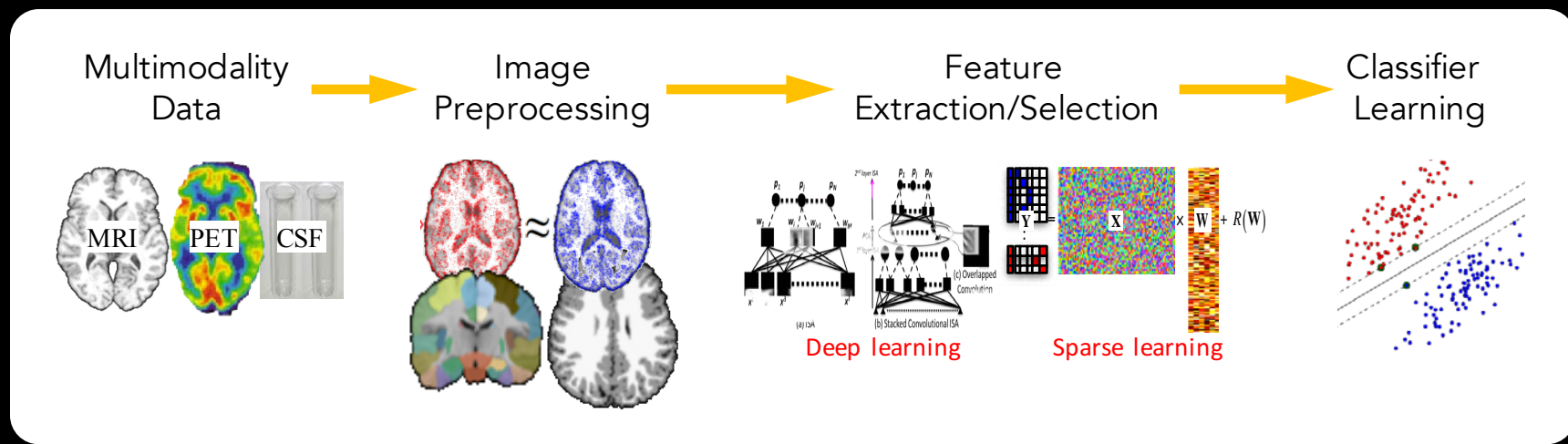
- No parameter tuning
- No iterative optimization
- Good generalization for different datasets
- Better robustness and accuracy

X. Cao, J. Yang, J. Zhang, D. Nie, M. Kim, Q. Wang, D. Shen, "Deformable Image Registration based on Similarity-Steered CNN Regression", MICCAI 2017.

Disease Diagnosis

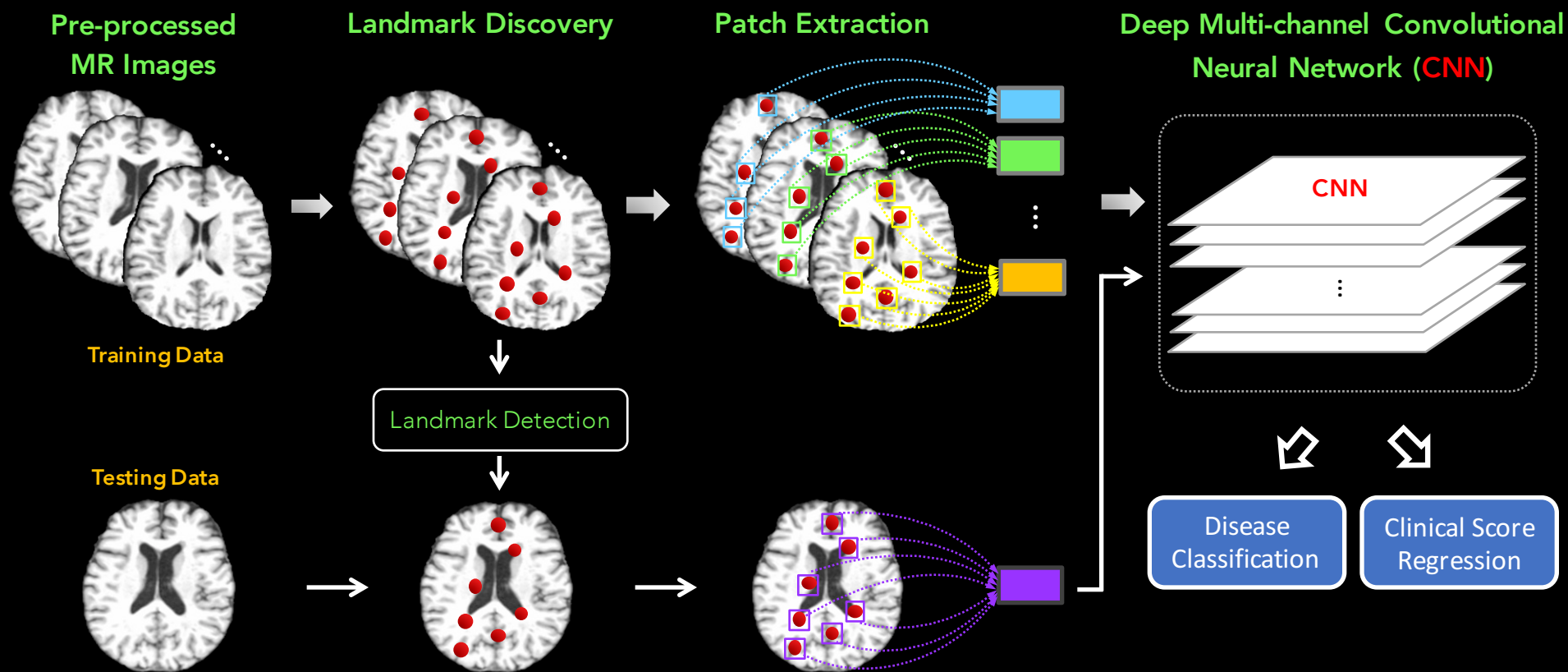
Landmark-based Deep Multi-task Multi-channel Learning

Diagnosis of Neurodegenerative Disorders – Typical Pipeline



M. Liu, D. Zhang, D. Shen, "View-centralized multi-atlas classification for Alzheimer's disease diagnosis," *Human Brain Mapping*, 36(5):1847-1865, 2015.

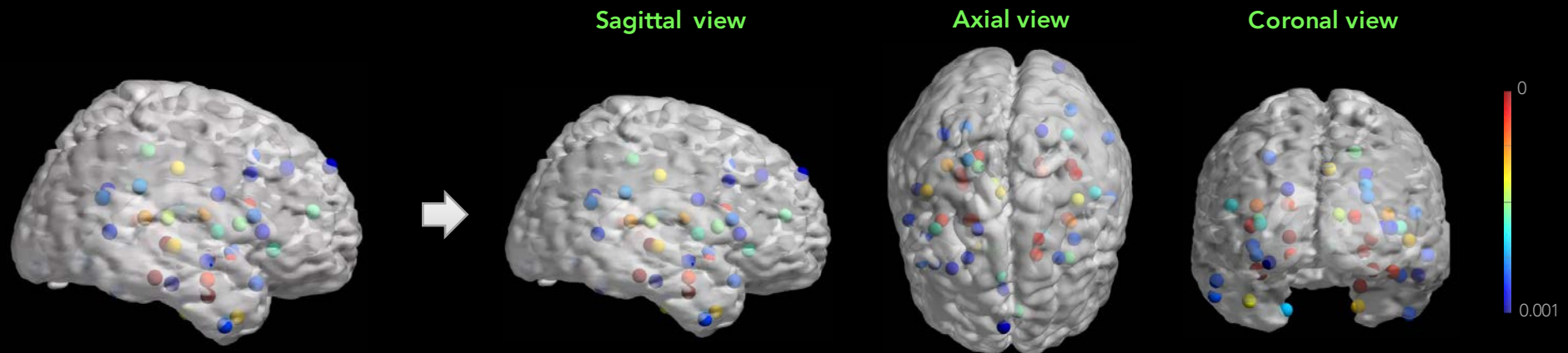
Landmark-based Deep Multi-task Multi-channel Learning (DM²L)



M. Liu, J. Zhang, E. Adeli, D. Shen, "Deep Multi-task Multi-channel Learning for Joint Classification and Regression of Brain Status", *MICCAI* 2017.

Landmark Discovery

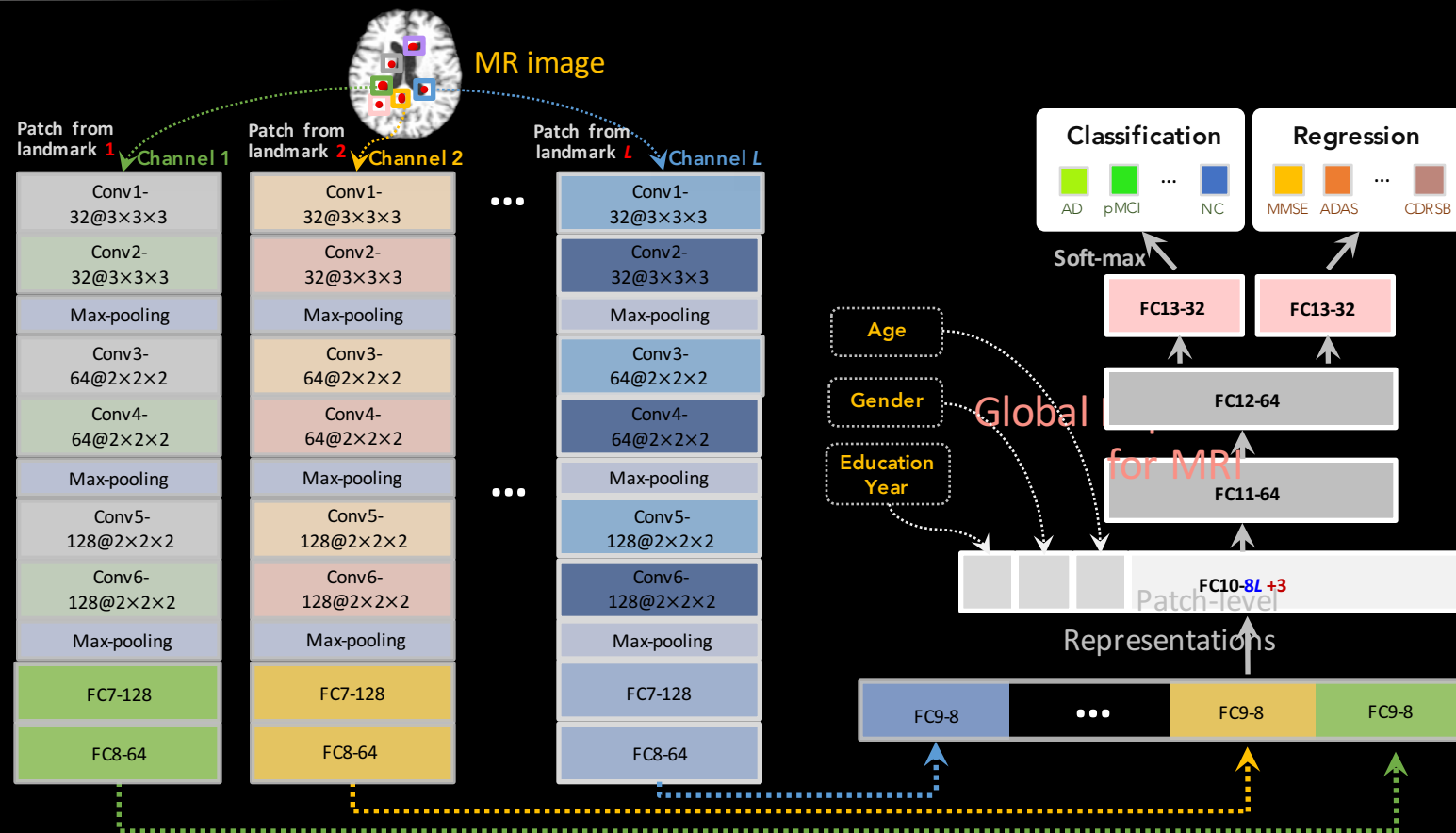
- Top 50 landmarks identified from AD and NC subjects in ADNI-1 with baseline MRI:



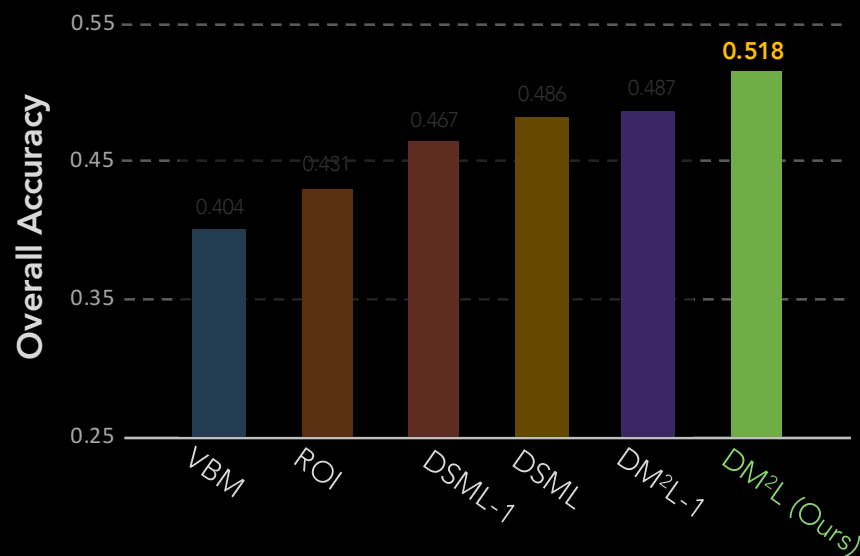
Landmark selection criteria:

- 1) Discriminative power (p -value in group comparison)
- 2) Euclidean distance ≥ 20

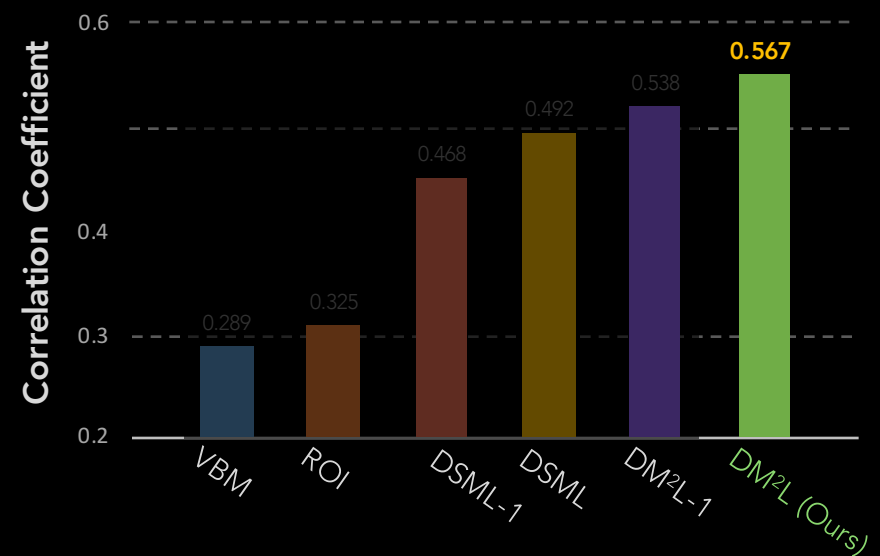
Deep Multi-task Multi-channel CNN



Results of Classification and Regression



Classification Results for AD vs. sMCI
vs. pMCI vs. NC diagnosis



Regression Results for MMSE



Image Synthesis

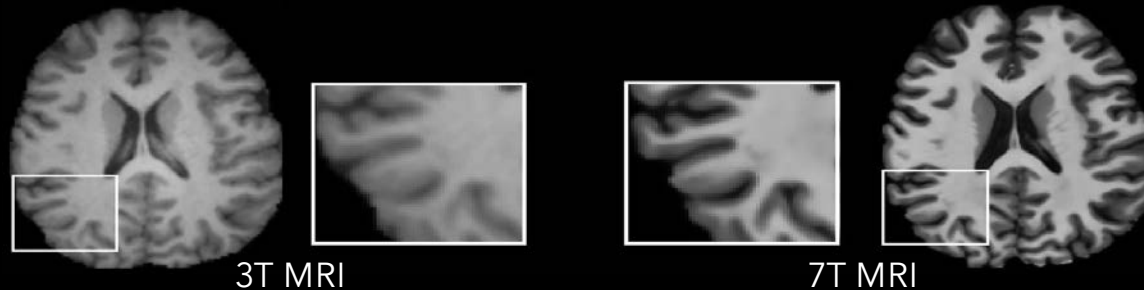
- MRI Enhancement (3T $\rightarrow$ 7T)
- Estimating CT from MRI

MRI Enhancement

7T-MRI-Guided 3T MRI Enhancement and Segmentation using Deep Learning

7T MRI vs. 3T MRI

- 7T MRI
 - Higher spatial resolution and better tissue contrast, compared to 3T MRI
 - SNR of 7T MRI = 2.3 * SNR of 3T MRI

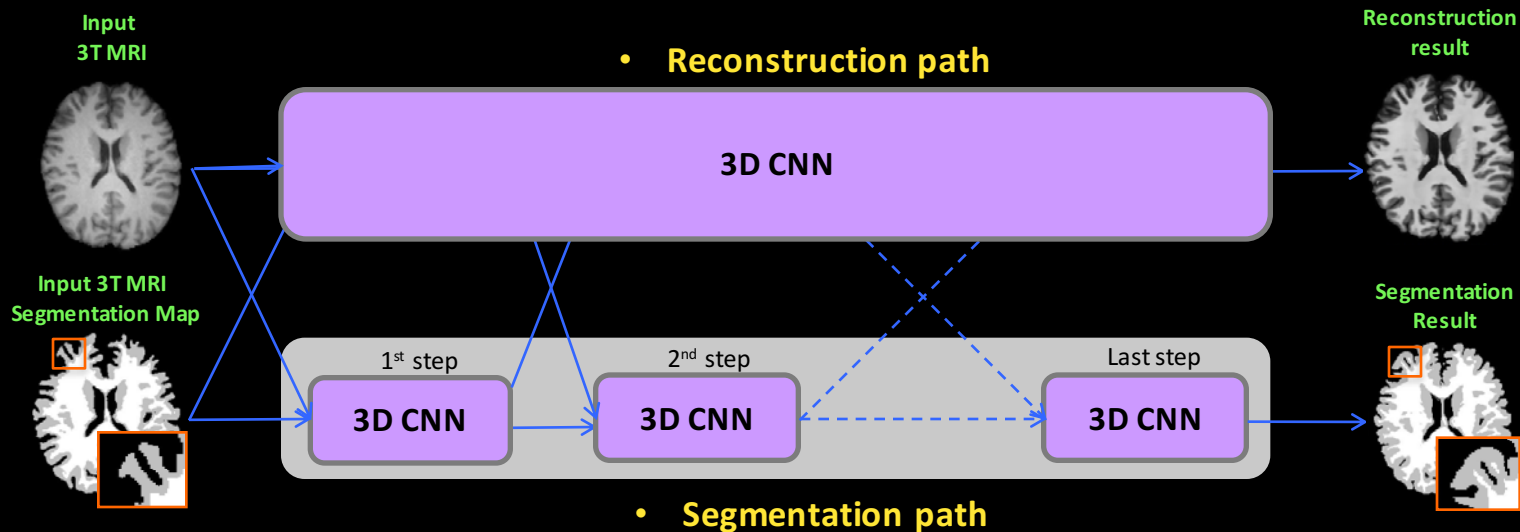


- Lower availability and higher price of 7T MRI scanners
 - 20,000 3T scanners vs. 50 7T scanners in the world

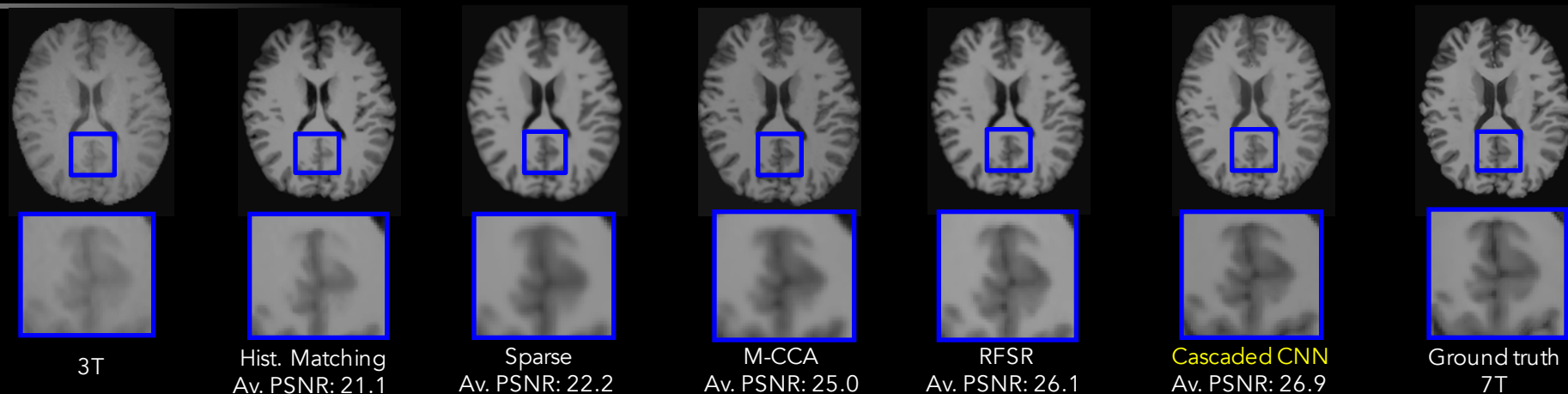
➡ Reconstruction of 7T-like images from 3T MRI

Cascaded 3D CNN for Joint Reconstruction-Segmentation

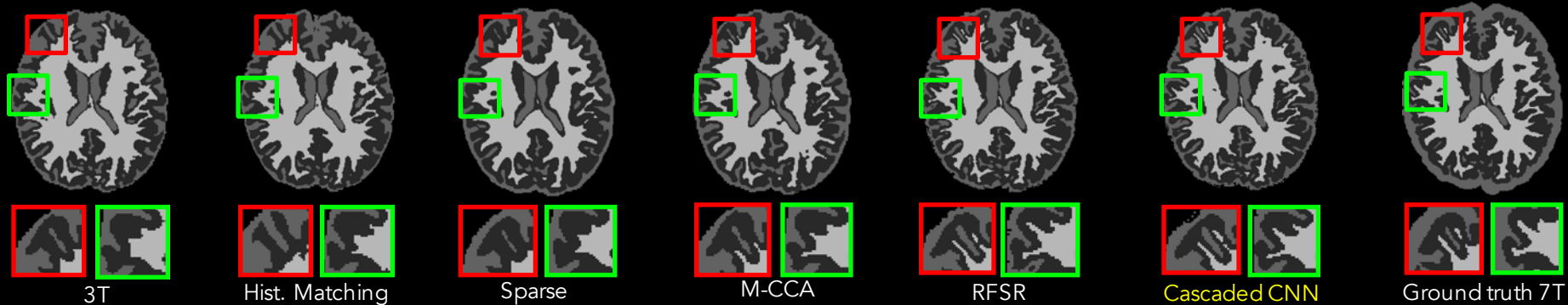
- Joint reconstruction and tissue segmentation
 - Improve both reconstruction of 7T-like MRI and tissue segmentation for 3T MRI



Improved Reconstruction and Tissue Segmentation



Reconstruction results



Segmentation results

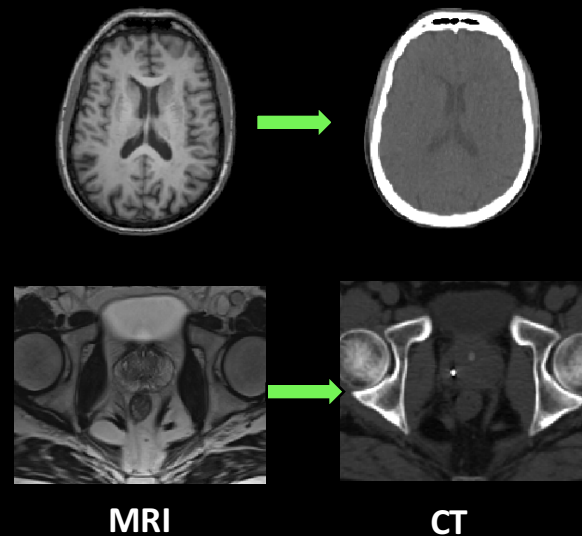
K. Bahrami, I. Rekik, F. Shi, D. Shen, "Joint Reconstruction and Segmentation of 7T-like MR images from 3T MRI based on Cascaded Convolutional Neural Networks", *MICCAI* 2017.

Estimating CT from MRI

Deep Learning-based Automatic Estimation of CT from MRI

CT

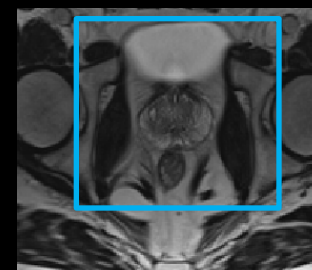
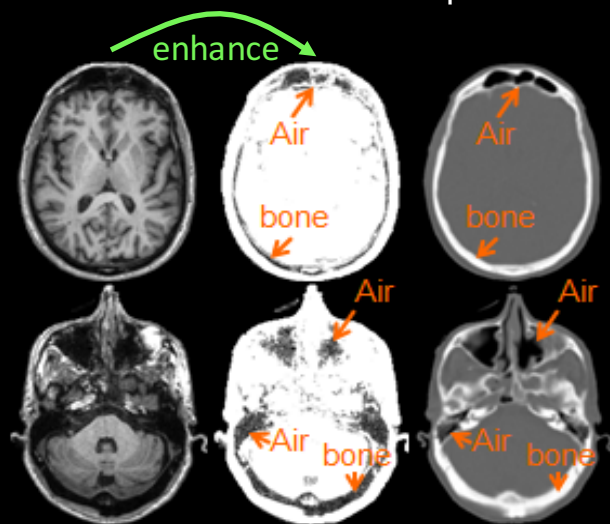
- CT images are highly desired for:
 - Specific diagnosis
 - Dose planning
 - PET attenuation correction
- Issues:
 - Health concerns of CT scan
 - Unavailability of CT images



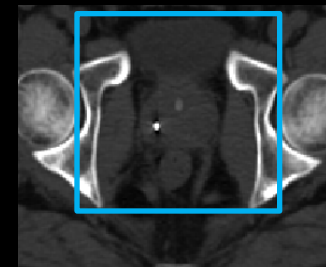
Can we synthesize CT image from a single MRI image?

CT vs. MRI

- Different structures in MRI and CT
 - Similarity of some regions (e.g., **air** and **bone**) in MRI
- Difficulty in accurate deformable registration between MRI and CT
 - High deformation around prostate area



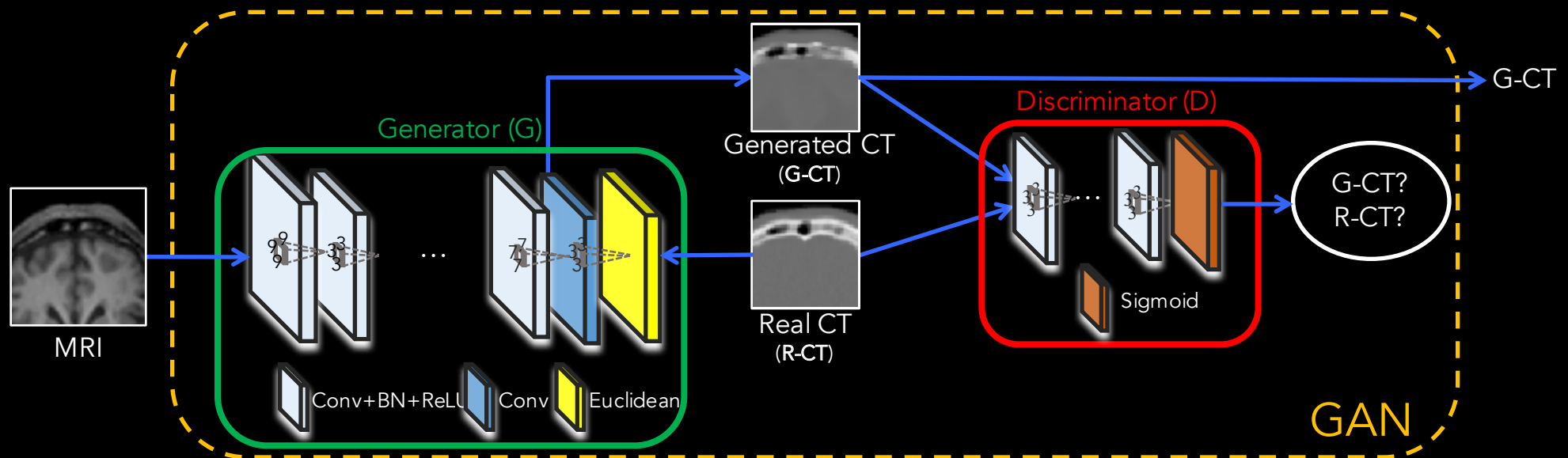
MRI



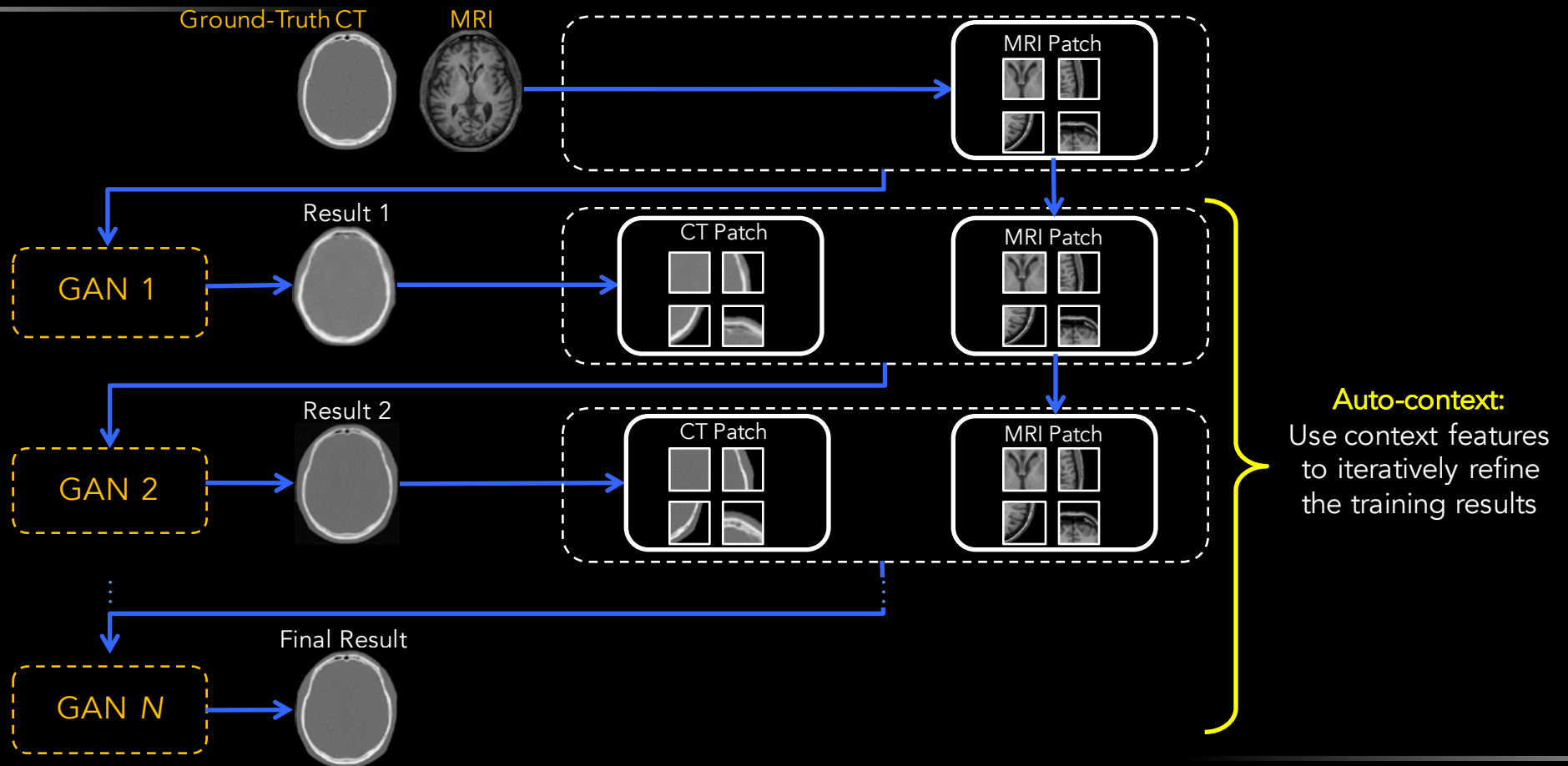
CT

Generative Adversarial Networks (GAN)

- A game between Discriminator (**D**) and Generator (**G**)
 - G**: Generate CT as real as possible to fool the **D**
 - D**: Distinguish the real CT and generated CT as much as possible

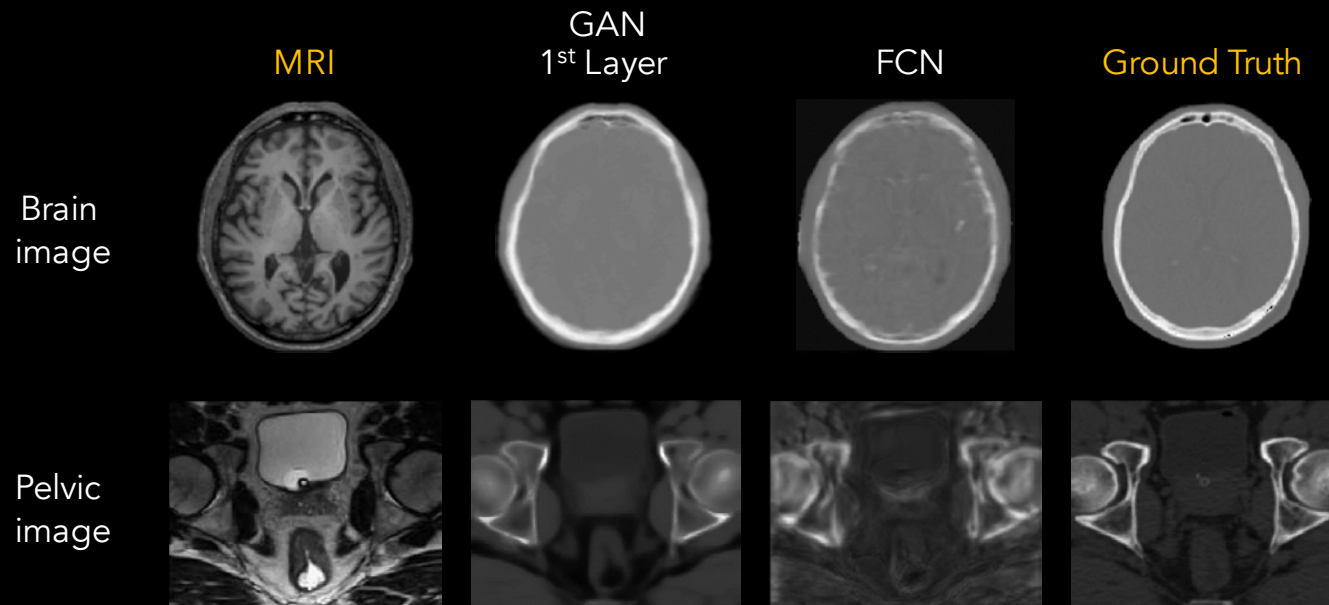


Context-aware GAN



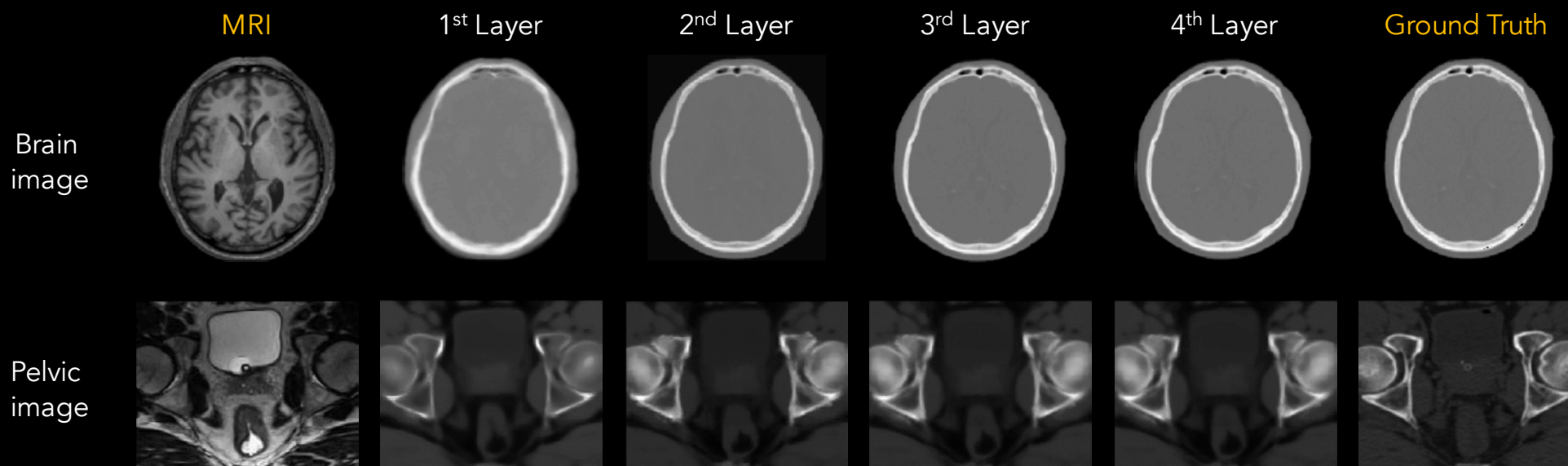
D. Nie*, R. Trullo*, J. Lian, C. Petitjean, S. Ruan, D. Shen, "Medical Image Synthesis with Context-Aware Generative Adversarial Networks", MICCAI, 2017.

AGAN Cost-FCN Refinement



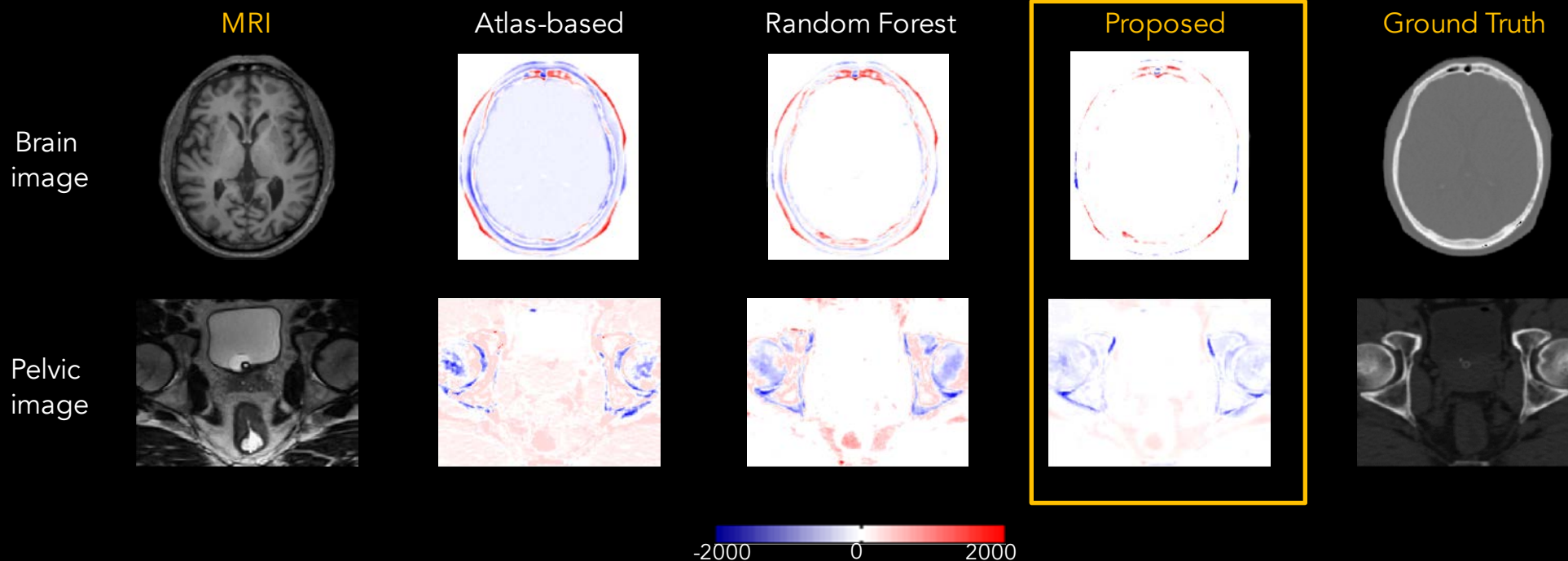
D. Nie*, R. Trullo*, J. Lian, C. Petitjean, S. Ruan, D. Shen, "Medical Image Synthesis with Context-Aware Generative Adversarial Networks", MICCAI, 2017.

Auto-context Refinement



D. Nie*, R. Trullo*, J. Lian, C. Petitjean, S. Ruan, D. Shen, "Medical Image Synthesis with Context-Aware Generative Adversarial Networks", MICCAI, 2017.

Comparison with Other Methods



D. Nie*, R. Trullo*, J. Lian, C. Petitjean, S. Ruan, D. Shen, "Medical Image Synthesis with Context-Aware Generative Adversarial Networks", MICCAI, 2017.



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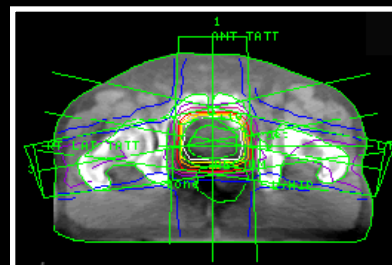
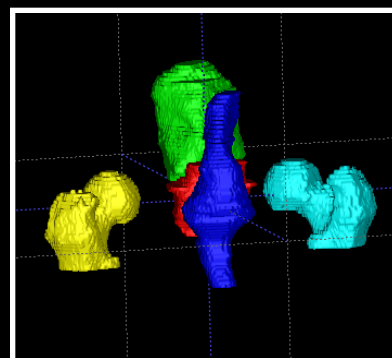
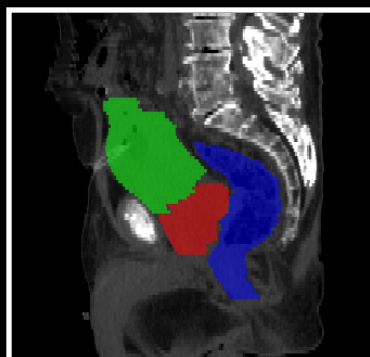
Cancer Radiotherapy

- Segmenting Planning CT

Segmenting Planning CT

Automatic Segmentation of Planning CT for Prostate Cancer Therapy

Planning CT Pelvic Segmentation for External Beam Radiotherapy



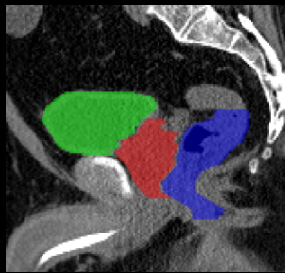
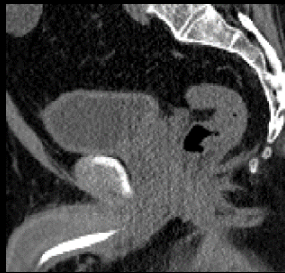
Planning CT Segmentation
(prostate, bladder, rectum,
left femoral head, right femoral head)

Dose Planning

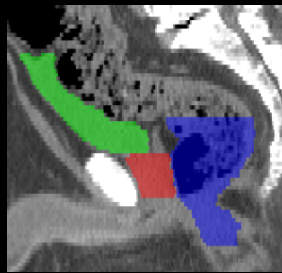
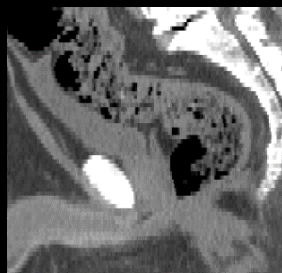
Daily Treatment

Planning CT Pelvic Segmentation

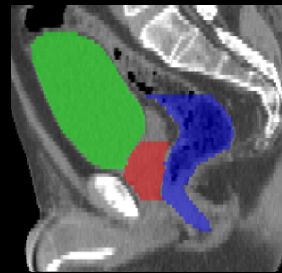
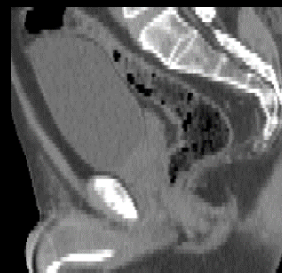
- Challenges
 - Low contrast
 - Large shape and appearance variations



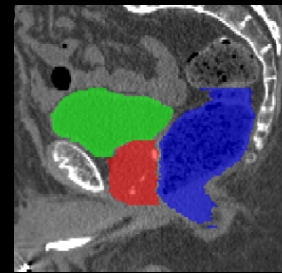
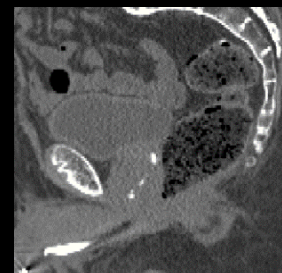
Subj 1



Subj 2



Subj 3



Subj 4

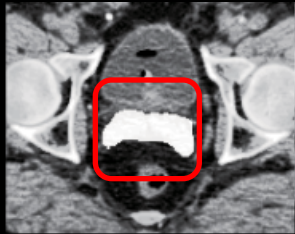


Motivation

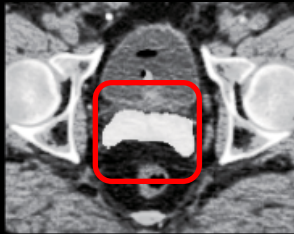
- Use manual delineations to guide better feature learning
 - Overlay manual delineations to original CT with different ratios ("0.2" → "0")

Simple Case

Difficult Case



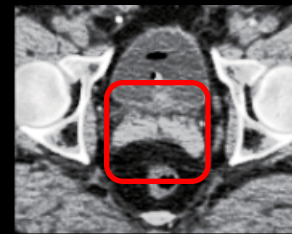
"0.2"



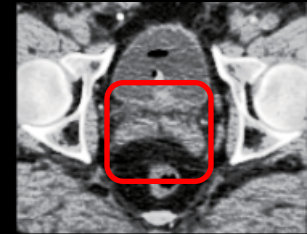
"0.1"



"0.05"



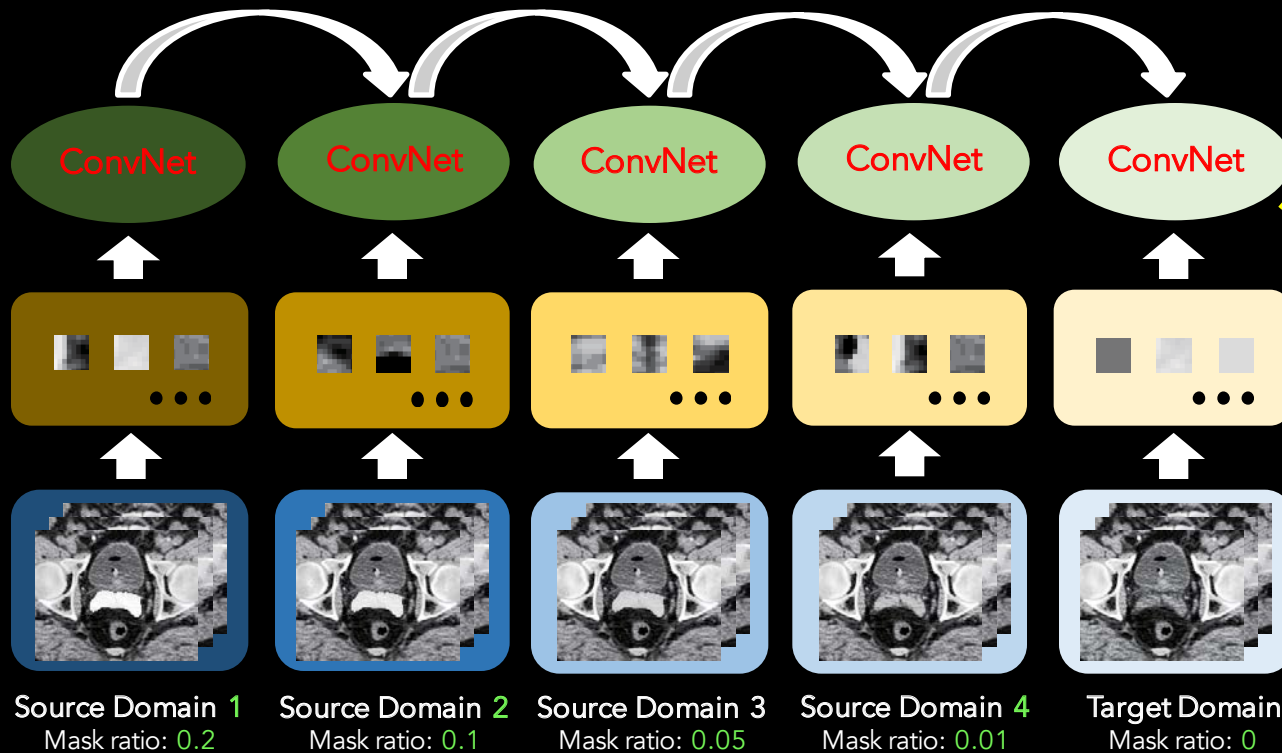
"0.01"



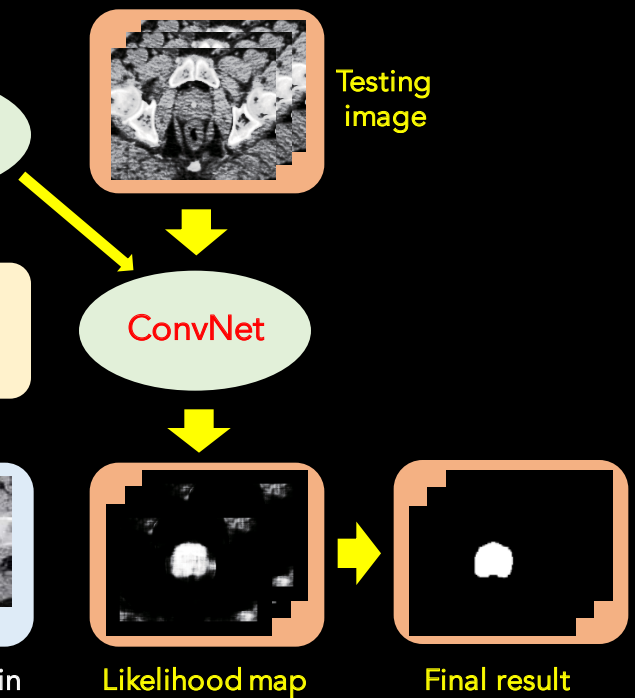
"0"

Cascaded Deep Domain Adaptation (CDDA)

- Training Stage

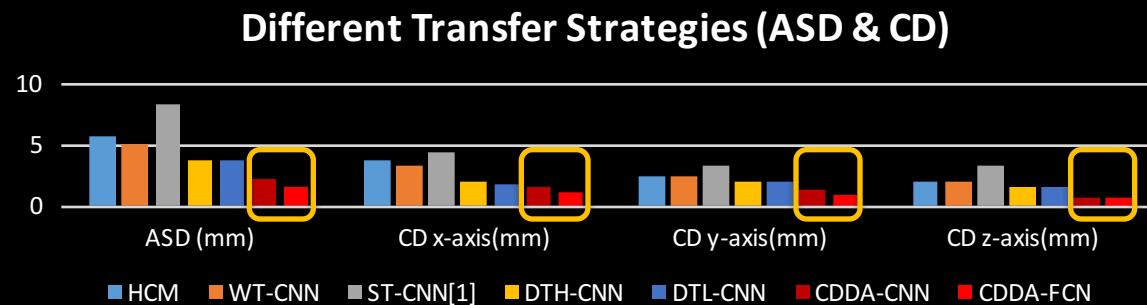
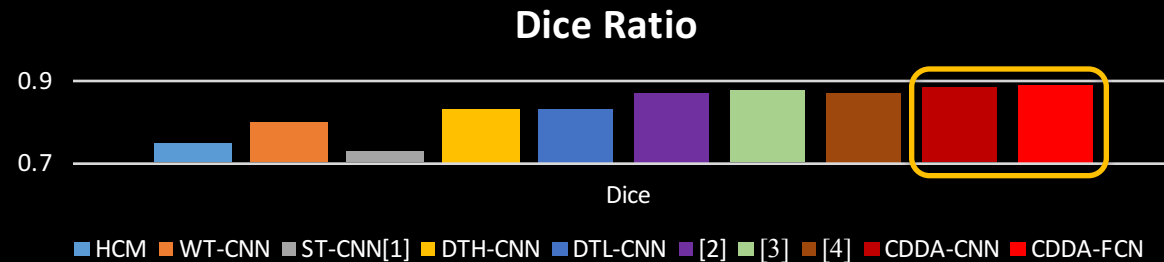


- Testing Stage



Y. Shi, W. Yang, Y. Gao, D. Shen, "Does Manual Delineation Only Provide the Side Information in CT Prostate Segmentation?", MICCAI, 2017.

Results



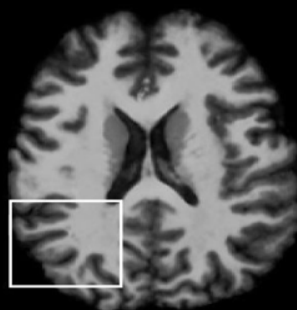
HCM: Hand-crafted Method
 WT-CNN: Without Transfer
 ST-CNN: Selective Transfer
 DTH-CNN: 0.2->0
 DTL-CNN: 0.01->0

- [1] J. Yosinski, J. Clune, Y. Bengio, H. Lipson. How transferable are features in deep neural networks? In NIPS, 2014.
- [2] F. Martinez, et al., Segmentation of pelvic structures for planning CT using a geometrical shape model tuned by a multi-scale edge detector. Physics in Medicine and Biology, 2014.
- [3] Y. Shao, Y. Gao, Q. Wang, X. Yang, and D. Shen. Locally-constrained boundary regression for segmentation of prostate and rectum in the planning CT images. Medical Image Analysis, 2015.
- [4] Y. Gao, et al. Accurate segmentation of CT male pelvic organs via regression-based deformable models and multi-task random forests. IEEE TMI, 2016.

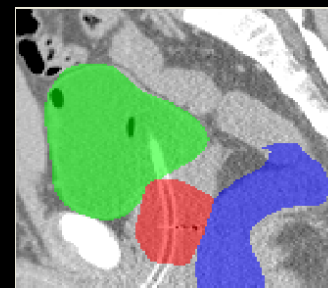
Outline



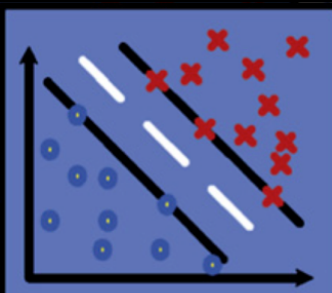
Segmentation /
Registration



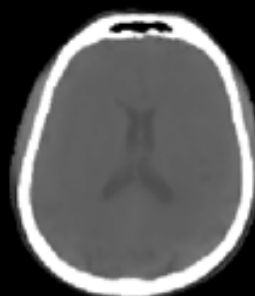
MRI
Enhancement



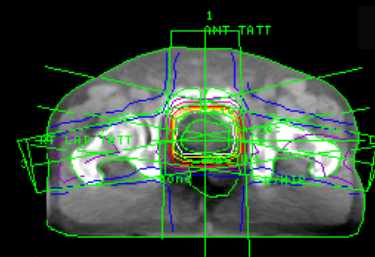
Planning CT
Segmentation



Disease Diagnosis



CT Estimation from MRI



Dose Planning

Neuroimaging Analysis

Image Synthesis

Cancer Radiotherapy



Thank you!

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