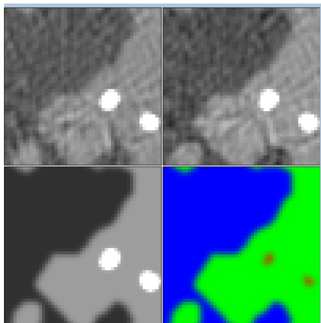


Overview of the DL-spectral CT Grand Challenge

Organizers: Emil Sidky and Xiaochuan Pan

The AAPM Working Group on Grand Challenges

THE UNIVERSITY OF CHICAGO

Inverse problems in Imaging

IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 68, NO. 6, JUNE 2021 1799

Do CNNs Solve the CT Inverse Problem?

Emil Y. Sidky, *Member, IEEE*, Iris Lorente, Jovan G. Brankov, *Senior Member, IEEE*,
and Xiaochuan Pan, *Fellow, IEEE*

Inverse problems in Imaging

Measurement model: $y = \mathcal{M}(x)$

Inverse of Measurement model: $\mathcal{M}^{-1}\mathcal{M}(x) = x$

Empirical studies with digital phantoms, root-mean-square-error (RMSE) as the metric

Inverse problems in Imaging

$$\mathcal{M}_{\text{phys}}(x) = \mathcal{M}(x) + \epsilon_{\text{det}}(x) + \epsilon_{\text{noise}}(x)$$ **Measurement model**

$$\mathcal{M}^{-1}\mathcal{M}_{\text{phys}}(x) = x + \delta$$

inverse

$$\mathcal{M}^{-1}\mathcal{M}(x) = x$$

stability

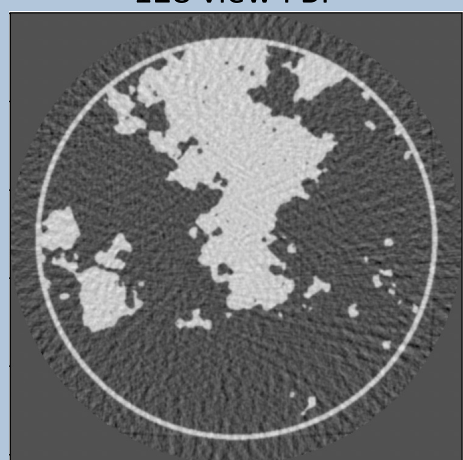
$$\|\mathcal{M}^{-1}(y_1) - \mathcal{M}^{-1}(y_2)\| \leq \epsilon\|y_1 - y_2\|$$

DL-sparse-view CT (2021 AAPM Grand Challenge)

128 views x 1024 bins (g)

2D fan-beam CT
360 degree scanning
noiseless sinogram

128 view FBP



512x512 image (f)

$$g = Rf$$

R partially known
4,000 training cases provided

2021 DL-sparse-view CT winners

Team:
Robust and Stable

Institution:
Technical University of Berlin

Utrecht University

Martin Genzel

Jan Macdonald

Maximillian Maerz

MEDICAL PHYSICS
The International Journal of Medical Physics Research and Practice

SPECIAL REPORT

Report on the AAPM deep-learning sparse-view CT grand challenge

Emil Y. Sidky, Xiaochuan Pan

First published: 26 January 2022 | **https://doi.org/10.1002/mp.15489**

Oral presentation at ICML 2022
https://arxiv.org/abs/2206.07050

2021 DL-sparse view CT

IEEE JOURNAL ON SELECTED AREAS IN INFORMATION THEORY, VOL. 1, NO. 1, MAY 2020 39

Deep Learning Techniques for Inverse Problems in Imaging

Gregory Ongie, Ajil Jalal, Christopher A. Metzler, Richard G. Baraniuk, Alexandros G. Dimakis, and Rebecca Willett

Circular, fan-beam CT
geometric parameters and line-intersection weights
NOT provided

TABLE II
MAJOR CATEGORIES OF METHODS LEARNING TO SOLVE INVERSE PROBLEMS BASED ON WHAT IS KNOWN ABOUT THE FORWARD MODEL $\mathcal{A}$ AND THE NATURE OF THE TRAINING DATA, WITH EXAMPLES FOR EACH. DETAILS ARE DESCRIBED THROUGHOUT SECTION IV

	Supervised with matched $(\boldsymbol{x},\boldsymbol{y})$ pairs	**Train from unpaired $\boldsymbol{x}$'s and $\boldsymbol{y}$'s (Unpaired ground truths and Measurements)**	**Train from $\boldsymbol{x}$'s only (Ground truth only)**	**Train from $\boldsymbol{y}$'s only (Measurements only)**
$\mathcal{A}$ fully known during training and testing (§4.1)	§4.1.1: Denoising autoencoders [16], U-Net [78], Deep convolutional framelets [79] Unrolled optimization [80–83], Neumann networks [84]	*amounts to training from $(\boldsymbol{x},\boldsymbol{y})$ pairs*	*amounts to training from $(\boldsymbol{x},\boldsymbol{y})$ pairs*	§4.1.2: SURE LDAMP [85, 86], Deep Basis Pursuit [87]
$\mathcal{A}$ known only at test time (§4.2)	§4.2.2	§4.2.2	§4.2.1: CSGM [25], LDAMP [88], OneNet [22], Plug-and-play [89], RED [90]	§4.2.2
$\mathcal{A}$ partially known (§4.3)	§4.3.1	§4.3.2: CycleGAN [91]	§4.3.3: Blind deconvolution with GAN's [92–94]	§4.3.4: AmbientGAN [76], Noise2Noise [95], UAIR [96]
$\mathcal{A}$ unknown (§4.4)	§4.4.1: AUTOMAP [97]	§4.4.2	§4.4.2	§4.4.2

2022 DL-spectral CT

Known forward model
Inverse problem solution unknown
(optimization-based, DL-based, or hybrid)

Non-linear forward model that leads
to non-convex optimization

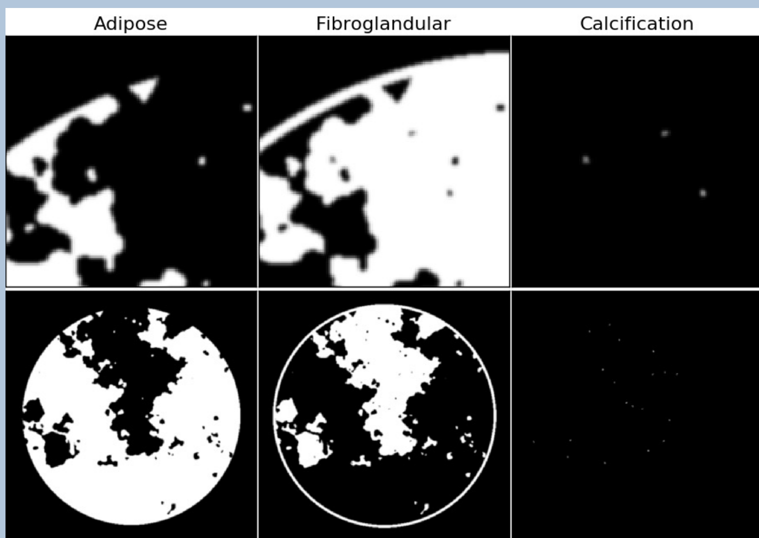
Not too burdensome for participants
2D CT, 1000 training cases

Models fast kV-switching dual-energy
Unregistered transmission measurements

TABLE II
MAJOR CATEGORIES OF METHODS LEARNING TO SOLVE INVERSE PROBLEMS BASED ON WHAT IS KNOWN ABOUT THE FORWARD MODEL $\mathcal{A}$ AND THE NATURE OF THE TRAINING DATA, WITH EXAMPLES FOR EACH. DETAILS ARE DESCRIBED THROUGHOUT SECTION IV

	Supervised with matched (x, y) pairs	**Train from unpaired x's and y's (Unpaired ground truths and Measurements)**	**Train from x's only (Ground truth only)**	**Train from y's only (Measurements only)**
$\mathcal{A}$ fully known during training and testing (§4.1)	§4.1.1: Denoising auto-encoders [16], U-Net [78], Deep convolutional framelets [79] Unrolled optimization [80–83], Neumann networks [84]	*amounts to training from $(\boldsymbol{x}, \boldsymbol{y})$ pairs*	*amounts to training from $(\boldsymbol{x}, \boldsymbol{y})$ pairs*	§4.1.2: SURE LDAMP [85, 86], Deep Basis Pursuit [87]
$\mathcal{A}$ known only at test time (§4.2)	§4.2.2	§4.2.2	§4.2.1: CSGM [25], LDAMP [88], OneNet [22], Plug-and-play [89], RED [90]	§4.2.2
$\mathcal{A}$ partially known (§4.3)	§4.3.1	§4.3.2: CycleGAN [91]	§4.3.3: Blind deconvolution with GAN's [92–94]	§4.3.4: AmbientGAN [76], Noise2Noise [95], UAIR [96]
$\mathcal{A}$ unknown (§4.4)	§4.4.1: AUTOMAP [97]	§4.4.2	§4.4.2	§4.4.2

DL-spectral CT Phantom model

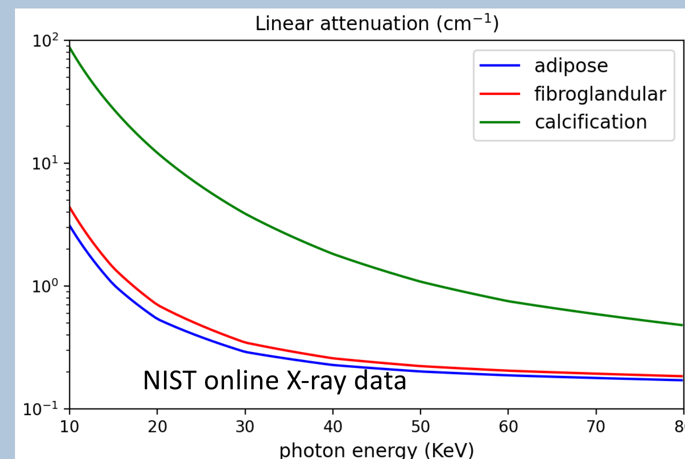


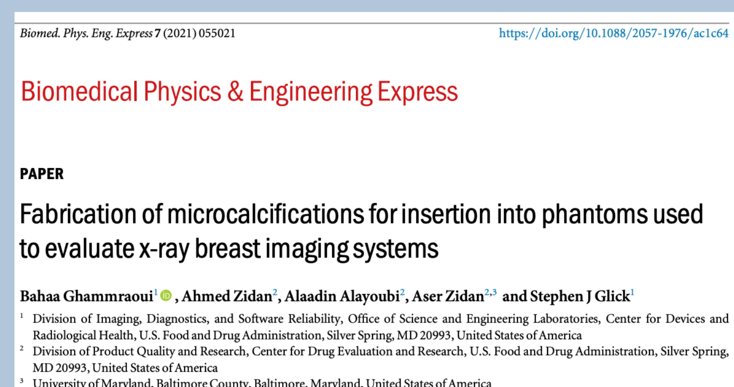
x_a x_f x_c

hydroxyapatite

$$\sum_m x_m = 1$$

$$0 \leq x_m \leq 1$$





Biomed. Phys. Eng. Express **7** (2021) 055021 https://doi.org/10.1088/2057-1976/ac1c64

Biomedical Physics & Engineering Express

PAPER

Fabrication of microcalcifications for insertion into phantoms used to evaluate x-ray breast imaging systems

Bahaa Ghammraoui[1], **Ahmed Zidan**[2], **Alaadin Alayoubi**[2], **Aser Zidan**[2,3] **and Stephen J Glick**[1]

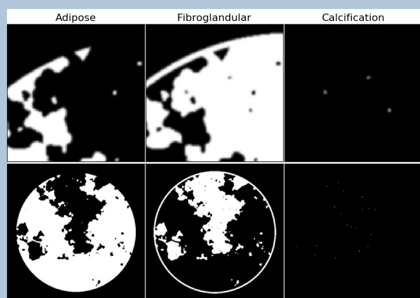
[1] Division of Imaging, Diagnostics, and Software Reliability, Office of Science and Engineering Laboratories, Center for Devices and Radiological Health, U.S. Food and Drug Administration, Silver Spring, MD 20993, United States of America

[2] Division of Product Quality and Research, Center for Drug Evaluation and Research, U.S. Food and Drug Administration, Silver Spring, MD 20993, United States of America

[3] University of Maryland, Baltimore County, Baltimore, Maryland, United States of America

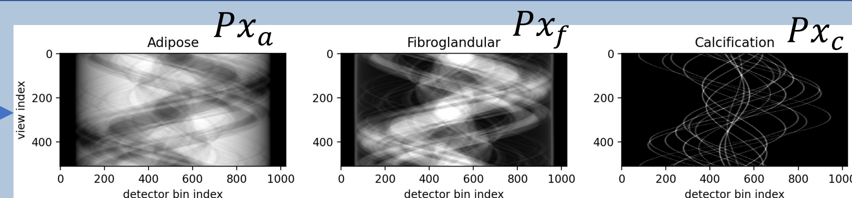
Spectral CT model

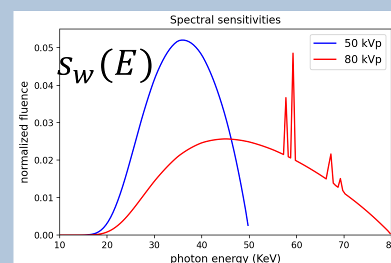
$$I_w = \int s_w(E)\exp\left[-\mu_a(E)Px_a - \mu_f(E)Px_f - \mu_c(E)Px_c\right] dE$$

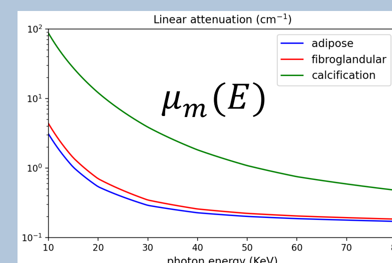


P

projection.py

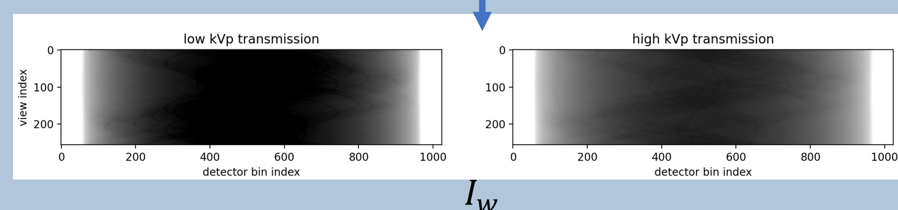




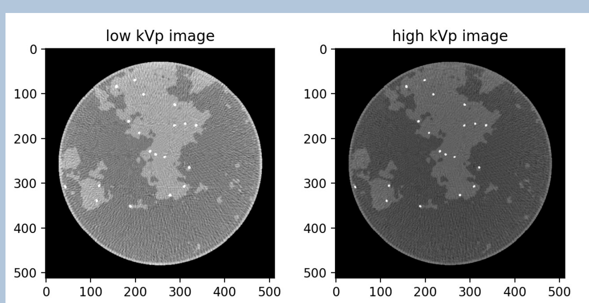


w index is either 50 or 80 kVp
m index is either adipose (*a*), fibroglandular (*f*), or calcification (*c*)
FBP stands for filtered back-projection

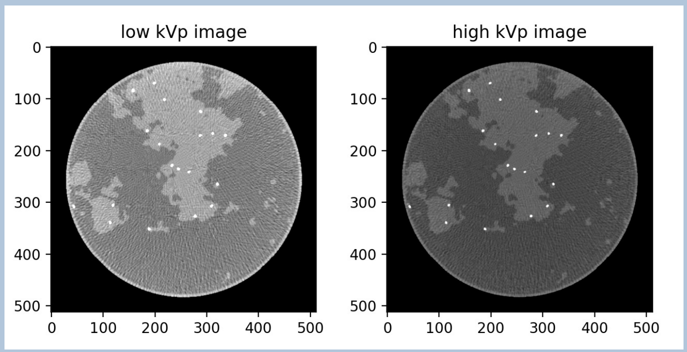
dualEnergyTransmission.py

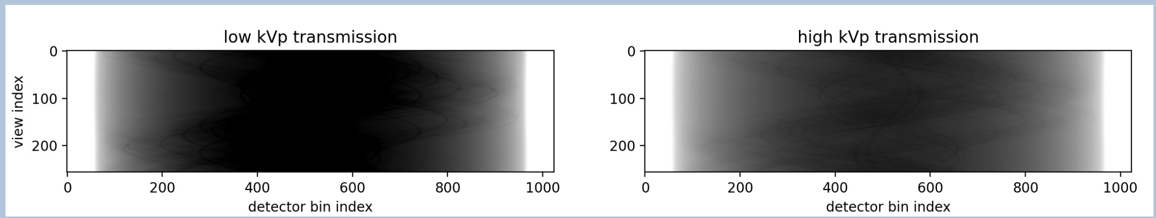


$\mathrm{FBP}(-\ln(I_w))$



DL spectral CT objective:
obtain tissue maps from kVp images, kVp transmission, or both





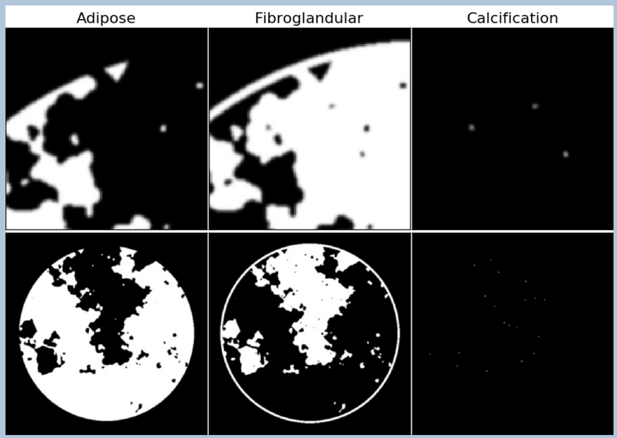


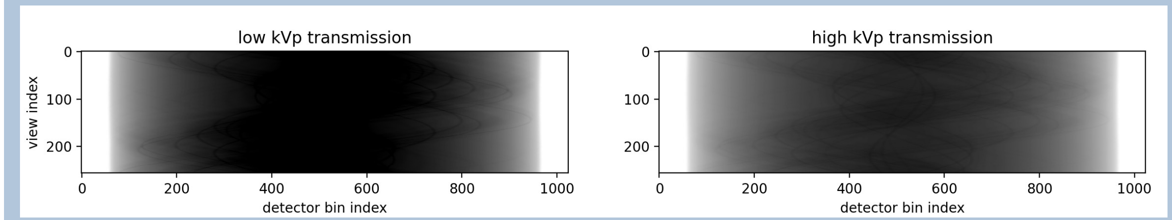
Image-to-Image approach

kVp images are shown in a [0.15,0.35] gray scale window. Note that they have streak and cupping artifacts. Also, the tissue contrasts are different for the low and high kVp images. In the image-to-image approach, the training data needs to be exploited to remove the artifacts; and the different contrast levels of the low and high kVp image training data then need to be exploited to estimate the tissue maps.

Transmission-to-Image approach

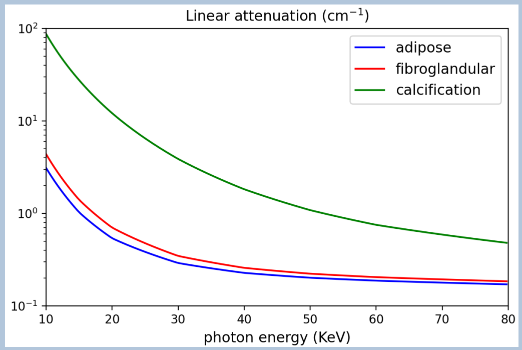
DL-spectral CT
the inverse problem

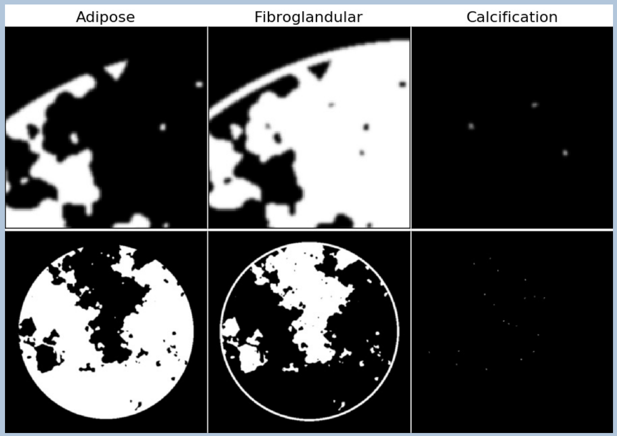
$$I_w = \int s_w(E) \exp\left[-\mu_a(E) P x_a - \mu_f(E) P x_f - \mu_c(E) P x_c\right] dE$$



I_{low} and I_{high} are not registered

Data size: 2x256x1024 (0.5 MB)





Data size: 3x512x512 (0.75 MB)

$$\sum_m x_m = 1$$

$$0 \le x_m \le 1$$

DL-spectral CT platform and schedule

MedICI
Medical Imaging Challenge Infrastructure
www.medici-challenges.org

Benjamin Bearce (programmer)
Jayashree Kalpathy-Cramer (PI)

Schedule
March 17: release of training – 1000 datasets, known truth
March 31: validation phase – 10 datasets, unknown truth
May 17: testing phase – 100 datasets, unknown truth
June 1: challenge end

DL-spectral CT scoring

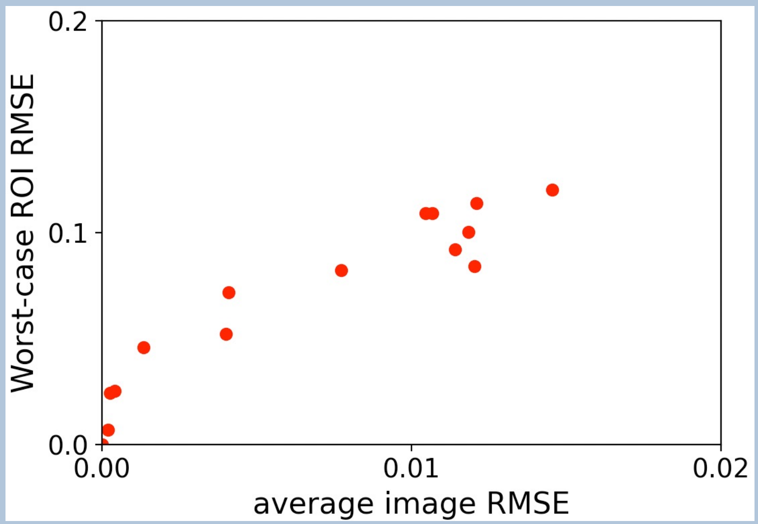
Ranking by average RMSE over 100 test cases
three tissue maps for each case

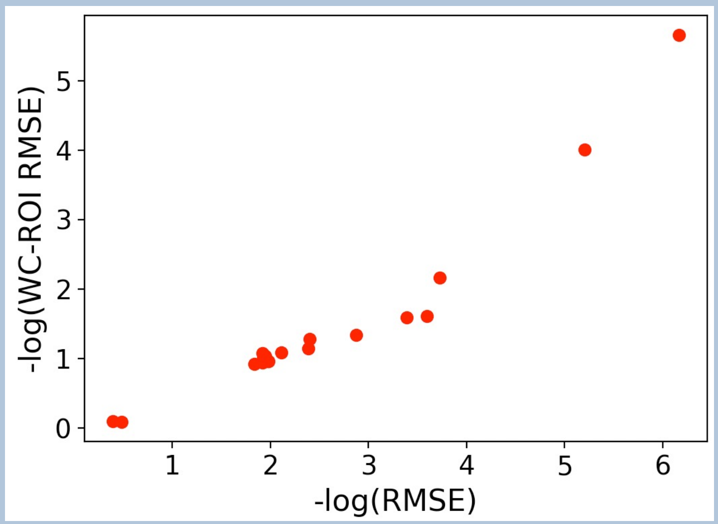
Tie-breaker:
Worst-case region of interest (ROI) RMSE
ROI is 25x25 pixels
Over all 100 cases

DL-spectral CT test phase results

Results					
#	User	Entries	Date of Last Entry	RMSE ▲	WC_ROI-RMSE ▲
1	GenweiMa	3	05/31/22	0.00000068 (1)	0.00000220 (1)
2	huxiaoyu090	3	05/31/22	0.00000621 (2)	0.00009767 (2)
3	kimhs369	2	05/31/22	0.00018666 (3)	0.00680786 (3)
4	WashUDEAM	2	05/31/22	0.00025205 (4)	0.02440356 (4)
5	dhlee91	1	05/31/22	0.00040848 (5)	0.02544221 (5)
6	jaspernijkamp	3	05/31/22	0.00133719 (6)	0.04595653 (6)
7	Duke_QIAL	2	05/30/22	0.00400783 (7)	0.05213956 (7)
8	leekunpeng	3	05/25/22	0.00409590 (8)	0.07176514 (8)
9	flutexu	1	05/26/22	0.00773430 (9)	0.08237529 (9)
10	Z-VCT	2	05/31/22	0.01045535 (10)	0.10902996 (13)
11	WangYZ	3	05/31/22	0.01067686 (11)	0.10916580 (14)
12	duysal	1	05/31/22	0.01141161 (12)	0.09213256 (11)
13	gopalakrishm	1	05/30/22	0.01184738 (13)	0.10020318 (12)
14	satoru	2	05/24/22	0.01203003 (14)	0.08405824 (10)
15	NJUP	3	05/30/22	0.01209367 (15)	0.11389498 (15)
16	ZXRM	1	05/31/22	0.01453637 (16)	0.12020124 (16)
17	Yang_Yoonjeong	3	05/29/22	0.33054769 (17)	0.81837457 (18)
18	liuliu	1	05/31/22	0.40556404 (18)	0.79846686 (17)

DL-spectral CT test phase results

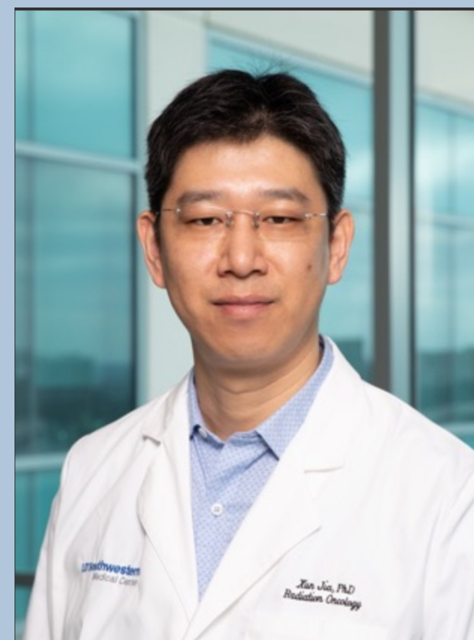




DL-spectral CT runner up team

Xiaoyu Hu

Xun Jia

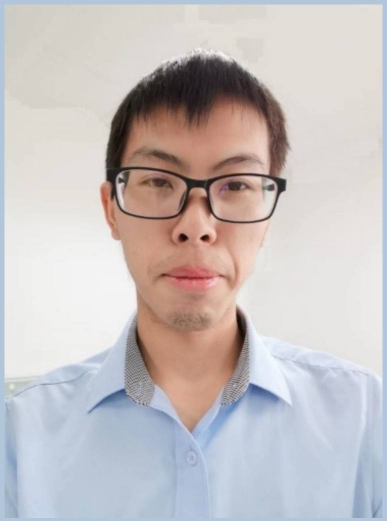


Institution:
University of Texas Southwestern
Medical Center

RMSE: 6.21×10^{-6}
Worst case ROI RMSE: 9.77×10^{-5}

DL-spectral CT winning team

Xiaoyu Hu



Prof. Xun Jia

Institutions:
Capital Normal University, Beijing

Southern University of Science and Technology, Shenzen

RMSE: 6.8×10^{-7}
Worst case ROI RMSE: 2.2×10^{-6}

DL-spectral CT top 5

USERNAME	TEAM NAME	MEMBERS	INSTITUTIONS(S)	RMSE SCORE
GenweiMa	GM_CNU	Genwei Ma Xing Zhao	Capital Normal University, Beijing, China Southern University of Science and Technology, Shenzhen, China	6.8 x 10^(-7)
Huxiaoyu090	iTORCH	Xiaoyu Hu Xun Jia	University of Texas Southwestern Medical Center, Dallas	6.21 x 10^(-6)
kimhs		Hyeongseok Kim Seungryong Cho	Korea Advanced Institute of Science & Technology, Daejon, South Korea	1.19 x 10^(-4)
WashUDEAM	WashUDEAM	Tao Ge Maria Medrano Joseph A. O'Sullivan	Washington University, St. Louis	2.52 x 10^(-4)
dhlee91		Donghyeon Lee Katsuyuki Taguchi	Johns Hopkins University School of Medicine, Baltimore	4.08 x 10^(-4)

Acknowledgements

AAPM WGGC
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Keyvan Farahani
Reshma Munbodh
Kenny Cha

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Emily Townley

MedICI
Benjamin Bearce
Jayashree Kalpathy-Cramer