Ultrasound Imaging: Deep & Beyond

Christopher Wiedeman, Hongming Shan, Wenxiang Cong, Ge Wang
AI-based X-ray Imaging System (AXIS) Lab
GE Deep Reconstruction Workshop, Niskayuna, New York, USA

3:20-3:50pm, January 15, 2020

Outline

Ultrasound

Hybrid Ultrasound & X-ray CT

(Chris)

Photoacoustic Tomography

(Hongming)

X-ray

X-ray Optical Tomography

(Ge)

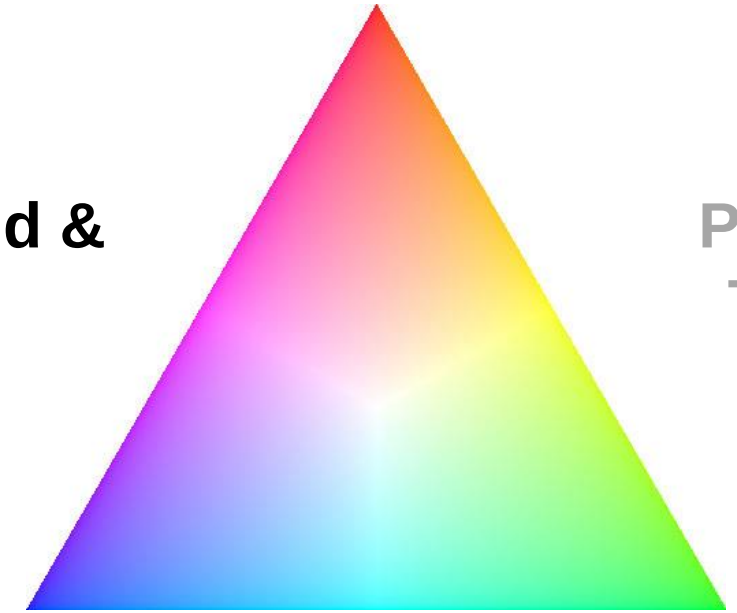
Light

Outline

Ultrasound

Hybrid Ultrasound & X-ray CT

(Chris)



Photoacoustic Tomography

(Hongming)

X-ray

X-ray Optical Tomography

(Ge)

Light

Motivation

‘Sophisticated’ Imaging

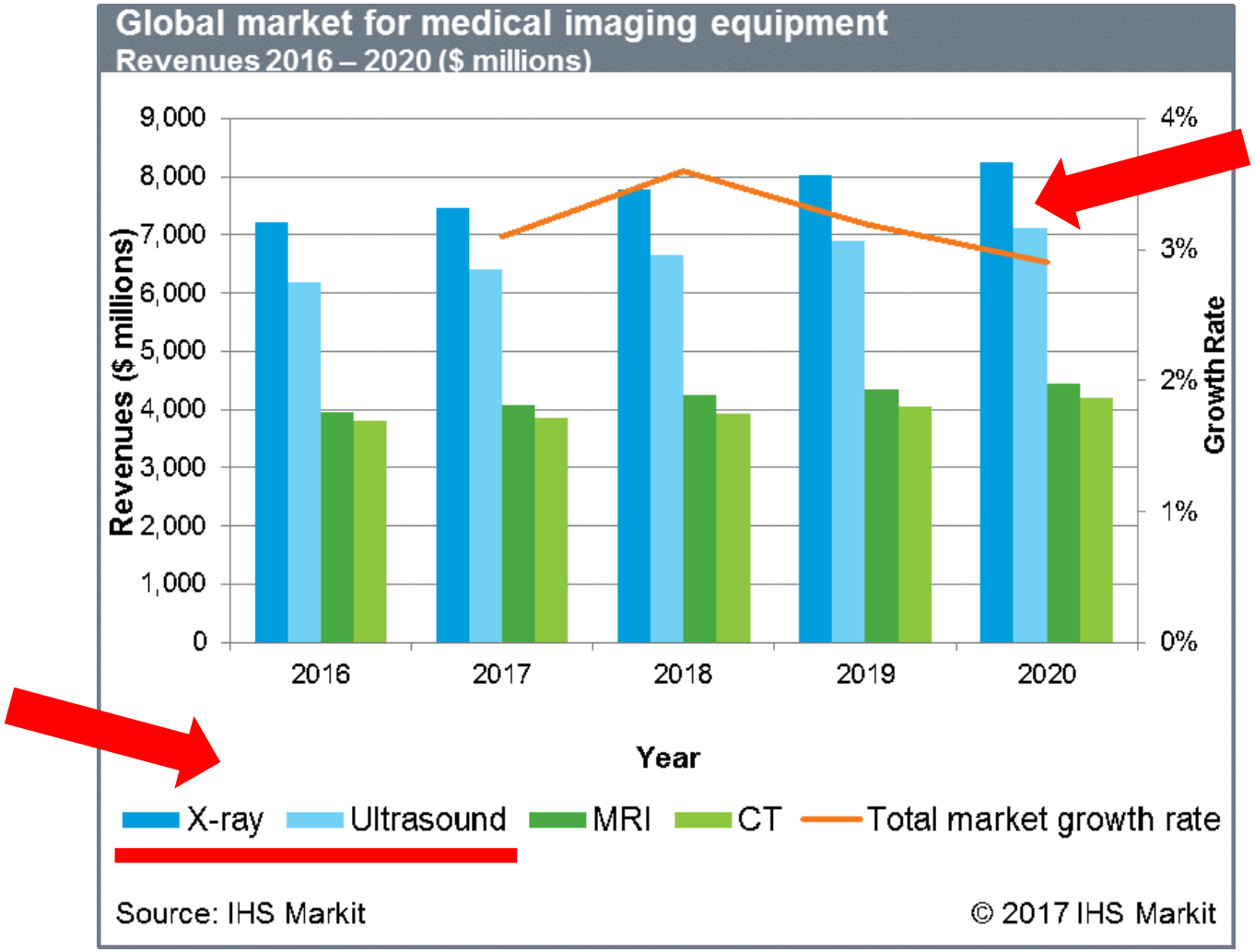
CT: Found in Hospitals

‘Accessible’ Imaging

X-ray: in Small Clinics

How can we get more mileage from more accessible modalities?

Combination of Two Most Valuable Tools



Recent Relevant Work

ARTICLES
https://doi.org/10.1038/s41551-019-0466-4

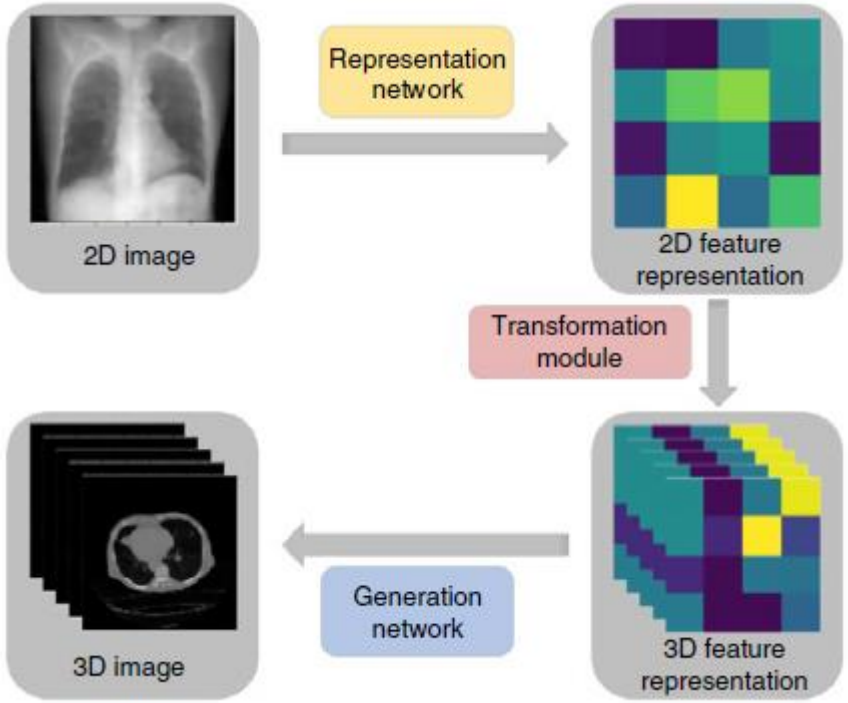
nature biomedical engineering

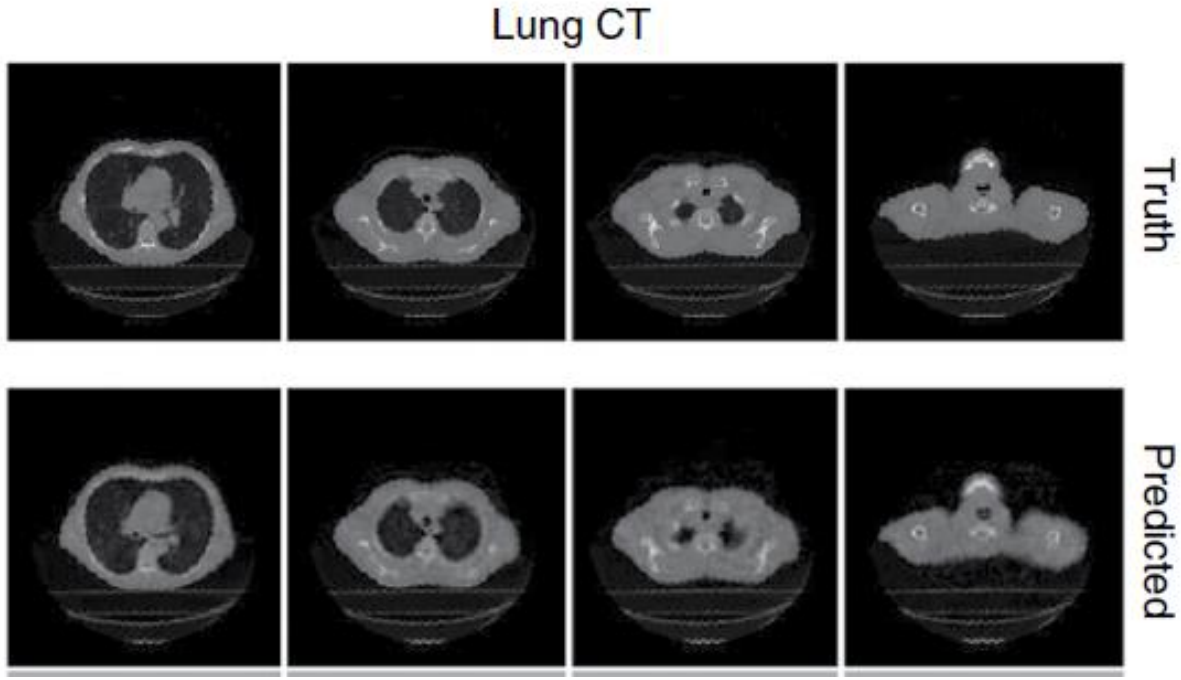
Patient-specific reconstruction of volumetric computed tomography images from a single projection view via deep learning

Liyue Shen[1,2,3], Wei Zhao[1,3] and Lei Xing[1,2*]

3D Reconstruction from a Single 2D View

- **Translation of 2D to 3D Representations**
- **Basis on Patient-specific Training & Limitations**





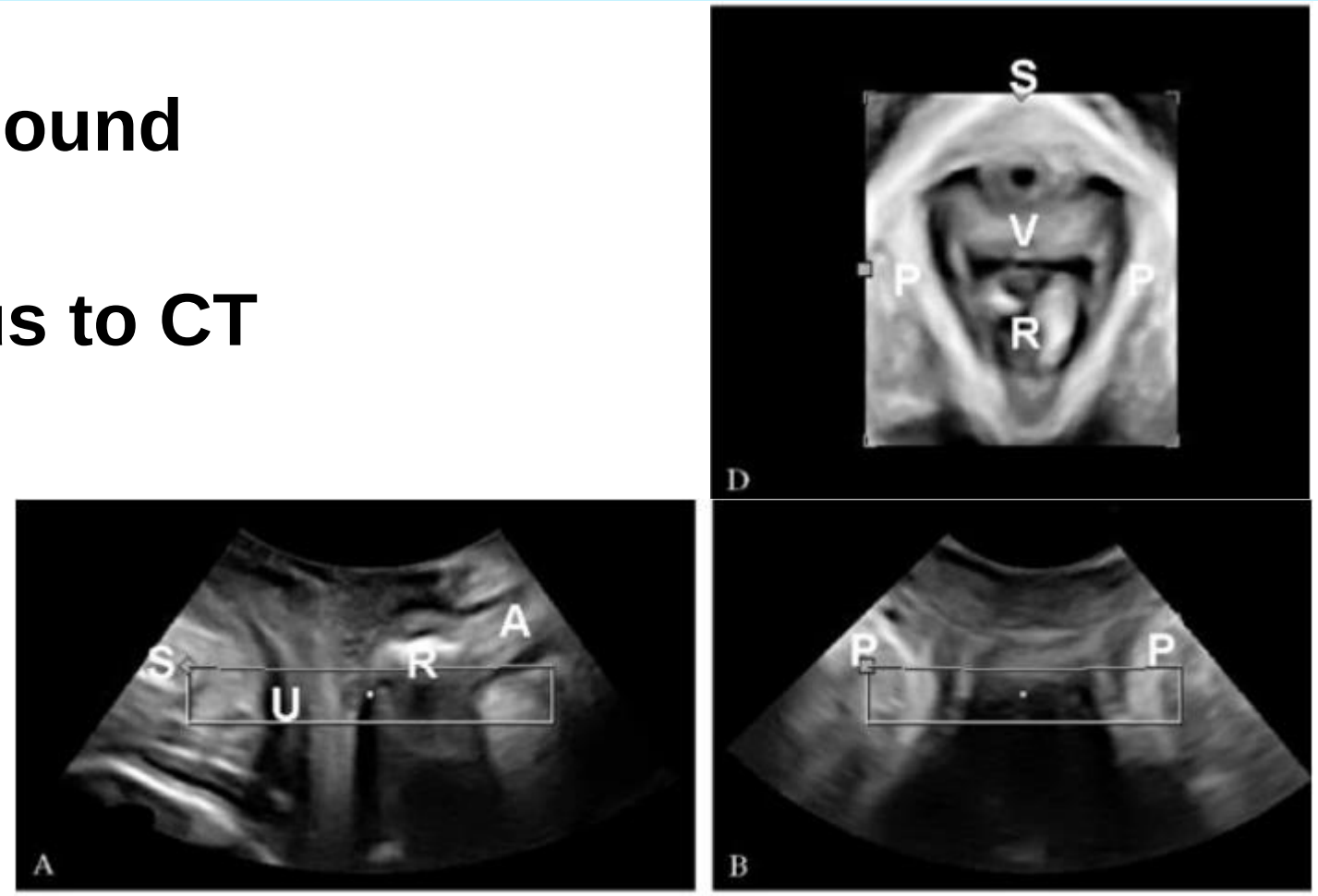
Figures from [1]

How to Collect Superior Priors?

- Introduce Additional, Complementary Information with Ultrasound Imaging
- Ultrasound (acoustic impedance) & CT (x-ray attenuation) images are Synergistic

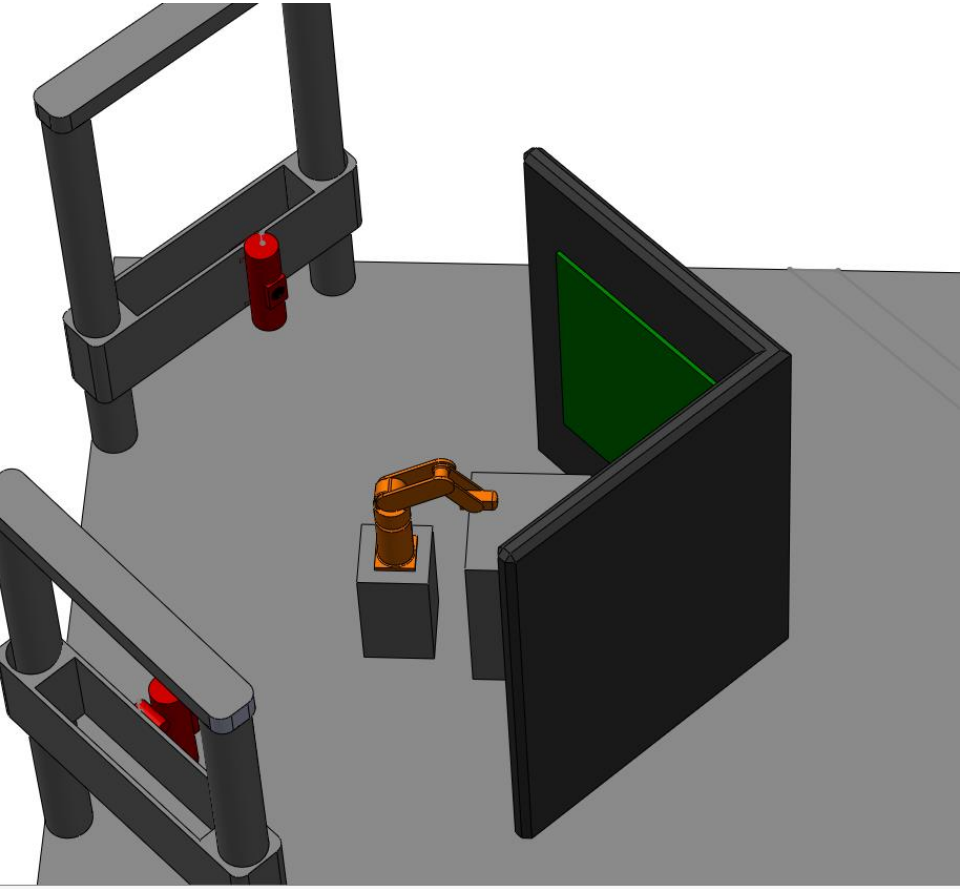
3D Ultrasound Imaging

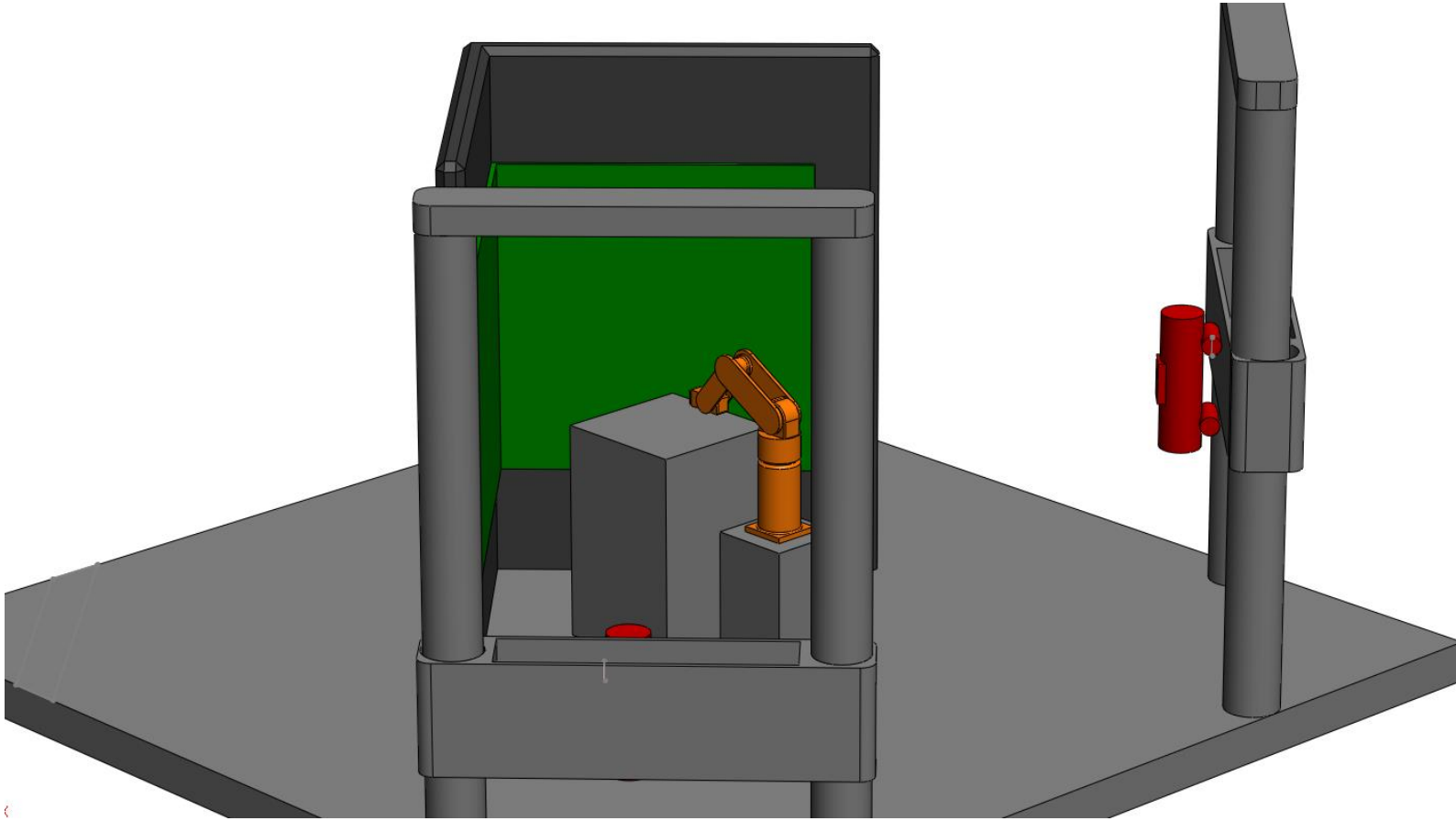
- **Motion-tracked Ultrasound Creates 3D Images**
- **3D volumes analogous to CT**
- **Ultrasound May**
  - **be Less Useful**
  - **for Head & Lungs**



Acoustic rendering of pelvic floor from midsaggital (left) and crornal (right) planes. Images from [2].

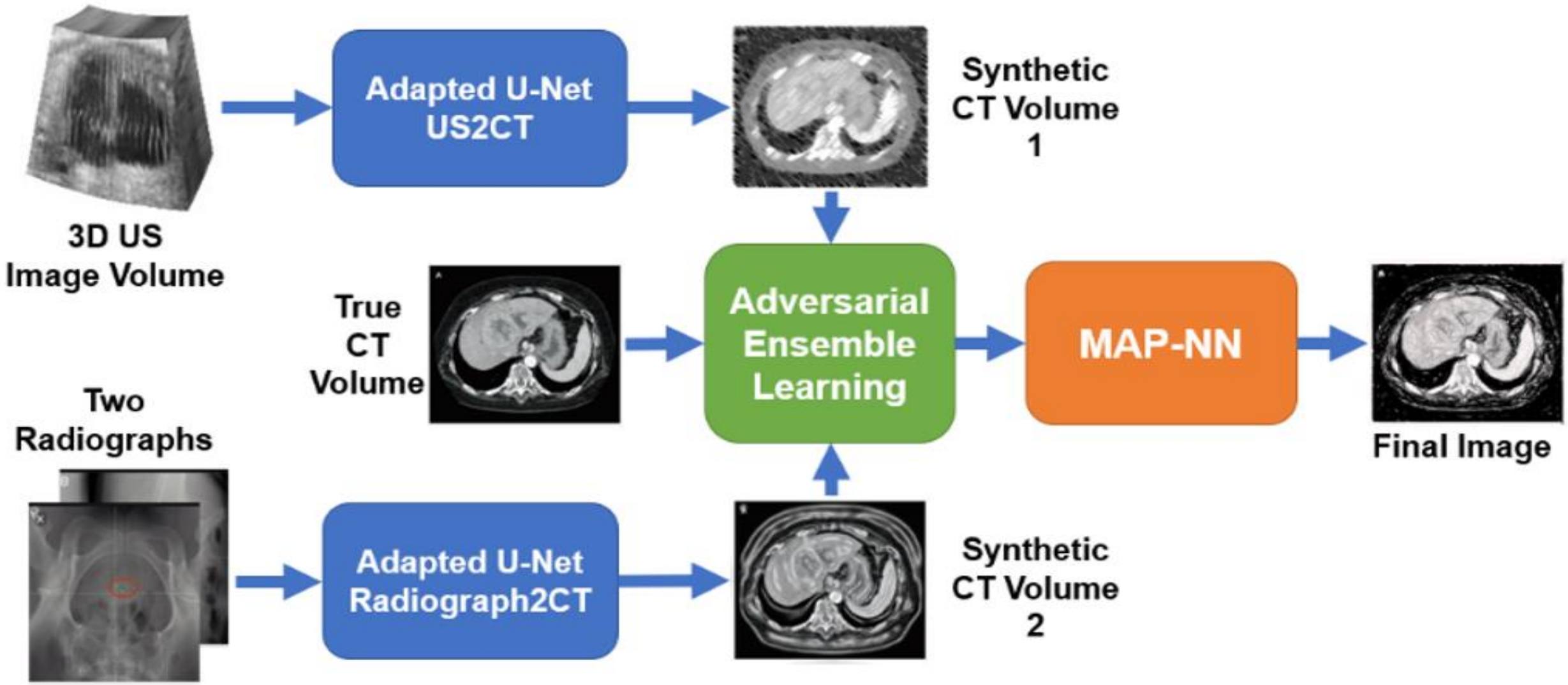
Hybrid Imaging System (Joint Work with MGH)





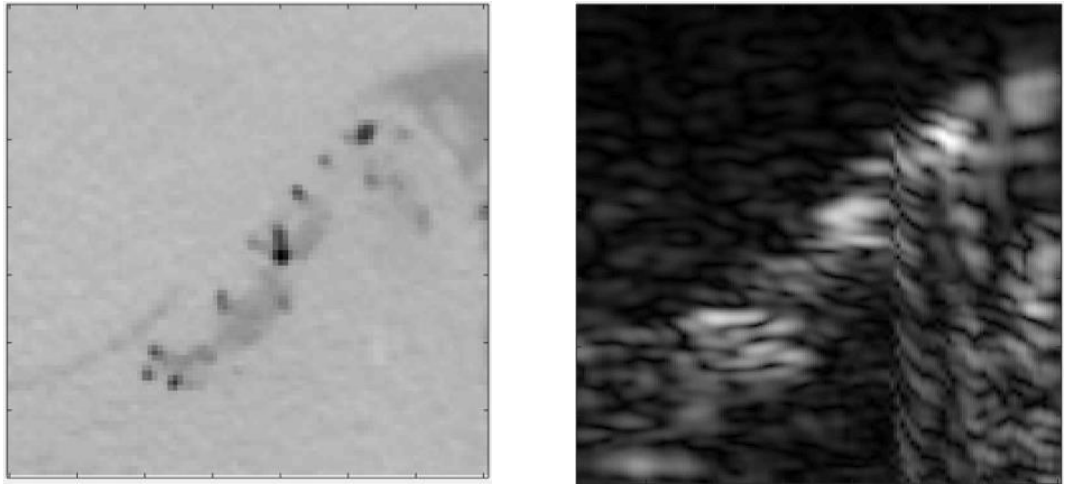
Visualized imaging studio: Robotic arm with 3D US scanner (orange), x-ray detector panels (green), x-ray tubes (red)

Hybrid Reconstruction Network



Preliminary Results

- **Captured CT images with Corresponding 3D Ultrasound Unavailable**
- **Simulation of Ultrasound from CT volumes for Pre-training**



Preliminary attempts simulating ultrasound section (right) from section of CT volume (left) using k-wave toolbox [3]

Project Aspirations

- **Affordable, Accessible, & Portable Tomographic Imaging**
- **Cross-modality Imaging**
- **Enabled Applications in Special Scenarios**

References

[1] Shen, L., Zhao, W. & Xing, L. Patient-specific reconstruction of volumetric computed tomography images from a single projection view via deep learning. Nat Biomed Eng 3, 880–888 (2019)

[2] Shek, Ka & Dietz, Hans, Pelvic floor ultrasonography: An update. Minerva ginecologica. 65. 1-20. (2013)

[3] B. E. Treeby and B. T. Cox, k-Wave: MATLAB toolbox for the simulation and reconstruction of photoacoustic wave-fields, J. Biomed. Opt., vol. 15, no. 2, p. 021314, (2010)

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(Ge)

Light

Pressure & Speed Tomography (Joint with MSU)

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9 September 2019

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Translator Disclaimer

Simultaneous reconstruction of the initial pressure and sound speed in photoacoustic tomography using a deep-learning approach

Hongming Shan; Christopher Wiedeman; Ge Wang; Yang Yang

Author Affiliations +

Proceedings Volume 11105, Novel Optical Systems, Methods, and Applications XXII; 1110504 (2019)

https://doi.org/10.1117/12.2529984

Event: SPIE Optical Engineering + Applications, 2019, San Diego, California, United States

Photo-Acoustic Effect

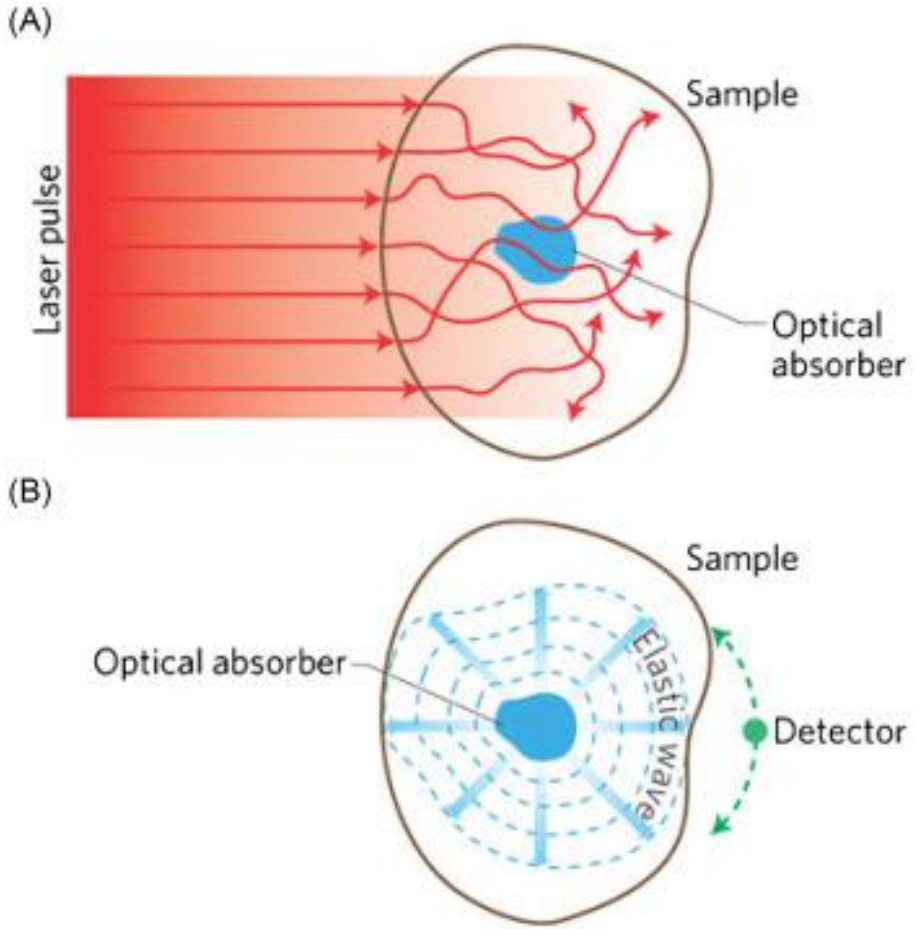
Graham Bell

Step 1:

Pulse of Light ⇒ Radiation Absorption

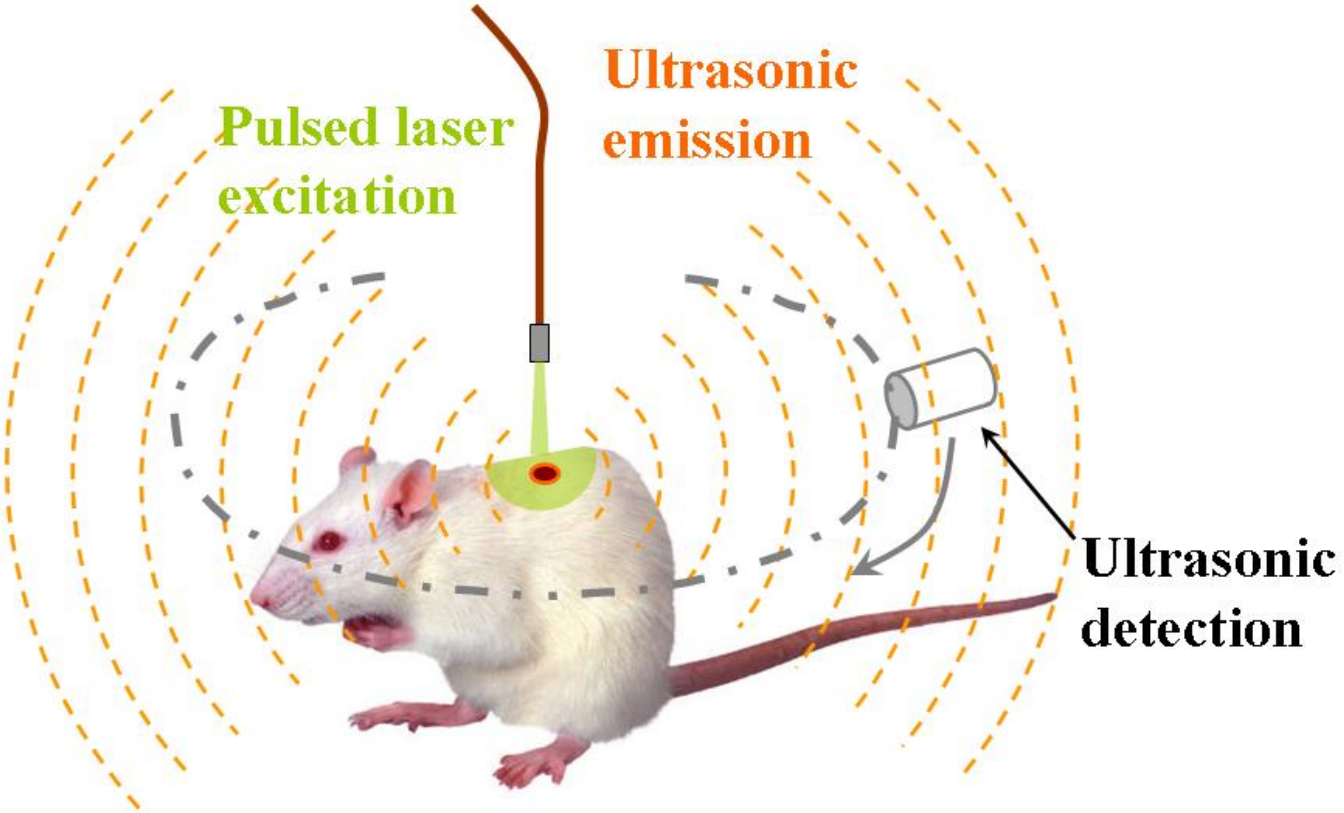
Step 2:

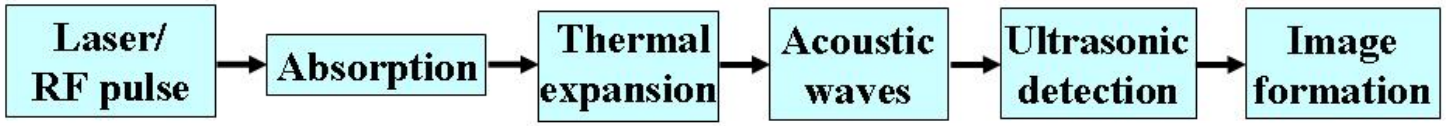
Thermo-Expansion ⇒ Acoustic Waves



https://www.sciencedirect.com/topics/medicine-and-dentistry/photoacoustic-tomography

Photo-acoustic Tomography





https://en.wikipedia.org/wiki/Photoacoustic_imaging#/media/File:PASchematics_v2.png

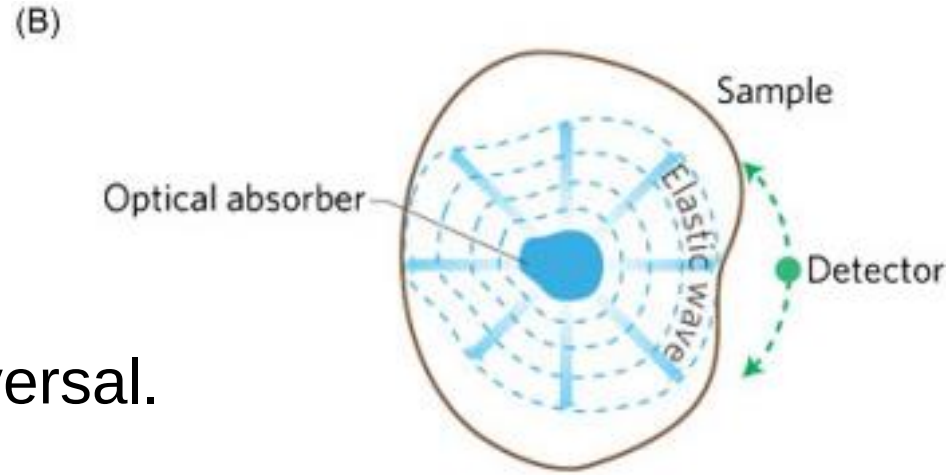
Mathematical Model (Known Speed)

$$\begin{cases} \rho(r)\frac{\partial u}{\partial t}(r,t) + \nabla p(r,t) &= 0, & \text{in } (0,T)\times\mathbb{R}^d \\ \frac{1}{\rho(r)c(r)^2}\frac{\partial p}{\partial t}(r,t) + \nabla\cdot u(r,t) &= 0, & \text{in } (0,T)\times\mathbb{R}^d \\ p(r,0) &= p_0(r), \\ u(r,0) &= 0, \end{cases}$$

$\rho(r)$: Mass density
$c(r)$: Sound speed
$u(r)$: Acoustic pressure
$p_0(r)$: Initial pressure

Inverse Problem: Recover $p_0(r)$ from $\{\, u(t,r): 0 \le t \le T,\ r$ on the boundary of $\Omega \,\}$

- In **homogeneous** media
  $c(r)$ is constant => Filtered back-projection;
- In **heterogeneous** media
  $c(r)$ is spatially varying but *known* => Time reversal.



Mathematical Model (Unknown Speed)

In reality, $c(r)$ is unknown! - Two popular solutions:

- **Reconstruct $c(r)$ using other modalities, e.g., ultrasound transmission tomography;**
- **Reconstruct $c(r)$ and $p_0(r)$ simultaneously.**

Matthews-Poudel-Li-Wang-Anastasio
SIAM J. Imaging Sciences, 2018 :

$$\widehat{p_0}, \widehat{c} = \underset{p_0 \geq 0, c \geq 0}{\operatorname{argmin}} F(p_0, c) + \beta R(p_0)$$

where the data fidelity term is defined as $F(p_0, c) := \frac{1}{2}\|g - H(c)p_0\|^2$ and R denotes the regularization term

Matthews, Thomas P., et al. "Parameterized joint reconstruction of the initial pressure and sound speed distributions for photoacoustic computed tomography." *SIAM journal on imaging sciences* 11.2 (2018): 1560-1588.

Iterative Recon Algorithm

Algorithm 1 Simultaneous Reconstruction by iterative algorithm[56]

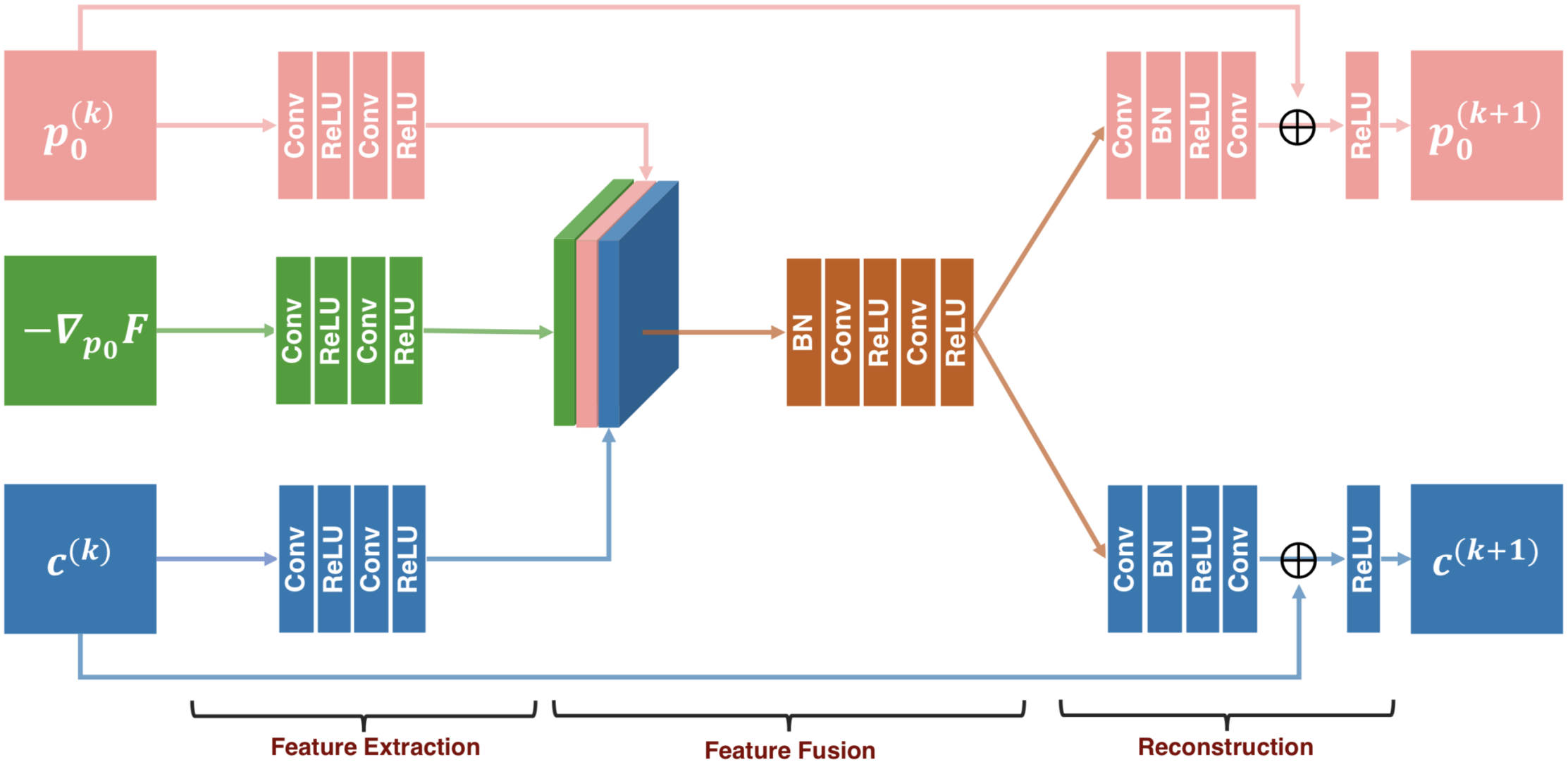
Input: $p_0^{(0)}, c^{(0)}, \beta$
Output: $\widehat{p_0}, \widehat{c}$

```
k ← 0
while stopping criterion is not satisfied do
    Calculate gradients ∇_{p_0} F and ∇_c F
    Choose step length α_k^p and α_k^c
    p_0^{(k+1)} = prox_{α_k^p β R}(p_0^{(k)} − α_k^p ∇_{p_0} F)
    c^{(k+1)} = c^{(k)} − α_k^c ∇_c F
    k ← k + 1
end while
p̂_0 ← p_0^{(k+1)}
ĉ ← c^{(k+1)}
```

Model-based iteration:

- **Repeated selection of step length is time-consuming**
- **Choice of R and β is empirical**
- **Turning trade-off parameter is tedious**

Simultaneous Recon Network (SR-Net)



Loss Function & Network Structure

Loss Function for *k*-th Iteration

$$\min_{\theta_{\mathrm{SR}}} \quad \mathbb{E}_{(p_0^{(k)}, -\nabla_{p_0} F, c^{(k)}, p_0, c)} \left[\left| p_0^{(k+1)} - p_0 \right| + \frac{1}{1000} \left| c^{(k+1)} - c \right| \right]$$

$$\text{s.t.} \quad p_0^{(k+1)}, c^{(k+1)} = \text{SR-Net}(p_0^{(k)}, -\nabla_{p_0} F, c^{(k)})$$

Network Structure

Table 1: Network architectures of feature extraction, feature fusion, and reconstruction in SR-Net.

Layer	**Feature Extraction** $\times 3$		**Feature Fusion**		**Reconstruction** $\times 2$	
1	3×3	**conv**, 32, stride 1	**Batch Normalization**		3×3	**conv**, 16, stride 1
2	3×3	**conv**, 32, stride 1	3×3	**conv**, 64, stride 1	**Batch Normalization**	
3			3×3	**conv**, 32, stride 1	3×3	**conv**, 1, stride 1

Simultaneous Recon via Deep Learning

Algorithm 2 Simultaneous reconstruction via Deep learning

Input: $p_0^{(0)}, c^{(0)}, k_{max}$

Output: $\widehat{p_0}, \widehat{c}$

$k \leftarrow 0$

while $k < k_{max}$ **do**

  Calculate gradient $\nabla_{p_0} F$

  $p_0^{(k+1)}, c^{(k+1)} = \text{SR-Net}(p_0^{(k)}, -\nabla_{p_0} F, c^{(k)})$

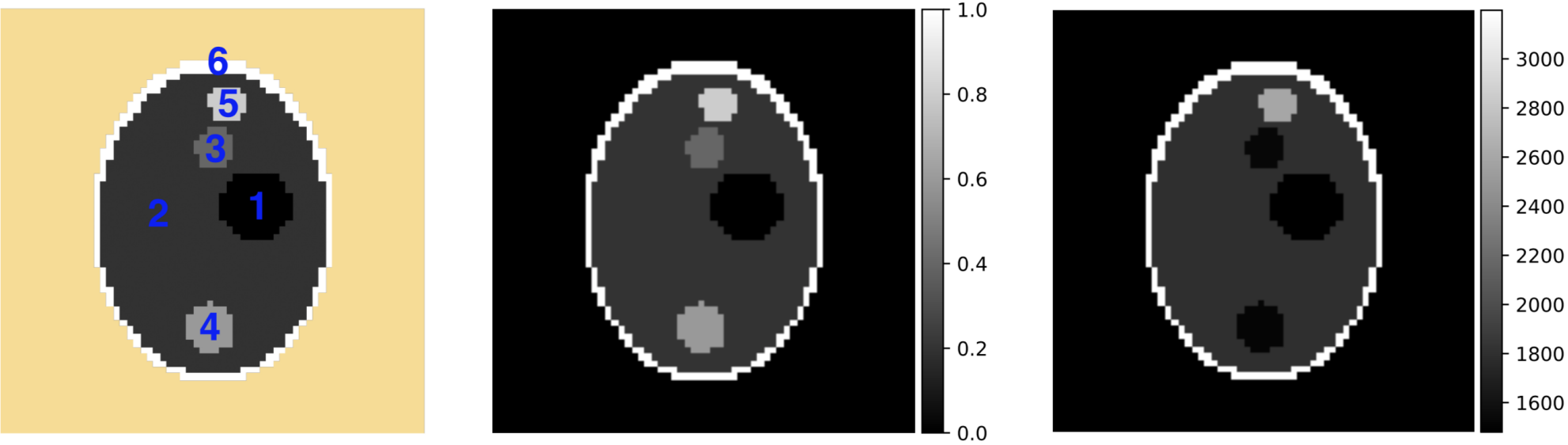
  $k \leftarrow k + 1$

end while

$\widehat{p_0} \leftarrow p_0^{(k+1)}$

$\widehat{c} \leftarrow c^{(k+1)}$

Numerical Phantom



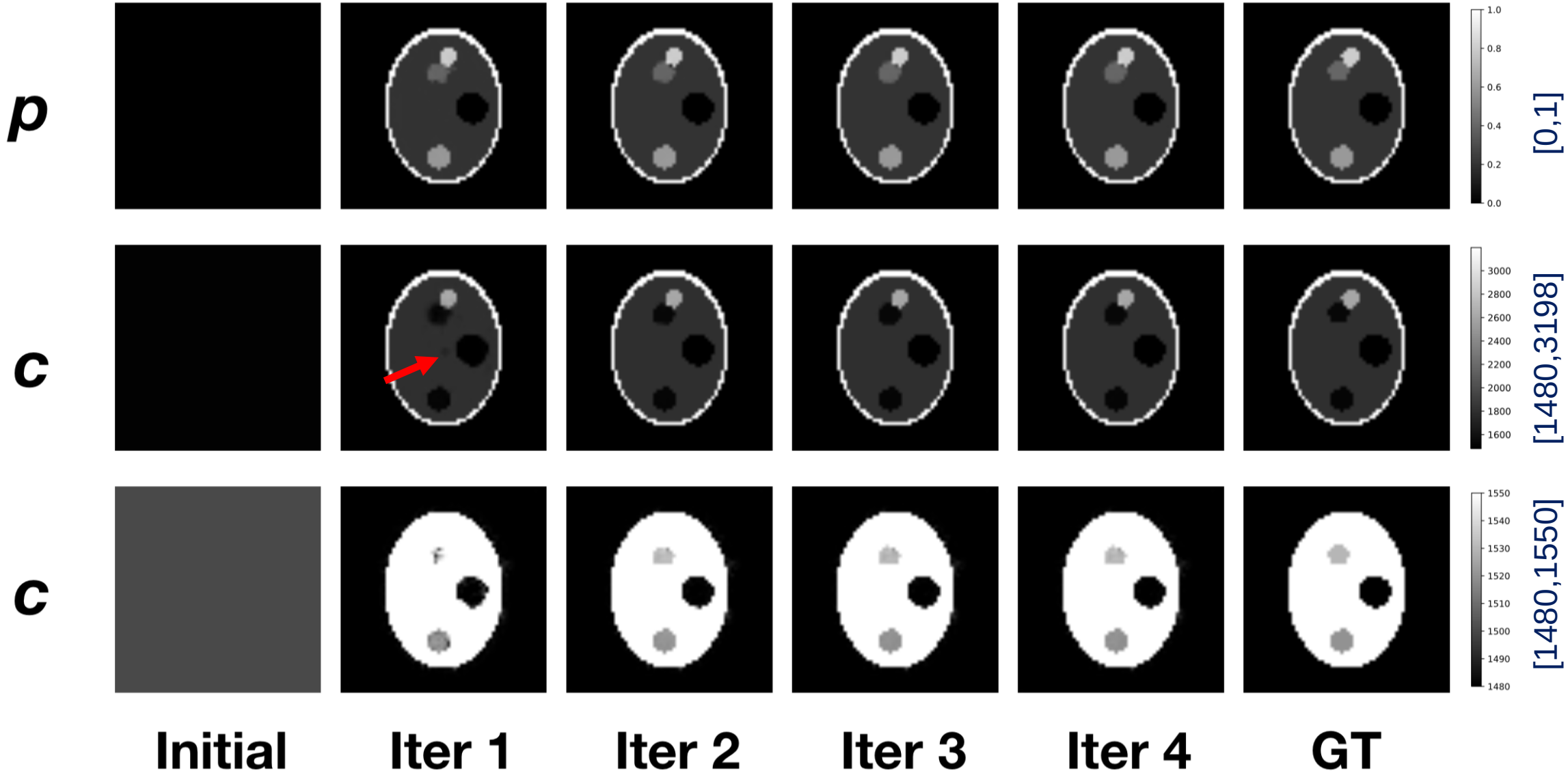
(a) (b) (c)

Table 2: The initial pressure and sound speed for each region.

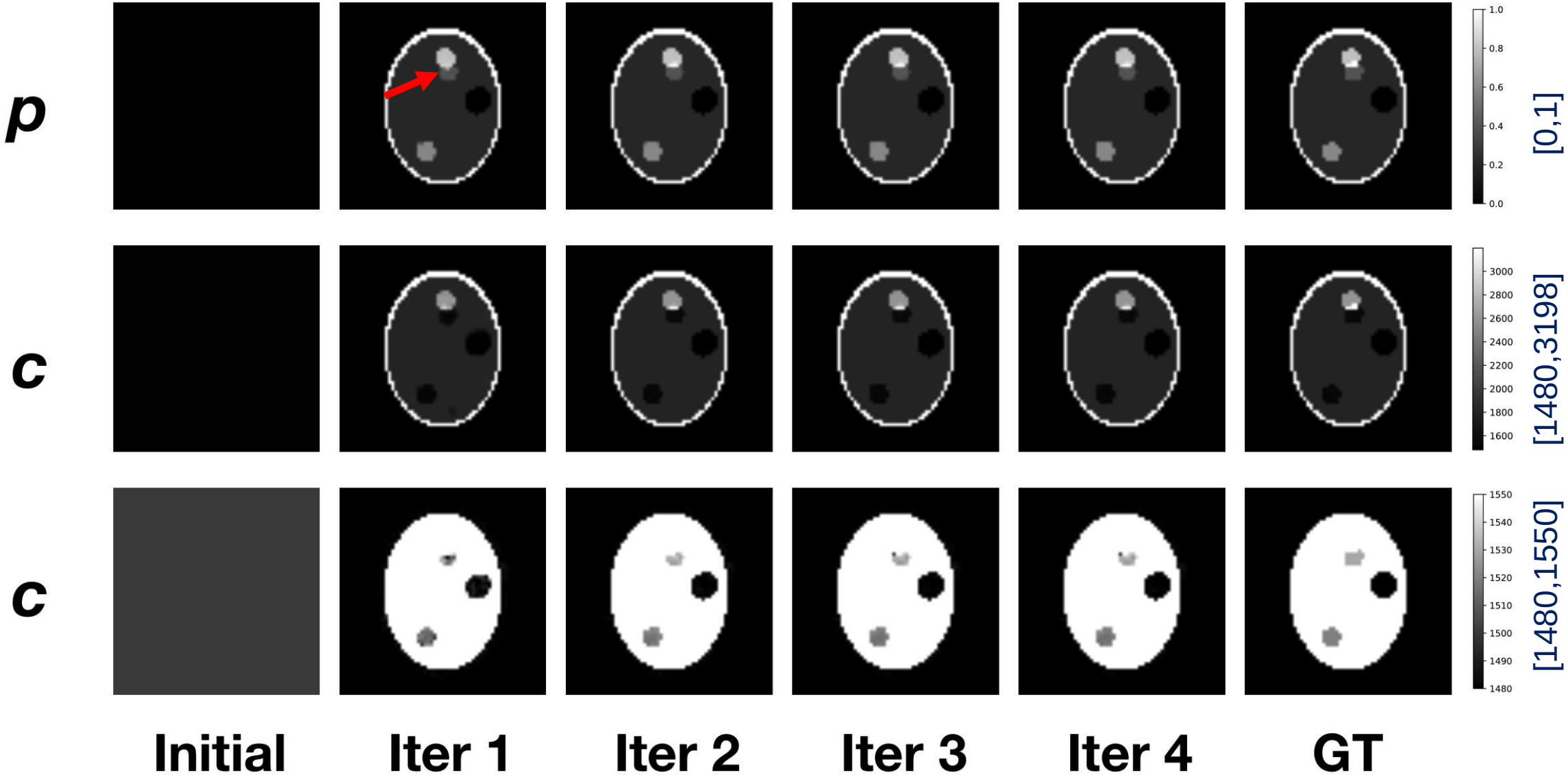
Index	Initial Pressure	Sound Speed [m/s]
1	0.0	1480
2	0.2	1800
3	0.4	1530
4	0.6	1520
5	0.8	2600
6	1.0	3198

Image size: 64 x 64
 # detector: 252
 # time step: 652
 # training sample: 5,120

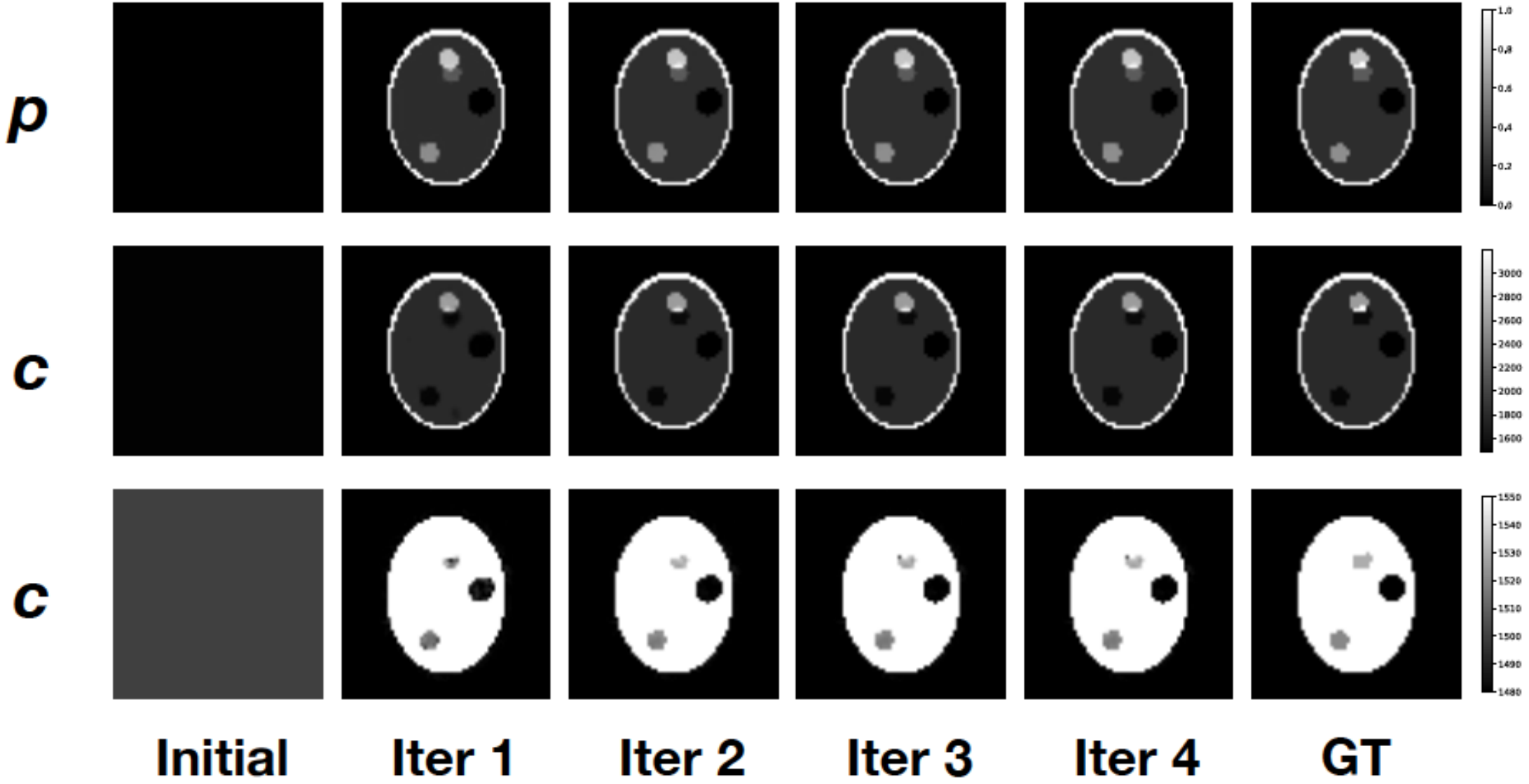
Result 1


p
c
c
1.0
0.8
0.6
0.4
0.2
0.0
[0,1]
3000
2800
2600
2400
2200
2000
1800
1600
[1480,3198]
1550
1540
1530
1520
1510
1500
1490
1480
[1480,1550]
Initial
Iter 1
Iter 2
Iter 3
Iter 4
GT

Result 2


p
c
c
1.0
0.8
0.6
0.4
0.2
0.0
[0,1]
3000
2800
2600
2400
2200
2000
1800
1600
[1480,3198]
1550
1540
1530
1520
1510
1500
1490
1480
[1480,1550]
Initial
Iter 1
Iter 2
Iter 3
Iter 4
GT

Result 3


p
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c
1.0
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0.0
3000
2800
2600
2400
2200
2000
1800
1600
1550
1540
1530
1520
1510
1500
1490
1480
Initial
Iter 1
Iter 2
Iter 3
Iter 4
GT

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X-ray Optical Tomography

(Ge)

SPIE Work (in Press, with UC Merced & Clemens U)

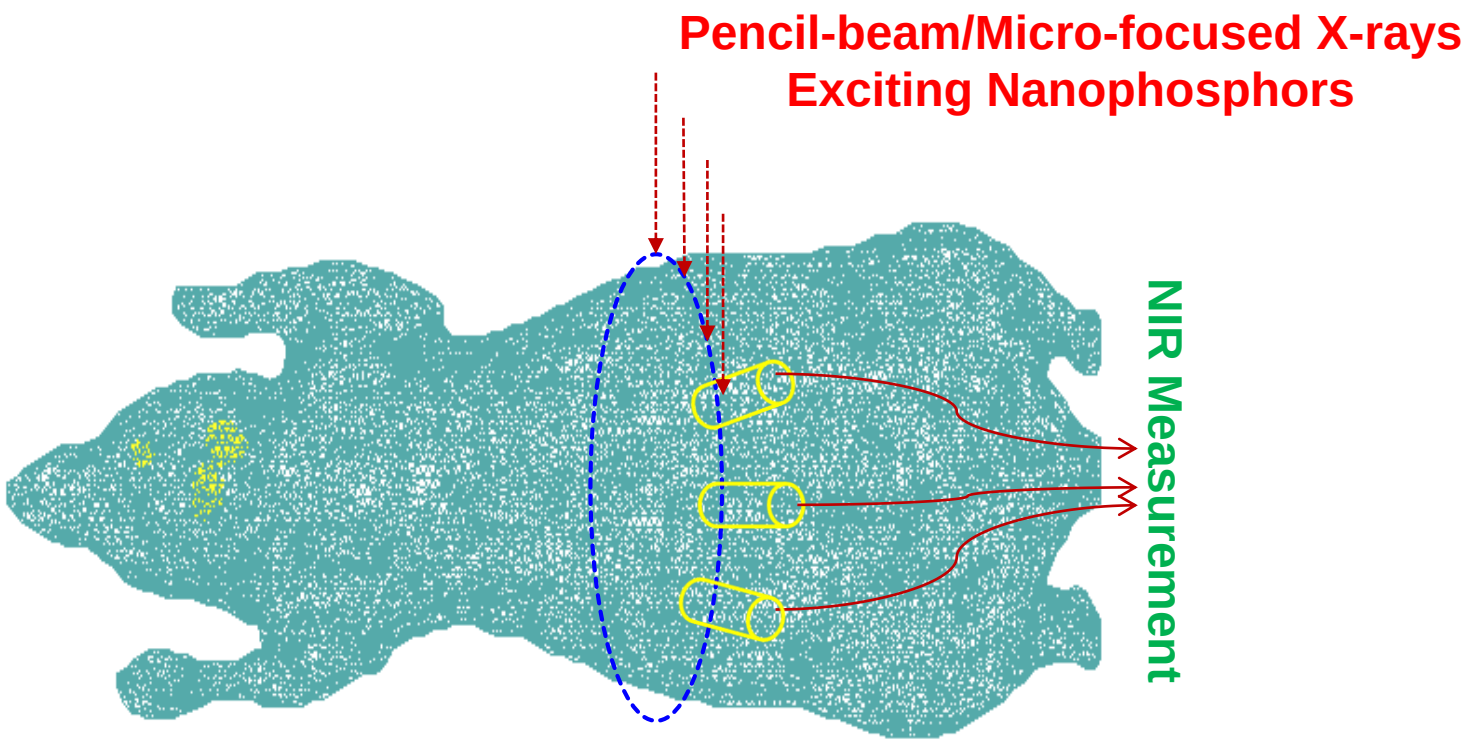
SPIE.
CONNECTING MINDS.
ADVANCING LIGHT.

X-ray luminescence imaging for small-animals

Michael C Lun[1], Wenxiang Cong[2], Md. Arifuzzaman[3], Meenakshi Ranasinghe[3], Sriparna Bhattacharya[4], Jeffery Anker[3,5], Ge Wang[2], and Changqing Li[1]*

[1]Department of Bioengineering, University of California, Merced, Merced, CA 95343, USA.
[2]Department of Biomedical Engineering, Biomedical Imaging Center, Center for Biotechnology and Interdisciplinary Studies, Rensselaer Polytechnic Institute, Troy, NY 12180, USA.
[3] Department of Chemistry, Clemson University, Clemson, SC 29634, USA.
[4]Clemson Nanomaterials Institute, Department of Physics & Astronomy, Clemson University, Clemson, SC 29634, USA.
[5]Department of Bioengineering, Center for Optical Materials Science and Engineering Technology (COMSET), and Institute of Environment Toxicology (CU-ENTOX), Clemson University, Clemson, SC 29634, USA.

X-ray Luminescence Tomography



Physical Model

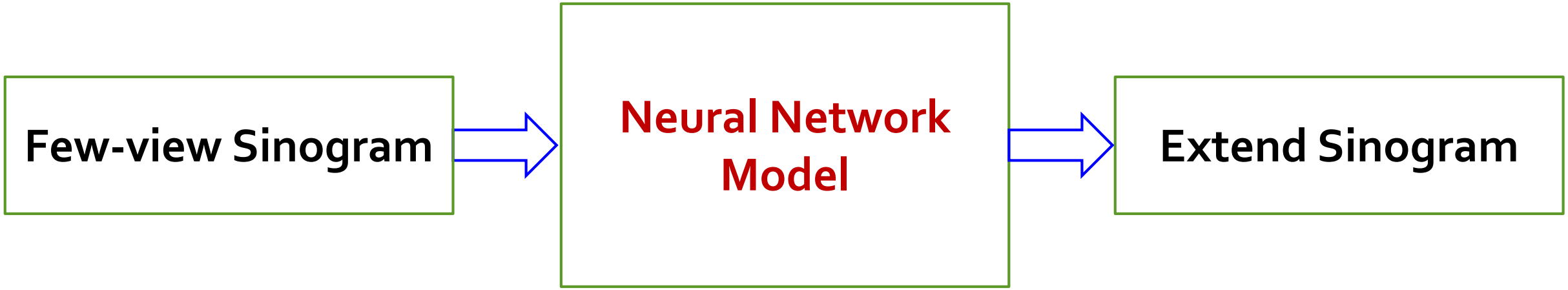
$$\boldsymbol{\Phi}(\boldsymbol{r}) = \iiint \boldsymbol{G}(\boldsymbol{r}, \boldsymbol{r}')\boldsymbol{\eta}\boldsymbol{X}(\boldsymbol{r})\boldsymbol{\rho}(\boldsymbol{r})\, d\boldsymbol{r}' , \qquad \boldsymbol{r} \in \boldsymbol{\partial\Omega}$$

$\boldsymbol{\Phi}(\boldsymbol{r})$: **Photon Fluence Rate**

$\boldsymbol{\rho}(\boldsymbol{r})$: **Nanophosphor concentration**

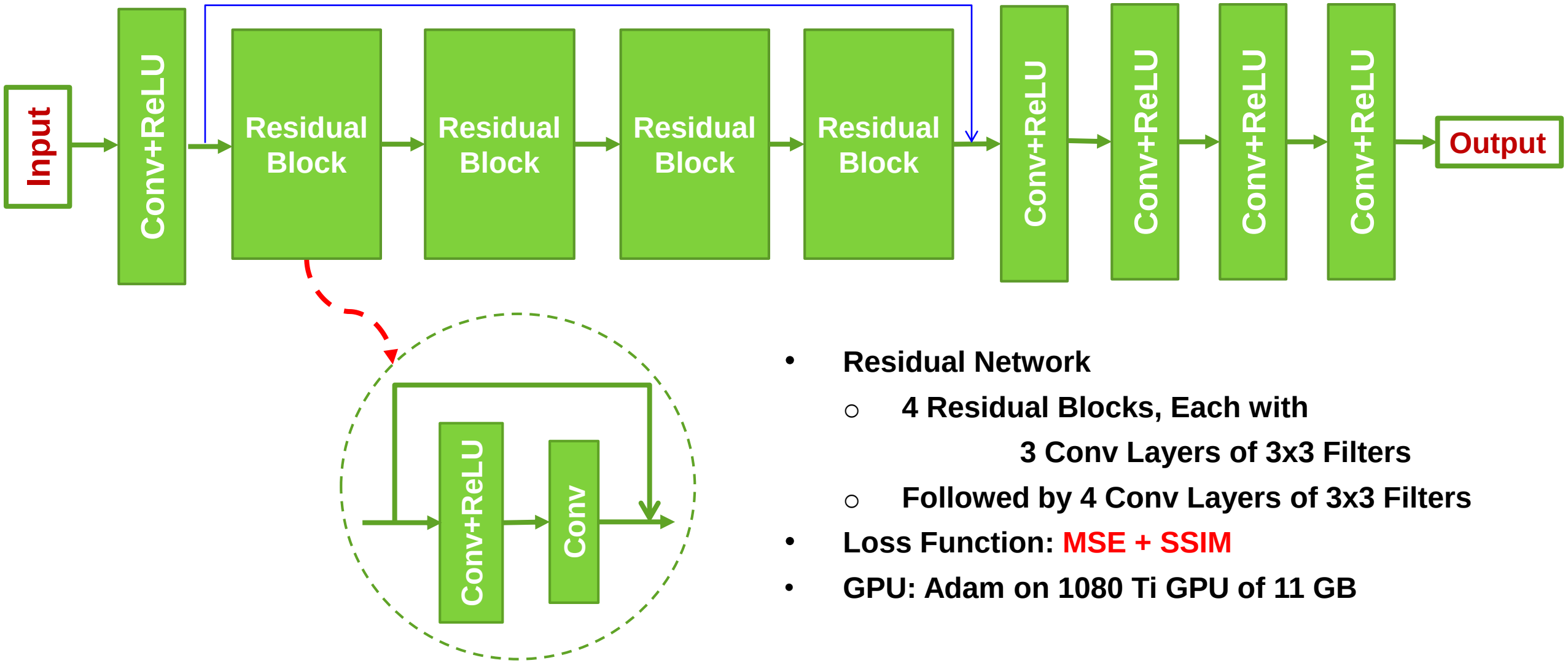
$\boldsymbol{X}(\boldsymbol{r})$: **X-ray Intensity Distribution**

Extended Sinogram



- X-ray Luminescence Imaging with Few-view Data
  For Fast scanning & Low Radiation Dose
- Extended Sinogram Method for Missing Views
  From Measured Data through Deep Learning

Residual Network

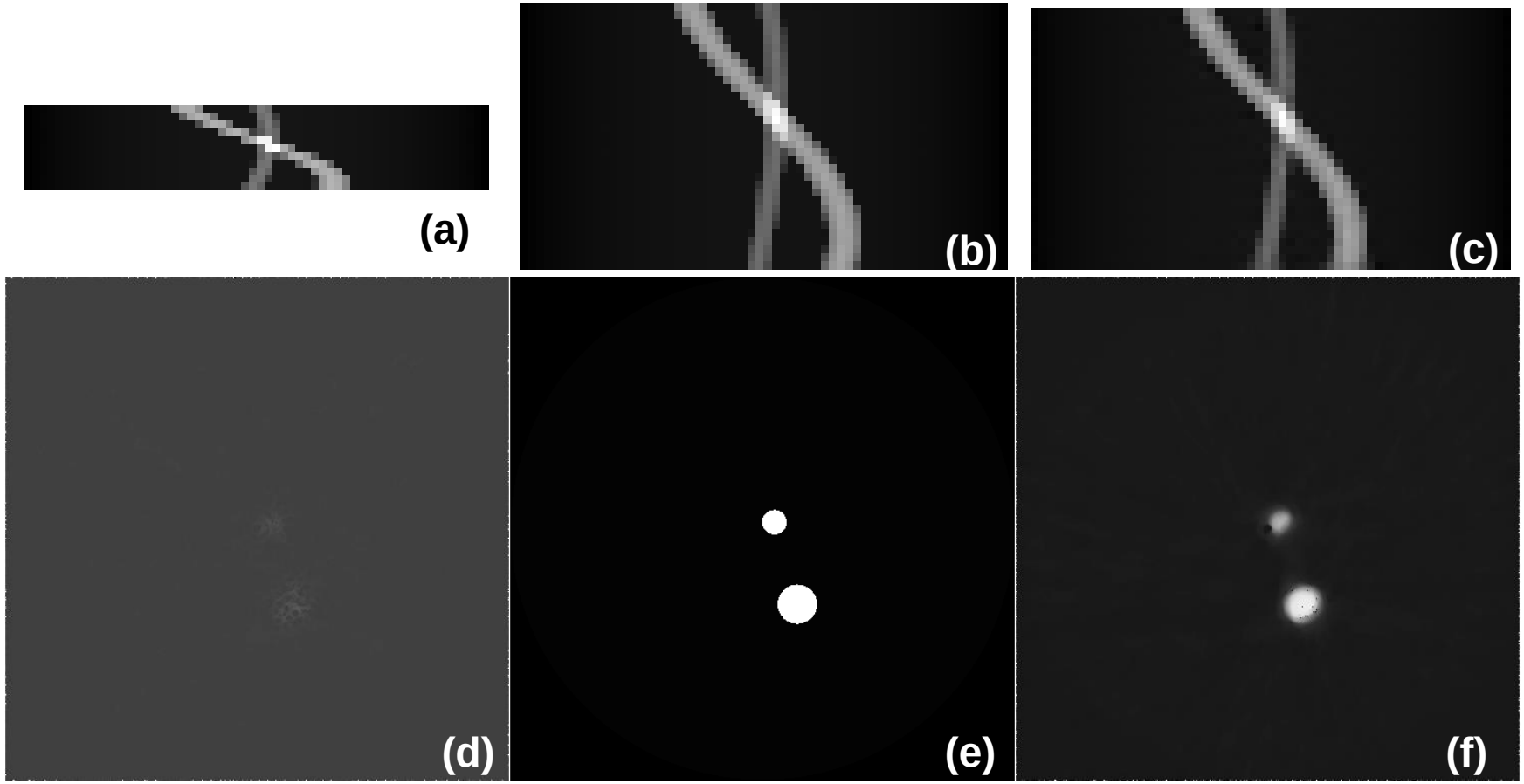


- Residual Network
  - 4 Residual Blocks, Each with 3 Conv Layers of 3x3 Filters
  - Followed by 4 Conv Layers of 3x3 Filters
- Loss Function: MSE + SSIM
- GPU: Adam on 1080 Ti GPU of 11 GB

Simulated Training Dataset

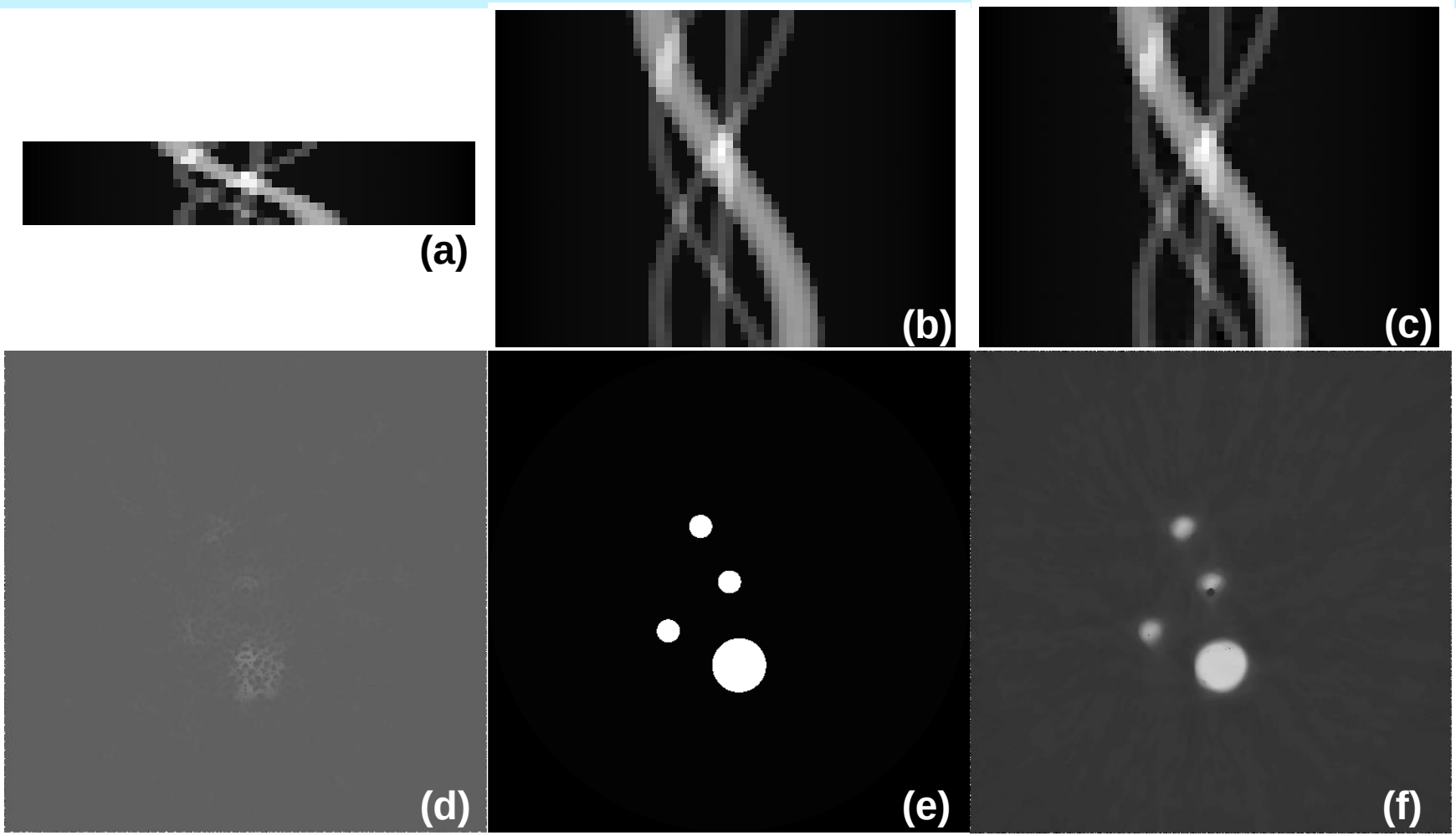
- **500 Numerical Phantoms of Different Structures & Nanophosphors Distributions**
- **Label Sinogram from Full Views of the Phantoms**
- **Input Data from Few-views of the Phantoms**

Result 1



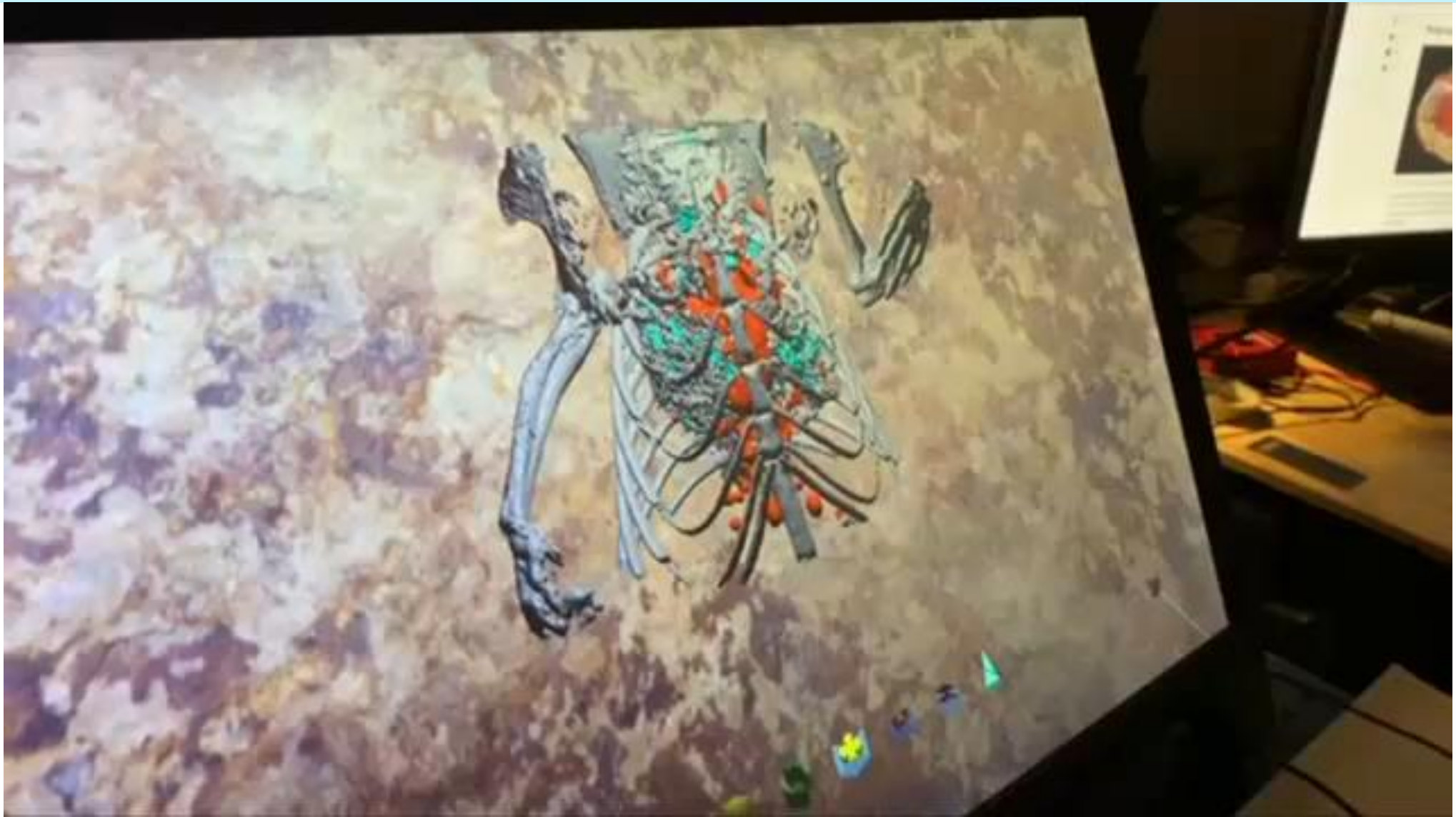
(a) Sinogram of 10 views; (b) Sinogram of 30 views; (c) Sinogram reconstructed from 10 views; (d) Image from 10 views; (e) Ground truth; (f) Image from 30 reconstructed views.

Result 2



(a) Sinogram of 10 views; (b) Sinogram of 40 views; (c) Sinogram reconstructed from 10 views; (d) Image from 10 views; (e) Ground truth; (f) Image from 40 reconstructed views.

Fluorescence Lifetime + X-ray Photon-Counting



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Machine Learning for Tomographic Imaging

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The area of machine learning, especially deep learning, has exploded in recent years, producing advances in everything from speech recognition and gaming to drug discovery. Tomographic imaging is another major area that is being transformed by machine learning, and its potential to revolutionise medical imaging is highly significant. Written by active researchers in the field, *Machine Learning for Tomographic Imaging* presents a unified overview of deep-learning-based tomographic imaging. Key concepts, including classic reconstruction ideas and human vision inspired insights, are introduced as a foundation for a thorough examination of artificial neural networks and deep tomographic reconstruction. X-ray CT and MRI reconstruction methods are covered in detail, and other medical imaging applications are discussed as well. An engaging and accessible style makes this book an ideal introduction for those in applied disciplines, as well as those in more theoretical disciplines who wish to learn about application contexts. Hands-on projects are also suggested, and links to open source software, working datasets, and network models are included. Part of Series in Physics and Engineering in Medicine and Biology.

Authors
Ge Wang, Yi Zhang, Xiaojing Ye and Xuanqin Mou

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