CT Reconstruction: From Filtered Back-Projection to Deep Learning

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CTECC
CT EDUCATION AND COLLABORATION CENTER

54 Years of History

The first CT scanner, designed by Sir Godfrey Hounsfield, 1971

108 Years of History

Über die Bestimmung von Funktionen durch ihre Integralwerte längs gewisser Mannigfaltigkeiten

On the determination of functions from their integral values along certain manifolds

Satz II: Bildet man den Mittelwert von $F(p, \varphi)$ für die Tangenten des Kreises mit dem Zentrum $P = [x, y]$ und dem Radius q:

$$\text{(II)} \qquad F_P(q) = \frac{1}{2\pi}\int_0^{2\pi} F(x\cos\varphi + y\sin\varphi + q, \varphi)\,d\varphi,$$

so konvergiert dieses Integral für alle P, q absolut.

Satz III: Der Wert von f ist durch F eindeutig bestimmt und läßt sich folgendermaßen berechnen:

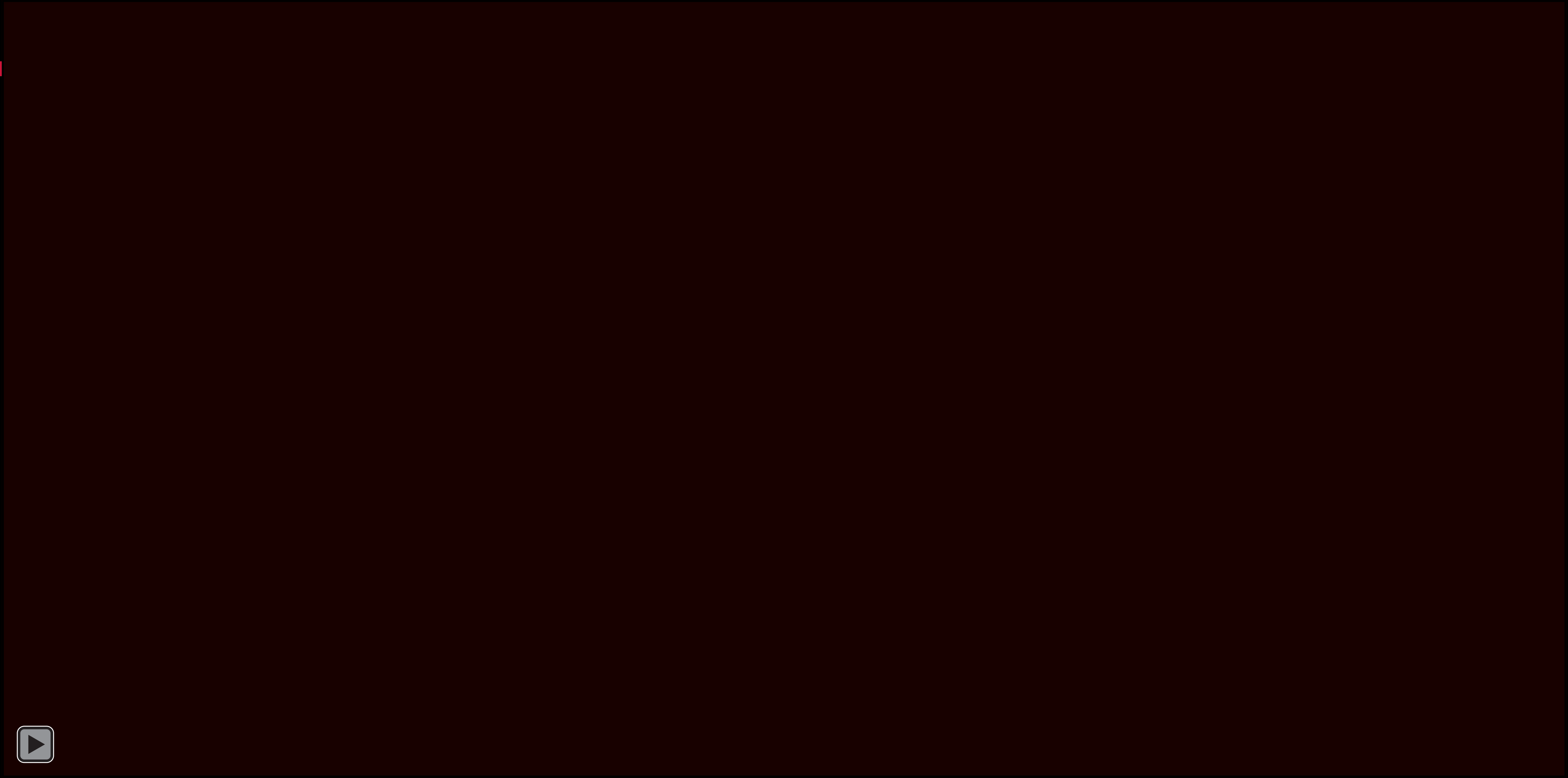
$$\text{(III)} \qquad f(P) = -\frac{1}{\pi}\int_0^{\infty}\frac{dF_P(q)}{q}.$$

Johann Radon's inversion formula: the mathematical foundation of CT reconstruction, 1917

Evolution of CT Reconstruction Methods

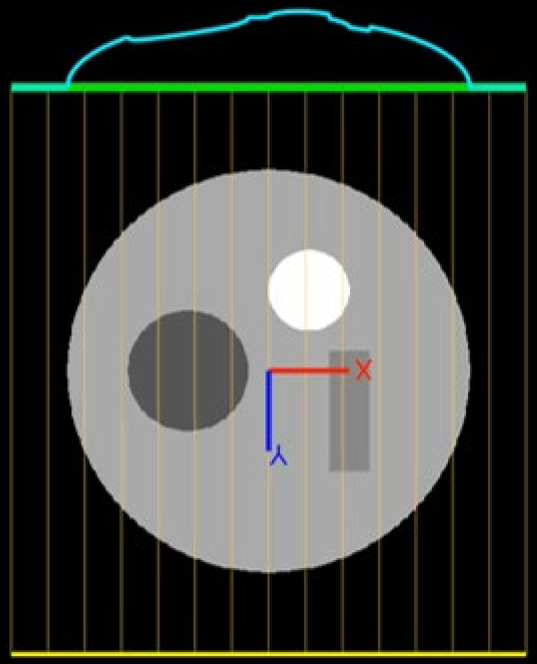
- 1970s: Filtered Back-Projection (FBP)
- 2010s: Iterative Reconstruction (IR)
- 2019+: Deep Learning Reconstruction (DLR)

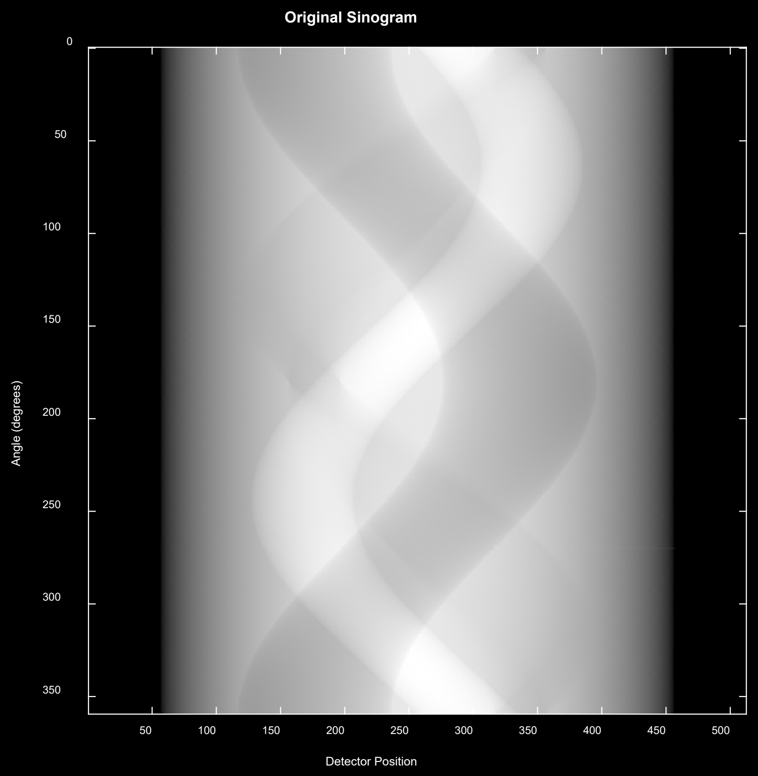
The “Sinogram”

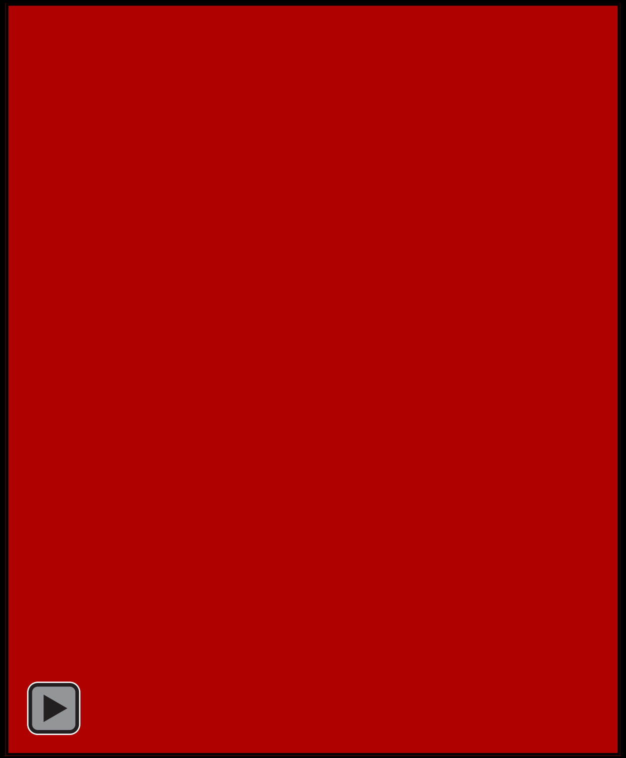


Section 1: Filtered Back Projection (FBP)

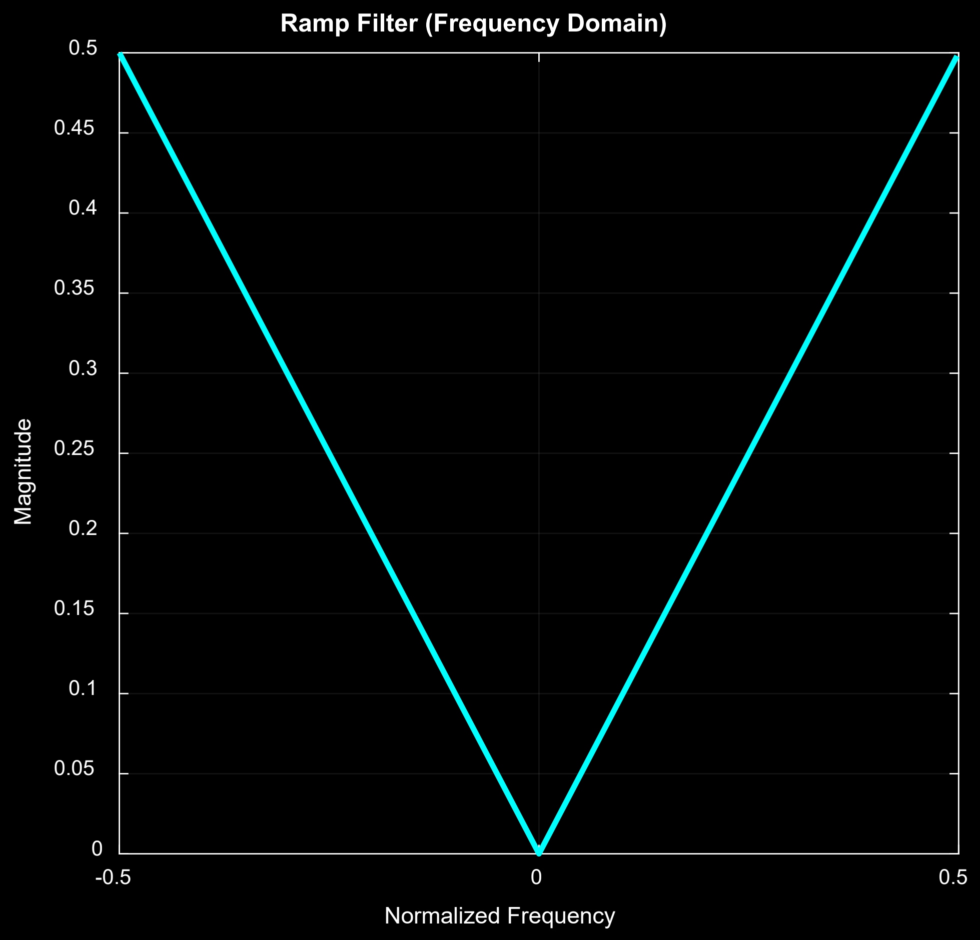
Back-Projection

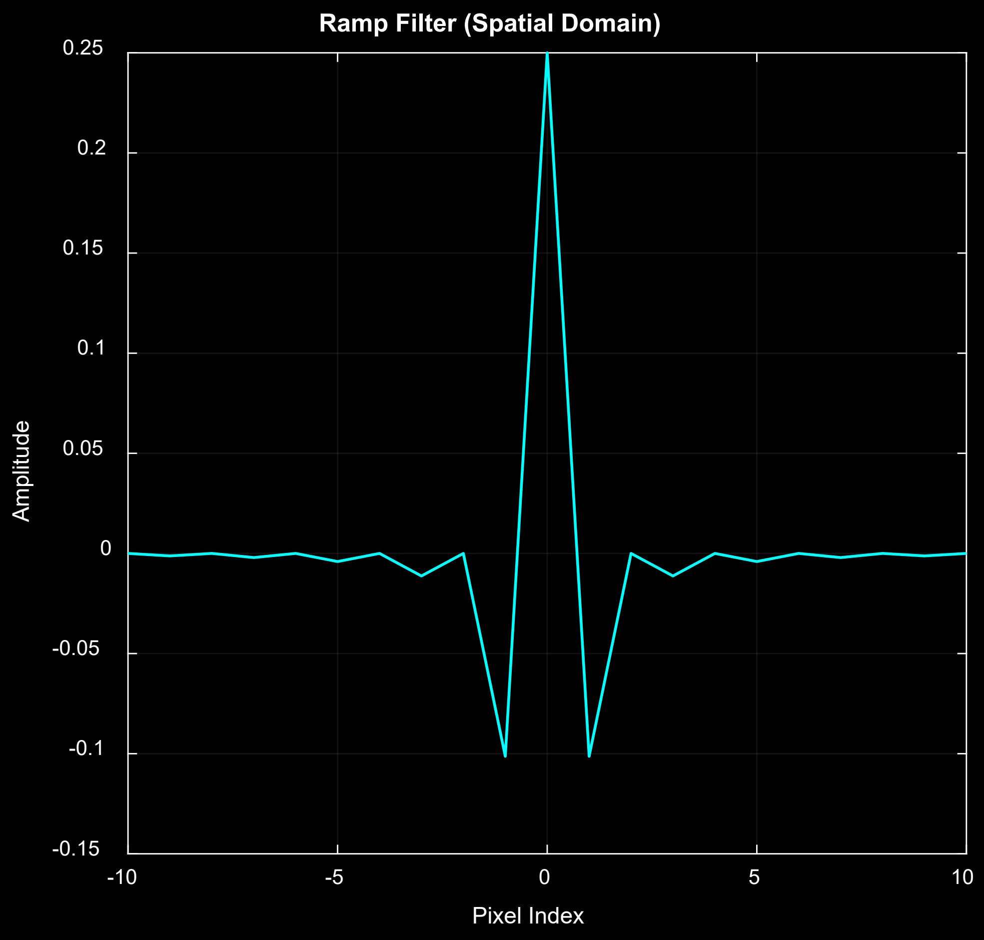






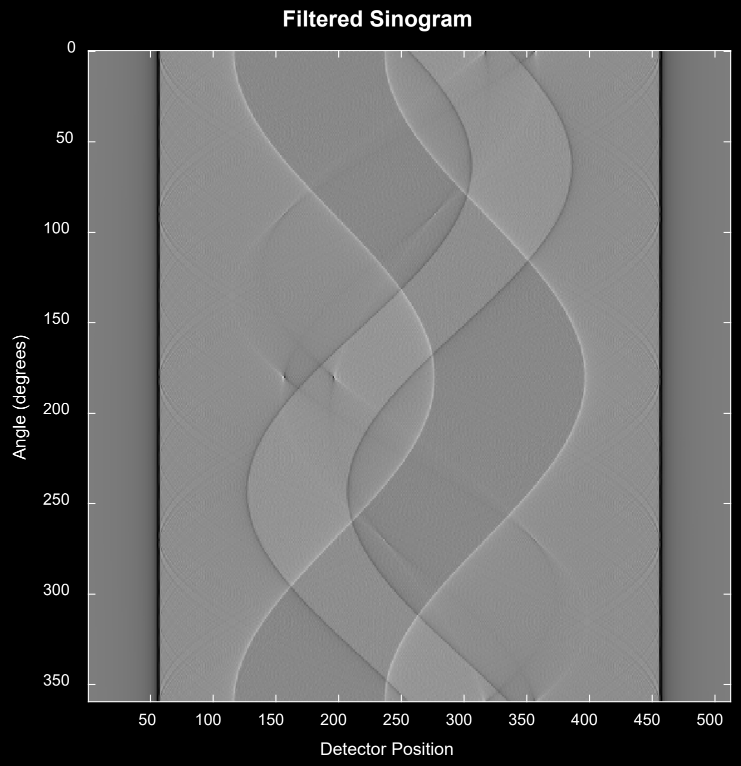
The Magic: Ramp Filter / Kernel

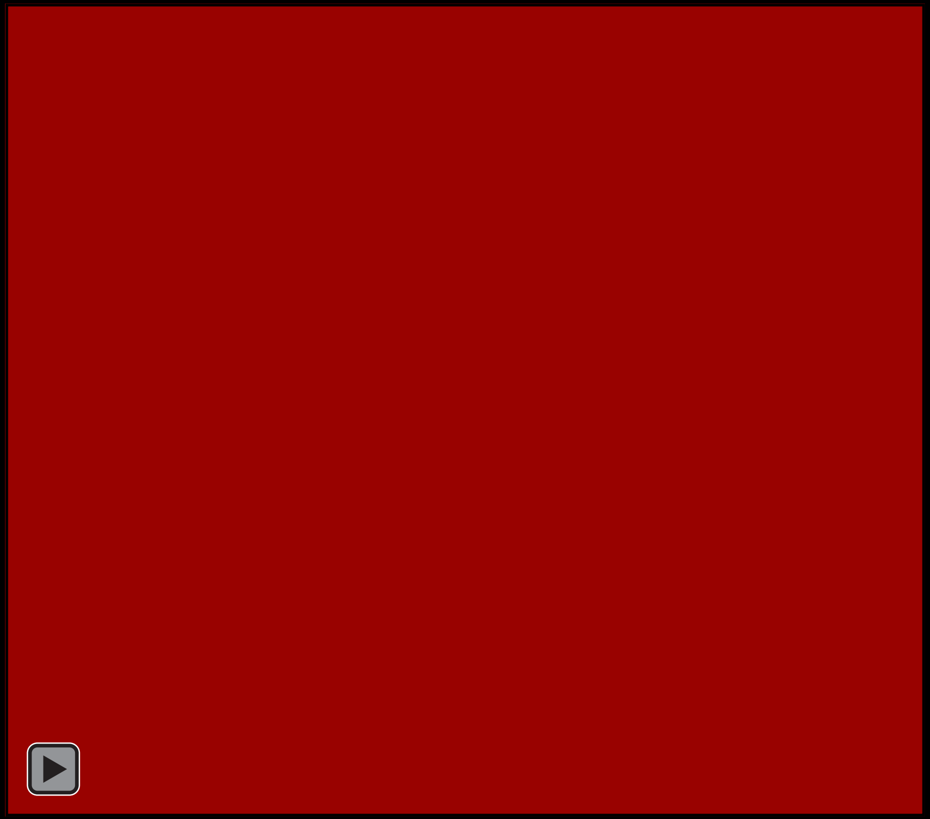




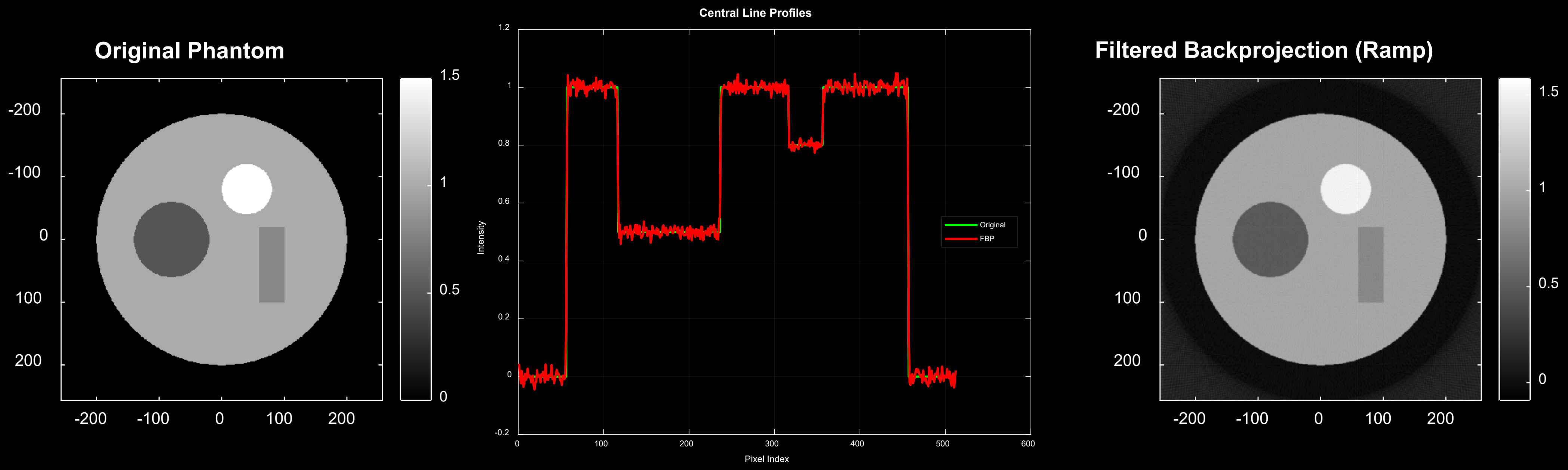
Filtered Projections

Filtered Back-Projection (FBP)



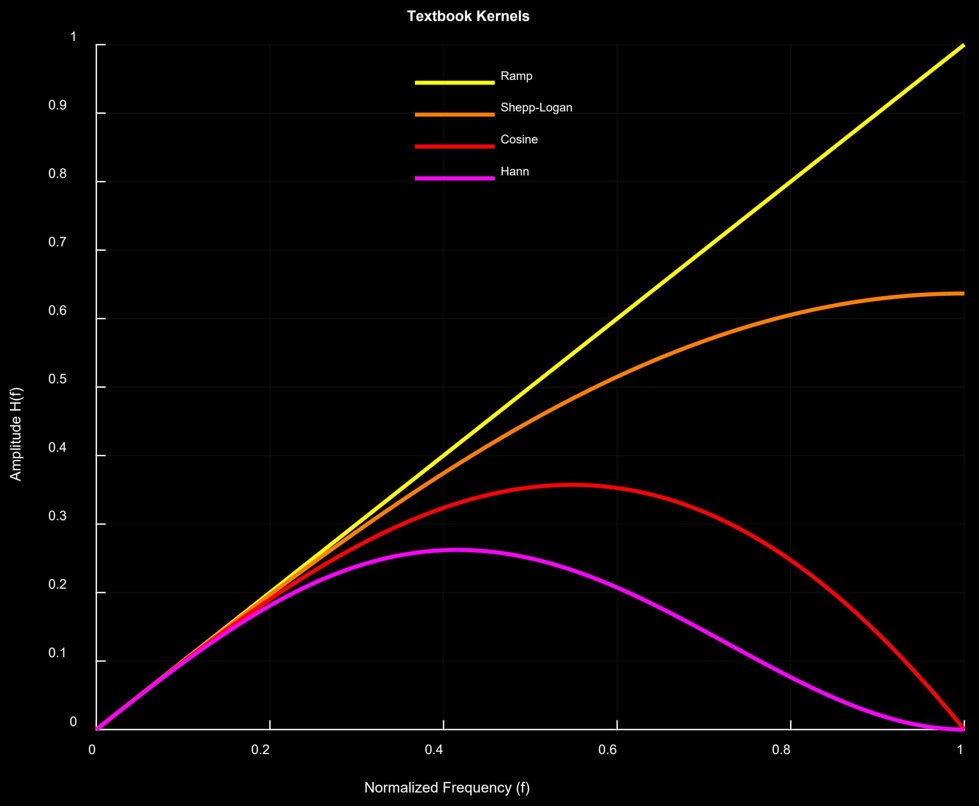


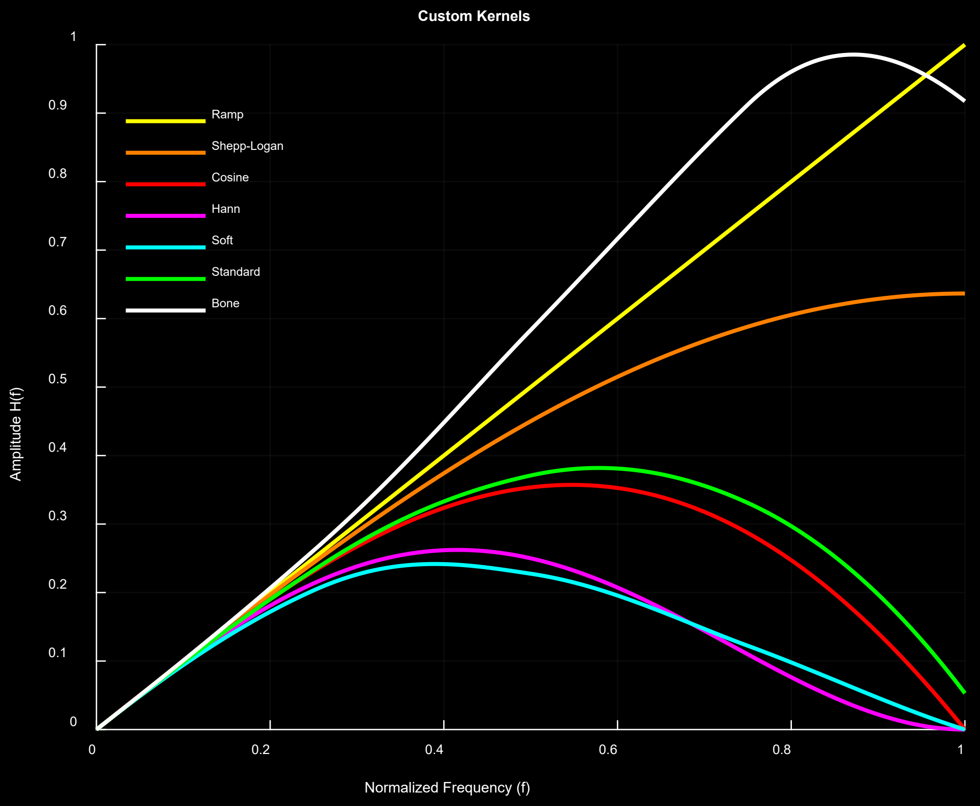
Reconstruction Accuracy



FBP reconstruction is “accurate”, which can be mathematically proved by the Central Slice Theorem.

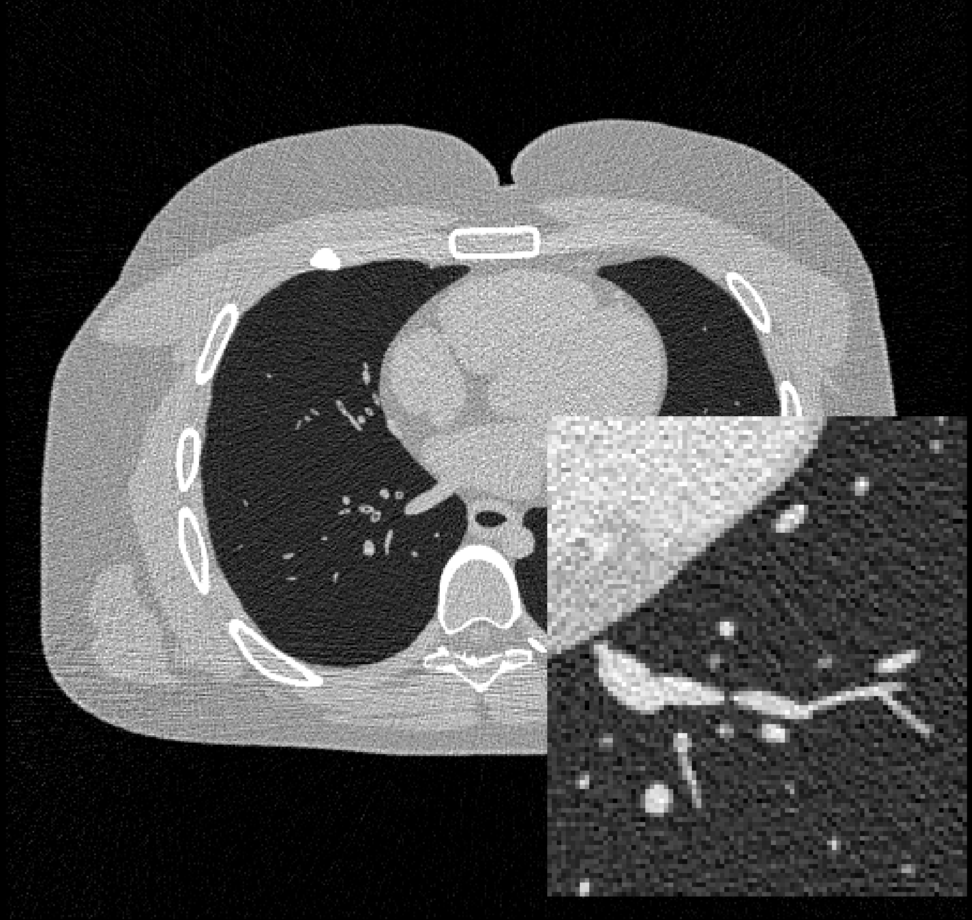
Different Kernels



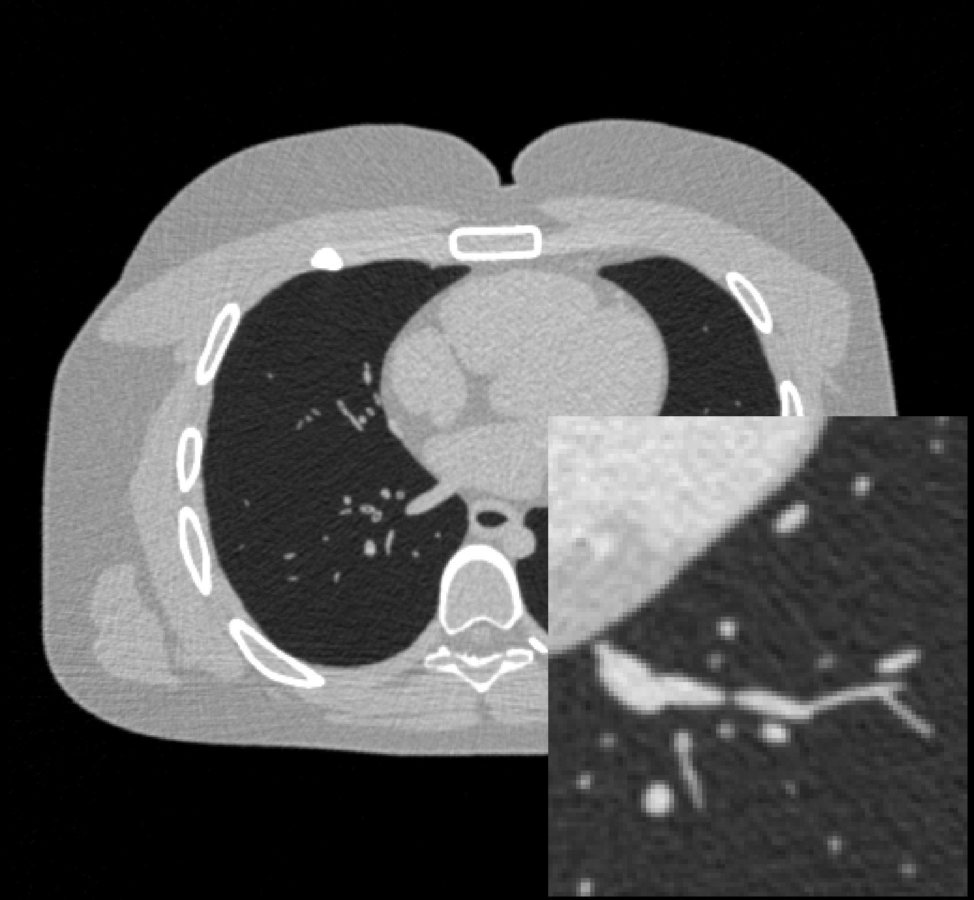


Bone Kernel vs. Soft Kernel

bone



soft



FBP: Strengths and Limitations

Pros:

✅ Extremely fast and computationally efficient
✅ High spatial resolution
✅ Natural noise texture, familiar to radiologists

Cons:

❌ Highly sensitive to noise
❌ Prone to artifacts with imperfect data

Section 2: Iterative Reconstruction (IR)

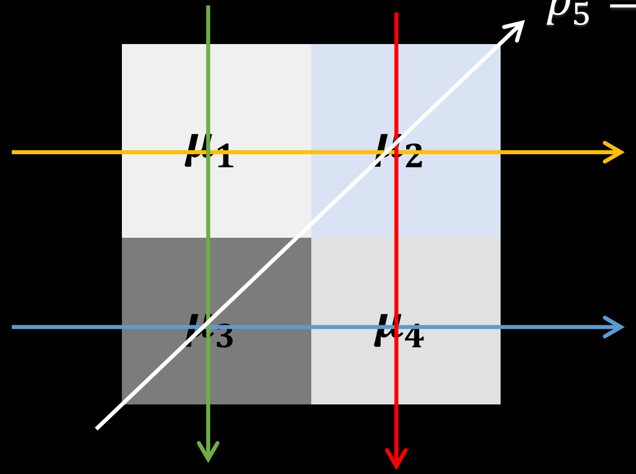
Iterative Reconstruction

FBP View: Image as a Smooth, Countinuous Object

IR View: Image as a Discretized Matrix of Pixels

A Simple Example

$p_5 = \mu_2 + \mu_3$



$p_1 = \mu_1 + \mu_2$

$p_2 = \mu_3 + \mu_4$

$p_3 = \mu_1 + \mu_3$ $\quad p_4 = \mu_2 + \mu_4$

1	2
3	4

$p_1 = 3 \quad p_2 = 7$

$p_3 = 4 \quad p_4 = 6$

$p_5 = 5$

Initial Guess

2.5	2.5
2.5	2.5

Forward Projection

$q_1 = 5$

$q_2 = 5$

Back Projection

$\Delta_1 = q_1 - p_1 = 2$

$\Delta_2 = q_2 - p_2 = -2$

1.5	1.5
3.5	3.5

$\Delta_3 = q_3 - p_3 = 1$

$\Delta_4 = q_4 - p_4 = -1$

1	2
3	4

Final Estimation

$\Delta_5 = q_5 - p_5 = 0$

$\Delta_1, \Delta_2, \Delta_3, \Delta_4 = 0$

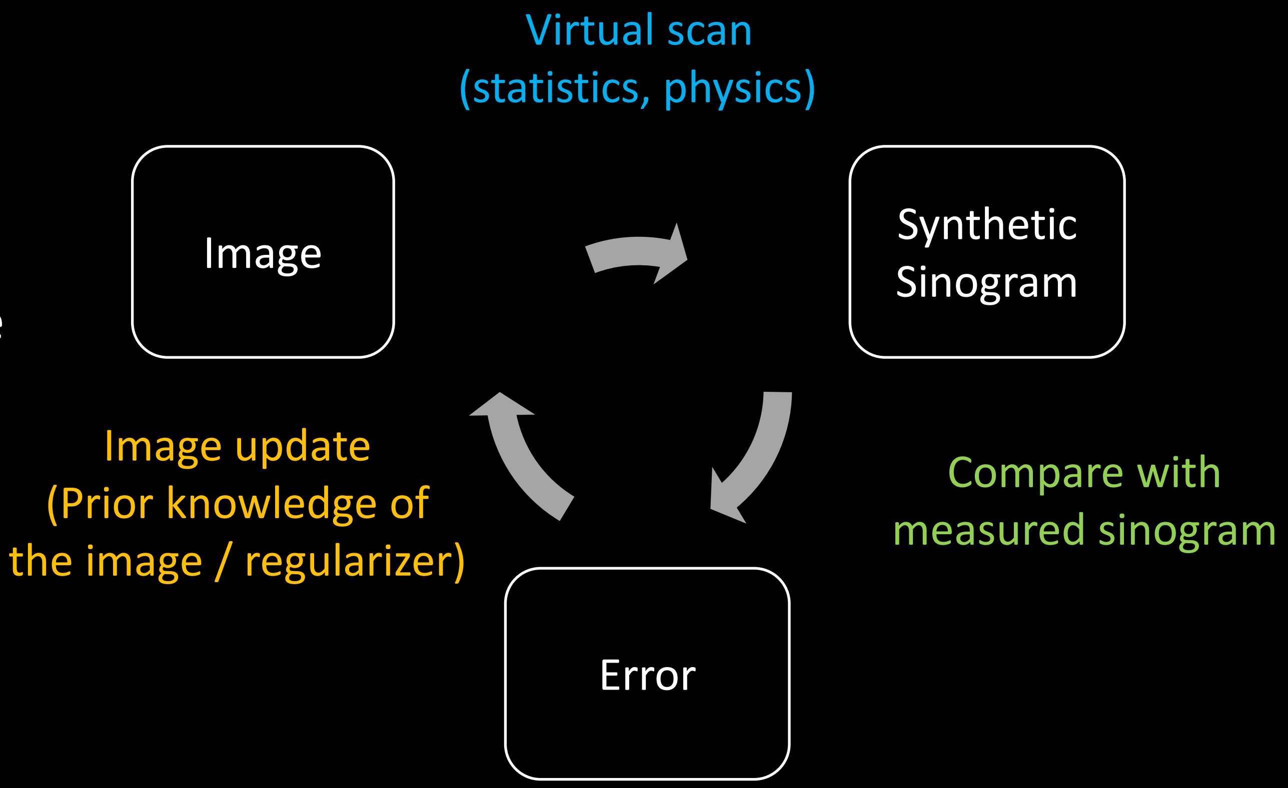
Iterative Reconstruction (1970s)

- 1970s: Algebraic Reconstruction Technique (ART)
  - The Kaczmarz method developed in 1937 provided the mathematical foundation for ART
  - Used in EMI Mark 1 CT

- In most cases, FBP and ART should generate the “same” image
  - FBP is much faster and more stable
  - FBP quickly replaced IR as the reconstruction algorithm in CT

The Return of IR (2000s-2010s)

- Driving forces: low dose CT and GPU computing
- Compared with FBP, IR can better handle noise and non-ideal system conditions
  - Statistics modeling (noise)
  - Physics modeling (focal spot, spectrum, detector response…)
  - Image modeling (prior knowledge of the image: smoothness, sparsity)

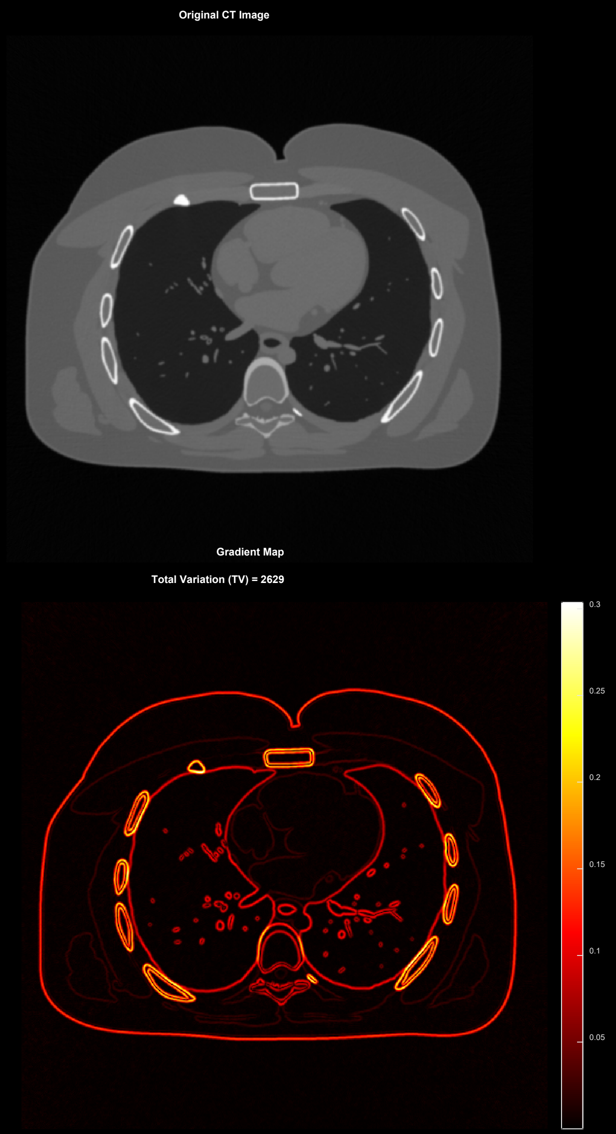


$$\hat{x} = \arg\min_{x} \left[\frac{1}{2} \|y - Ax\|_W^2 + \lambda R(x) \right]$$

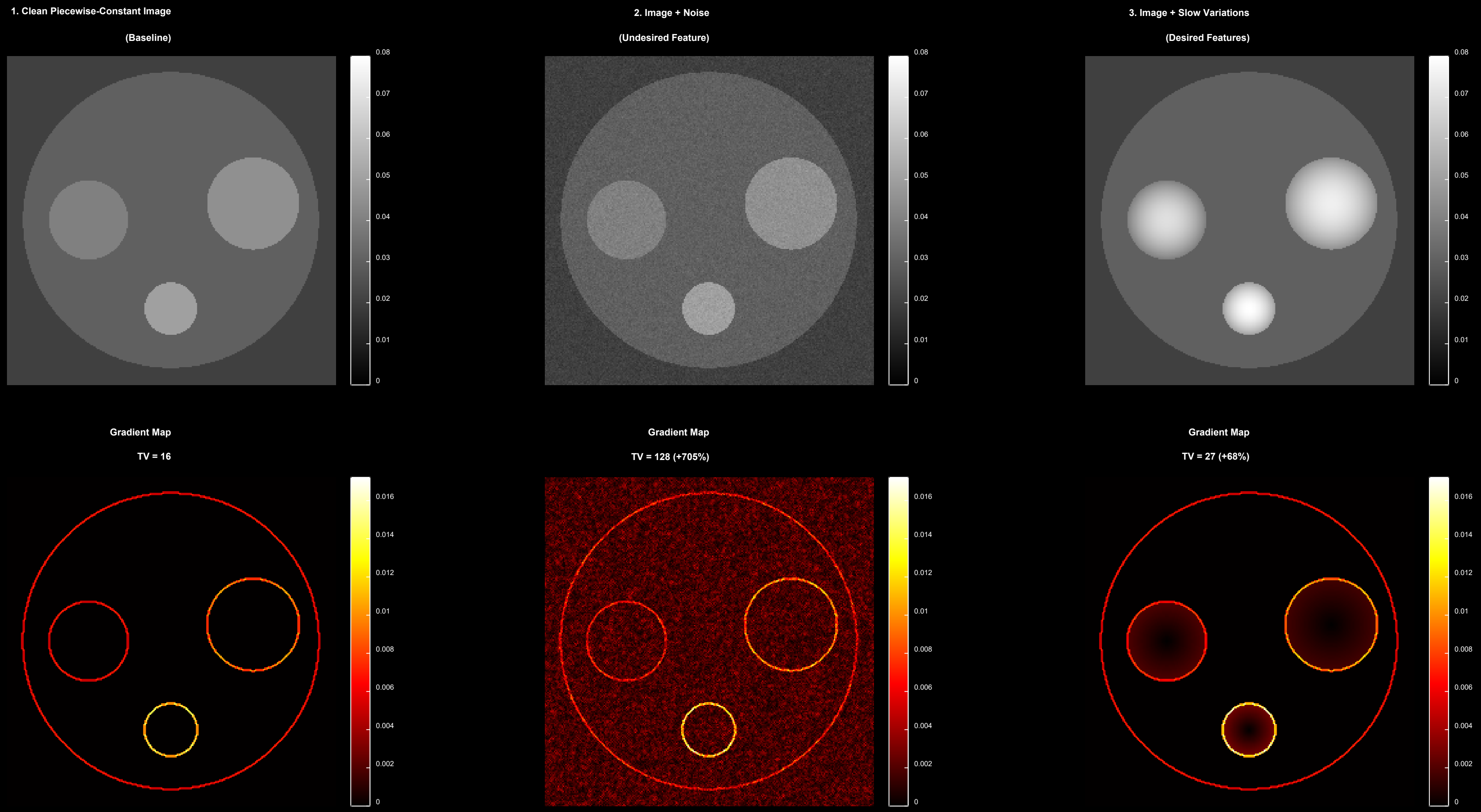
The $R(x)$ term

- $R(x)$ is often being called
  - Regularizer (The mathematician’s view)
  - Denoiser (The image processor’s view)
  - Image prior (The Statistician’s view)

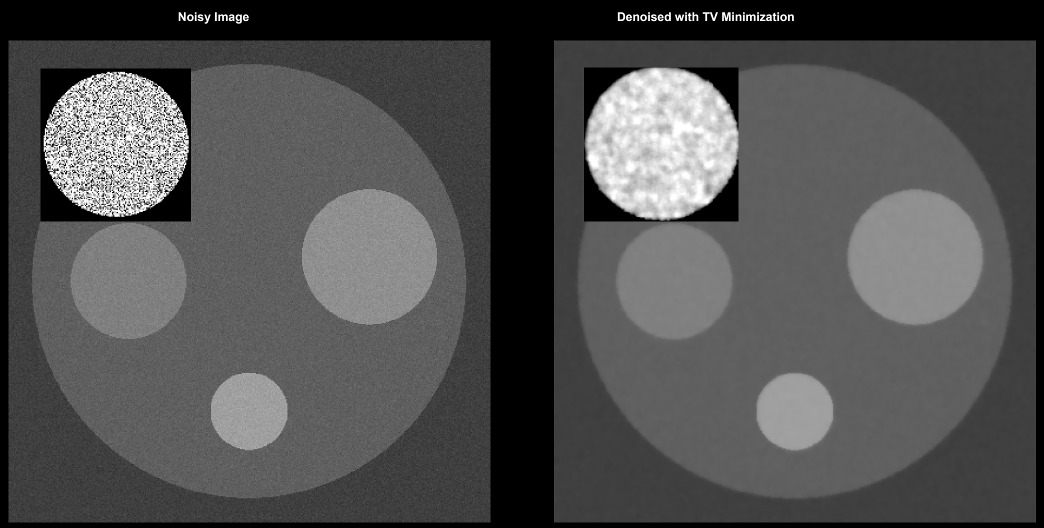
- Total Variation (TV)
  - Calculate the discrete gradient map
  - Sum the values

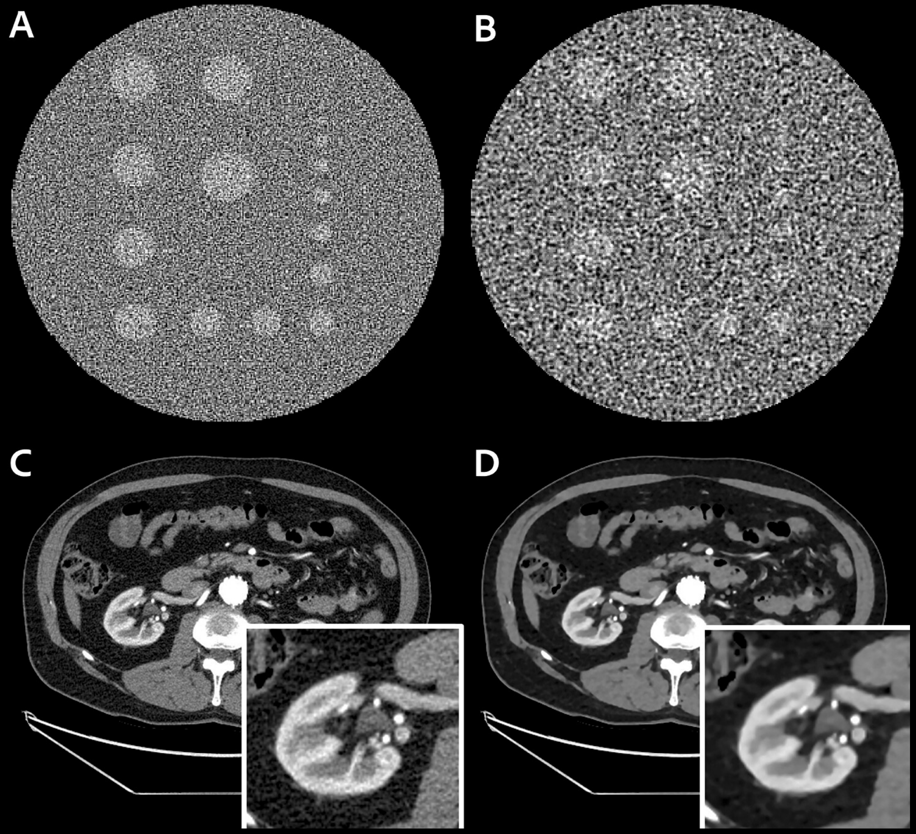


TV Minimization: the Good and the Bad



The Noise Texture Problem



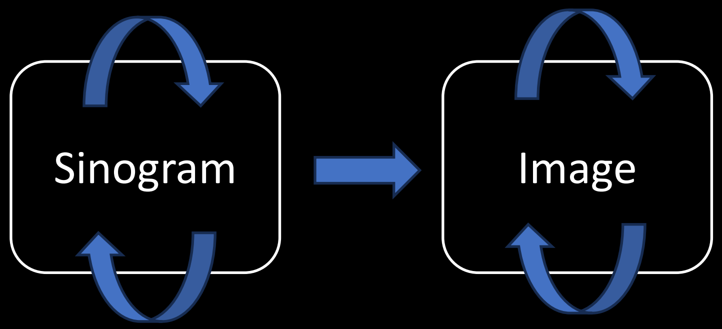


Szczykutowicz TP. Optimizing Protocols for Today's Feature-Rich Scanners. Medical Physics Publishing, 2020.

Commercial IR Algorithms

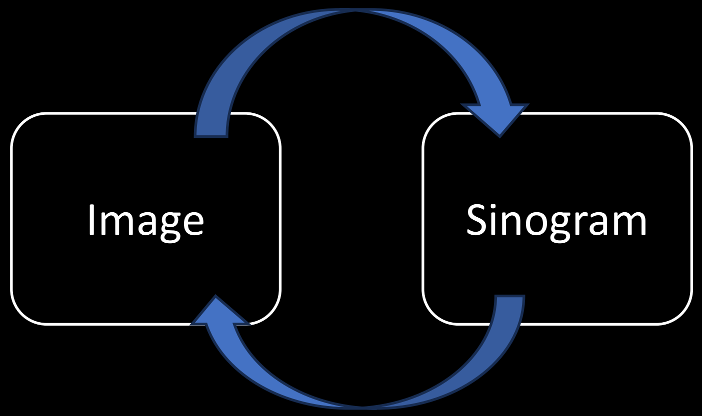
Hybrid IR

- IRIS, Siemens Healthineers, 2009
- ASIR, GE Healthcare, 2011
- SAFIRE, Siemens Healthineers, 2011
- iDose, Philips Healthcare, 2011
- ASIR-V, GE Healthcare 2014
- AIDR3D, Canon Medical Systems, 2012



MBIR

- Veo, GE Healthcare, 2011
- ADMIRE, Siemens Healthineers, 2012
- IMR, Philips Healthcare, 2013
- FIRST, Canon Medical Systems, 2016



Section 3: Deep Learning Reconstruction

Review of Classical Reconstruction Methods

FBP

Pros:

✅ Extremely fast, and efficient
✅ High spatial resolution
✅ Natural noise texture, familiar to radiologists

Cons:

❌ Sensitive to Noise
❌ Prone to artifacts for non-ideal imaging conditions

Iterative Reconstruction

Pros:

✅ Handle noise and imperfect data
✅ Incorporate system models and object models

Cons:

❌ Slow due to iteration
❌ Noise texture problem introduced by the regularization term

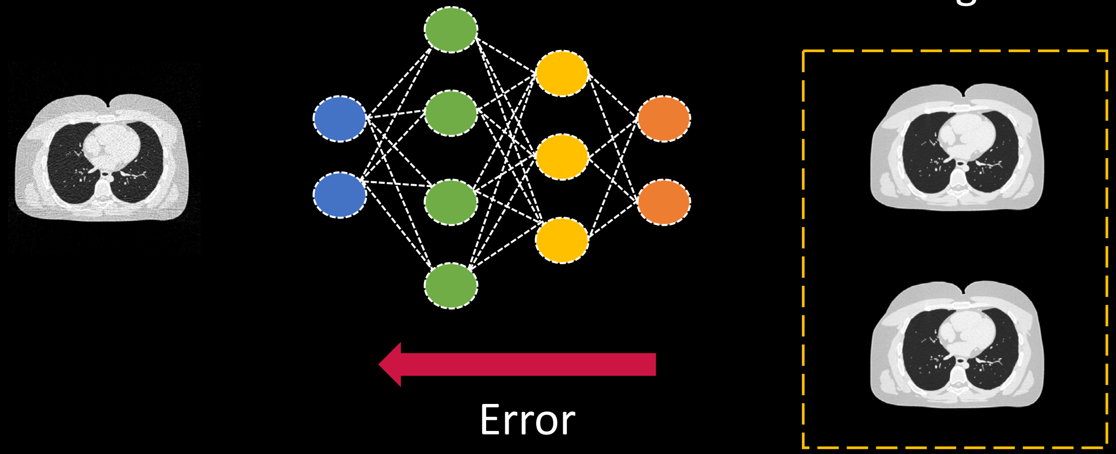
Why Deep Learning?

The Fundamental Limitation of Classical Methods: Overly Simplified Models

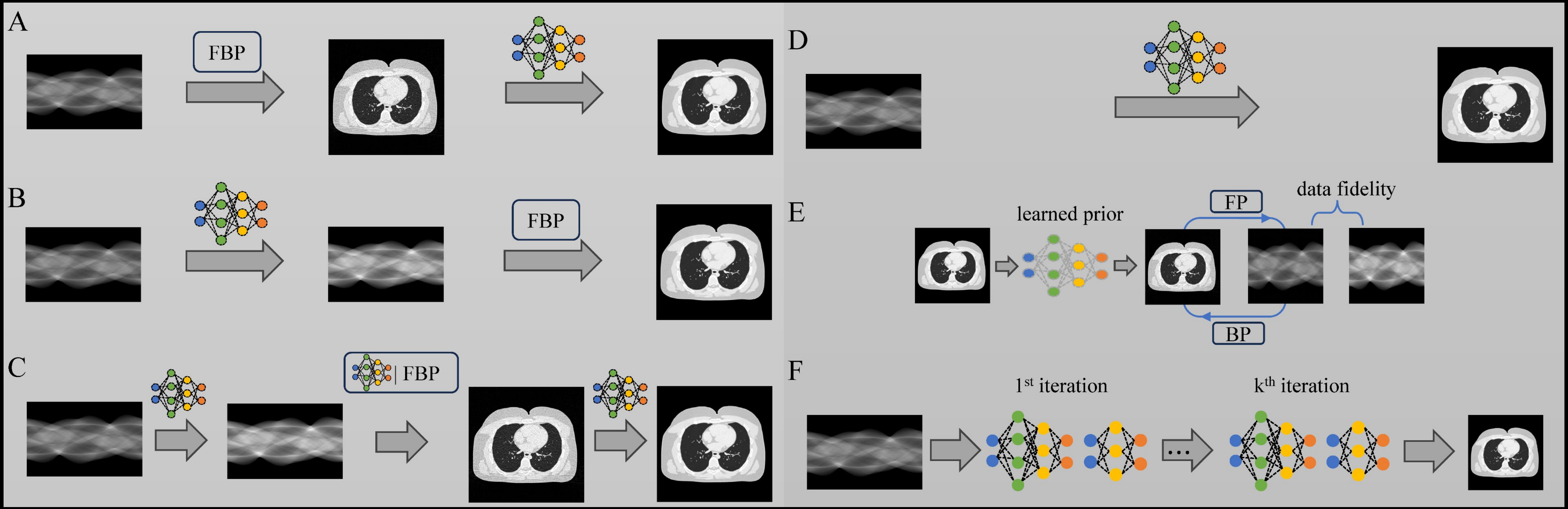
- FBP: idealized mathematical model
- IR: overly simplified object model

A Better Approach: Learn from Data

- Build a model with millions/billions of parameters
- Use millions/billions of data to “fit” model parameters



DLR Implementations



Commercial DLR Algorithms

Vendor-specific

- TrueFidelity, GE Healthcare, 2019
- AiCE, Canon Medical Systems, 2019
- Deep Resolve, Siemens Healthineers, 2021
- Precise Image, Philips Healthcare, 2022

Vendor-neutral (Denoising)

- PixelShine, AlgoMedica, 2020
- ClariCT.AI, ClariPi, 2020

Image Quality Improvements

Zhang R, Szczykutowicz TP, Toia GV. Artificial intelligence in computed tomography image reconstruction: a review of recent advances. Journal of Computer Assisted Tomography. 2025 Jul 1;49(4):521-30.

Challenges of DLR

- The generalizability problem
- Risk of hallucinations
- The “Black Box” problem
- Instability

Thank you!