

Recent advances in filter based tomographic reconstruction methods

D.M. Pelt and K.J. Batenburg

Centrum Wiskunde & Informatica

Meeting on Tomography and Applications
Discrete Tomography and Image Reconstruction
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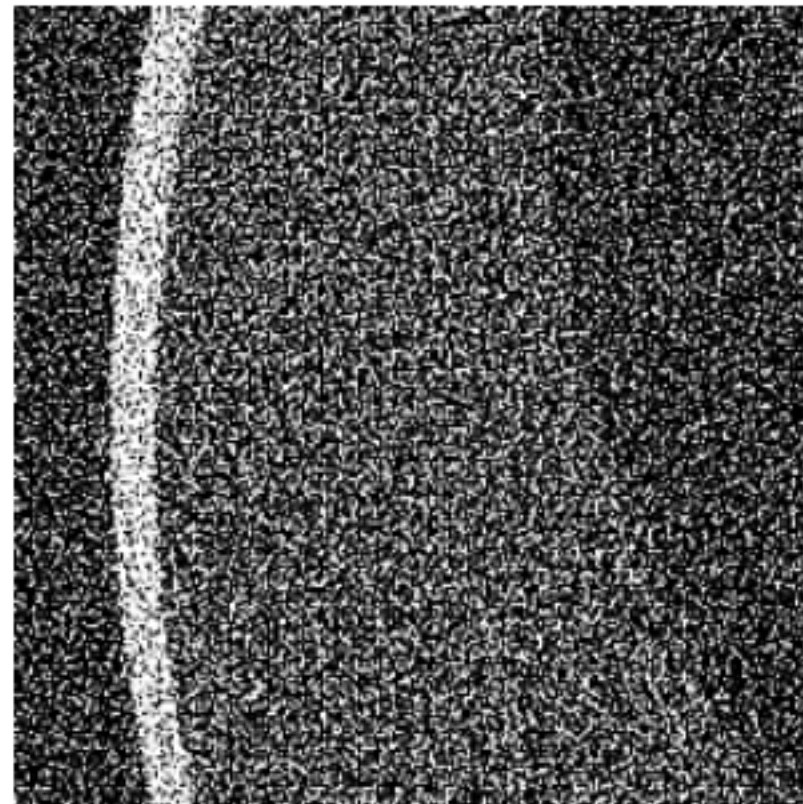
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Introduction

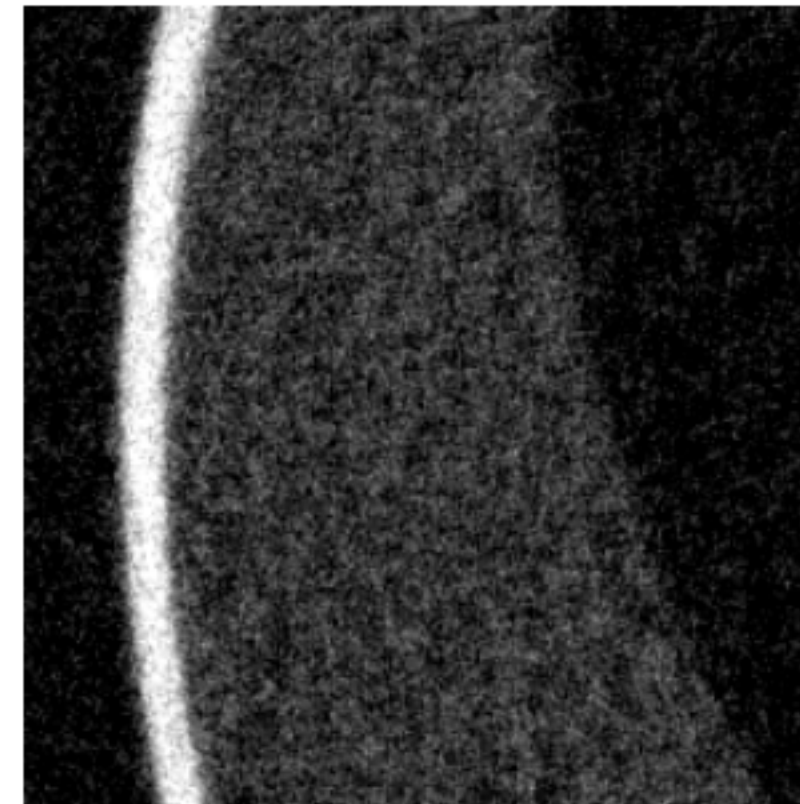
- Modern advanced tomographic experiments produce **increasingly limited data**
 - 4D tomography, in-vivo tomography, ...
- Advanced reconstruction methods can produce **accurate reconstructions** from limited data



(a) Phantom



(b) FBP



(c) SIRT



(d) TV-MIN

- Observation: advanced methods are **rarely used** in practice

Problems with advanced methods

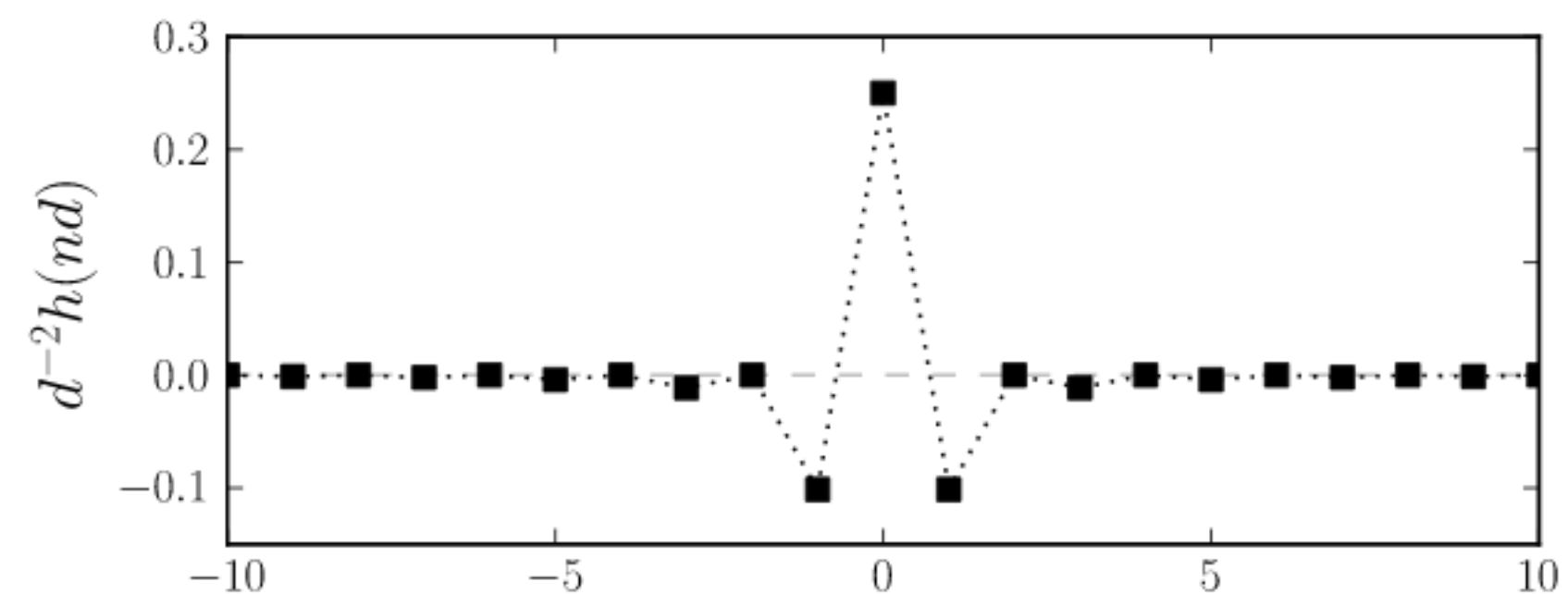
- Observation: advanced methods are **rarely used** in practice
- Several **causes**:
 - Computation time
 - Unknown parameters
 - Difficult practical implementation
- **Filtered backprojection** is very efficient and easy to use
 - Good implementations often available at experimental facilities
- Idea: **improve** FBP to resemble advanced methods

Filtered backprojection

- FBP first convolves the projection data with a **filter** h , then backprojects the result:

$$FBP(\mathbf{p}, \mathbf{h}) = \mathbf{W}^T \mathbf{C}_h \mathbf{p}$$

- Usually a **standard filter** is used (e.g. the ram-lak filter):



- Idea: **Change** the filter of FBP to approximate slower methods

Three approaches

- Idea: **Change** the filter of FBP to approximate slower methods
- This talk: Discuss **three** recent approaches
- Use a filter that **depends on the data**
- Use a filter that approximates an algebraic method
- Use a filter that is trained by neural networks

Approach #1: Data-dependent filter

- Many algebraic methods find an **image** that minimizes projection error:

$$\mathbf{x}_{alg} = \operatorname{argmin}_{\mathbf{x}} \|\mathbf{p} - \mathbf{W}\mathbf{x}\|_2$$

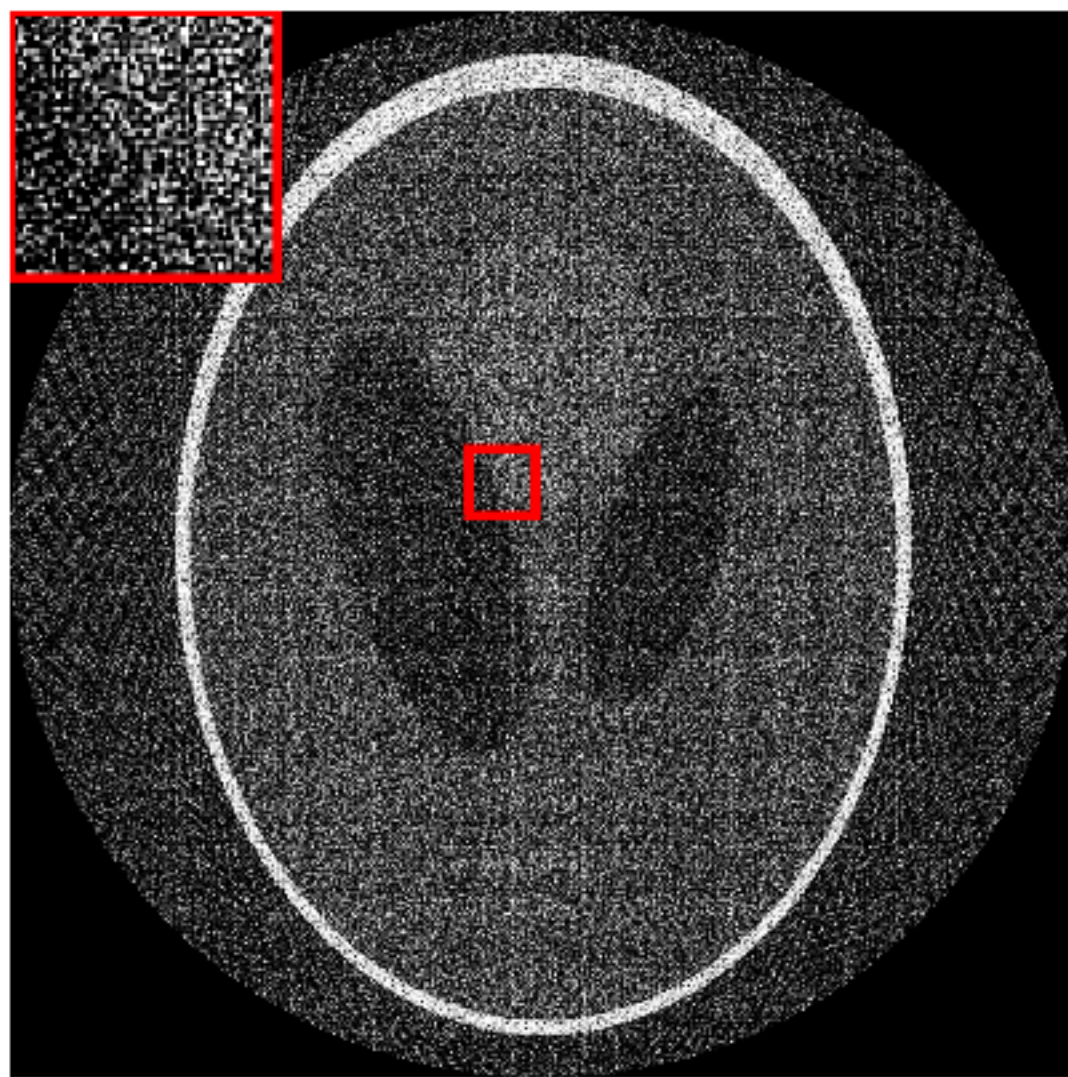
- Idea: find a **filter** such that the resulting FBP reconstruction minimizes projection error:

$$\mathbf{h}^* = \operatorname{argmin}_{\mathbf{h}} \|\mathbf{p} - \mathbf{W}FBP(\mathbf{p}, \mathbf{h})\|_2$$

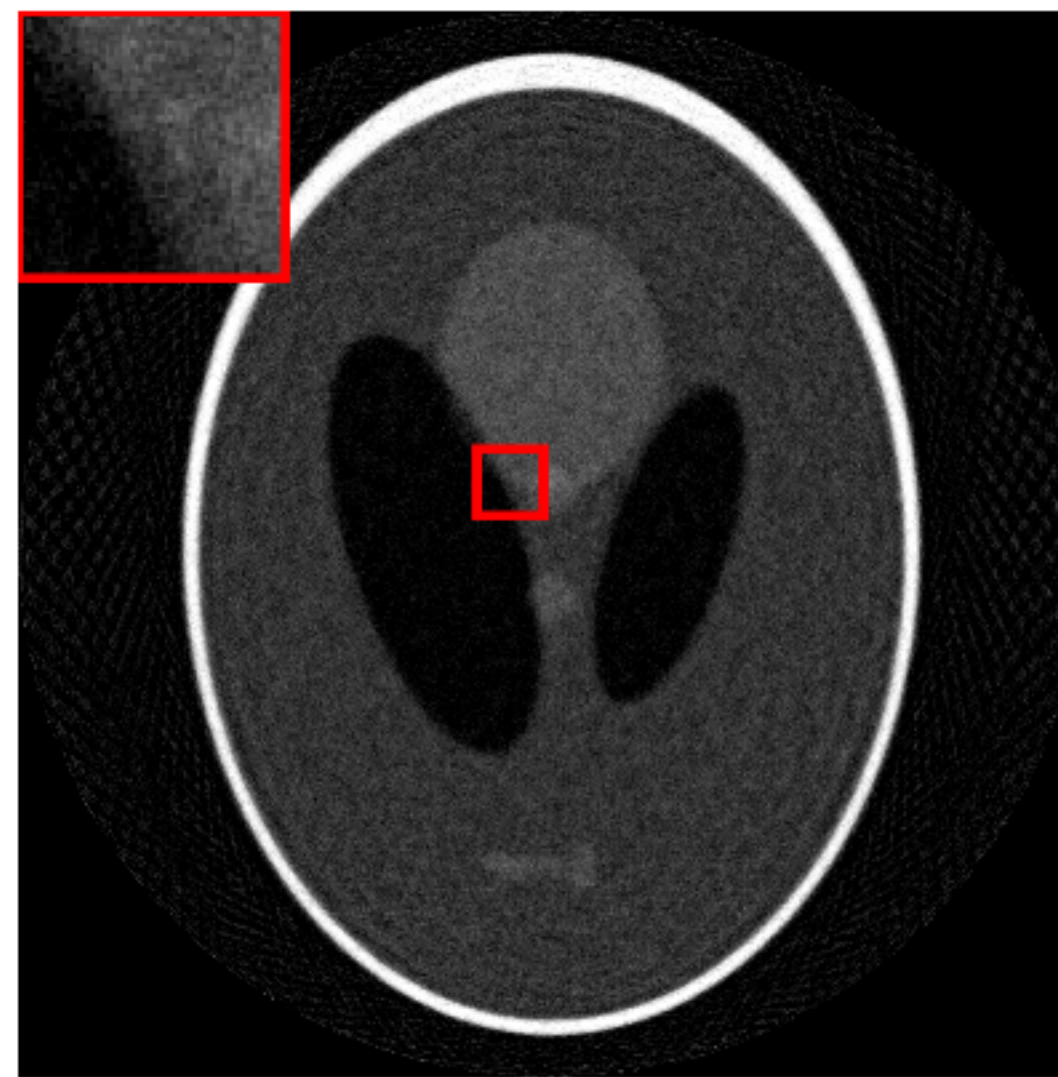
- Advantage: a much **smaller linear system**
 - Faster to solve

Approach #1: Data-dependent filter

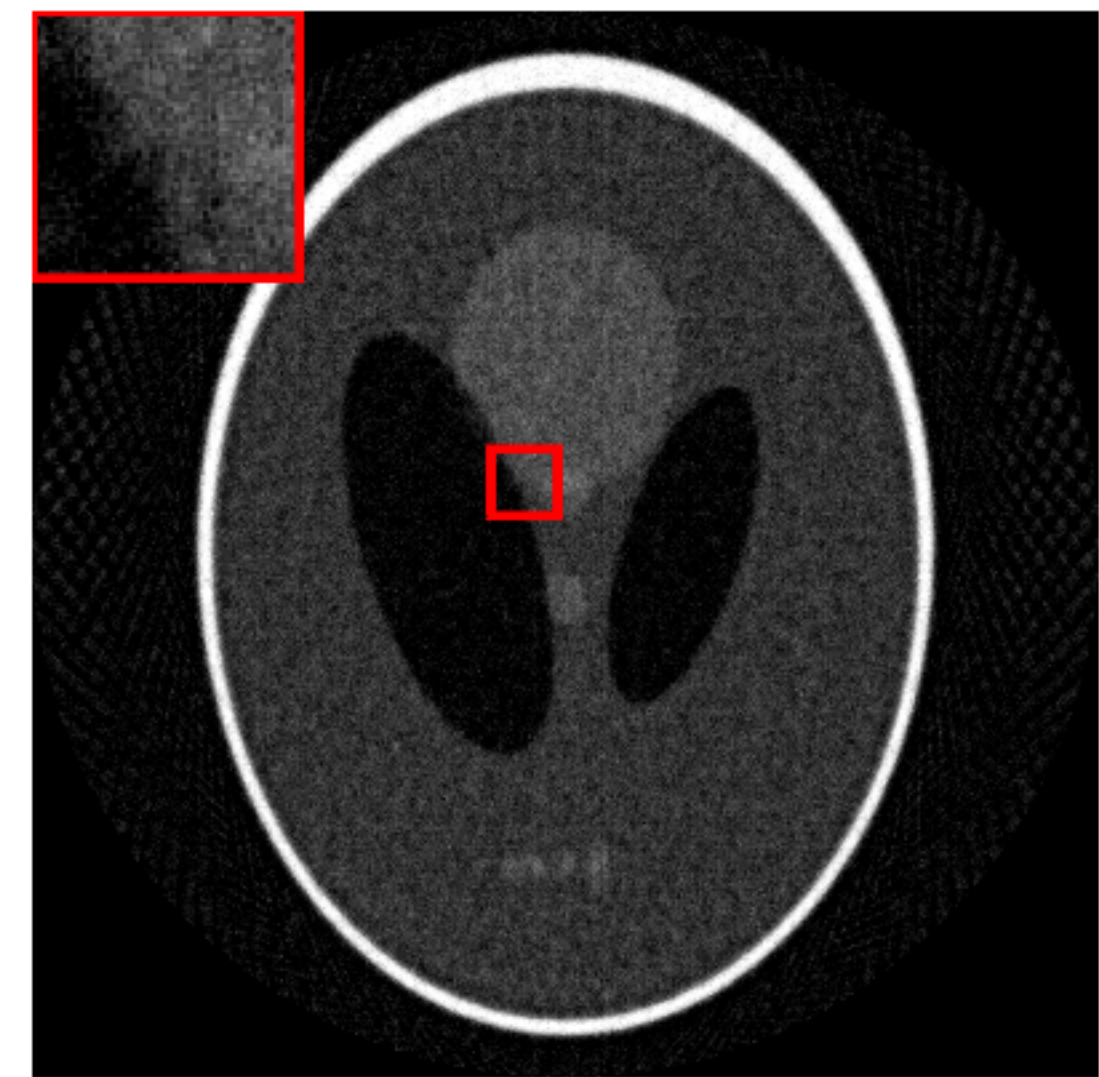
1024 x 1024 pixels, 64 projections, Poisson noise



(a) FBP



(b) SIRT

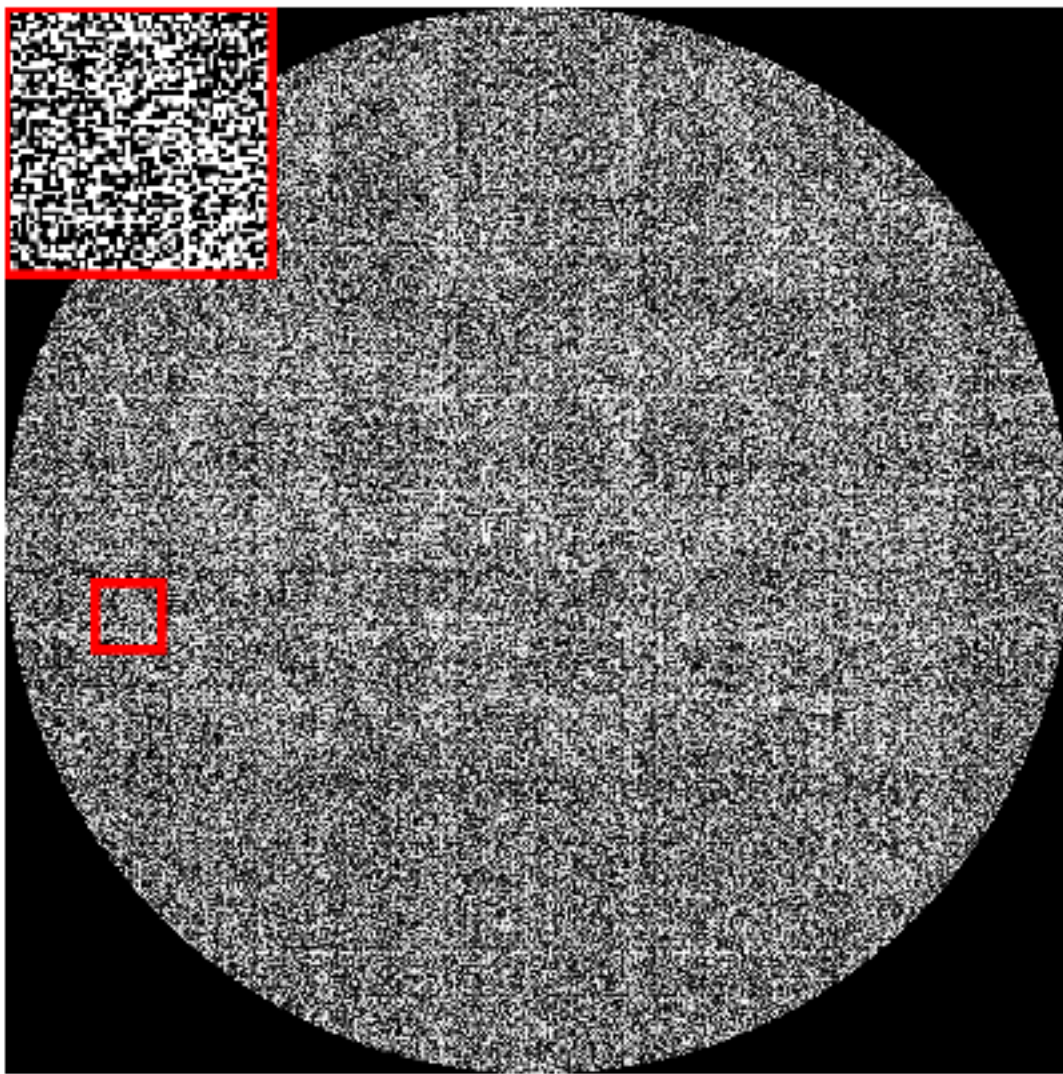


(c) MR-FBP

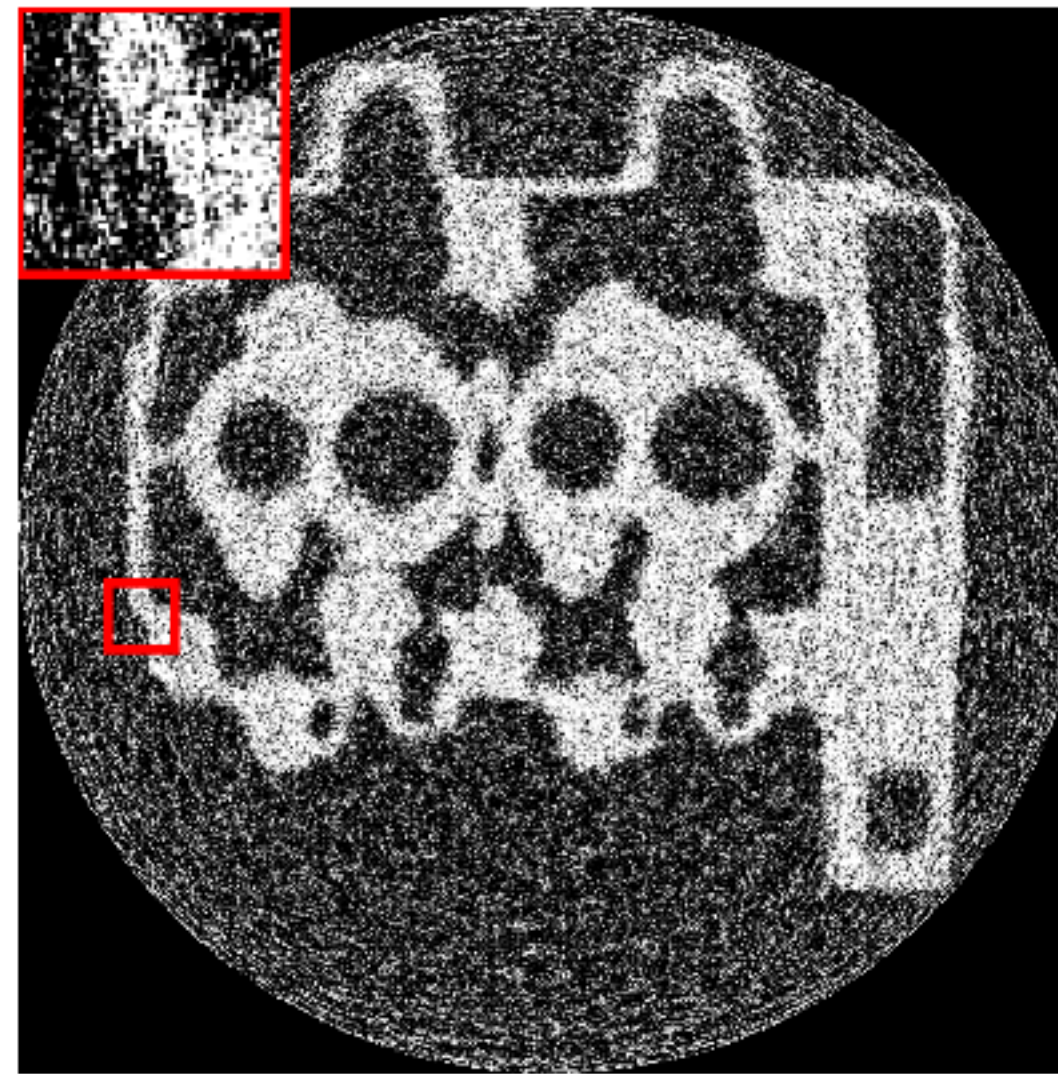
Approach #1: Data-dependent filter

- Prior knowledge can be added to improve quality

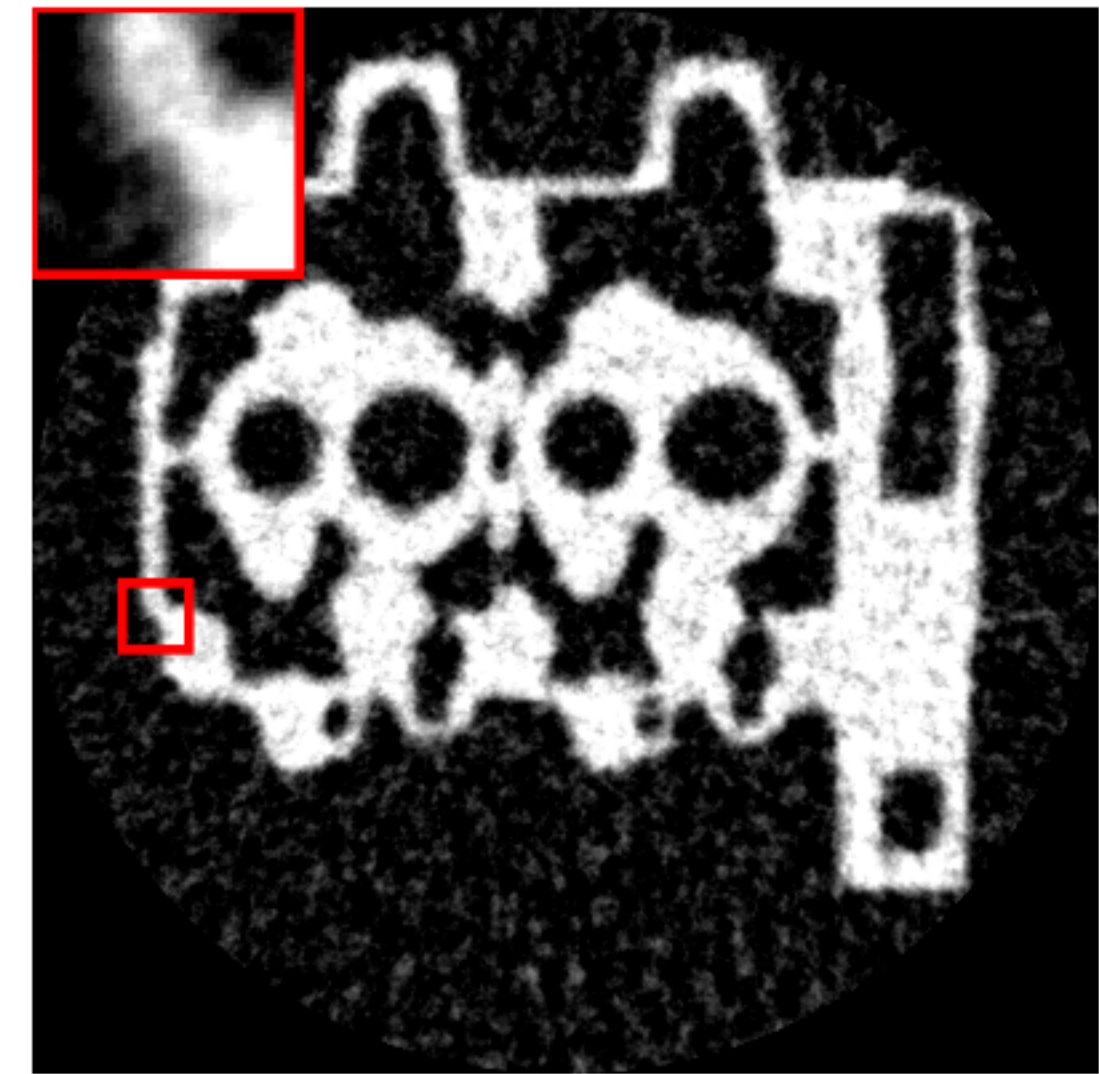
1024 x 1024 pixels, 64 projections, Poisson noise



(a) FBP



(b) SIRT



(c) MR-FBP + prior

Three approaches

- Idea: **Change** the filter of FBP to approximate slower methods
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- Use a filter that **approximates an algebraic method**
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[2] Pelt, D. M., & Batenburg, K. J. (2015). Accurately approximating algebraic tomographic reconstruction by filtered backprojection. To appear in *Proceedings of the 2015 International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine*.

Approach #2: Approximate algebraic method

- Take the standard equation for the algebraic **SIRT** method:

$$\mathbf{x}^{i+1} = \mathbf{x}^i + \alpha \mathbf{W}^T (\mathbf{p} - \mathbf{W} \mathbf{x}^i)$$

- We can rewrite this in **matrix form**:

$$\mathbf{x}^{i+1} = (\mathbf{I} - \alpha \mathbf{W}^T \mathbf{W}) \mathbf{x}^i + \alpha \mathbf{W}^T \mathbf{p}$$

- This is a **recurrence relation**, with solution for iteration n :

$$\mathbf{x}^n = \mathbf{A}^n \mathbf{x}^0 + \alpha \left[\sum_{k=0}^{n-1} \mathbf{A}^k \right] \mathbf{W}^T \mathbf{p}, \quad \mathbf{A} = (\mathbf{I} - \alpha \mathbf{W}^T \mathbf{W})$$

Approach #2: Approximate algebraic method

- We have rewritten the **SIRT equation** to:

$$\mathbf{x}^n = \alpha \left[\sum_{k=0}^{n-1} \mathbf{A}^k \right] \mathbf{W}^T \mathbf{p}$$

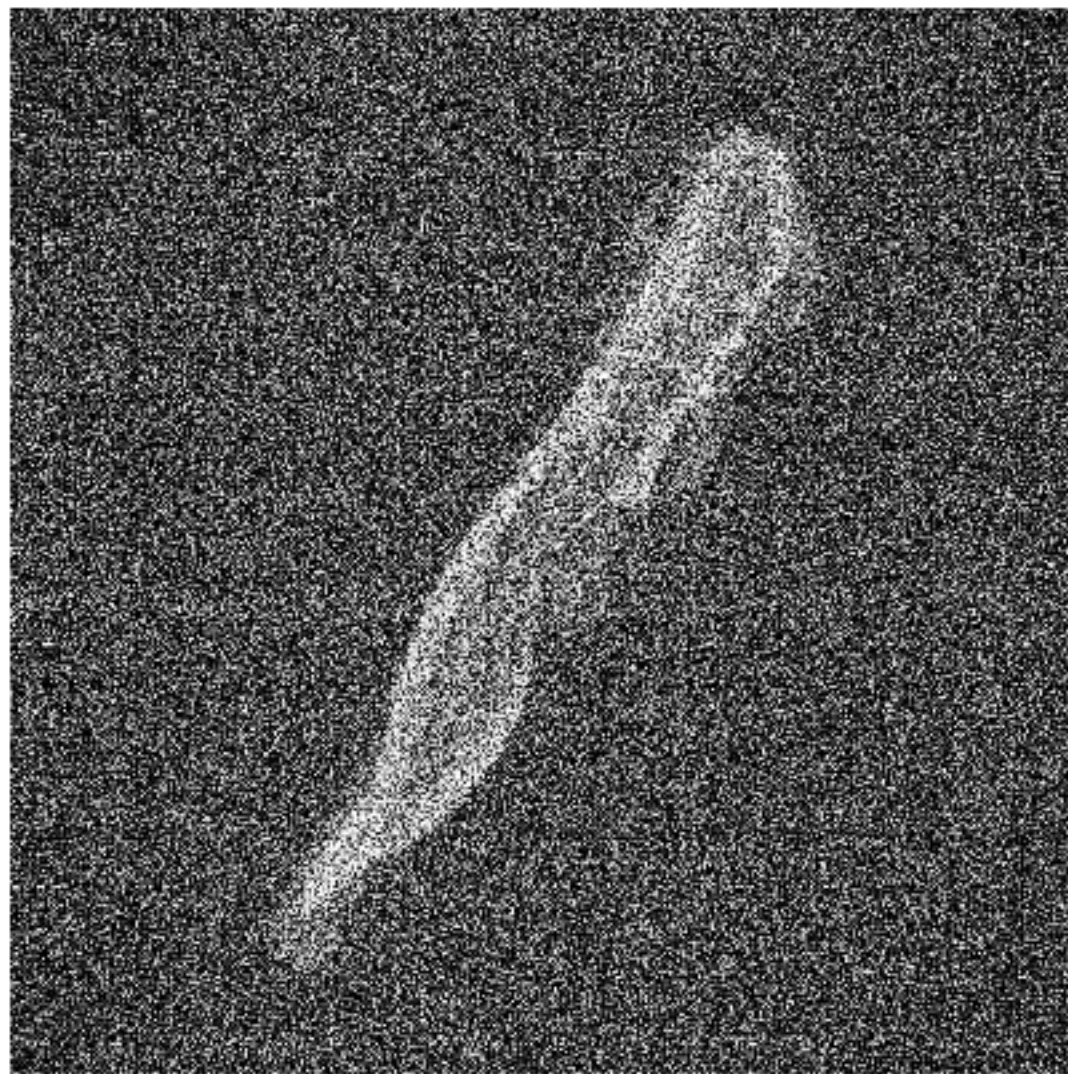
- Compare with the “backproject, then filter” **FBP equation**:

$$FBP(\mathbf{p}, \mathbf{h}') = \mathbf{C}_{\mathbf{h}'} \mathbf{W}^T \mathbf{p}$$

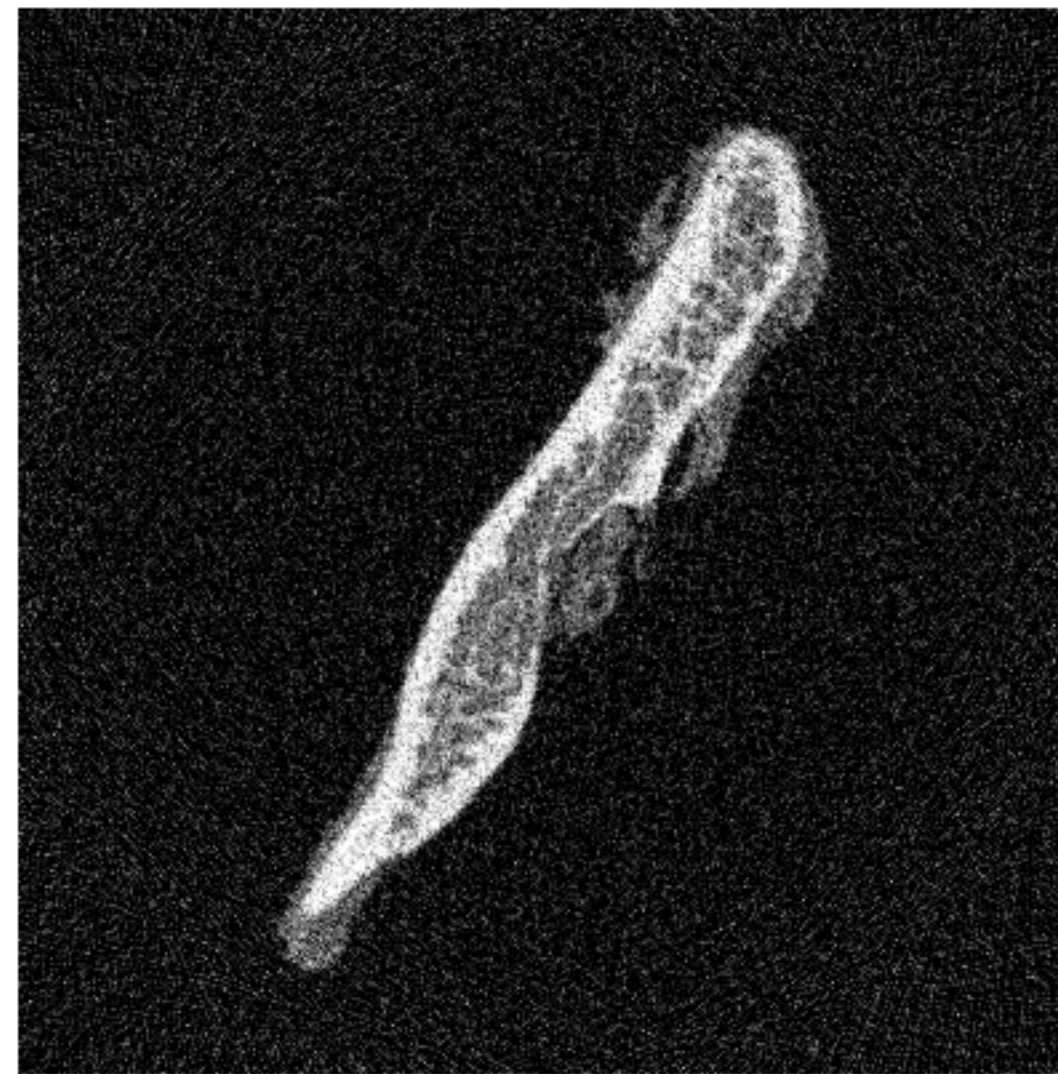
- **Approximate** the \mathbf{A}^k sum with a convolution
 - Filter can be precalculated for a certain acquisition geometry
- Computation time of reconstruction is **identical** to FBP

Approach #2: Approximate algebraic method

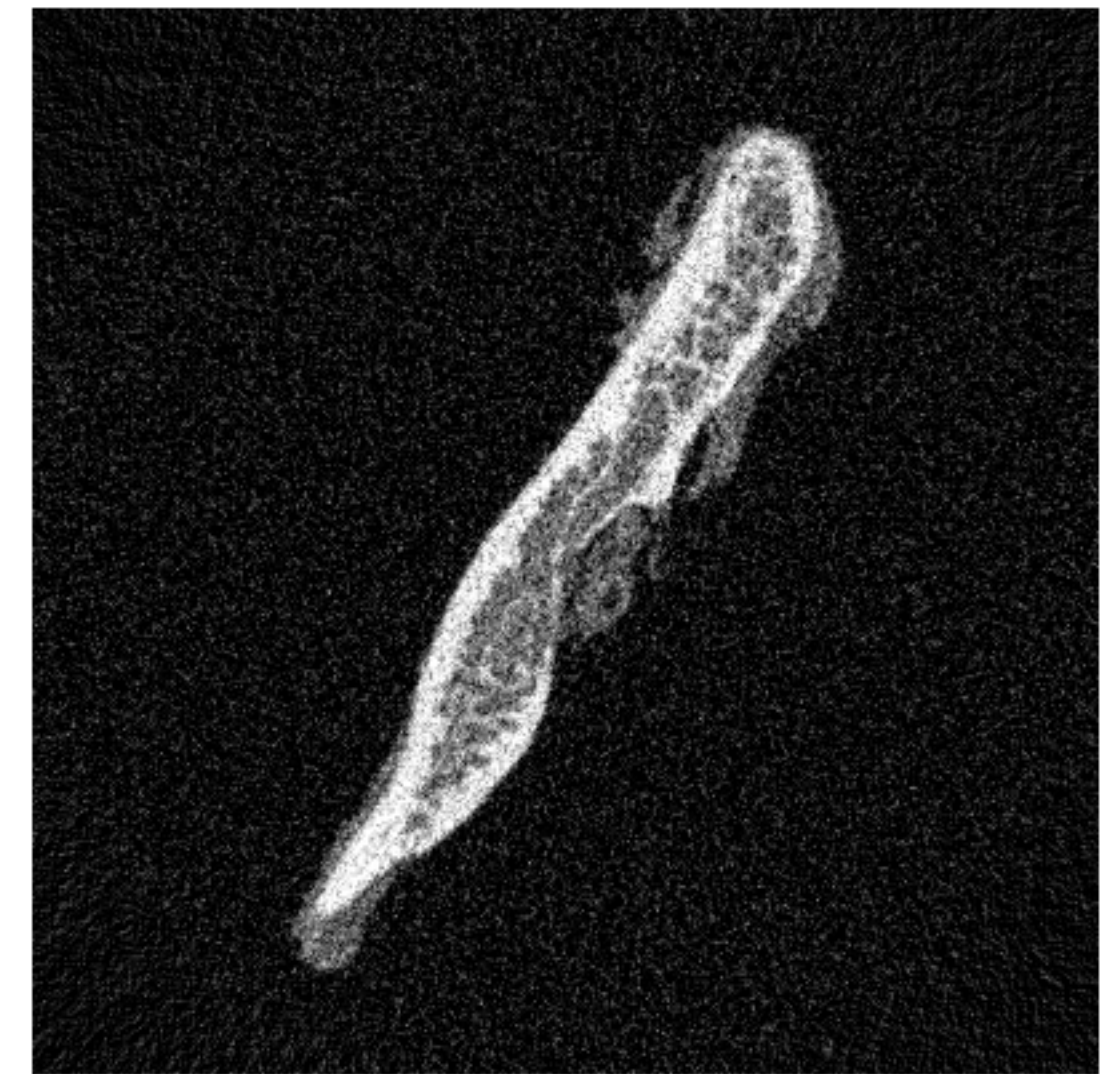
1024 x 1024 pixels, 256 projections, Poisson noise



(a) FBP



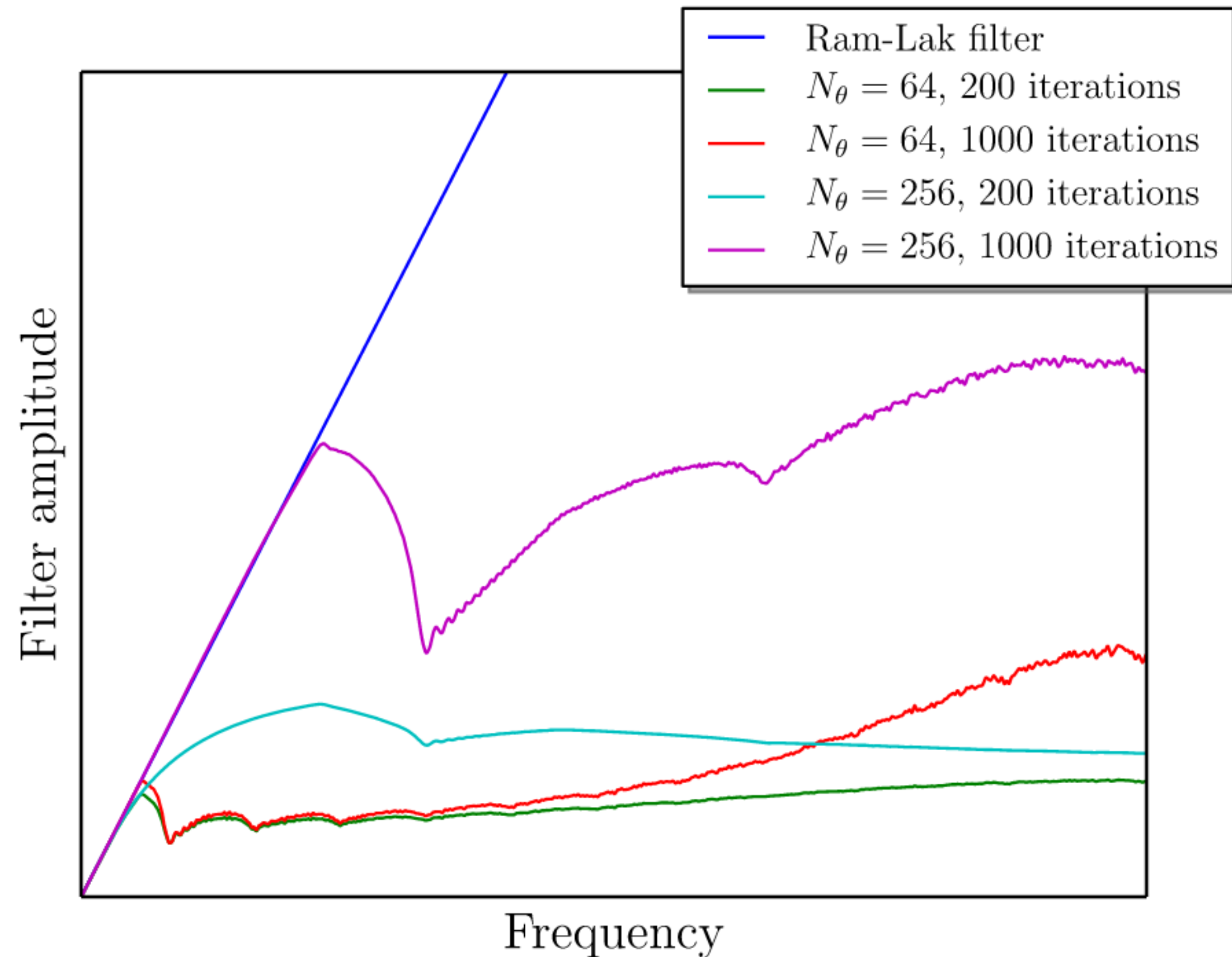
(b) SIRT



(c) SIRT-FBP

Approach #2: Approximate algebraic method

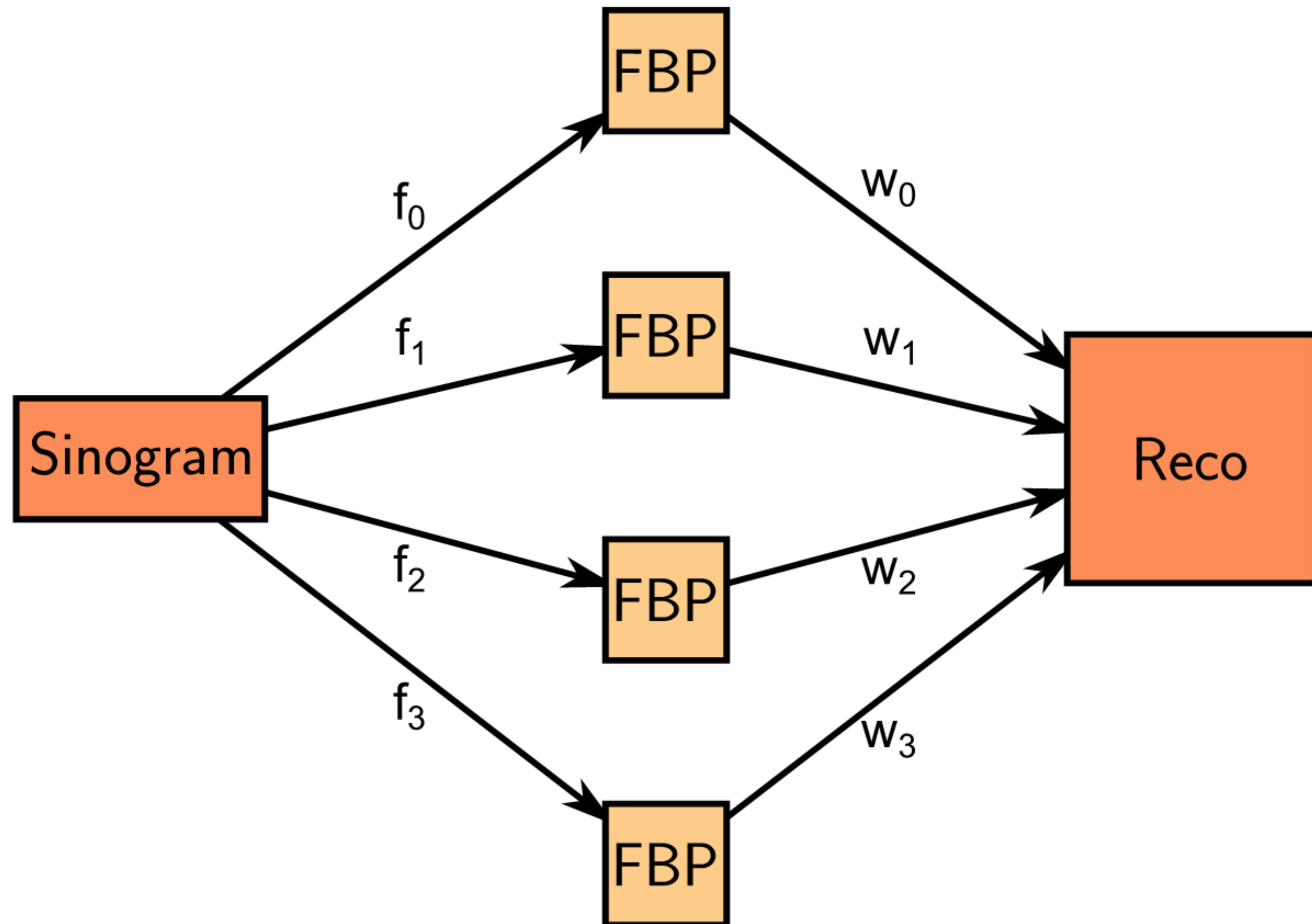
Comparison of algebraic approximation filters



Three approaches

- Idea: **Change** the filter of FBP to approximate slower methods
- This talk: Discuss **three** recent approaches
- Use a filter that depends on the data
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- Use a filter that is **trained by neural networks**

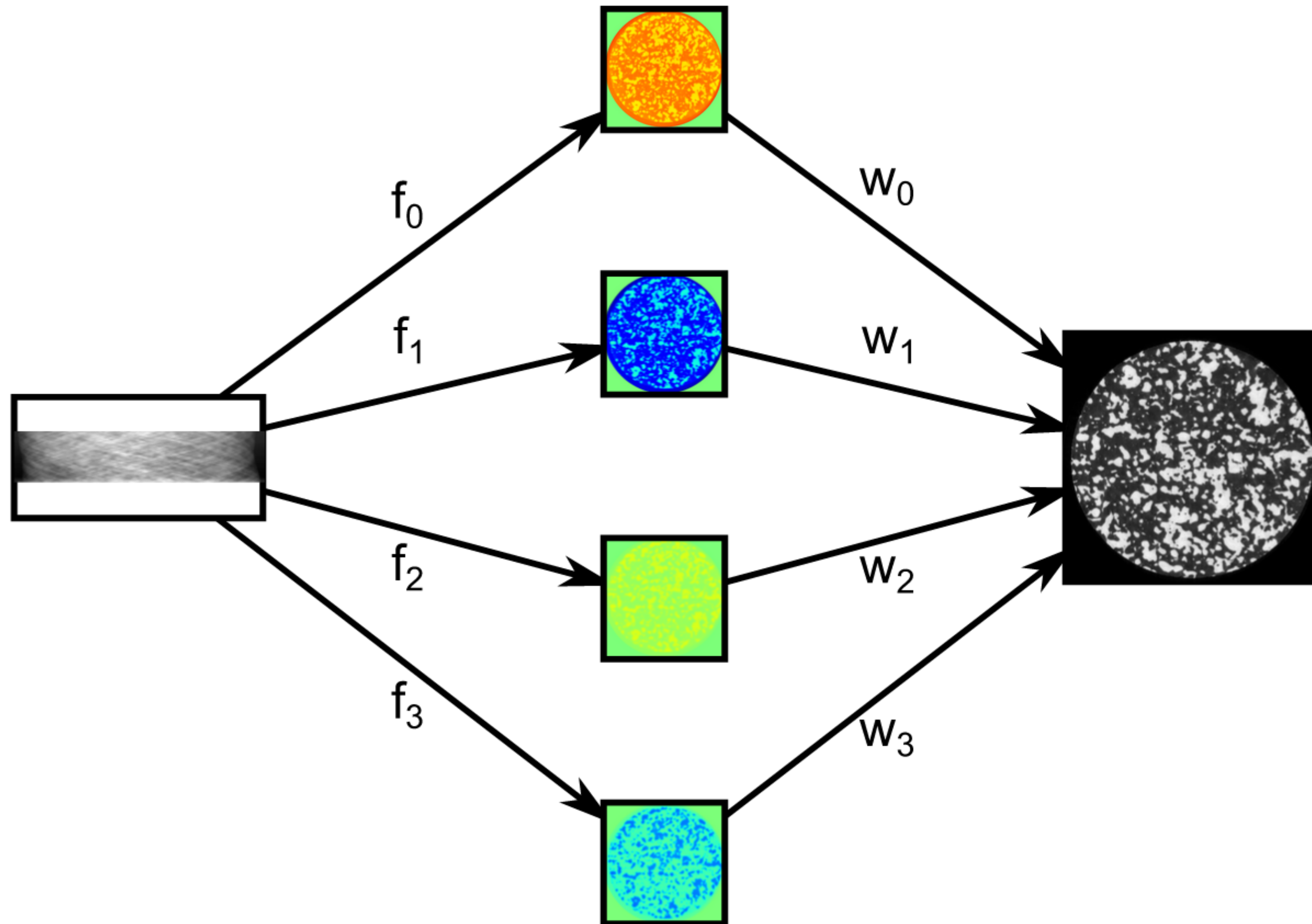
Approach #3: Neural networks



Approach #3: Neural networks

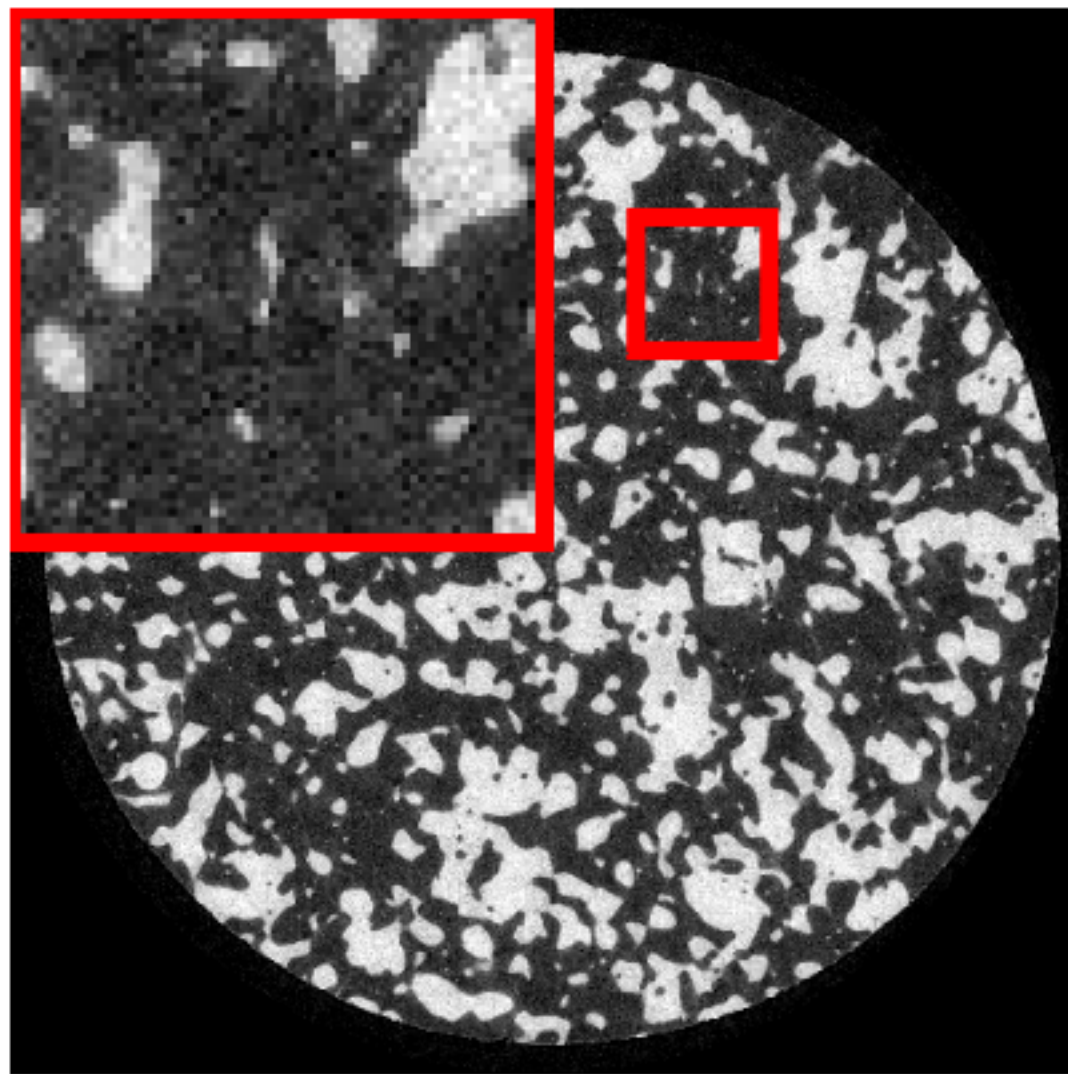
- Filters and weights are **trained** using neural network theory
- To train, **high-quality** reconstructions of objects are needed
 - Scan representative objects with high dose
 - Scan at the start/end of a dynamic experiment
 - ...
- The network will learn filters that **exploit**:
 - Acquisition details (noise profile, # projections, ...)
 - Object characteristics
- After training, reconstruction is **fast and accurate**

Approach #3: Neural networks

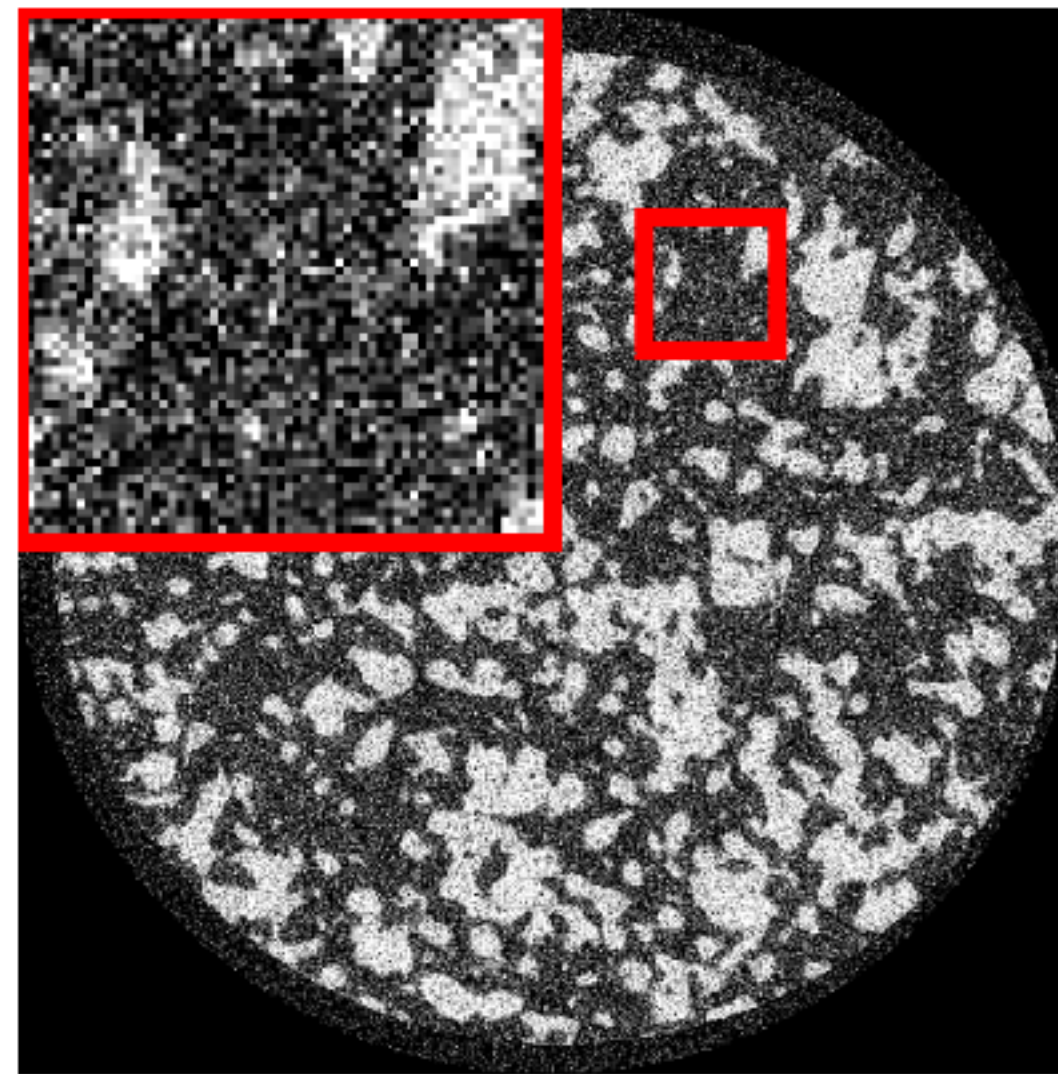


Approach #3: Neural networks

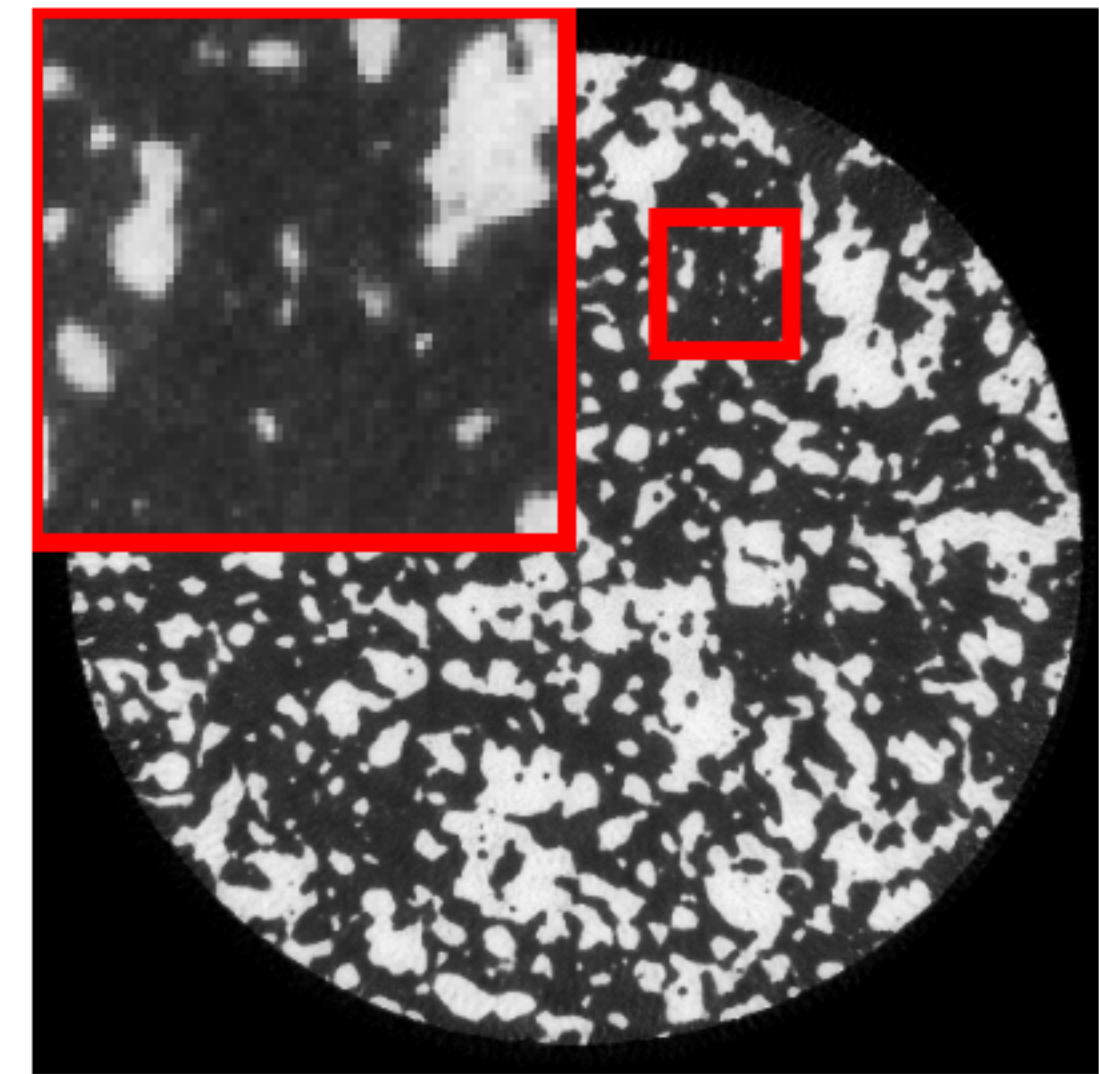
4k x 4k pixels, synchrotron data (ESRF)



(a) FBP (all projections)

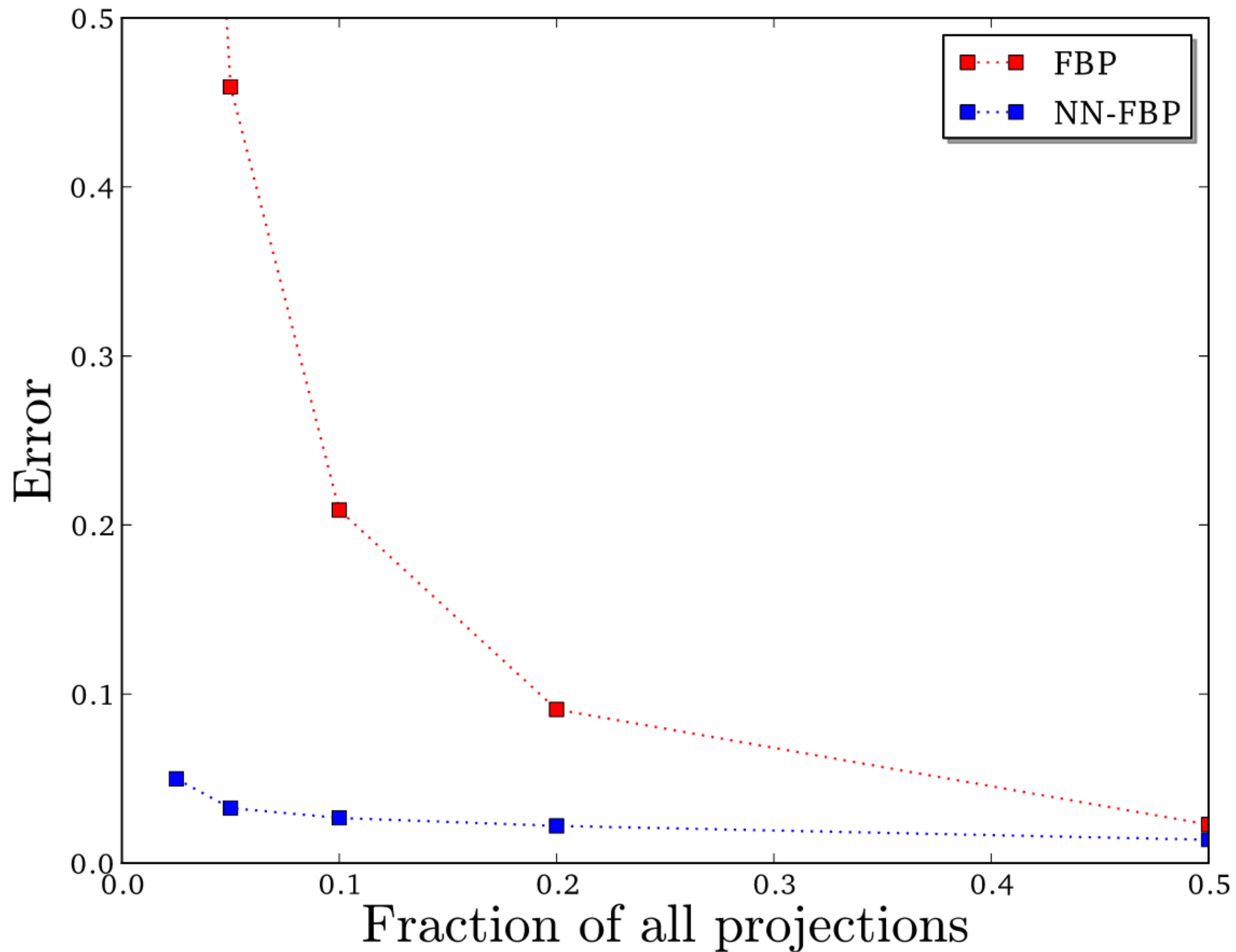


(b) FBP (5%)



(c) NN-FBP (5%)

Approach #3: Neural networks



Conclusions

- FBP with **non-standard filters** can produce very accurate reconstructions
- The filter can be chosen in **different ways**, each with advantages and disadvantages
- **MR-FBP**
 - Use a data-dependent filter that minimizes the projection error
- **SIRT-FBP**
 - Use a filter that approximates an algebraic method
- **NN-FBP**
 - Train filters using high-quality training datasets

Thank you for listening!

For more information: `D.M.Pelt@cwi.nl`

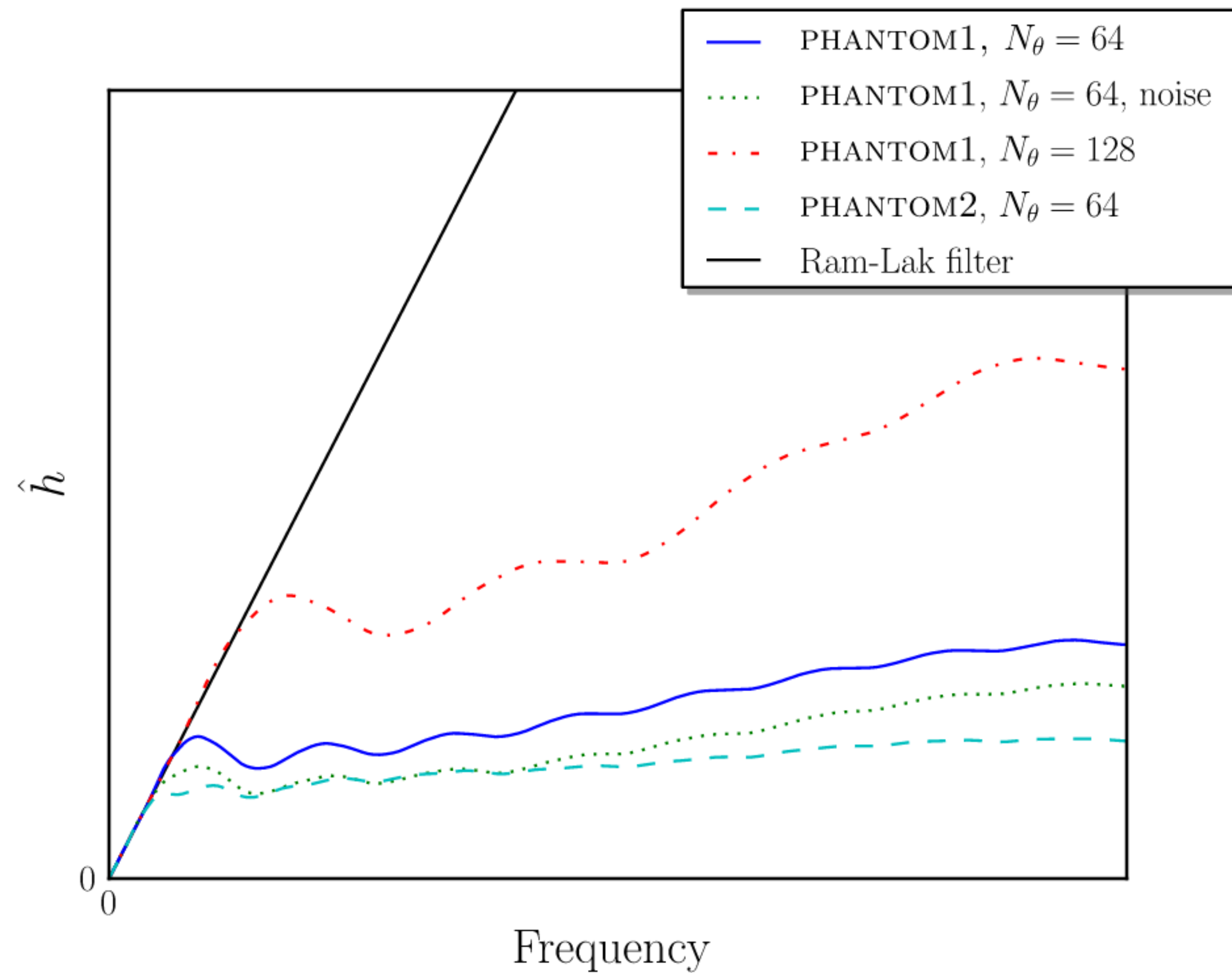
Open source implementations available at: <https://github.com/dmpelt/>

References:

- [1] Pelt, D. M., & Batenburg, K. J. (2014). Improving Filtered Backprojection Reconstruction by Data-Dependent Filtering. *Image Processing, IEEE Transactions on*, 23(11), 4750-4762.
- [2] Pelt, D. M., & Batenburg, K. J. (2015). Accurately approximating algebraic tomographic reconstruction by filtered backprojection. To appear in *Proceedings of the 2015 International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine*.
- [3] Pelt, D. M., & Batenburg, K. J. (2013). Fast Tomographic Reconstruction From Limited Data Using Artificial Neural Networks. *Image Processing, IEEE Transactions on*, 22(12), 5238-5251.

Approach #1: Data-dependent filter

Comparison of data-dependent filters



Approach #3: Neural networks

Trained filters

