

Projection and Reconstruction-Based Noise Filtering Methods in Cone Beam CT

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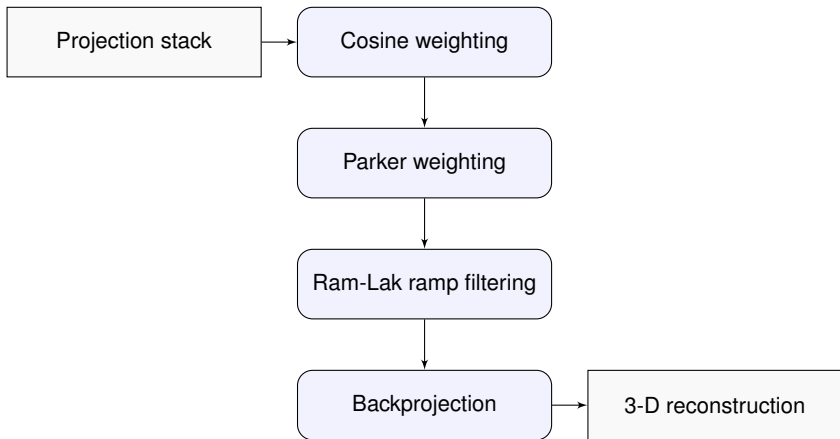


Introduction

- Reduce radiation dose while preserving diagnostic value
- Reduced dose leads to increased noise
- Linear filters incorporated into ramp filtering step cannot preserve image resolution
- Can non-linear filtering methods keep resolution constant while decreasing noise in homogeneous areas?



FDK Reconstruction for Cone Beam CT

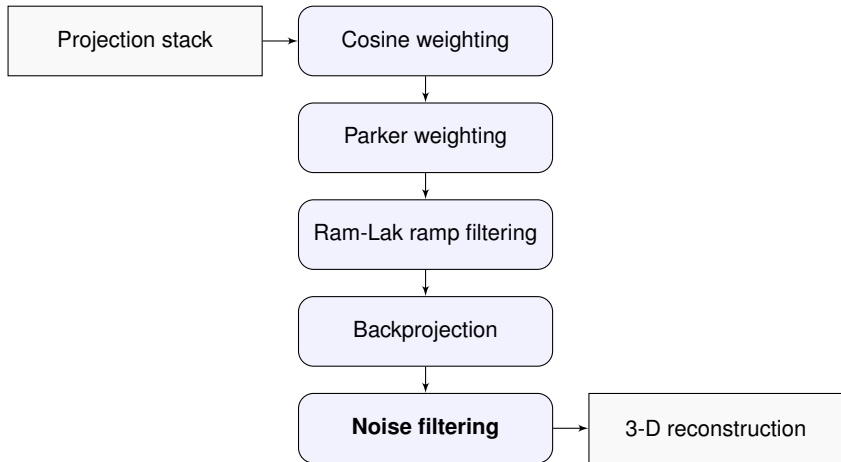


Materials and Methods



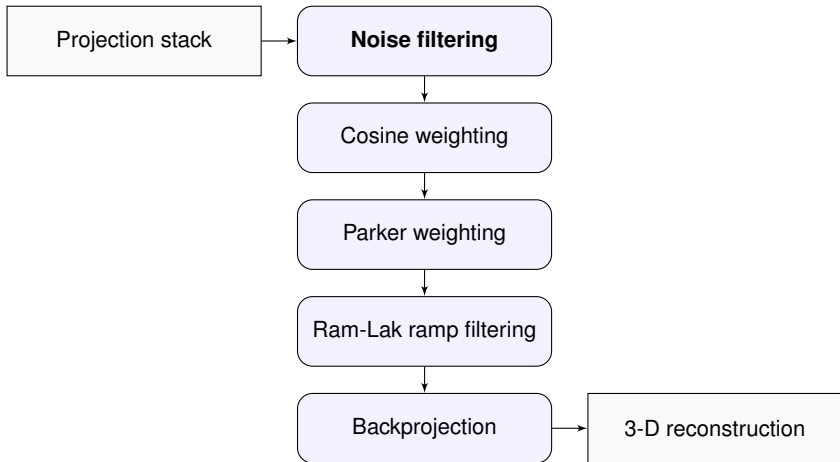


Reconstruction-Based Noise Filtering





Projection-Based Noise Filtering





Gaussian Filter

$$\hat{f}(\mathbf{x}, \sigma_g) = \sum_{\mu \in \Omega} f(\mu) \cdot c(\mathbf{x}, \mu, \sigma_g)$$
$$c(\mathbf{x}, \mu, \sigma_g) = \frac{1}{\sqrt{(2\pi\sigma_g^2)^d}} \exp\left(-\frac{1}{2\sigma_g^2} (\mathbf{x} - \mu)^T (\mathbf{x} - \mu)\right) \quad (1)$$

where

- f is the noisy image, \hat{f} the filtered image
- \mathbf{x} geometric position in image, Ω defines neighborhood of \mathbf{x}
- σ_g spherical standard deviation of d -dimensional filter kernel
- Notation: **GP-2D**, **GP-3D**, **GV-3D**



Bilateral Filter

$$\begin{aligned}\tilde{f}(\mathbf{x}, \sigma_g, \sigma_p) &= \frac{1}{k(\mathbf{x}, \sigma_p)} \sum_{\mu \in \Omega} f(\mathbf{x}) \cdot c(\mathbf{x}, \mu, \sigma_g) \cdot s(f(\mathbf{x}), f(\mu), \sigma_p) \\ s(f(\mathbf{x}), f(\mu), \sigma_p) &= \exp\left(-\frac{1}{2\sigma_p^2}(f(\mathbf{x}) - f(\mu))^2\right)\end{aligned}\quad (2)$$

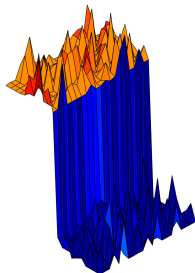
where

- σ_p standard deviation used for the photometric distance
- normalization factor $k(\mathbf{x}, \sigma_p)$ formed by sum of all kernel values
- Notation: **BP-2D**, **BP-3D**, **BV-3D**

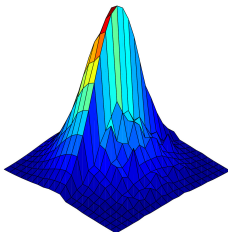
Tomasi et al. (1998). Bilateral filtering for gray and color images.
In: Computer Vision, 1998. Sixth International Conference on (pp. 839-846).

Bilateral Filter

Unfiltered region



Filtering kernel



Filtered region

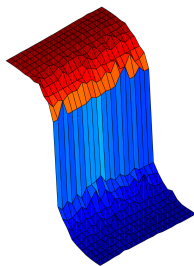


Figure: Kernel of bilateral filter for a neighborhood close to the edge (center) and final filtering result (right)

Experiments and Quality Metrics

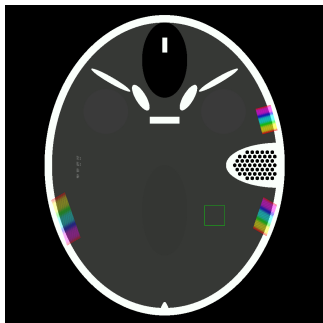


Figure: Forbild phantom

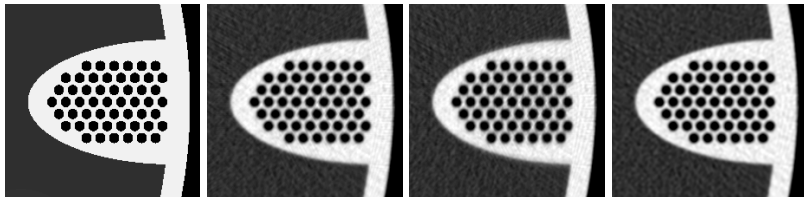
- **Standard deviation** σ_{sd}
calculated inside 3-D box shaped
homogeneous region
- **Modulation transfer function**
(MTF) along skull edges
- **Low noise** (50×10^3 photons with
80keV) and **high noise** dataset
(30×10^3 photons with 50keV)
- 248 projection images:
 640×480 (1.2 mm spacing)

Results





Filtering Methods at $\sigma_{sd} = 0.01$ (80keV Dataset)

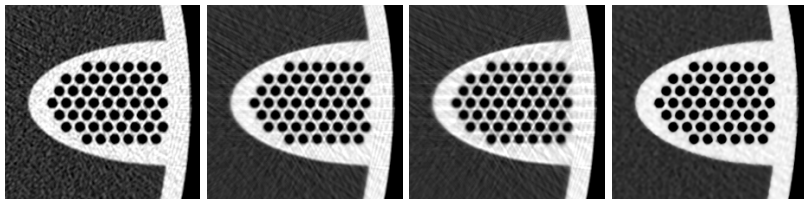


Ground Truth

GP-2D

GP-3D

GV-3D



Unfiltered

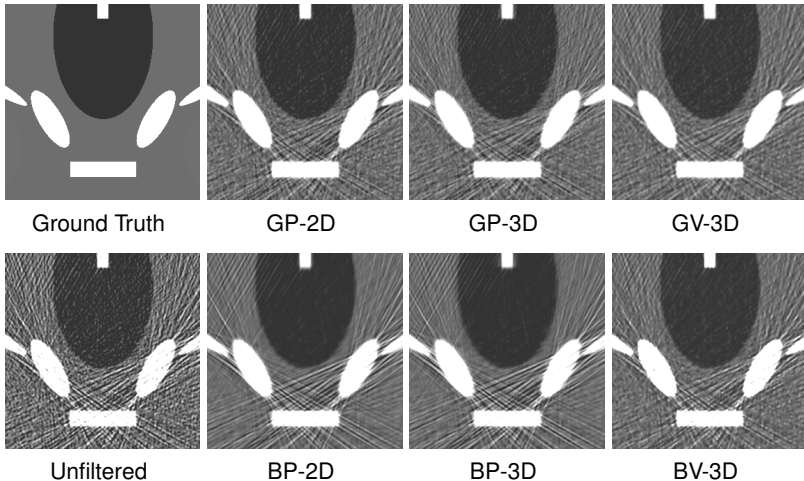
BP-2D

BP-3D

BV-3D

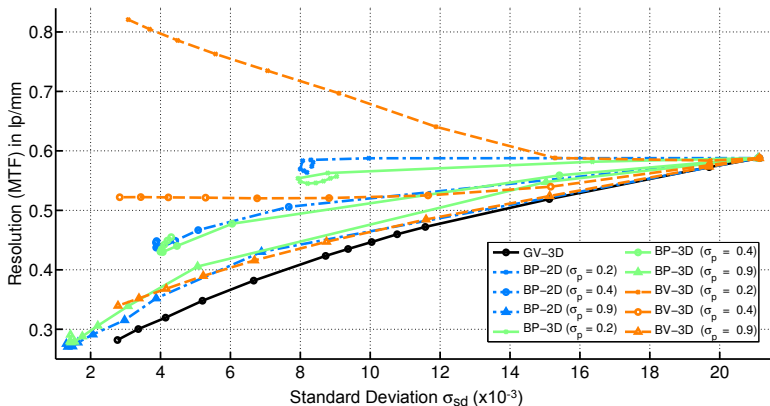


Filtering Methods at $\sigma_{sd} = 0.07$ (50keV Dataset)





Comparison of Bilateral Filters (80keV dataset)





Conclusion

- Bilateral filtering in reconstruction domain yielded best results
- Projection-based filtering can preserve edges, but might incorporate streaking artifacts
- Measurement requires independence of noise and resolution
- Independence **not** given, especially for noisy data
- Traditional evaluations not ideal for non-linear methods



Outlook

- Combine 2D and 3D noise filtering in projection and reconstruction domain
- Evaluation of further non-linear noise filtering methods
- Task-based evaluation, e.g., detection of a lesion
- Use a model-observer evaluation pipeline

Thank you for your attention! Questions?

