

# Image Reconstruction 1 – Planar reconstruction from projections

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# Outline

- 1 Introduction
- 2 The 2D Radon transform
  - Projection
- 3 Inverting the 2D Radon transform
  - Backprojection
  - Central Slice theorem
  - The filtered backprojection (FBP) algorithm
- 4 Practical implementation

# Invention of Computerized Tomography (CT)

Sir Godfrey N. Hounsfield  
(Electrical Engineer)  
EMI

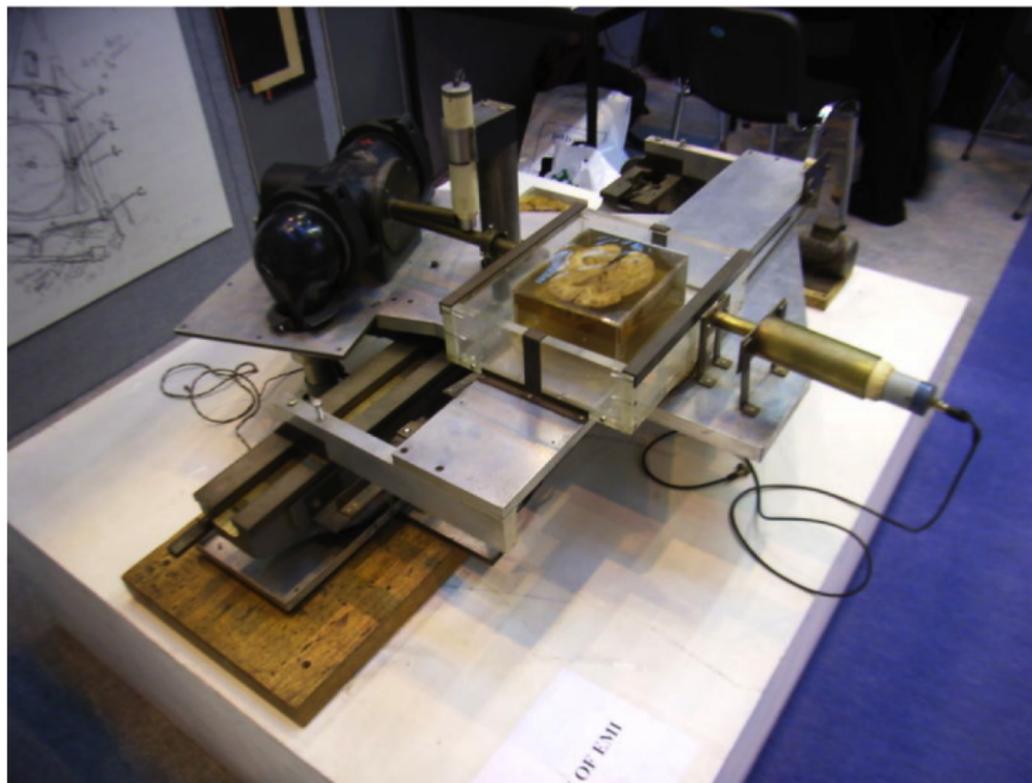


Allan M. Cormack  
(Physicist)  
South Africa, Boston



Joint Nobel Prize for Physiology or Medicine, 1979

# First CT scanner prototype (Hounsfield apparatus)



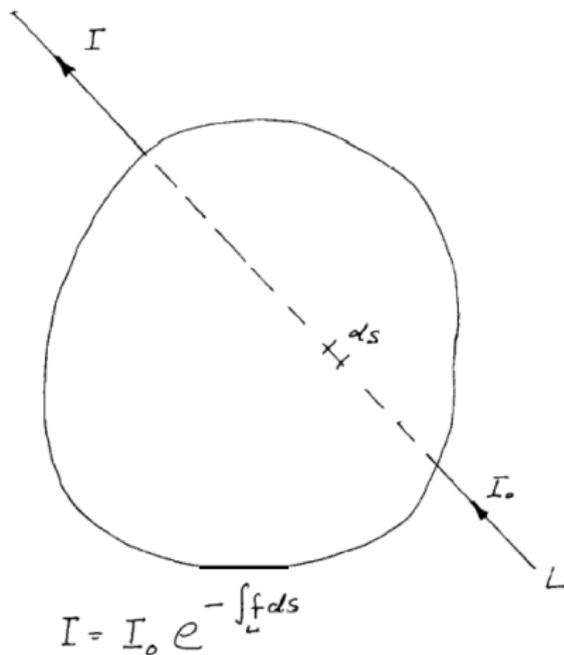
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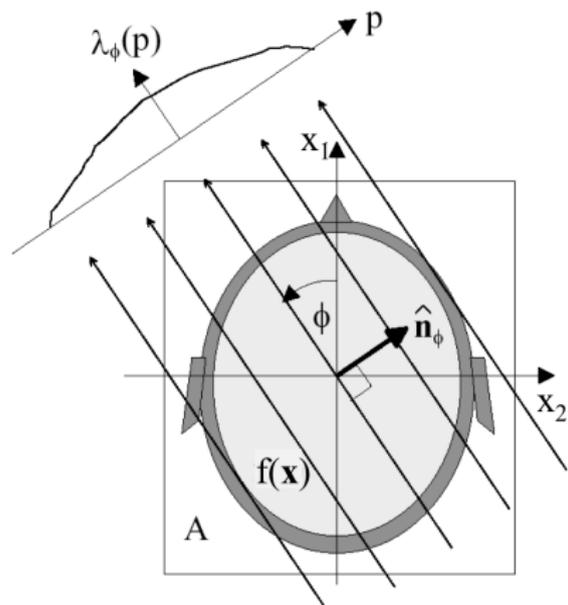
# Projection

- Consider a function  $f(\mathbf{x})$  of the variables  $\mathbf{x} = (x_1, x_2)$  in the plane  $A$ .
- In CT,  $f(\mathbf{x})$  stands for the distribution of attenuation coefficients in a planar cut through the patient's body.
- Let us assume that we know the “projections” (x-ray projections) of  $f(\mathbf{x})$  for arbitrary projection angles.

# From transmission to projection



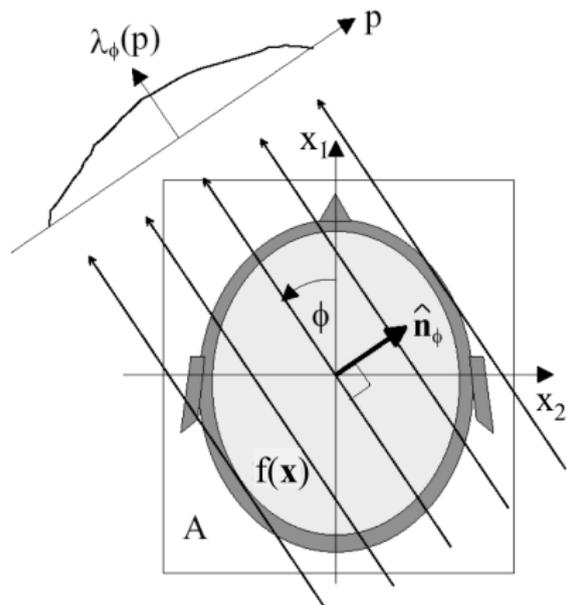
# Projection



- Mathematically, the projection  $\lambda$  is the integral of  $f(\mathbf{x})$  along a (parallel) set of projection lines:

$$\lambda_\phi(p) = \int_A f(\mathbf{x}) \delta(p - \mathbf{x} \cdot \hat{\mathbf{n}}_\phi) d^2x$$

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- Note: A projection line is described in the Hessian normal form by the equation  $p = \mathbf{x} \cdot \hat{\mathbf{n}}_\phi$ .
- Note also: The  $\delta$ -function “picks” those points  $\mathbf{x}$  from the plane  $A$  that lie on the projection line.

# Radon Transform

- We will consider all projections of  $f$  as a two-dimensional function with the arguments  $p$  and  $\phi$ , and write it as  $\lambda(p, \phi)$ . The transform  $f(x_1, x_2) \rightarrow \lambda(p, \phi)$  is called a **Radon transform**<sup>1</sup>
- In symbols:

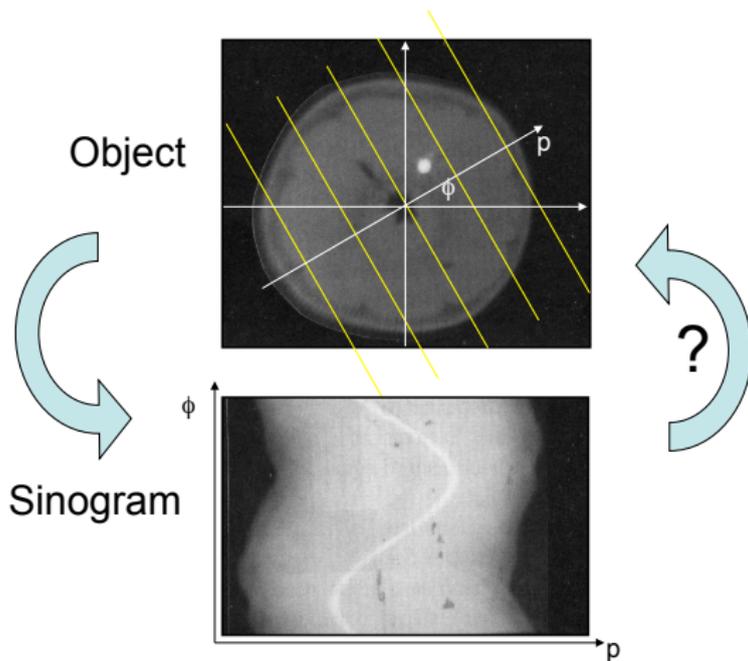
$$\lambda(p, \phi) = \mathfrak{R} \{ f(x) \}.$$

The problem of reconstructing  $f(x)$  from the (known) projections  $\lambda(p, \phi)$  is basically the determination of the inverse Radon transform,  $\mathfrak{R}^{-1}$ .

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<sup>1</sup>After the mathematician Johann Radon, who described the first mathematical method for a reconstruction from projections as early as in 1917 

# The problem: inverting the Radon transform



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# Backprojection

By backprojection we mean “smearing out” of the values of  $\lambda_\phi(p)$  along the projection lines, over the plane  $A$ , which results in a streak image. Mathematically, backprojection under an angle  $\phi$  is simply given by:

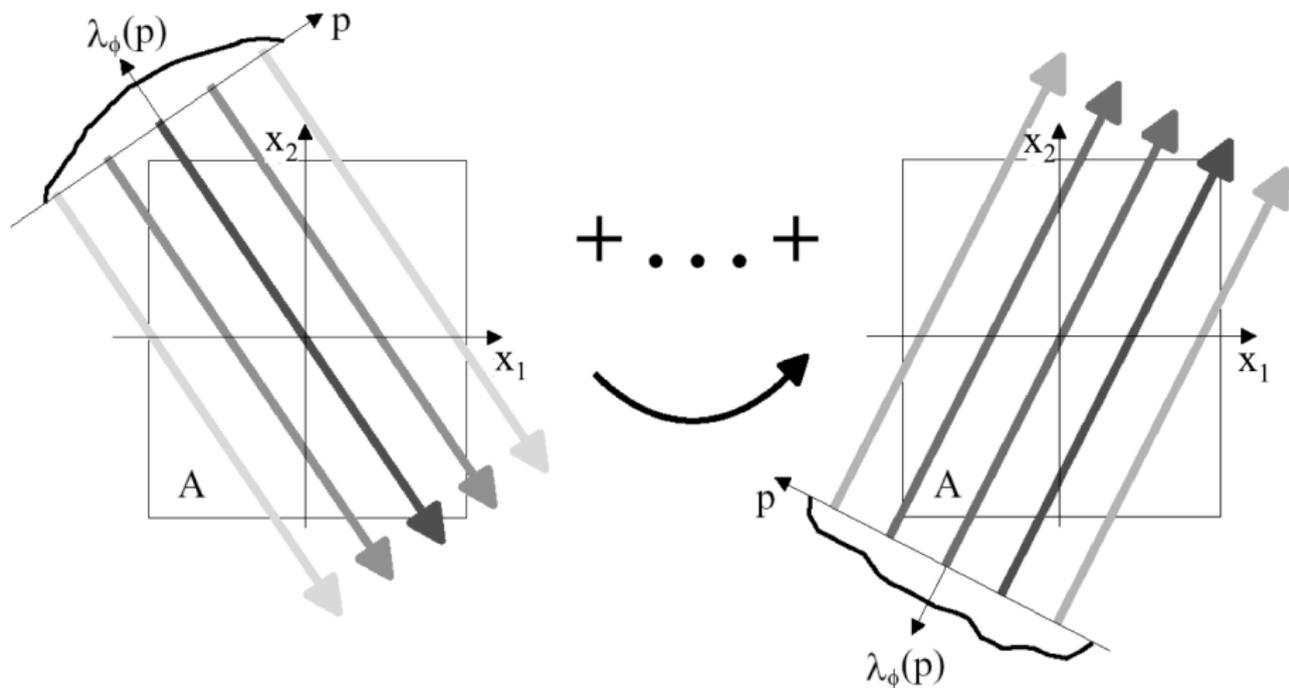
$$f_\phi(\mathbf{x}) = \lambda_\phi(\mathbf{x} \cdot \hat{\mathbf{n}}_\phi).$$

If we perform backprojections for all angles within the interval  $[0, \pi)$  and integrate the results, we get

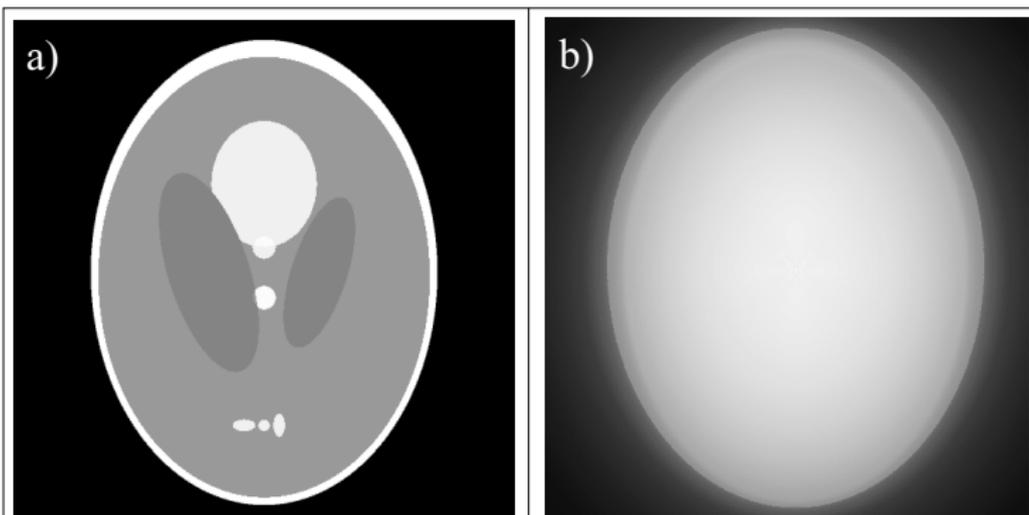
$$f_b(\mathbf{x}) = \int_0^\pi \lambda_\phi(\mathbf{x} \cdot \hat{\mathbf{n}}_\phi) d\phi.$$

$$f_b(\mathbf{x}) = \mathfrak{B} \{ \lambda(p, \phi) \} = \mathfrak{B} \mathfrak{R} \{ f(\mathbf{x}) \}.$$

# Backprojection



# Backprojection alone does not reconstruct the object!



(a) Shepp and Logan phantom

(b) "Reconstruction" of (a) with backprojection

# Backprojection alone does not reconstruct the object!

The **Central Slice Theorem** provides the relationship between the one-dimensional (1-D) FT of a projection  $\lambda_\phi(p) = \mathfrak{R}_\phi \{f(\mathbf{x})\}$  and the 2-D FT of  $f(\mathbf{x})$ :

$$\begin{aligned}
 \Lambda_\phi(\nu) &= \mathfrak{F}_1 \{ \mathfrak{R}_\phi \{ f(\mathbf{x}) \} \} \\
 &= \int_{-\infty}^{\infty} \left[ \int_A f(\mathbf{x}) \delta(p - \mathbf{x} \cdot \hat{\mathbf{n}}_\phi) d^2x \right] \exp(-2\pi i \nu p) dp \\
 &= \int_A f(\mathbf{x}) \left[ \int_{-\infty}^{\infty} \delta(p - \mathbf{x} \cdot \hat{\mathbf{n}}_\phi) \exp(-2\pi i \nu p) dp \right] d^2x \\
 &= \int_A f(\mathbf{x}) \exp(-2\pi i \nu \mathbf{x} \cdot \hat{\mathbf{n}}_\phi) d^2x.
 \end{aligned}$$

The last integral is the 2-D Fourier transform  $F(\boldsymbol{\rho})$  of the function  $f(\mathbf{x})$  along the line  $\boldsymbol{\rho} = \nu \hat{\mathbf{n}}_\phi$ .

# Central Slice Theorem

## Theorem (Central Slice Theorem)

*The 1-D FT of the projection of a 2-D function yields the 2-D FT of the function along a line through the origin of the frequency domain.*

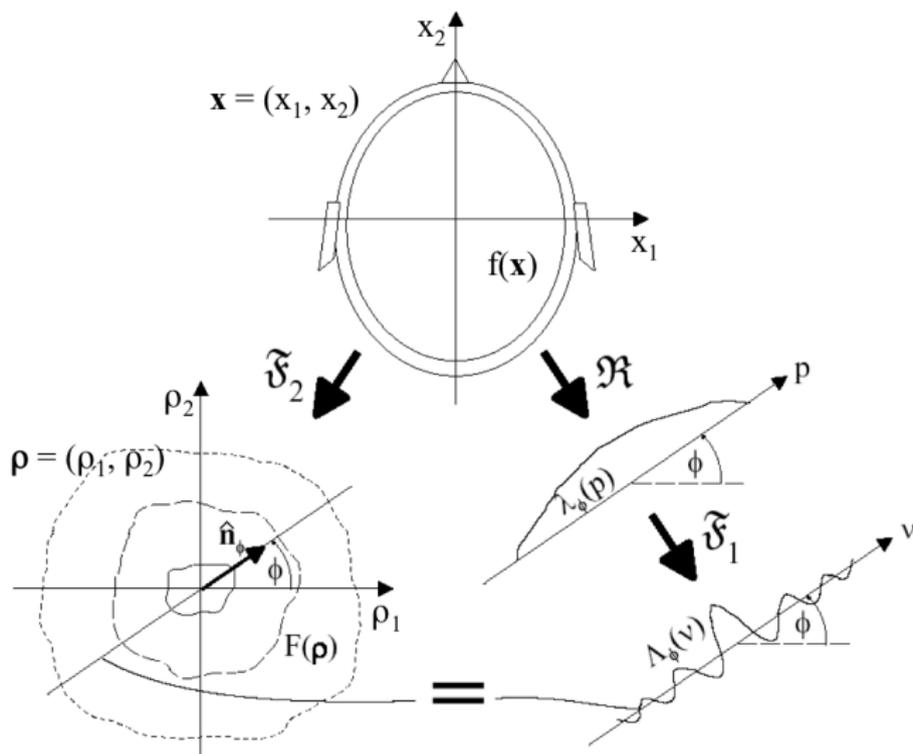
Using operator notation we can write this as:

$$\mathfrak{F}_1 \{ \mathfrak{R}_\phi \{ f(\mathbf{x}) \} \} (\nu) = \mathfrak{F}_2 \{ f(\mathbf{x}) \} (\boldsymbol{\rho} = \nu \hat{\mathbf{n}}_\phi)$$

or just

$$\mathfrak{F}_1 \mathfrak{R} = \mathfrak{F}_2.$$

# Central Slice Theorem



## Filtered Backprojection: formal derivation

Write  $f(\mathbf{x})$  as the inverse Fourier transform of  $F(\boldsymbol{\rho})$ , in polar coordinates:

$$\begin{aligned} f(\mathbf{x}) &= \int_{-\infty}^{\infty} F(\boldsymbol{\rho}) \exp(2\pi i \mathbf{x} \cdot \boldsymbol{\rho}) \, d^2 \boldsymbol{\rho} \\ &= \int_0^{2\pi} \int_0^{\infty} \nu F(\nu \hat{\mathbf{n}}_{\phi}) \exp(2\pi i \nu \mathbf{x} \cdot \hat{\mathbf{n}}_{\phi}) \, d\nu \, d\phi \end{aligned}$$

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For symmetry reasons:

$$f(\mathbf{x}) = \int_0^{\pi} \int_{-\infty}^{\infty} |\nu| F(\nu \hat{\mathbf{n}}_{\phi}) \exp(2\pi i \nu \mathbf{x} \cdot \hat{\mathbf{n}}_{\phi}) \, d\nu \, d\phi$$

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With the Central Slice Theorem we obtain finally:

$$f(\mathbf{x}) = \int_0^{\pi} \int_{-\infty}^{\infty} |\nu| \Lambda_{\phi}(\nu) \exp(2\pi i \nu \mathbf{x} \cdot \hat{\mathbf{n}}_{\phi}) \, d\nu \, d\phi$$

## Filtered Backprojection: algorithm

The function  $f(\mathbf{x})$  can be reconstructed from the projection profiles  $\lambda_\phi(p)$  using the following steps:

- 1 *Fourier transform of  $\lambda_\phi(p) \rightarrow \Lambda_\phi(\nu)$ ;*
- 2 *multiplication of  $\Lambda_\phi(\nu)$  with  $|\nu| \rightarrow \Lambda_\phi^*(\nu)$ ;*
- 3 *inverse Fourier transform of  $\Lambda_\phi^*(\nu) \rightarrow \lambda_\phi^*(p')$ ;*
- 4 *backprojection of  $\lambda_\phi^*(p')$  and integration over  $\phi \rightarrow f(\mathbf{x})$ .*

The first three steps are a filtering (convolution) of the projection profiles with the filter  $h^{-1}(p)$ , which is the inverse FT of  $H^{-1}(\nu) = |\nu|$ .

# Filtered Backprojection: intuitive explanation

- 1 Backprojection of  $\lambda_\phi(p)$  under angle  $\phi$  corresponds with creating a line through the origin of the 2D Fourier space.

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- 2 Backprojection from many directions results in higher line density near the origin, lower density away from the origin - suppression of higher spatial frequencies with  $1/|\nu|$ .
- 3 This results in a low-pass filtering (blurring) of the image.
- 4 Can be corrected with  $|\nu|$  filter.

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Discrete projection data (sinogram):

- We know  $\lambda_{m \cdot \Delta \phi}(n \cdot \Delta p)$  for  $n = -N, \dots, N$ , and  $m = 1, \dots, M$  with  $M = \pi / \Delta \phi$ .
- Assume that the sampling interval,  $\Delta p$ , satisfies the Nyquist sampling condition. This means, we assume that projection profiles in the Fourier domain,  $\Lambda_{\phi}(\nu)$ , are bandlimited within  $-\frac{1}{2\Delta p} < \nu < \frac{1}{2\Delta p}$ .
- Then the inverse transfer function  $H^{-1}(\nu) = |\nu|$  can be restricted to the same interval,  $\left[-\frac{1}{2\Delta p}, \frac{1}{2\Delta p}\right]$ .
- The modified function

$$H_r^{-1}(\nu) = \begin{cases} |\nu| & \text{for } |\nu| \leq \frac{1}{2\Delta p} \\ 0 & \text{otherwise} \end{cases}$$

is called **“ramp filter”**.

To determine the filter  $h_r^{-1}(p)$  in the **spatial domain** we have to do an inverse Fourier transform of  $H_r^{-1}(\nu)$  which yields:

$$\begin{aligned} h_r^{-1}(p) &= \mathfrak{F}_1^{-1} \{ H_r^{-1}(\nu) \} \\ &= \frac{1}{4\Delta p^2} \left( 2 \operatorname{sinc} \left( \frac{p}{\Delta p} \right) - \operatorname{sinc}^2 \left( \frac{p}{2\Delta p} \right) \right), \end{aligned}$$

where  $\operatorname{sinc}(x)$  stands for  $\sin(\pi x)/(\pi x)$ .

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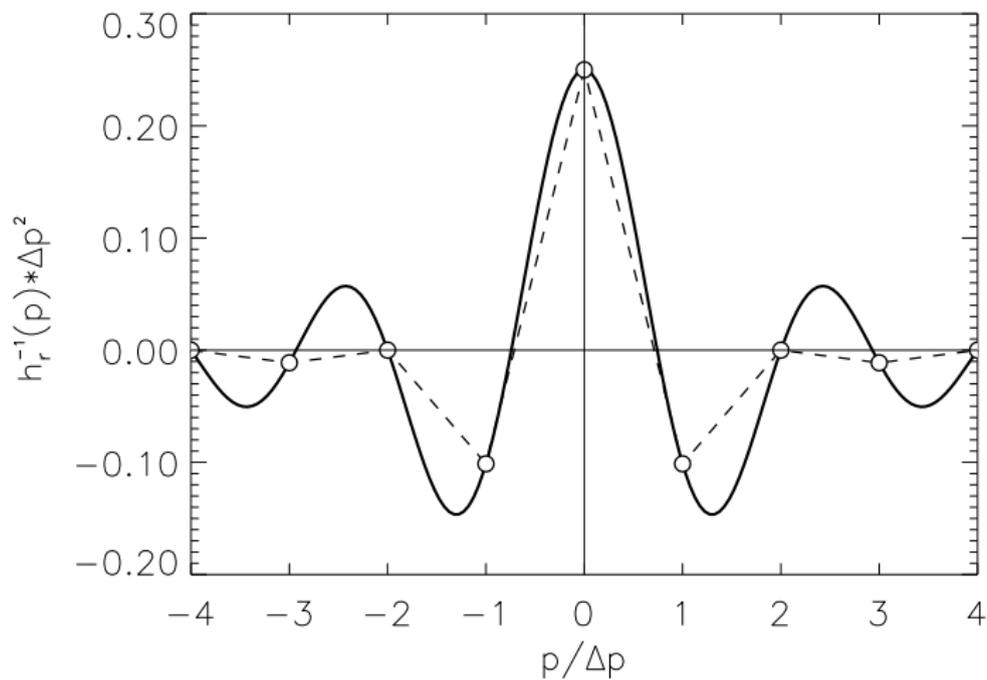
where  $\operatorname{sinc}(x)$  stands for  $\sin(\pi x)/(\pi x)$ .

A sampling at discrete positions  $p = n\Delta p$  yields the discrete version:

$$h_r^{-1}(n\Delta p) = \begin{cases} \frac{1}{4\Delta p^2} & \text{for } n = 0 \\ 0 & \text{for } n \text{ even, } \neq 0 \\ -\frac{1}{n^2\pi^2\Delta p^2} & \text{for } n \text{ odd.} \end{cases}$$

This filter goes back to Ramachandran and Lakshminarayanan. It is known as **“Ram-Lak”** filter.

## Ram-Lak filter



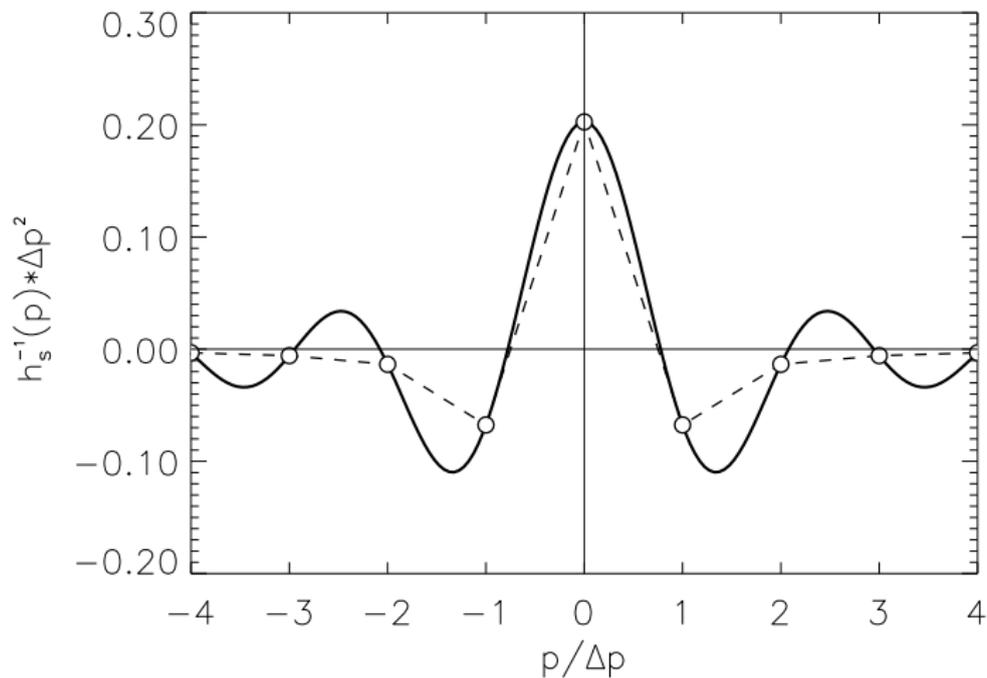
Another commonly used filter is the so-called “Shepp and Logan” filter, which results from averaging (smoothing) of the Ram-Lak filter over intervals of the width  $\Delta p$  (or in the frequency domain from the ramp filter  $|\nu|$  by multiplication with  $\text{sinc}(\nu\Delta p)$ ):

$$h_s^{-1}(p) = -\frac{2}{\pi^2\Delta p^2} \frac{1 - 2(p/\Delta p) \sin(\pi p/\Delta p)}{4(p/\Delta p)^2 - 1}.$$

The discrete version of this filter is very simple:

$$h_s^{-1}(n\Delta p) = -\frac{2}{\pi^2\Delta p^2(4n^2 - 1)}.$$

## Shepp-Logan filter



Simple backprojection

Filtered backprojection

# Homework

Homework 1: reconstruct yourself!

- a) Take a picture of yourself and convert it to a grayscale  $100 \times 100$  pixel square image.
- b) Create your sinogram space for 100 projection angles.
- c) Reconstruct your image by filtered backprojection using (i) the Ram-Lak filter, and (ii) the Shepp-Logan filter. Do the filtering in the **spatial domain** using filters  $h_r^{-1}$  (Ram-Lak) and  $h_s^{-1}$  (Shepp-Logan).

## Further Reading

- **A.C. Kak, M. Slaney:** *Principles of Computerized Tomographic Imaging*. Reprint: SIAM Classics in Applied Mathematics, 2001. PDF available: <http://www.slaney.org/pct/pct-toc.html>
- **F. Natterer:** *The Mathematics of Computerized Tomography*. Reprint: SIAM Classics in Applied Mathematics, 2001.
- **R.N. Bracewell:** *The Fourier Transform and its Applications*. McGraw-Hill, New York, 3rd edition, revised, 1999.
- **T. Bortfeld:** *Röntgencomputertomographie: Mathematische Grundlagen*. In: Schlegel W, Bille J, eds. *Medizinische Physik 2 (Medizinische Strahlenphysik)*. Heidelberg: Springer; 2002: 229-245. English translation available from author.
- **J. Radon:** *Über die Bestimmung von Funktionen durch ihre Integralwerte längs gewisser Mannigfaltigkeiten*. *Berichte der Sächsischen Akademie der Wissenschaften – Math.-Phys. Klasse*, 69:262–277, 1917.