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Advanced Topics in Sampling (049029)
Winter 2008/9

## Talk Outline

- Motivation
- Brief physical background
- Radon transform and the slice theorem
- Filtered back-projection
- Extensions
- Haar-based reconstructions
- Discretization with spline convolutions
- Discussion



### Motivation (1)

Primary use: in medical imaging



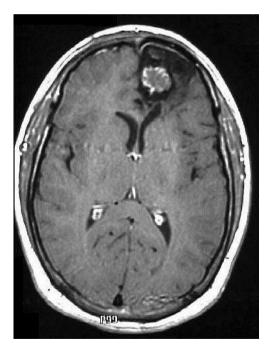
http://orthoinfo.aaos.org
(American Academy of Orthopaedic Surgeons)

## Motivation (2)

#### Computerized Tomography (CT)



http://www.southernhealth.org.au (Casey Hospital CT Department)



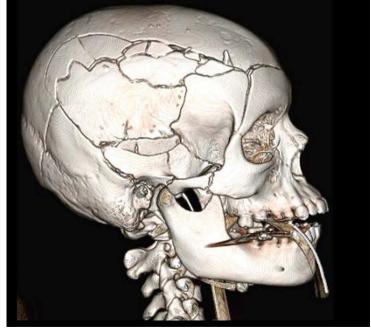
http://path.upmc.edu (University of Pittsburgh, School of Medicine, Department of Pathology)

### Motivation (3)

#### ■ 3D imaging, selective display



http://www.medscape.com (Medscape Today)



http://www.rsna.org
(Radiological Society of North America)

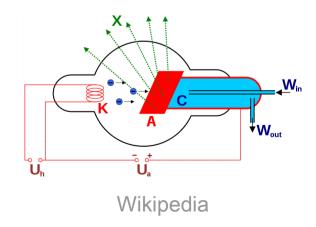


- [Bro66] J. G. Brown, X-rays and their applications, New York:
  Plenum Press, 1966
- [Kak88] A. C. Kak and M. Slaney, Principles of computerized tomographic imaging, New York: IEEE Press, 1988
- [Gué94] J. P. Guédon and Y. Bizais, Bandlimited and Haar filtered back-projection reconstructions, IEEE Trans. Med. Imaging, vol. 13, no. 3, pp. 340-440, 1994
- [Hor02] S. Horbelt, M. Leibling and M. Unser, Discretization of the Radon transform and of its inverse by spline convolutions, IEEE Trans. Med. Imaging, vol. 21, no. 4, pp. 363-376, 2002



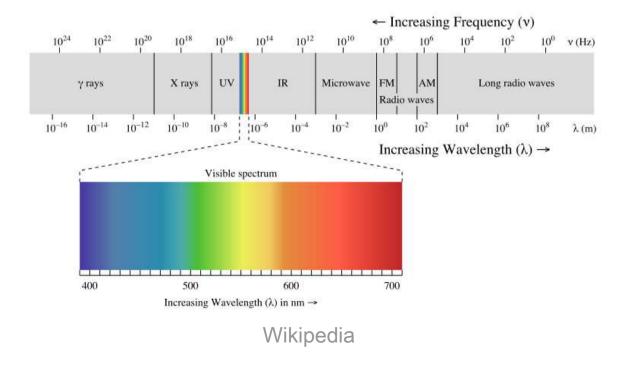
## Brief Physical Background (1)

- X-rays (Röntgen)
  - Cathode ray source
  - Accelerating voltage
  - Solid target → electromagnetic radiation





- X-rays (Röntgen)
  - Very energetic (wavelengths: 0.01-10 [nm])



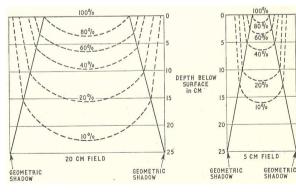


## Brief Physical Background (3)

- Interaction with matter
  - Narrow beam: linear absorption coefficient

$$dI = -\mu I dx \implies I(x) = I_0 e^{-\mu x}$$

Wide beam: no analytical expression



[Bro66]

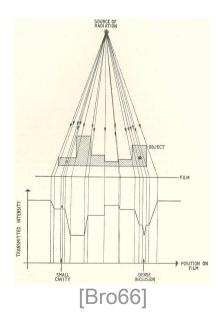


## Brief Physical Background (4)

- Interaction with matter
  - Serial connection of different substances

$$I(x) = I_0 e^{-\mu_1 x_1} e^{-\mu_2 x_2} \cdots e^{-\mu_N x_N} \xrightarrow{x_i \to 0} I_0 e^{-\int_0^x \mu(x') dx'}$$

■ Indication of density -  $\mu \propto \rho$ 

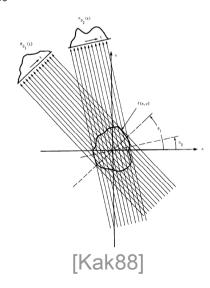




# Radon Transform and The Slice Theorem (1)

- Single beam:  $\ln(I_0/I_L) = \int_0^L \mu(s) ds$
- Radon transform (projection)  $(f(x,y) = \mu(x,y))$

$$P_{\theta}(t) \triangleq \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x \cos(\theta) + y \sin(\theta) - t) dx dy$$



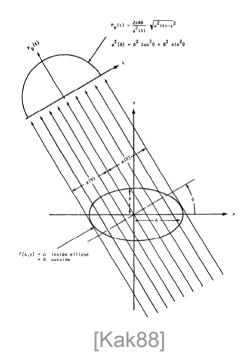
## Radon Transform and The Slice Theorem (2)

#### Analytical expression for simple ellipse

$$P_{\theta}(t) = \begin{cases} \frac{2\rho AB}{a^{2}(\theta)} \sqrt{(a^{2}(\theta) - t^{2})}, & |t| \leq a(\theta) \\ 0, & |t| > a(\theta) \end{cases}$$
$$a^{2}(\theta) = A^{2} \cos^{2}(\theta) + B^{2} \sin^{2}(\theta)$$

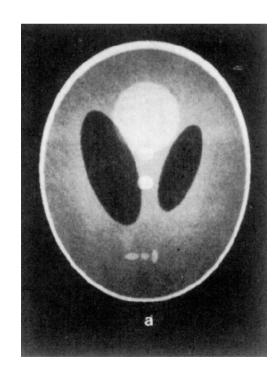
#### Translation + rotation

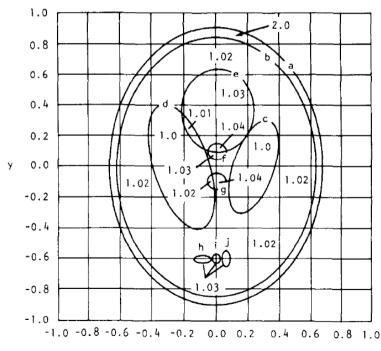
$$P_{\theta}'(t) = P_{\theta-\alpha} \left[ t - s \cos(\gamma - \theta) \right]$$
$$s = \sqrt{x_1^2 + y_1^2}, \quad \gamma = \arctan(y_1/x_1)$$



# Radon Transform and The Slice Theorem (3)

#### Shepp-Logan phantom





[Kak88]

# Radon Transform and The Slice Theorem (4)

Fourier transform of a section

$$F(u,v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y)e^{-j2\pi(ux+vy)}dxdy$$

Radon transform in frequency domain

$$\begin{bmatrix} t \\ s \end{bmatrix} = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

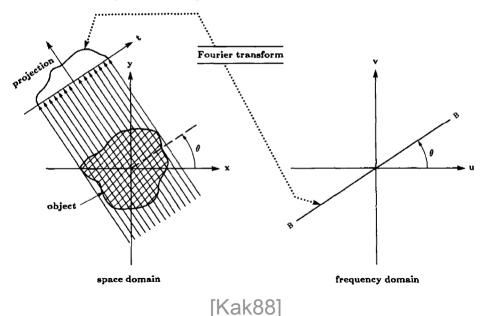
$$P_{\theta}(t) = \int_{-\infty}^{\infty} f(t,s)ds \implies S_{\theta}(w) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(t,s)e^{-j2\pi wt}dsdt$$

$$S_{\theta}(w) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-j2\pi w(x\cos(\theta) + y\sin(\theta))} dxdy = F(w\cos(\theta), w\sin(\theta))$$



#### The Slice Theorem:

The Fourier transform of a parallel projection of an image f(x,y) taken at angle  $\theta$  gives a slice of the two-dimensional transform, F(u,v), subtending at angle  $\theta$  with the u-axis.



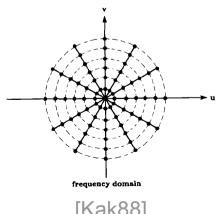
## Radon Transform and The Slice Theorem (6)

Naïve reconstruction of bounded image

$$-A/2 \le x, y \le A/2$$

$$f(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u,v)e^{j2\pi(ux+vy)}dudv = \frac{1}{A^2} \sum_{m} \sum_{n} F\left(\frac{m}{A},\frac{n}{A}\right)e^{j2\pi((m/A)x+(n/A)y)}$$

- Approximation:  $-N/2 \le m, n \le N/2$
- The catch:



[Kak88]



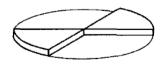
## Filtered Back-Projection (1)

- Reconstruction approaches:
  - Frequency domain interpolation \*
    - Reconstruction procedure awaits all projections
    - High sensitivity to interpolation error
  - Filtered back-projection
    - Almost real-time reconstruction
    - Low sensitivity to space domain interpolation error

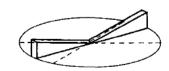


## Filtered Back-Projection (2)

- The concept
  - Each slice is obtained by convolving the image with a filter of line-shaped support
  - Desire: filter of sector-shaped support
  - Compromise: ramp filter of line-shaped support  $S_{\theta}(w) \rightarrow (2\pi |w|/K) S_{\theta}(w)$







## Filtered Back-Projection (3)

#### The mathematics

$$f(x,y) = \int_{-\infty-\infty}^{\infty} F(u,v)e^{j2\pi(ux+vy)}dudv = \int_{0}^{u=w\cos(\theta)} \int_{0}^{2\pi\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}wdwd\theta$$

$$= \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}wdwd\theta + \int_{0}^{\pi} \int_{0}^{\infty} F(w,\theta+\pi)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}wdwd\theta$$

$$= \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}wdwd\theta + \int_{0}^{\pi} \int_{0}^{\infty} F(w,\theta+\pi)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

$$= \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}wdwd\theta + \int_{0}^{\pi} \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

$$= \int_{0}^{\infty} \int_{-\infty}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}|w|dwd\theta + \int_{0}^{\pi} \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

$$= \int_{0}^{\infty} \int_{-\infty}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}|w|dwd\theta + \int_{0}^{\pi} \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

$$= \int_{0}^{\infty} \int_{-\infty}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}|w|dwd\theta + \int_{0}^{\infty} \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

$$= \int_{0}^{\infty} \int_{-\infty}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}|w|dwd\theta + \int_{0}^{\infty} \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

$$= \int_{0}^{\infty} \int_{-\infty}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}|w|dwd\theta + \int_{0}^{\infty} \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

$$= \int_{0}^{\infty} \int_{-\infty}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}|w|dwd\theta + \int_{0}^{\infty} \int_{0}^{\infty} F(w,\theta)e^{j2\pi w(x\cos(\theta)+y\sin(\theta))}(-w)dwd\theta$$

## Filtered Back-Projection (4)

#### Discrete formulation

- Sampling in space:  $P_{\theta}(kT)$ ,  $k = -(N/2), \dots, (N/2) 1$
- Fourier transform:  $S_{\theta}(w) \approx T \cdot \sum_{k=-N/2}^{N/2-1} P_{\theta}(kT) e^{-j2\pi(mk/N)}$
- Filtering:

$$Q_{\theta}(kT) \approx \left(\frac{1}{NT}\right) \sum_{m=-N/2}^{N/2} S_{\theta}\left(\frac{m}{NT}\right) \left|\frac{m}{NT}\right| e^{j2\pi(mk/N)}, \quad k = -\frac{N}{2}, \dots, \frac{N}{2}$$

$$\Rightarrow Q_{\theta}(kT) \approx \frac{1}{NT} P_{\theta}(kT) \otimes \phi(kT), \quad \phi(kT) = IDFT \left\{ \left|\frac{m}{NT}\right| H\left(\frac{m}{NT}\right) \right\}$$

■ Back-Projecting:  $f(x,y) \approx \frac{\pi}{K} \sum_{i=1}^{K} Q_{\theta_i} \left(x \cos(\theta_i) + y \sin(\theta_i)\right)$ 



## Filtered Back-Projection (5)

- Problem: Finite projection bandwidth + finite projection order = contradiction!
- Sources of artifacts:
  - Cyclic convolution instead of linear conv.
  - Frequency information deleted in the entire m=0 "cell" instead of w=0
- Optional solution: zero-padding



### Filtered Back-Projection (6)

#### Alternative computer implementation

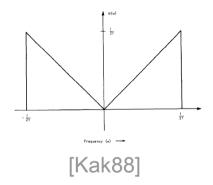
Finite bandwidth W:

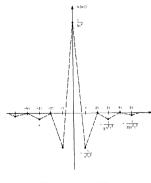
$$Q_{\theta}(t) = \int_{-\infty}^{\infty} S_{\theta}(w) H(w) e^{j2\pi wt} dw$$

$$H(w) = \begin{cases} |w| & |w| < W \\ 0 & otherwise \end{cases}$$

Sampled filter:

$$h(nT) = \begin{cases} (2T)^{-2} & n = 0 \\ 0 & n \text{ even} \\ -(\pi nT)^{-2} & n \text{ odd} \end{cases}$$





[Kak88]

### Filtered Back-Projection (7)

- Alternative computer implementation
  - Whittaker-Shannon interpolation formula

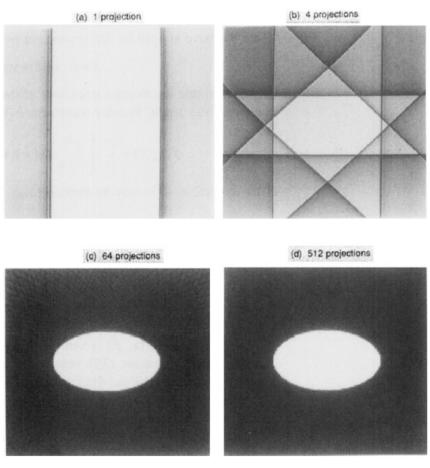
$$\underbrace{P_{\theta}(t)}_{or\ h(t)} = \sum_{k=-\infty}^{\infty} \underbrace{P_{\theta}(kT)}_{or\ h(kT)} \frac{\sin[2\pi W(t-kT)]}{2\pi W(t-kT)}$$

The convolution simplifies:

$$Q_{\theta}(nT) = T \sum_{k=-\infty}^{\infty} P_{\theta}(kT) h(nT - kT)$$

Filter of length 2N+1 suffices

## Filtered Back-Projection (8)

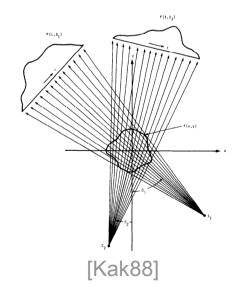


[Kak88]



### Extensions (1)

- Fan beam
  - Static point source at each angle
  - Simultaneous detection



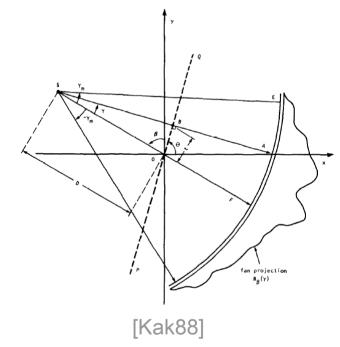


http://smugpuppies.com

### Extensions (2)

- Equiangular rays
  - The trick: handle each ray as part of parallel beam

$$R_{\beta}(\gamma) = P_{\beta+\gamma}(D\sin(\gamma))$$
$$(x, y) \to (r\cos(\phi), r\sin(\phi))$$



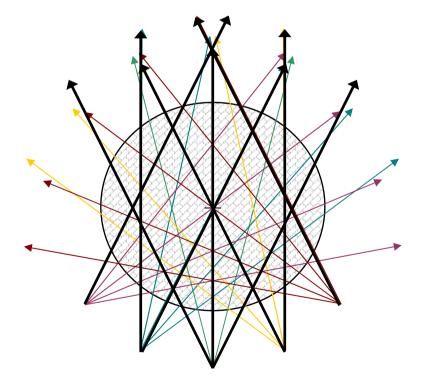
$$f(r,\phi) = \frac{1}{2} \int_{0}^{2\pi} \int_{-\gamma_{m}}^{\gamma_{m}} R_{\beta}(\gamma) h(r\cos(\beta + \gamma - \phi) - D\sin(\gamma)) D\cos(\gamma) d\gamma d\beta$$

Equispaced collinear detectors: similar trick



## Extensions (3)

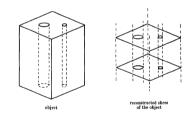
#### Demonstration





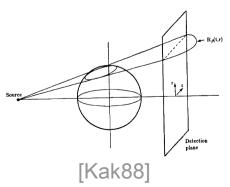
### Extensions (4)

- 3D reconstruction
  - Simple straight-forward method



[Kak88]

More efficient (time-saving) methods





#### Suggestions:





#### Haar-Based Reconstructions (1)

Inverse Radon transform – ill-posed

$$f(x,y) = \mathbf{R}^* \underbrace{\mathbf{K}}_{ramp} \underbrace{\mathbf{R}f(x,y)}_{transform}$$

$$k(t,\theta) = \lim_{\varepsilon \to 0} k_{\varepsilon}(t,\theta), \quad k_{\varepsilon}(t,\theta) = \begin{cases} \varepsilon^{2} & \text{if } |t| < \varepsilon \\ \frac{-1}{t^{2}} & \text{if } |t| \ge \varepsilon \end{cases}$$

Discretization after anti-aliasing filtering

$$\hat{f}(k,l) = b(x,y) **f(x,y)_{|x=k,y=l}$$

$$\Rightarrow \hat{f}(k,l) = \mathbf{R}^* \left( k_b(t,\theta) * p_f(t,\theta) \right)_{|x=k,y=l}, \quad k_b(t,\theta) = \mathbf{F}^{-1} \left\{ \pi |v| P_b(v,\theta) \right\}$$

#### Haar-Based Reconstructions (2)

Pixel Intensity Distribution Model (PIDM)

$$s_{0,\Delta}(z) = \begin{cases} 1, & \text{if } |z| < \frac{\Delta}{2} \\ \frac{1}{2}, & \text{if } |z| = \frac{\Delta}{2} \\ 0 & \text{if } |z| > \frac{\Delta}{2} \end{cases}$$

$$s_{0,\Delta}(x-k, y-l) = s_{0,\Delta}(x-k) \cdot s_{0,\Delta}(y-l), \quad \Delta = \text{pixel size}$$

■ Sampled function → continuum form

$$f_0(x,y) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f_0(k,l) s_{0,\Delta}(x-k,y-l)$$

#### Haar-Based Reconstructions (3)

In the space of piecewise constant functions, the optimal filter:  $b(x,y) = s_{0,\Delta}(x,y)$ 

$$f_0(k,l) = \mathbf{R}^* (Kw_0(t,\theta) * p_f(t,\theta))_{x=k,y=l}, \quad w_0(t,\theta) = \mathbf{R}(s_{0,\Delta}(x,y))$$

Sampling kernel projections (incorrect!)

$$W_{0}(t,\theta) = s_{0,\Delta\cos\theta}(t) * s_{0,\Delta\sin\theta}(t)$$

$$W_{0}(v,\theta) = \Delta^{2}\operatorname{sinc}(v\Delta\cos\theta)\operatorname{sinc}(v\Delta\sin\theta)$$

$$k_{0}(t,\theta\neq0) = \frac{1}{\pi\sin(2\theta)}\left(\ln\left|\frac{4t^{2} - \Delta^{2}(1+\sin(2\theta))}{4t^{2} - \Delta^{2}(1-\sin(2\theta))}\right|\right)$$
[Gué94]

• Oversampling is needed:  $\rho = \Delta/\tau > 1$ 

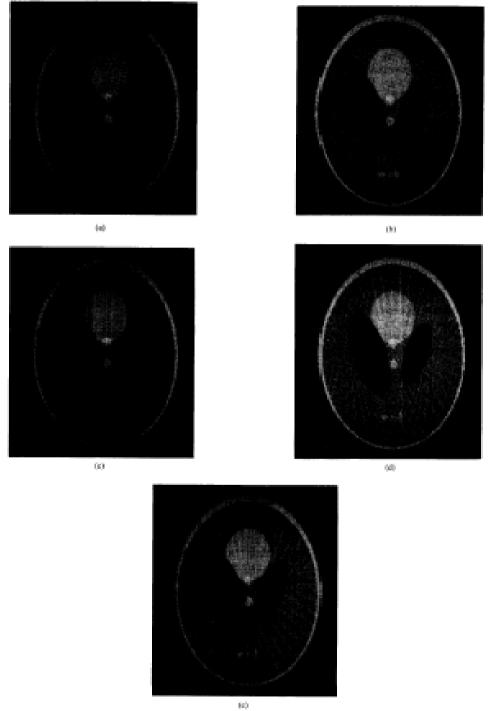
## Haar-Based Reconstructions (4)

#### Digital filter

- Sampling times:  $t = n\tau = \frac{n\Delta}{\rho}$
- Discretization through averaging

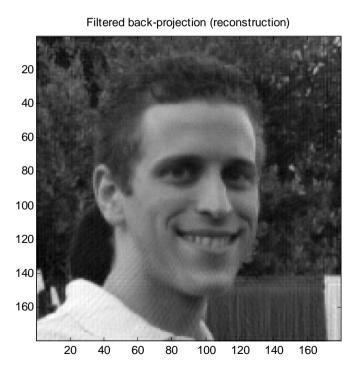
$$\begin{aligned} k_d \left( n\tau, \theta \right) &= \left( k_0 \left( t, \theta \right) * rect \left( t/\tau \right) \right)_{t=n\tau} = \int_{(n-1/2)\tau}^{(n+1/2)\tau} k_0 \left( u, \theta \right) du \\ k_d \left( n\tau, \theta \right) &= \frac{1}{\pi \sin(2\theta)} \left[ \left( t - \alpha \right) \ln \left| t - \alpha \right| + \left( t + \alpha \right) \ln \left| t + \alpha \right| - \left( t - \beta \right) \ln \left| t - \beta \right| + \left( t + \beta \right) \ln \left| t + \beta \right| \right]_{(n-1/2)\tau}^{(n-1/2)\tau} \\ \alpha &= \frac{\rho \tau}{2} \left( \cos \theta + \sin \theta \right), \quad \beta &= \frac{\rho \tau}{2} \left( \cos \theta - \sin \theta \right) \end{aligned}$$

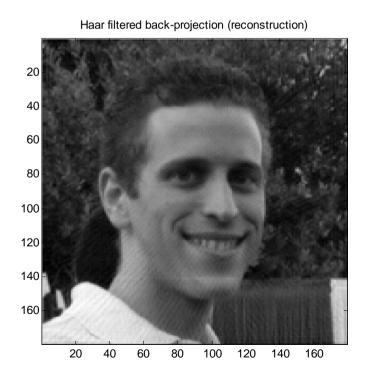
- Singular case:  $k_d(n\tau,0) = \frac{\Delta}{2\pi} \left( \ln \left| n^2 \left( \frac{1+\rho}{2} \right)^2 \right| \ln \left| n^2 \left( \frac{1-\rho}{2} \right)^2 \right| \right)$
- Is oversampling enough?



### Haar-Based Reconstructions (6)

#### Demonstration for the ignorant...





## Discretization with Spline Convolutions (1)

#### B-spline functions

$$\beta_h^0(x) = \begin{cases} \frac{1}{h}, & -\frac{h}{2} \le x < \frac{h}{2} \\ 0, & otherwise \end{cases}$$

$$\beta_h^n(x) = \beta_h^0(x) * \beta_h^{n-1}(x) = \underbrace{\beta_h^0(x) * ... * \beta_h^0(x)}_{n+1 \text{ times}} \qquad \beta_h^n = \Delta_h^{n+1} * \frac{x_+^n}{n!}$$

#### One-sided power function

$$x_{+}^{n} = \begin{cases} x^{n}, & x \ge 0 \\ 0, & otherwise \end{cases}$$
  $\frac{x_{+}^{n}}{n!} = x_{+}^{0} * ... * x_{+}^{0}$ 

#### Finite difference operator

$$\Delta_h^{n+1} = \sum_{k=0}^{n+1} \left(-1\right)^k \binom{n+1}{k} \frac{\delta\left(x+h\cdot\left(\frac{n+1}{2}-k\right)\right)}{h^{n+1}} \qquad \Delta_h^{n+1} = \overline{\Delta_h^1*\dots*\Delta_h^1}$$

$$\Delta_h^{n+1} = \overbrace{\Delta_h^1 * ... * \Delta_h^1}^{n+1 \ times}$$

# Discretization with Spline Convolutions (2)

#### B-spline convolution kernels

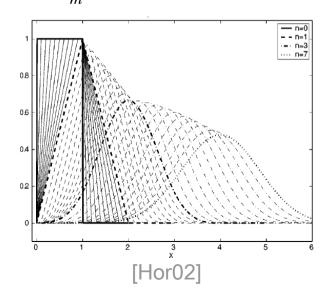
Spline m-kernel

$$\beta_{h_1,\dots,h_m}^{n_1,\dots,n_m}(x) = \beta_{h_1}^{n_1} * \dots * \beta_{h_m}^{n_m}(x) = \Delta_{h_1,\dots,h_m}^{n_1+1,\dots,n_m+1} * \frac{x_+^{N_m}}{N_m!}, \quad N_m = m-1 + \sum_{i=1}^m n_i$$

Spline bikernel

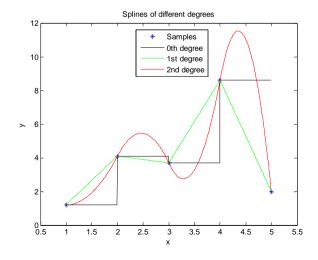
$$\beta_{h_1,h_2}^{n_1,n_2}(x) = \Delta_{h_1,h_2}^{n_1+1,n_2+1} * \frac{x_+^{n_1+n_2+1}}{(n_1+n_2+1)!} = \dots$$

Fig. 1. Spline bikernels by convolution of two causal B-splines  $\beta_1^n * \beta_h^n(x)$  with  $n = \{0, 1, 3\}$  and  $h \in [0.1]$ . The kernels generate a smooth transition between B-splines of degree n and degree 2n + 1. For h = 0 and h = 1, the kernels are B-splines, as  $\lim_{h\to 0} \beta_1^n * \beta_h^n(x) = \beta_1^n(x)$  and  $\beta_1^n * \beta_1^n(x) = \beta_1^{2n+1}(x)$ .





- Polynomial splines
  - Alternative to Shannon's sampling theorem
  - Spline: Smooth Piecewise-Polynomial Line



# Discretization with Spline Convolutions (4)

Representation in B-spline basis

$$f_h(x) = \sum_{k \in \mathbb{Z}} c_k \beta_h^n (x - hk)$$

- Interpolation approach
- Least squares approximation
  - Optimal coefficients:  $c_k = h \cdot \langle f(x), \tilde{\varphi}_h(x hk) \rangle$  $\langle \varphi(x), \tilde{\varphi}(x - k) \rangle = \delta_k$
  - Basis functions and their dual functions can be interchanged

# Discretization with Spline Convolutions (5)

#### Spline-based Radon transform

$$f_h(\vec{x}) = \sum_{k,l \in \mathbb{Z}} c_{k,l} \beta_h^{n_1} \left( \vec{x} - h\vec{k} \right)$$

- Linearity:  $R_{\theta}\beta_h^n(t) = \beta_{h|\cos\theta|}^n * \beta_{h|\sin\theta|}^n(t) = \beta_{h|\cos\theta|,h|\sin\theta|}^{n,n}(t)$
- Shift-invariance:  $R_{\theta} \{ \varphi(\vec{x} \vec{x}_0) \} = (R_{\theta} \varphi)(t t_0), \quad t_0 = \vec{x}_0^T \cdot \vec{\theta}$   $g_{\theta}(t) = \sum_{k,l \in \mathbb{Z}} c_{k,l} \beta_{h|\cos\theta|,h|\sin\theta|}^{n_1,n_1} \left( t h\vec{k}^T \vec{\theta} \right)$

#### Sinogram discretization with dual splines

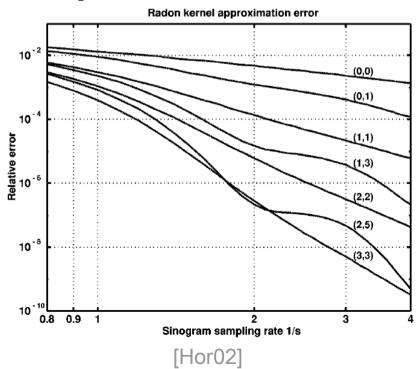
$$g_{\theta,s}(t) = P_s g_{\theta}(t) = \sum_{i \in \mathbb{Z}} \overline{s \left\langle g_{\theta}(t), \beta_s^{n_2}(t - is) \right\rangle} \cdot \widetilde{\beta}_s^{n_2}(t - is)$$

$$\widetilde{e}_{i,\theta} = \sum_{k,l \in \mathbb{Z}} d_{i,\theta,k,l} \cdot c_{k,l} \cdot s, \qquad d_{i,\theta,k,l} = \beta_{h|\cos\theta|,h|\sin\theta|,s}^{n_1,n_1,n_2}(h\vec{k}^T \vec{\theta} - is)$$

# Discretization with Spline Convolutions (6)

#### Error analysis

$$e^{2}(s) = ||f - f_{s}||_{L_{2}}^{2}$$



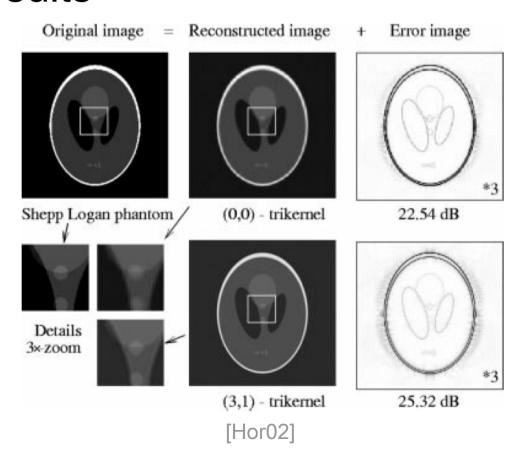
# Discretization with Spline Convolutions (7)

- Spline-based back-projection
  - Filtering:  $\hat{p}_{\theta}(\omega) = \hat{g}_{\theta}(\omega) \cdot \hat{q}(\omega)$
  - **Discretization:**  $p_{\theta,s}(t) = \sum_{i \in \mathbb{Z}} c_{\theta,i} \cdot \beta_s^{n_2}(t-is)$
  - Back-projecting to dual splines space

$$\tilde{f}_h(\vec{x}) = \sum_{k,l \in \mathbb{Z}} \tilde{c}_{k,l} \cdot \tilde{\beta}_h^{n_1}(\vec{x} - h\vec{k}), \qquad \tilde{c}_{k,l} = \sum_{i \in \mathbb{Z}, \theta} c_{\theta,i} \cdot h^2 \cdot d_{i,\theta,k,l}$$

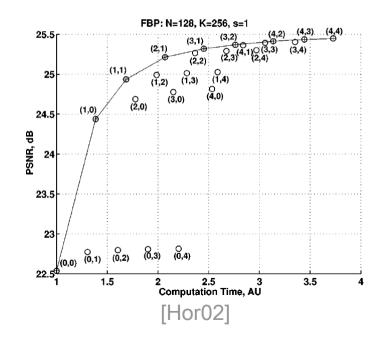
# Discretization with Spline Convolutions (8)

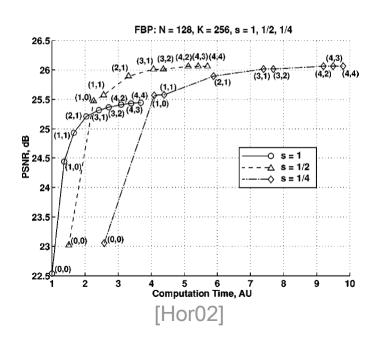
#### Results



# Discretization with Spline Convolutions (9)

- Complexity considerations
  - Run time:  $t \propto N_x \cdot N_y \cdot K \cdot \frac{1}{s} \cdot \left( \overline{\operatorname{supp}} \left( \beta_{h|\cos\theta|,h|\sin\theta|,s}^{n_1,n_1,n_2} \right) + c \right)$







- What we had:
  - Physical method for acquiring projections
  - Derivation of filtering requirements
  - Efficient basic reconstruction algorithm
  - Suggested methods for improvement
    - Pixel shape taken into account
    - Smooth-basis representation replaces sampling

### The End

