

Medical Image Reconstruction Term II – 2012

Topic 6: Tomography

Professor Yasser Mostafa Kadah

Tomography

- The Greek word "tomos" means a section, a slice, or a cut.
- Tomography is the process of imaging a cross section
- Particularly useful in medical imaging
 - Nobody wants to be cut open to see what is inside!



Example

Can you compute the locations of the trees from 2 images?
Answer:Yes



Example

Can you compute the values of this matrix given its projections?

 x_1

X3

xo

XA

Answer:Yes



Projection

Also termed ray sum, line integral, or Radon transform



Sinogram

Displays angle dependence of projections

• Example: point source on the y-axis to further illustrate the angle θ dependency of the projection $p(s, \theta)$



Projection of Discrete Object

Projections are weighted by the line-length within each pixel



 $p(i,\theta) = a_{i1}x_1 + a_{i2}x_2 + a_{i3}x_3 + a_{i4}x_4, \qquad i = 1, 2, 3, 4.$

Image Reconstruction of a Point Source

- In image reconstruction, we not only need to find the location but also the intensity value of the object of interest
- Backprojection (a) Project a point source (b) Backproject from one view Intensity $p(s,\theta)$

(c) Backproject from a few views

(d) Backproject from all views

Backprojection Example

Blurred version of original

Backprojection

5

$b_1 = 5 + 7 = 12$	<i>b</i> ₂ = 5 + 2 = 7
$b_3 = 4 + 7 = 11$	$b_4 = 4 + 2 = 6$

Projection

D



Backprojection in Algebraic Form

Projection P

$$P = AX, X = [x_1, x_2, x_3, x_4]^{\mathrm{T}}$$

$$A = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}$$

$$x_{1+3} = \begin{bmatrix} x_{1+1}, x_{2+1}, x_{3+1}, x_{4+1} \end{bmatrix}$$

7 2 * *

 $P = [p(1,0^{\circ}), p(2,0^{\circ}), p(1,270^{\circ}), p(2,270^{\circ})]^{\mathrm{T}} = [7,2,5,4]^{\mathrm{T}}.$

Backprojection: use adjoint operator A^T

$$B = A^{\mathrm{T}}P = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} 7 \\ 2 \\ 5 \\ 4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 7 \\ 2 \\ 5 \\ 4 \end{bmatrix} = \begin{bmatrix} 12 \\ 7 \\ 11 \\ 6 \end{bmatrix}$$

Radon Transform Detector Computes parallel projections at specific angles $f(x,y) \rightarrow p(s,\theta)$ $p(s,\theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y)\delta(x\cos\theta + y\sin\theta - s)dxdy,$ $p(s,\theta) = \int_{-\infty}^{\infty} f(s\cos\theta - t\sin\theta, s\sin\theta + t\cos\theta) dt,$ $\mathscr{R}f(t,\theta) := \int f \, ds = \int_{s=-\infty}^{\infty} f(t\cos(\theta) - s\sin(\theta), t\sin(\theta) + s\cos(\theta)) \, ds.$

Inverse Radon Transform

Parallel Beam Backprojection

$$p(s,\theta) \rightarrow f(x,y)$$

$$b(x,y) = \int_0^{\pi} p(s,\theta) \Big|_{s=x\cos\theta + y\sin\theta} \mathrm{d}\theta,$$

$$b(x,y) = \int_0^{\pi} p(\boldsymbol{x} \cdot \boldsymbol{\theta}, \theta) \mathrm{d}\theta,$$



Backprojection in Frequency Domain

Each view adds a line in the Fourier space

Central area in k-space has higher sample density and results in effective lowpass filtered spectrum



Filtered Backprojection

To counter this blurring effect, we must compensate for the non-uniformity in the Fourier space

 $\omega_{x}^{2} + \omega_{x}^{2}$

 $|\omega|$

Ramp Filter

- Density in the Fourier space is proportional to:
- Solution: multiply k-space by ramp filter,
 - Method I: Filter individual projections
 - Method 2: Filter whole Image
- Practical Realization



Hilbert Transform Based Formulation

$$\mathscr{F}\left(\frac{df}{dx}\right)(\boldsymbol{\omega}) = i\boldsymbol{\omega}\mathscr{F}(f)(\boldsymbol{\omega}). \implies \mathscr{F}\left(\frac{\partial(\mathscr{R}f)(t,\boldsymbol{\theta})}{\partial t}\right)(S,\boldsymbol{\theta}) = iS\mathscr{F}(\mathscr{R}f)(S,\boldsymbol{\theta}).$$

 $|\mathbf{S}| = \mathbf{S} \cdot \operatorname{sgn}(\mathbf{S})$

$$\begin{split} |S| &= S \cdot \operatorname{sgn}(S) \\ i \cdot \operatorname{sgn}(S) \cdot \mathscr{F}\left(\frac{\partial (\mathscr{R}f)(t,\theta)}{\partial t}\right)(S,\theta) = -|S| \mathscr{F}(\mathscr{R}f)(S,\theta). \\ & \\ f(x,y) &= \frac{-1}{2} \mathscr{B}\left\{\mathscr{F}^{-1}\left[i \cdot \operatorname{sgn}(S) \cdot \mathscr{F}\left(\frac{\partial (\mathscr{R}f)(t,\theta)}{\partial t}\right)(S,\theta)\right]\right\}(x,y). \end{split}$$

Define Hilbert Transform as: $\mathscr{H}g(t) = \mathscr{F}^{-1}[i \cdot \operatorname{sgn}(\omega) \cdot \mathscr{F}g(\omega)](t).$

$$f(x,y) = \frac{-1}{2} \mathscr{B}\left[\mathscr{H}\left(\frac{\partial(\mathscr{R}f)(t,\theta)}{\partial t}\right)(S,\theta)\right](x,y).$$

Parallel Beam Reconstruction Methods

Method	Step 1	Step 2	Step 3
1	1D Ramp filter with Fourier transform	Backprojection	
2	1D Ramp filter with convolution	Backprojection	
4	Backprojection	2D Ramp filter with Fourier transform	
	Backprojection 2D Ramp filter with convolution	2D Ramp filter with 2D convolution	
3	Derivative	Hilbert transform	Backprojection
5	Derivative	Backprojection	Hilbert transform
	Backprojection	Derivative	Hilbert transform
	Hilbert transform Hilbert transform	Derivative	Backprojection
		Backprojection	Derivative
	Backprojection	Hilbert transform	Derivative

Fan Beam Reconstruction Problem

- Almost all present CT systems use fan beam rather than parallel beam projections
 - Much more efficient: faster acquisition, lower patient dose



(a) Parallel Beam

(b) Fan Beam

Fan Beam Reconstruction Problem

• rebin every fan-beam ray into a parallel-beam ray. For each fan-beam ray-sum $g(\gamma, \beta)$, we can find a parallel beam ray-sum $p(s, \theta)$ that has same orientation as the fan-beam ray with the relations,

$$\theta = \gamma + \beta, \quad s = D \sin \gamma, \quad \Longrightarrow \quad p(s, \theta) = g(\gamma, \beta).$$
Projection Ray $p(s, \theta) = g(\gamma, \beta)$

$$p(s, \theta) = g(\gamma, \beta)$$



Algebraic Reconstruction Technique

10.00

$$p_{3}$$

$$p_{4}$$

$$p_{7}$$

$$x_{1}$$

$$x_{2}$$

$$x_{3}$$

$$x_{4}$$

$$x_{2}$$

$$x_{5}$$

$$x_{4}$$

$$x_{5}$$

$$x_{6}$$

$$p_{2}$$

$$x_{7}$$

$$x_{8}$$

$$x_{9}$$

$$p_{3}$$

$$x_{1}$$

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 $AX = P, \qquad X = A^+P = V\Sigma^+U^{\mathrm{T}}P.$

 $\begin{bmatrix} \boldsymbol{x}^{next} \\ = \boldsymbol{x}^{current} - Backproject_{ray} \left\{ \frac{Project_{ray}(\boldsymbol{x}^{current}) - Measurement_{ray}}{Normalization \ Factor} \right\}.$

Other Algebraic Methods

Gradient descent

$$\boldsymbol{x}^{next} = \boldsymbol{x}^{current} - a_{current} \boldsymbol{\Delta}(\boldsymbol{x}^{current}),$$

Maximum-Likelihood Expectation-Maximization

$$\boldsymbol{x}^{next} = \boldsymbol{x}^{current} \frac{Backproject \ \left\{ \frac{Measurement}{Project \ (\boldsymbol{x}^{current})} \right\}}{Backproject \ \{\mathbf{1}\}}$$

Advanced Tomography Problems

Reconstruction from incomplete data

- Truncated projections
- Limited-angle projections
- Exterior data
- ROI reconstruction
- Extension to 3D
- Stability of reconstruction





Matlab Functions

- Look up the help for the following function:
 - radon
 - iradon
 - ▶ fan2para
 - fanbeam
 - ifanbeam
 - para2fan
 - phantom

D

Exercise

- PI. For a medical image of your choice:
 - A. Generate the Radon transform and display its sinogram
 - B. Reconstruct the image back from its projections
 - C. Compare the two images and record the error for different numbers of projections and provide your comments.
- P2. Repeat the above problem P1 for a fan beam system (rather than the parallel beam system in P1). Also, compare the parallel beams obtained from rebinning the fan rays and comment on what you found.
- P3. Compare different filtering strategies and provide your choice of the best methodology based on an experimental study. (study filter type and support, ID vs. 2D implementation, etc.)
- P4. Compare the parallel beam projections obtained from a Shepp-Logan phantom to the ones you generate using the analytical Shepp-Logan phantom and comment on the results.
- P5. Do a literature review on ONE advanced tomography problem and come up with a 1 page summary of the state of the art and a comprehensive list of references.