### Introduction to X-ray tomography

Vesa Kaarnioja

LUT School of Engineering Science

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The content of this lecture follows roughly the material presented in the following monographs.

- J. Kaipio and E. Somersalo. Statistical and Computational Inverse Problems. 2005.
- J. L. Mueller and S. Siltanen. Linear and Nonlinear Inverse Problems with Practical Applications. 2012.

ASTRA Toolbox for 2D and 3D tomography: https://www.astra-toolbox.com/













# Radon transform in $\mathbb{R}^2$

Let *L* be a straight line in  $\mathbb{R}^2$ .

Any line in  $\mathbb{R}^2$  can be parameterized as

$$L = \{ s\omega + t\omega^{\perp}; t \in \mathbb{R} \}$$
 for some  $s \in \mathbb{R}$  and  $\omega \in S^1$ ,

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Writing 
$$\omega = \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}$$
, we get  
 $L = L(s, \theta) = \left\{ s \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix} + t \begin{bmatrix} \sin \theta \\ -\cos \theta \end{bmatrix}; \ t \in \mathbb{R} \right\}, \quad s \in \mathbb{R} \text{ and } \theta \in [0, \pi).$ 

The Radon transform of a continuous function  $f: \mathbb{R}^2 \to \mathbb{R}$  on L is defined as

$$\mathcal{R}f(L) = \int_{L} f(\mathbf{x}) |\mathrm{d}\mathbf{x}| = \int_{-\infty}^{\infty} f(s\cos\theta + t\sin\theta, s\sin\theta - t\cos\theta) \,\mathrm{d}t.$$

Let f be a nonnegative function modeling X-ray attenuation (density) inside a physical body.



Beer-Lambert law:

$$\mathcal{R}f(L) = \log \frac{I_0}{I_1}.$$

$f_{10,1}$	$f_{10,2}$	$f_{10,3}$	$f_{10,4}$	$f_{10,5}$	$f_{10,6}$	$f_{10,7}$	$f_{10,8}$	$f_{10,9}$	$f_{10,10}$
$f_{9,1}$	$f_{9,2}$	$f_{9,3}$	$f_{9,4}$	$f_{9,5}$	$f_{9,6}$	$f_{9,7}$	$f_{9,8}$	$f_{9,9}$	$f_{9,10}$
$f_{8,1}$	$f_{8,2}$	$f_{8,3}$	$f_{8,4}$	$f_{8,5}$	$f_{8,6}$	$f_{8,7}$	$f_{8,8}$	$f_{8,9}$	$f_{8,10}$
$f_{7,1}$	$f_{7,2}$	$f_{7,3}$	$f_{7,4}$	$f_{7,5}$	$f_{7,6}$	$f_{7,7}$	$f_{7,8}$	$f_{7,9}$	$f_{7,10}$
$f_{6,1}$	$f_{6,2}$	$f_{6,3}$	$f_{6,4}$	$f_{6,5}$	$f_{6,6}$	$f_{6,7}$	$f_{6,8}$	$f_{6,9}$	$f_{6,10}$
$f_{5,1}$	$f_{5,2}$	$f_{5,3}$	$f_{5,4}$	$f_{5,5}$	$f_{5,6}$	$f_{5,7}$	$f_{5,8}$	$f_{5,9}$	$f_{5,10}$
$f_{4,1}$	$f_{4,2}$	$f_{4,3}$	$f_{4,4}$	$f_{4,5}$	$f_{4,6}$	$f_{4,7}$	$f_{4,8}$	$f_{4,9}$	$f_{4,10}$
$f_{3,1}$	$f_{3,2}$	$f_{3,3}$	$f_{3,4}$	$f_{3,5}$	$f_{3,6}$	$f_{3,7}$	$f_{3,8}$	$f_{3,9}$	$f_{3,10}$
$f_{2,1}$	$f_{2,2}$	$f_{2,3}$	$f_{2,4}$	$f_{2,5}$	$f_{2,6}$	$f_{2,7}$	$f_{2,8}$	$f_{2,9}$	$f_{2,10}$
$f_{1,1}$	$f_{1,2}$	$f_{1,3}$	$f_{1,4}$	$f_{1,5}$	$f_{1,6}$	$f_{1,7}$	$f_{1,8}$	$f_{1,9}$	$f_{1,10}$

Let us consider the computational domain  $[-1, 1]^2$ . We divide this region into  $n \times n$  pixels and approximate the density by a piecewise constant function with constant value

$$f_{i,j}$$
 in pixel  $P_{i,j}$ 

for  $i, j \in \{1, ..., n\}$ .

 $P_{i,j} := \{(x,y); \ -1 + 2\frac{j-1}{n} < x < -1 + 2\frac{j}{n}, \ -1 + 2\frac{j-1}{n} < y < -1 + 2\frac{j}{n}\}$ 

$x_{91}$	$x_{92}$	$x_{93}$	$x_{94}$	$x_{95}$	$x_{96}$	<i>x</i> <sub>97</sub>	<i>x</i> <sub>98</sub>	<i>x</i> <sub>99</sub>	$x_{100}$
$x_{81}$	$x_{82}$	<i>x</i> <sub>83</sub>	$x_{84}$	$x_{85}$	$x_{86}$	<i>x</i> <sub>87</sub>	<i>x</i> <sub>88</sub>	<i>x</i> <sub>89</sub>	$x_{90}$
$x_{71}$	$x_{72}$	<i>x</i> <sub>73</sub>	$x_{74}$	$x_{75}$	$x_{76}$	<i>x</i> <sub>77</sub>	<i>x</i> <sub>78</sub>	<i>x</i> <sub>79</sub>	$x_{80}$
$x_{61}$	$x_{62}$	$x_{63}$	$x_{64}$	$x_{65}$	$x_{66}$	$x_{67}$	$x_{68}$	$x_{69}$	<i>x</i> <sub>70</sub>
$x_{51}$	$x_{52}$	$x_{53}$	$x_{54}$	$x_{55}$	$x_{56}$	$x_{57}$	$x_{58}$	$x_{59}$	$x_{60}$
$x_{41}$	$x_{42}$	$x_{43}$	$x_{44}$	$x_{45}$	$x_{46}$	$x_{47}$	$x_{48}$	$x_{49}$	$x_{50}$
$x_{31}$	$x_{32}$	$x_{33}$	$x_{34}$	$x_{35}$	$x_{36}$	$x_{37}$	$x_{38}$	$x_{39}$	$x_{40}$
$x_{21}$	$x_{22}$	$x_{23}$	$x_{24}$	$x_{25}$	$x_{26}$	$x_{27}$	$x_{28}$	$x_{29}$	$x_{30}$
$x_{11}$	$x_{12}$	$x_{13}$	$x_{14}$	$x_{15}$	$x_{16}$	$x_{17}$	$x_{18}$	$x_{19}$	$x_{20}$
$x_1$	$x_2$	$x_3$	$\overline{x_4}$	$x_5$	$x_6$	$x_7$	$x_8$	$x_9$	$x_{10}$

It is convenient to reshape the matrix/image  $(f_{i,j})$  into a vector x of length  $n^2$  so that

$$x_{(j-1)n+i} = f_{i,j}, \quad i,j \in \{1,\ldots,n\}.$$

The image on the left illustrates the new numbering corresponding to the pixels.

Note that x = f(:) and f = reshape(x,n,n).

#### Measurement model

Let us consider a measurement setup where we take X-ray measurements of an object using X-rays  $L(s_1, \theta), \ldots, L(s_K, \theta)$  taken at angles  $\theta \in \{\theta_1, \ldots, \theta_M\}$ . The total number of X-rays is Q = MK.

For brevity, let us write  $L_{(m-1)K+k} := L(s_k, \theta_m)$  for  $k \in \{1, \dots, K\}$  and  $m \in \{1, \dots, M\}$ .

The measurement model is

$$y = \begin{bmatrix} \int_{L_1} f(\mathbf{x}) |\mathrm{d}\mathbf{x}| \\ \vdots \\ \int_{L_Q} f(\mathbf{x}) |\mathrm{d}\mathbf{x}| \end{bmatrix} + \varepsilon \approx \begin{bmatrix} \sum_{j=1}^{n^2} A_{1,j} x_j \\ \vdots \\ \sum_{j=1}^{n^2} A_{Q,j} x_j \end{bmatrix} + \varepsilon = Ax + \varepsilon,$$

where  $A \in \mathbb{R}^{Q \times n^2}$  and  $A_{i,j}$  is the distance that ray  $L_i$  travels through pixel j. Here, x is a vector containing the (piecewise constant) densities within each pixel and  $\varepsilon$  is measurement noise.

$$L_{(m-1)K+k} = \left\{ s_k \begin{bmatrix} \cos \theta_m \\ \sin \theta_m \end{bmatrix} + t \begin{bmatrix} \sin \theta_m \\ -\cos \theta_m \end{bmatrix}; \ t \in \mathbb{R} \right\}, \quad \substack{k = 1, \dots, K, \\ m = 1, \dots, M.}$$

$$\theta = 0, \qquad \theta = 0.349066 \qquad \theta = 0.698132$$

$$\theta = 1.0472 \qquad \theta = 1.39626 \qquad \theta = 1.74533$$

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$$\theta = 2.0944 \qquad \theta = 2.44346 \qquad \theta = 2.79253$$

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Pixel-by-pixel construction of the tomography matrix A



$$A_{m,k} = \int_{L_m} \chi_k \left| \mathrm{d} \mathbf{x} \right| = \int_{\substack{x_\mathrm{d} < t \le x_\mathrm{u} \\ y_\mathrm{d} \le \mathbf{s} < y_\mathrm{u}}} \mathrm{d} t = \begin{cases} x_\mathrm{u} - x_\mathrm{d} & \text{if } y_\mathrm{d} \le \mathbf{s} < y_\mathrm{u}, \\ 0 & \text{otherwise.} \end{cases}$$

N.B. In here and in the following,  $\chi_k = \chi_k(\mathbf{x})$  denotes the characteristic function of the  $k^{\text{th}}$  pixel. In the above illustration, the pixel is denoted by the rectangle  $[x_d, x_u) \times [y_d, y_u)$ .



$$A_{m,k} = \int_{L_m} \chi_k \left| \mathrm{d} \mathbf{x} \right| = \int_{\substack{-y_u < t \le -y_d \\ x_d < \mathbf{s} \le x_u}} \mathrm{d} t = \begin{cases} y_u - y_d & \text{if } x_d < \mathbf{s} \le x_u, \\ 0 & \text{otherwise.} \end{cases}$$





# Discussion

Tomography problems can be classified into three brackets based on the nature of the measurement data:

- Full angle tomography
  - Sufficient number of measurements from all angles  $\rightarrow$  not a very ill-posed problem.
- Limited angle tomography
  - Data collected from a restricted angle of view  $\rightarrow$  reconstructions very sensitive to measurement error and it is not possible to reconstruct the object perfectly (even with noiseless data). Applications include, e.g., dental imaging.
- Sparse data tomography
  - The data consist of only a few projection images, possibly from any direction  $\rightarrow$  extremely ill-posed inverse problem and prior knowledge necessary for successful reconstructions. (E.g., minimizing a patient's radiation dose.)