# Microlocal Methods in X-ray Tomography

#### Plamen Stefanov

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Lecture I: Euclidean X-ray tomography

Mini Course, Fields Institute, 2012



- Sigurdur Helgason, Radon Transform
- Frank Natterer, The Mathematics of Computerized Tomography
- Microlocal Approach to Tensor Tomography and Boundary and Lens Rigidity, Serdica Math. J., 34(1)(2008), 67-112.

# X-ray transform

X-ray transform of a function f in  $\mathbf{R}^n$ :

$$Xf(\ell) = \int_{\ell} f \,\mathrm{d}s$$
 (1)

along any given (undirected) line  $\ell$  in  $\mathbb{R}^n$ . Here ds is the unit length measure on  $\ell$ . Lines in  $\mathbb{R}^n$  can be parameterized by initial points  $x \in \mathbb{R}^n$  and directions  $\theta \in S^{n-1}$ , thus we can write, without changing the notation,

$$Xf(x,\theta) = \int_{\mathbf{R}} f(x+s\theta) \,\mathrm{d}s, \quad (x,\theta) \in \mathbf{R}^n \times S^{n-1}.$$
 (2)

That parameterization is not unique because for any x,  $\theta$ , t,

$$Xf(x,\theta) = Xf(x+t\theta,\theta), \quad Xf(x,\theta) = Xf(x,-\theta).$$
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The latter identity reflects the fact that we consider the lines as undirected ones.

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# Motivation

Motivating example: X-ray medical imaging. An X-ray point source is placed at different points around patient's body, and the intensity I of the rays is measured after the rays go through the body. The intensity depends on the position x and the direction  $\theta$  of the rays. It solves the transport equation

$$(\theta \cdot \nabla_x + \sigma(x)) I(x, \theta) = 0, \qquad (4)$$

where  $\sigma$  is the absorption of the body. Equation (4) simply says that the directional derivative of I in the direction  $\theta$  equals  $-\sigma I$ . A natural initial/boundary condition is to require that

$$\lim_{s\to-\infty}I(x+s\theta,\theta)=I_0,$$

where  $I_0$  is the source intensity, that may depend on the line. Since f is of compact support in this case, the limit above is trivial. Then (4) has the explicit solution

$$I(x,\theta) = e^{-\int_{-\infty}^{0} \sigma(x+s\theta,\theta) \,\mathrm{d}s} I_0.$$

The measurement outside patent's body is modeled by

$$\lim_{s\to\infty}I(x+s\theta,\theta)=:I_1,$$

and this limit is trivial as well. Since both  $I_1$  and  $I_0$  are known, we may form the quantity

$$-\log(I_1/I_0) = \int_{-\infty}^{\infty} \sigma(x + s\theta, \theta) \, \mathrm{d}s$$

That is exactly  $X\sigma(x,\theta)$ . The problem then reduces to recovery of  $\sigma$  given  $X\sigma$ .

Count the number of variables that to parameterize Xf. For any  $\theta$ , it is enough to restrict x to a hyperplane perpendicular to  $\theta$ , that takes away one dimension. One such hyperplane is

$$\theta^{\perp} := \{ x \mid x \cdot \theta = 0 \}.$$
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Then  $Xf(x,\theta)$  is an even (w.r.t.  $\theta$ ) function of 2n-2 variables, while f depends on *n* variables. Therefore, if n = 2, Xf and f depends on the

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Then  $Xf(x,\theta)$  is an even (w.r.t.  $\theta$ ) function of 2n-2 variables, while f depends on *n* variables. Therefore, if n = 2, Xf and f depends on the same number of variables, 2. We say that the problem of inverting X is then a formally determined problem. If  $n \ge 3$ , then Xf depends on more variables, making the problem formally overdetermined. On the other hand, in dimensions n > 3, if we know  $Xf(\ell)$  for all lines, we also know  $Xf(\ell)$  for the *n*-dimensional family of lines that consists of all  $\ell$  parallel to a fixed 2-dimensional plane, say the one spanned by  $(1, 0, \ldots, 0)$  and  $(0, 1, 0, \ldots, 0)$ . It is then enough to solve the 2-dimensional problem of inverting R on each such plane. This is one way one can reduce the problem of inverting X to a formally determined one (that we can solve, as we will see later) using partial data. For this reason, very often the X-ray transform in analyzed in two dimensions only.

## The Radon Transform

The Radon transform Rf of a function f: integrals of f over all hyperplanes  $\pi$  in  $\mathbf{R}^n$ :

$$Rf(\pi) = \int_{\pi} f \, \mathrm{d}S. \tag{6}$$

Here dS is the Euclidean surface measure on each such hyperplane. Each such hyperplane can be written in exactly two different ways in the form

$$\pi = \{x \mid x \cdot \omega = p\} = \{x \mid x \cdot (-\omega) = -p\}$$

with  $p \in \mathbf{R}$ ,  $\omega \in S^{n-1}$ . We then write

$$Rf(p,\omega) = \int_{x\cdot\omega=p} f \,\mathrm{d}S_x. \tag{7}$$

Then Rf is an even function on  $\mathbf{R} \times S^{n-1}$ .

The problem of finding f given Rf is always a formally determined one since both f and Rf are functions of n variables. In  $\mathbf{R}^2$ , those two transforms are the same but parameterized differently.

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## The transpose X'

Since  $(x, \theta)$  and  $(x + s\theta, \theta)$  define the same line, a natural parameterization is

$$\Sigma = \left\{ (z, heta) | \ heta \in S^{n-1}, \ z \in heta^{\perp} 
ight\}.$$

Define a measure  $\mathrm{d}\sigma$  on  $\Sigma$ :

$$\mathrm{d}\sigma(z,\theta)=\mathrm{d}S_{z}\,\mathrm{d}\theta,$$

where,  $d\theta$  is the standard measure on  $S^{n-1}$ , and  $dS_z$  is the Euclidean measure on the hyperplane  $\theta^{\perp}$ . In this parameterization, each directed line has unique coordinates but each undirected one has two pairs of coordinates.

Another parameterization: Assume that we will apply X only to functions supported in some bounded domain  $\Omega$  with a strictly convex smooth boundary. The strict convexity assumption is not restrictive since we can always enlarge the domain to a strictly convex one, for example a ball, that contains the domain of interest.

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Set

$$\partial_{-}S\Omega = \left\{ (x,\theta) \in \partial\Omega \times S^{n-1} | \nu(x) \cdot \theta < 0 \right\},$$
(8)

where  $\nu$  is the exterior unit normal to  $\partial\Omega$ . On  $\partial_{-}S\Omega$ , define the measure

$$d\mu(x,\theta) = |\nu(x) \cdot \theta| dS_x d\theta, \tag{9}$$

where  $dS_x$  is the surface measure on  $\partial\Omega$ . There is a natural map

$$\partial_{-}S\Omega \ni (x,\theta) \longmapsto (z,\theta) \in \Sigma,$$
 (10)

where z is the intersection of the ray  $\{x + s\theta | s \in \mathbf{R}\}$  with  $\theta^{\perp}$ . The map (10) is invertible on its range. Given  $(z, \theta)$ , x is the intersection of the ray  $\{z + s\theta | s \in \mathbf{R}\}$  with  $\partial\Omega$  having the property that at x, the vector  $\theta$  points into  $\Omega$ .



Figure: Two ways to parameterize a line

Proposition 1

The map (10) and its inverse are isometries.

The proof is immediate. Fix  $\theta$ , and project locally  $\partial \Omega$  on  $\theta^{\perp}$ , in the direction of  $\theta$ , near some point x so that  $(x, \theta) \in \partial_{-}S\Omega$ . The Jacobian of that projection is  $1/|\nu(x) \cdot \theta|$ .



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We can compute now the transpose X' w.r.t. either parameterization:

$$X'\psi(x) = \int_{S^{n-1}} \psi(x - (x \cdot \theta)\theta, \theta) \,\mathrm{d}\theta. \tag{11}$$

We can interpret this formula in the following way. The function  $\psi$  is a function on the manifold of lines. Given  $x \in \mathbf{R}^n$ , for any  $\theta \in S^{n-1}$  we evaluate  $\psi$  on the line through x in the direction of  $\theta$ , and then integrate over  $\theta$ . In other words,  $X'\psi(x)$  is an integral of  $\psi = \psi(\ell)$  over all lines  $\ell$  through x

$$X'\psi(x) = \int_{\ell \ni x} \psi(\ell) \,\mathrm{d}\ell_x,$$

where  $d\ell_x$  is the unique measure on  $\{\ell \ni x\}$  invariant under orthogonal transformations, with total measure  $|S^{n-1}|$ , i.e.,  $d\ell_x = d\theta$  in the parameterization that we use. Compare this to (1) which can also be written in the form

$$Xf(\ell) = \int_{x \in \ell} f(x) \,\mathrm{d}s \tag{12}$$

The transform X' is often called a backprojection — it takes a function defined on lines to a function defined on the "x-space"  $\mathbf{R}^n$ .

## X can be extended to compactly supported distributions

# Note that X' does not preserve the compactness of the support, i.e., for $\psi \in C_0^{\infty}$ , X' $\psi$ may not be of compact support!

By duality, we define X on the space  $\mathcal{E}'(\mathbf{R}^n)$  of compactly supported distributions but we cannot do this on  $\mathcal{D}'(\mathbf{R}^n)$ , as it could be expected (even for smooth functions we need a certain decay at infinity).

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## The transpose of R

There is a natural measure on  $\mathbf{R} \times S^{n-1}$ , where Rf lives. The transpose R' w..r.t. it is well defined. A simple calculation yields, for  $\psi \in C_0^{\infty}(\mathbf{R} \times S^{n-1})$ ,

$$R'\psi(x) = \int_{S^{n-1}} \psi(x \cdot \omega, \omega) \,\mathrm{d}\omega.$$

Similarly to what we had before,  $\psi$  is a function on the set of oriented hyperplanes (and on the set of hyperplanes when  $\psi$  is even). Then we can think of  $\mathbf{R}'\psi$  as an integral of  $\psi = \psi(\pi)$  over the set of all hyperplanes  $\pi$  through x. Similarly to X', R' is also called sometimes a backprojection.

We extend R to compactly supported distributions as before.

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# The Fourier Slice Theorem

## Theorem 1 (The Fourier Slice Theorem)

For any  $f \in L^1(\mathbb{R}^n)$ ,

$$\hat{f}(\zeta) = \int_{\theta^{\perp}} e^{-\mathrm{i} z \cdot \zeta} X f(z, \theta) \, \mathrm{d} S_z, \quad \forall \theta \perp \zeta, \; \theta \in S^{n-1}.$$

Denote by  $\mathcal{F}_{\theta^{\perp}}$  the Fourier transform in the *z* variable on  $\theta^{\perp}$ . With this notation, the Fourier Slice Theorem reads: for any  $\theta$ ,  $\hat{f}|_{\theta^{\perp}} = \mathcal{F}_{\theta^{\perp}} X f$ .

#### Proof.

The integral on the right equals  $\int_{\theta^{\perp}} \int_{\mathbf{R}} e^{-iz \cdot \zeta} f(z + s\theta) ds dS_z$ . Set  $x = z + s\theta$  and note that  $x \cdot \zeta = z \cdot \zeta$  when  $\zeta \perp \theta$ . Then we see that the integral above equals  $\hat{f}(\zeta)$ .

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# Theorem 1 immediately implies injectivity of X on $L^1(\mathbb{R}^n)$ (also, on $\mathcal{E}'(\mathbb{R}^n)$ ). $\top$

Also, it says that knowing Xf for a fixed  $\theta$  recovers  $\hat{f}$  for  $\xi \perp \theta$ . This has a micolocal equivalent, as we will see later.

In fact, for compactly supported functions, the theorem implies a bit more. The decisive argument in the proof is the analyticity of the Fourier transform of compactly supported functions.

#### Corollary 2

Let  $f \in L^1(\mathbb{R}^n)$  have compact support and let  $Xf(\cdot, \theta) = 0$  for  $\theta$  in an infinite set of (distinct) unit vectors, then f = 0.

Finitely many "roentgenograms" however are not enough to recover f.

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# Intertwining properties

Intertwining properties for R

$$R\Delta = d_p^2 R, \quad R' d_p^2 = \Delta R',$$

on  $C_0^\infty(\mathbf{R}^n)$  and on  $C_0^\infty(\mathbf{R} \times S^{n-1})$ , respectively.

Proof: straightforward, either by direct computations or by using the Fourier Slice Theorem.

Let  $\Delta_z$  denote the Laplacian in the z variable on each  $heta^\perp$ . Set  $|D_z|=(-\Delta_z)^{1/2}$ . Similarly,

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#### Proposition 2

$$X'Xf(x) = 2\int_{\mathbf{R}^n} \frac{f(y)}{|x-y|^{n-1}} \mathrm{d}y, \quad \forall f \in \mathcal{S}(\mathbf{R}^n)$$

This is a convolution and therefore a Fourier multiplier! We need the Fourier transform of  $|x|^{-(n-1)}$  to find it, and the answer is  $c|\xi|^{-1}$ . Therefore,  $X'X = c|D|^{-1}$ , and to invert it, we need to apply c'|D|.

#### Theorem 3

For any  $f \in \mathcal{S}(\mathbf{R}^n)$ ,

# $f = c_n |D| X' X f, \quad c_n = (2\pi |S^{n-2}|)^{-1}$

## For n = 2, $|S^{n-2}| = 2$ , so $c_2 = (4\pi)^{-1}$ .

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The Fourier multiplier |D| is a non-local operator. Therefore, if we want to recover f only in a neighborhood of some  $x_0$  by means of formula above, it is not enough to know Xf for all lines  $\ell$  that intersect that neighborhood.

In particular, if f is compactly supported, we need to compute X'Xf for all  $x \in \mathbf{R}^n$  to be able to apply |D|. Numerically, one would just truncate the computational region but X'Xf does not decay very fast (only like  $|x|^{-n+1}$ ), and the error will be not so small. But such a truncated recovery would still be a parametrix (more — later).

This calls for another inversion formula.

Theorem 4 (A filtered back-projection)

For any  $f \in \mathcal{S}(\mathbf{R}^n)$ ,

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In particular, if f is compactly supported, we need to compute X'Xf for all  $x \in \mathbf{R}^n$  to be able to apply |D|. Numerically, one would just truncate the computational region but X'Xf does not decay very fast (only like  $|x|^{-n+1}$ ), and the error will be not so small. But such a truncated recovery would still be a parametrix (more — later).

This calls for another inversion formula.

#### Theorem 4 (A filtered back-projection)

For any  $f \in \mathcal{S}(\mathbf{R}^n)$ ,

$$f = c_n X' |D_z| X f$$
,  $c_n = (2\pi |S^{n-2}|)^{-1}$ .

The non-local operator  $|D_z|$  now appears between X' and X. Is that a progress (for computational purposes)? Yes — if f is compactly supported, we need to evaluate the result in a compact set, i.e., we need to know  $\chi X'|D_z|Xf$  for some  $\chi$  of compact support. This means that we need to evaluate  $|D_z|Xf$  on a compact set as well. But Xf is compactly supported. So we need to apply  $|D_z|$  from a comact set to a compact set

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# The Schwartz kernel of R'R

#### Proposition 3

## For any $f \in \mathcal{S}(\mathbf{R}^n)$ ,

$$R'Rf(x) = |S^{n-2}| \int_{\mathbf{R}^n} \frac{f(y)}{|x-y|} \mathrm{d}y.$$

We have a convolution again, with the Fourier transform of  $|x|^{-1}$ . The latter is  $c|\xi|^{-n+1}$ . Therefore,

#### Theorem 5

For any  $f \in \mathcal{S}(\mathbf{R}^n)$ ,

$$f = C_n |D|^{n-1} R' R f, \quad C_n = \frac{1}{2} (2\pi)^{1-n}.$$

## $|D|^{n-1}$ is <u>local</u> for *n* odd!

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Let H be the Hilbert transform

$$Hg(p) = \frac{1}{\pi} \operatorname{pv} \int_{\mathbf{R}} \frac{g(s)}{p-s} \, \mathrm{d}s, \qquad (13)$$

where " $pv \int$ " stands for an integral in a principal value sense.

#### Theorem 6 (filtered backprojection)

For any  $f \in \mathcal{S}(\mathbf{R}^n)$ ,

$$f = \begin{cases} C'_n R' d_p^{n-1} Rf, & n \text{ odd,} \\ C'_n R' H d_p^{n-1} Rf, & n \text{ even,} \end{cases}$$
(14)

where  $d_p$  stands for the derivative of  $Rf(p, \omega)$  w.r.t. p, H is the Hilbert transform w.r.t. p and

$$C'_{n} = \begin{cases} (-1)^{(n-1)/2} C_{n}, & n \text{ odd,} \\ (-1)^{(n-2)/2} C_{n}, & n \text{ even,} \end{cases}$$

with  $C_n = \frac{1}{2}(2\pi)^{1-n}$  (as in Theorem 5).

The appearance of the Hilbert transform H for n even, and the different constants for n odd/even may look strange at first glance, especially when compared to the inversion formula in Theorem 5, that looks the same for all  $n \ge 2$ . For n even, note first that  $H = -i \operatorname{sgn}(D_p)$ ,  $D_p = -id_p$ , therefore,

$$(-1)^{(n-2)/2} H d_p^{n-1} = |D_p|^{n-1}, \quad n \text{ even}.$$

On the other hand,

$$(-1)^{(n-1)/2} d_p^{n-1} = |D_p|^{n-1}, \quad n \text{ odd.}$$

Therefore, in both cases, (14) can be written as

$$f = C_n R' |D_\rho|^{n-1} Rf \tag{15}$$

## Stability estimates

Set

$$\|g\|_{\bar{H}^{s}(\Sigma)} = \left\| (1 - \Delta_{z})^{s/2} g \right\|_{L^{2}(\Sigma)},$$
  
$$\|g\|_{\bar{H}^{s}(\mathbb{R} \times S^{n-1})} = \left\| (1 - d_{p}^{2})^{s/2} g \right\|_{L^{2}(\mathbb{R} \times S^{n-1})},$$
 (16)

#### Theorem 7 (Stability estimates)

For any bounded domain  $\Omega \subset \mathbf{R}^n$  with smooth boundary, and any s, we have

$$\|f\|_{H^{s}(\mathbb{R}^{n})}/C \leq \|Xf\|_{\bar{H}^{s+1/2}(\Sigma)} \leq C\|f\|_{H^{s}(\mathbb{R}^{n})},$$
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The appearance of the same norm of f on the left and on the right makes those estimates sharp.

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Theorem 7 shows that we "gain 1/2 derivative" with the operator X, and (n-1)/2 derivatives with the operator R. Each one of those two operators involves an integration that has a smoothing effect. The gain is a half of the dimension of the linear submanifolds over which we integrate.

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# Stability estimates in terms of X'X and R'R

Why X'X (the normal operator)? It is the first step of the inversion; it lives in the same space; X'X is injective if and only if X is.

#### Theorem 8

Let  $\Omega \subset \mathbf{R}^n$  be open and bounded, and let  $\Omega_1 \supset \overline{\Omega}$  be another such set. Then for any integer s = 0, 1, ..., there is a constant C > 0 so that for any  $f \in H^s(\mathbf{R}^n)$  supported in  $\overline{\Omega}$ , we have

$$\|f\|_{H^{s}(\mathbf{R}^{n})}/C \leq \|X'Xf\|_{H^{s+1}(\Omega_{1})} \leq C\|f\|_{H^{s}(\mathbf{R}^{n})},$$

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The proof (of the inequalities on the left) seems to be straightforward as well — we have a formula for f in terms of X'Xf and R'Rf. Just apply c|D| to X'Xf, and we get f. Problem: we need X'Xf on the whole  $\mathbb{R}^n$  for that! The theorem requires to know this on  $\Omega_1$  only. ???

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To prove the first estimate, use the inversion formula  $f = c_n |D| X' X f$  and write

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We want to get rid of the last term. The following lemma solves the problem:

#### Lemma 9

Let X, Y, Z be Banach spaces, let  $A : X \to Y$  be a bounded linear operator, and  $K : X \to Z$  be a compact linear operator. Let

 $\|f\|_{X} \le C(\|Af\|_{Y} + \|Kf\|_{Z}), \quad \forall f \in X.$  (21)

Assume that A is injective. Then there exists C' > 0 so that

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We do know that  $X'X : H_0^s(\Omega) \to H^{s+1}(\Omega_1)$  is injective. So we can apply the lemma and get rid of that term (no control over C though!)

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# Support theorems

## Theorem 10 (Support theorem)

Let  $f \in C(\mathbf{R}^n)$  be such that

(i)  $|x|^k f(x)$  is bounded for any integer k,

(ii) there exists a constant A > 0 so that  $Rf(p, \omega) = 0$  for |p| > A.

Then f(x) = 0 for |x| > A.

#### Corollary 11

Let  $K \subset \mathbf{R}^n$  be a convex compact set. Let  $f \in C(\mathbf{R}^n)$  satisfy the assumption (i) above. Assume also that  $Rf(\pi) = 0$  for any hyperplane  $\pi$  not intersecting K. Then f = 0 outside K.

Support theorems for X can be derived directly from those for R by working in various 2D planes, where R and X are the same transforms. On the other hand, one can formulate stronger results for X since the lines in  $\mathbb{R}^n$  are "thinner" and can fit into smaller "holes."

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