

Inverse Transport Problems and Applications

II. Optical Tomography and Clear Layers

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Outline for the three lectures

I. Inverse problems in integral geometry

Radon transform and attenuated Radon transform

Ray transforms in hyperbolic geometry

II. Forward and Inverse problems in highly scattering media

Photon scattering in tissues within diffusion approximation

Inverse problems in Optical tomography

III. Inverse transport problems

Singular expansion of albedo operator

Perturbations about “scattering-free” problems

Unsolved practical inverse problems.

Outline for Lecture II

1. Optical tomography

Transport equations and examples of applications

2. Macroscopic modeling of clear layers

Diffusion approximation of transport

Macroscopic modeling of clear layers

3. Reconstruction via the Factorization method

Reconstruction of clear layer and enclosed coefficients

Shape derivative plus level set methods

Mathematical Problems in Optical Tomography

Optical Tomography consists in **reconstructing** absorption and scattering properties of human tissues by probing them with **Near-Infra-Red photons** (wavelength of roughly $1\mu\text{m}$).

What needs to be done:

- **Modeling** of **forward problem** using equations that are easy to solve: photons strongly interact with underlying tissues.
- Devising **reconstruction algorithms** to image tissue properties from **boundary measurements** of photon intensities.
- (● Address relevant questions and no more: **severely ill-posed** problem.)

Transport equations in Optical Tomography

The **photon density** $u(\mathbf{x}, \boldsymbol{\Omega}; \nu)$ solves the following transport (linear Boltzmann) equation

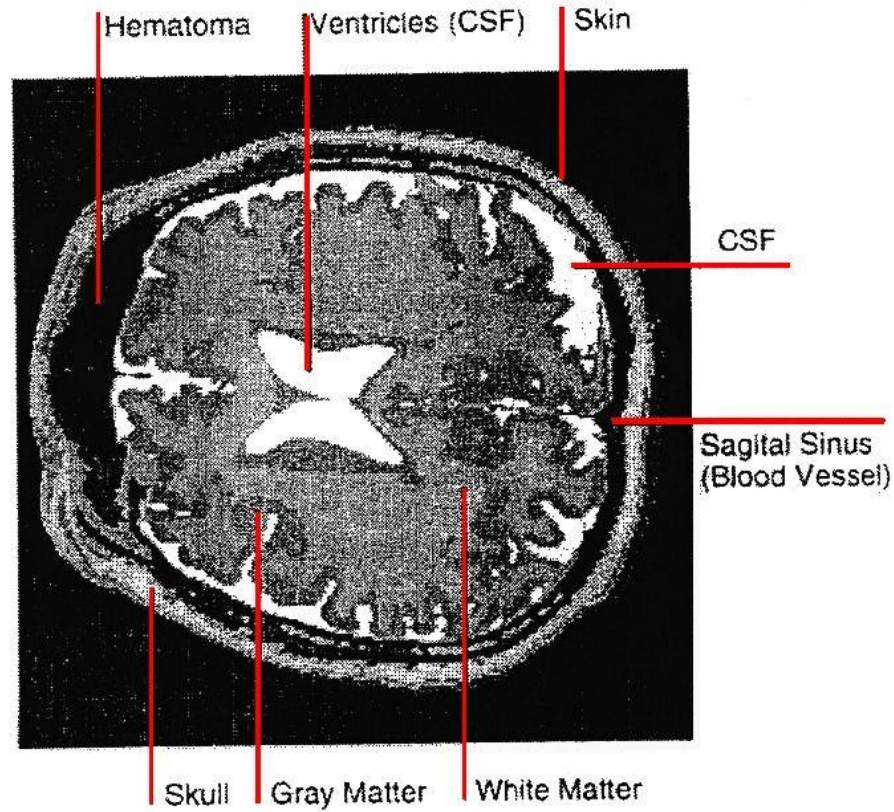
$$\frac{i\nu}{c}u + \boldsymbol{\Omega} \cdot \nabla u + \sigma_t(\mathbf{x})u = \sigma_s(\mathbf{x}) \int_{S^2} p(\boldsymbol{\Omega} \cdot \boldsymbol{\Omega}')u(\mathbf{x}, \boldsymbol{\Omega}'; \nu)d\mu(\boldsymbol{\Omega}'),$$

where ν is the (known) modulation of the illumination source, $p(\mu)$ is the phase function of the scattering process (often assumed to be known), $\sigma_t(\mathbf{x})$ is the **total absorption** coefficient and $\sigma_s(\mathbf{x})$ the **scattering coefficient**. The last three terms model photon interactions with the underlying medium (tissues).

The inverse problem in **OT** consists of reconstructing $\sigma_s(\mathbf{x})$ and $\sigma_t(\mathbf{x})$ (and possibly $p(\mu)$) from boundary measurements.

The **transport** equation is often replaced by its **diffusion** approximation.

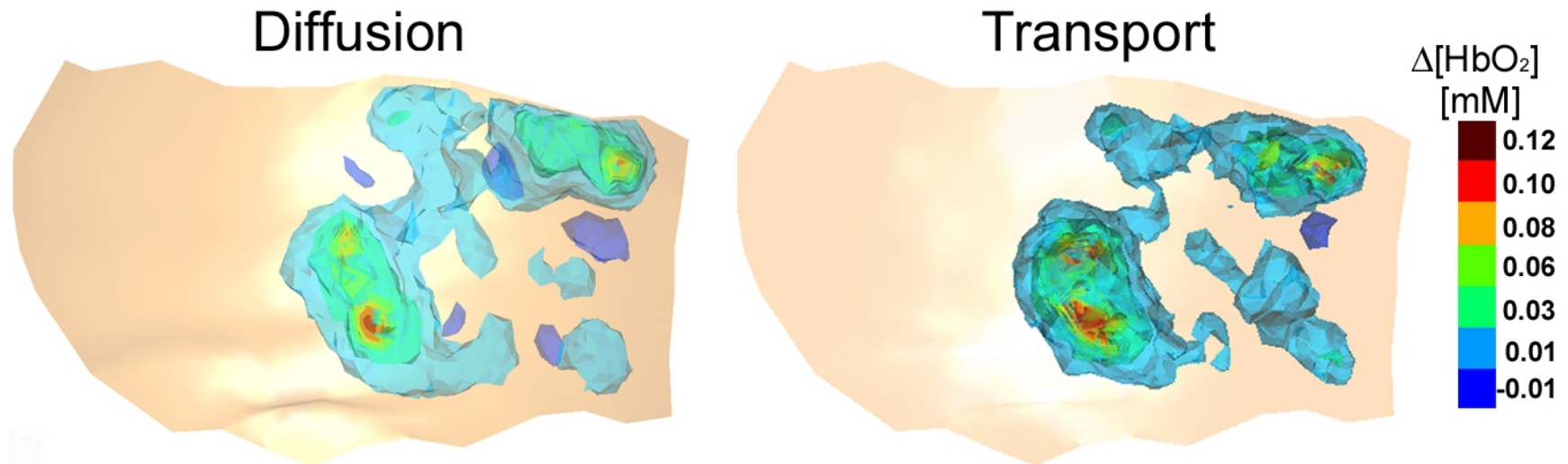
Applications in Near-Infra-Red Spectroscopy



Segmented MRI data for a human brain.

Imaging of human brains.

Applications in Near-Infra-Red Spectroscopy



Imaging of human brains (from A.H. Hielscher, biomedical Engineering, Columbia).

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Transport equations and examples of applications

2. Macroscopic modeling of clear layers

Diffusion approximation of transport

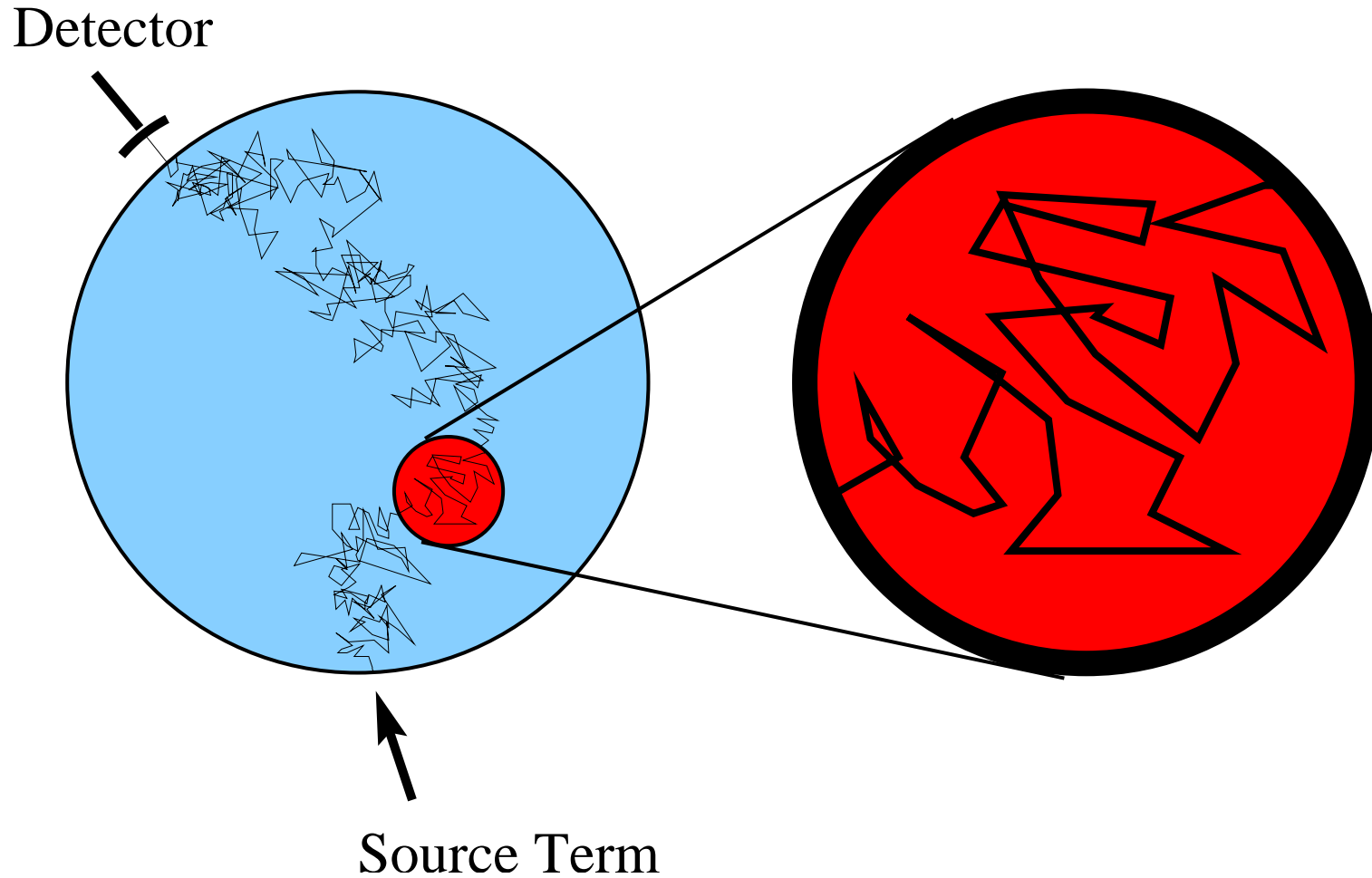
Macroscopic modeling of clear layers

3. Reconstruction via the Factorization method

Reconstruction of clear layer and enclosed coefficients

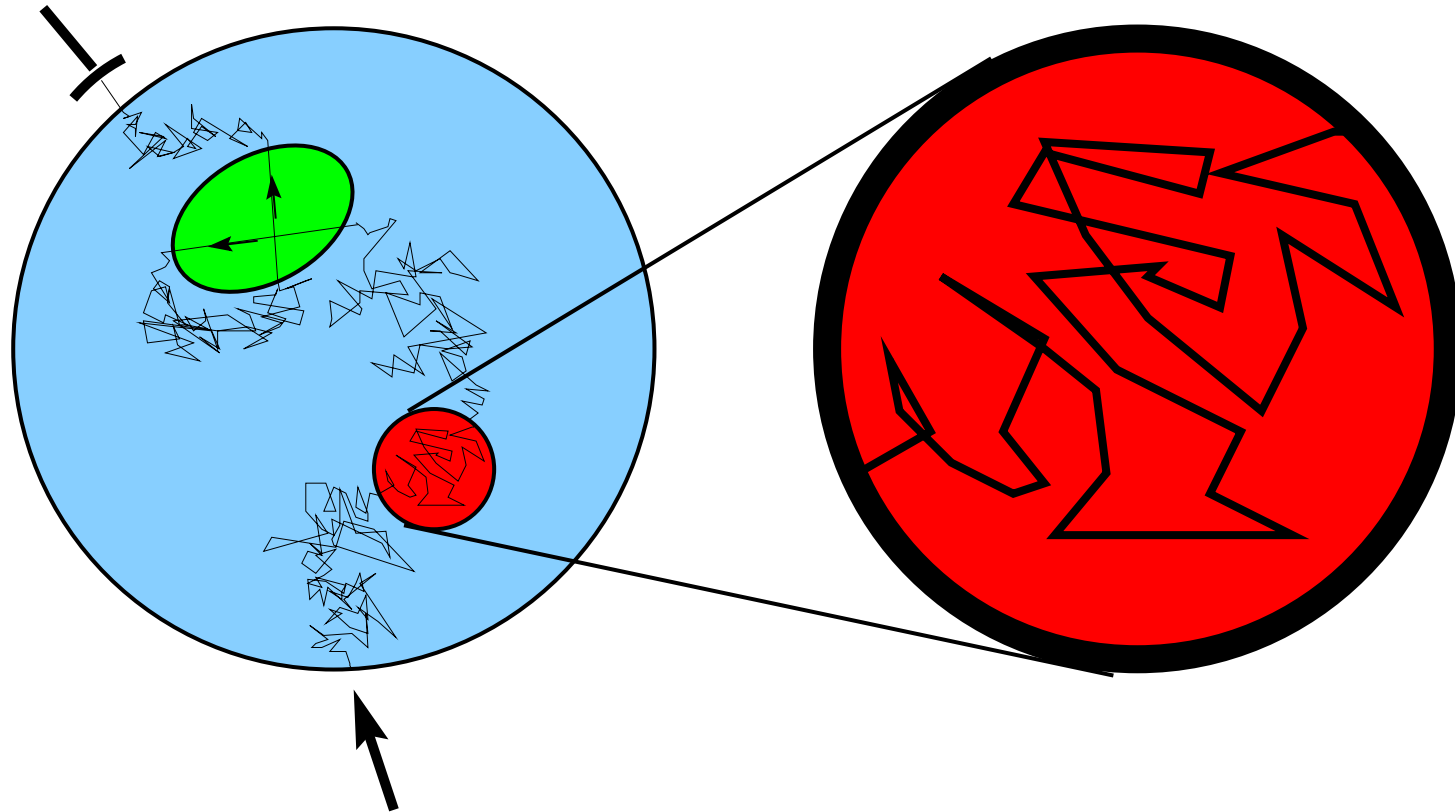
Shape derivative plus level set methods

Typical path of a detected photon in a DIFFUSIVE REGION



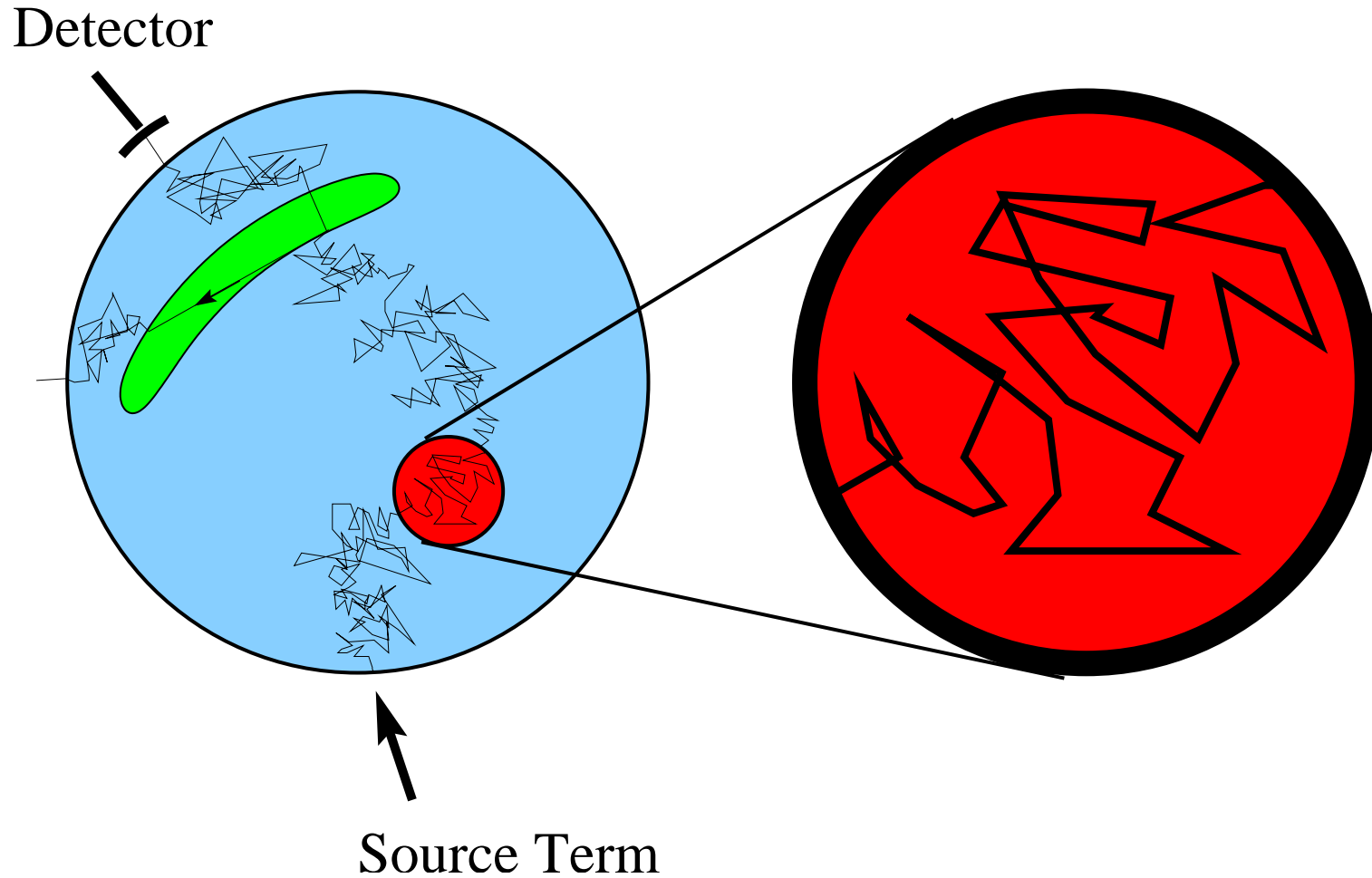
Same typical path in the presence of a **CLEAR INCLUSION**

Detector



Source Term

Same typical path in the presence of a **CLEAR LAYER**



Modeling the Forward Problem:

We want **macroscopic** equations that model photon propagation *both* in the **diffusive** and **non-diffusive** domains.

Outline:

1. Brief recall on the derivation of **diffusion** equations
2. **Generalized equations** in the presence of **Clear Layers**
3. **Numerical simulation** of transport and diffusion models

Transport Equation and Scaling

The **phase-space linear transport equation** is given by

$$\frac{1}{\varepsilon} v \cdot \nabla u_\varepsilon(x, v) + \frac{1}{\varepsilon^2} Q(u_\varepsilon)(x, v) + \sigma_a(x) u_\varepsilon(x, v) = 0 \quad \text{in } \Omega \times V,$$

$$u_\varepsilon(x, v) = g(x, v) \quad \text{on } \Gamma_- = \{(x, v) \in \partial\Omega \times V \text{ s.t. } v \cdot \nu(x) < 0\}.$$

$u_\varepsilon(x, v)$ is the **particle density** at $x \in \Omega \subset \mathbb{R}^3$ with direction $v \in V = S^2$.

The **scattering operator** Q is defined by

$$Q(u)(x, v) = \sigma_s(x) \left(u(x, v) - \int_V u(x, v') d\mu(v') \right).$$

The **mean free path** ε measures the mean distance between successive **interactions** of the particles with the **background medium**.

The **diffusion limit** occurs when $\varepsilon \rightarrow 0$.

Volume Diffusion Equation

Asymptotic Expansion: $u_\varepsilon(x, v) = u_0(x) + \varepsilon u_1(x, v) + \varepsilon^2 u_2(x, v) \dots$

Equating like powers of ε in the transport equation yields

$$\begin{aligned} \text{Order } \varepsilon^{-2} : & \quad Q(u_0) = 0 \\ \text{Order } \varepsilon^{-1} : & \quad v \cdot \nabla u_0 + Q(u_1) = 0 \\ \text{Order } \varepsilon^0 : & \quad v \cdot \nabla u_1 + Q(u_2) + \sigma_a u_0 = 0. \end{aligned}$$

Krein-Rutman theory:

$$\text{Order } \varepsilon^{-2} : \quad u_0(x, v) = u_0(x)$$

$$\text{Order } \varepsilon^{-1} : \quad u_1(x, v) = -\frac{1}{\sigma_s(x)} v \cdot \nabla u_0(x),$$

$$\text{Order } \varepsilon^0 : \quad \boxed{-\operatorname{div} D(x) \cdot \nabla u_0(x) + \sigma_a(x) u_0(x) = 0 \quad \text{in } \Omega}$$

where the **diffusion coefficient** is given by $\boxed{D(x) = \frac{1}{3\sigma_s(x)}}$

Diffusion Equations with Boundary Conditions

The volume asymptotic expansion **does not** hold in the vicinity of **boundaries**. After **boundary layer analysis** we obtain

$$-\operatorname{div} D(x) \cdot \nabla u_0(x) + \sigma_a(x) u_0(x) = 0 \quad \text{in } \Omega$$

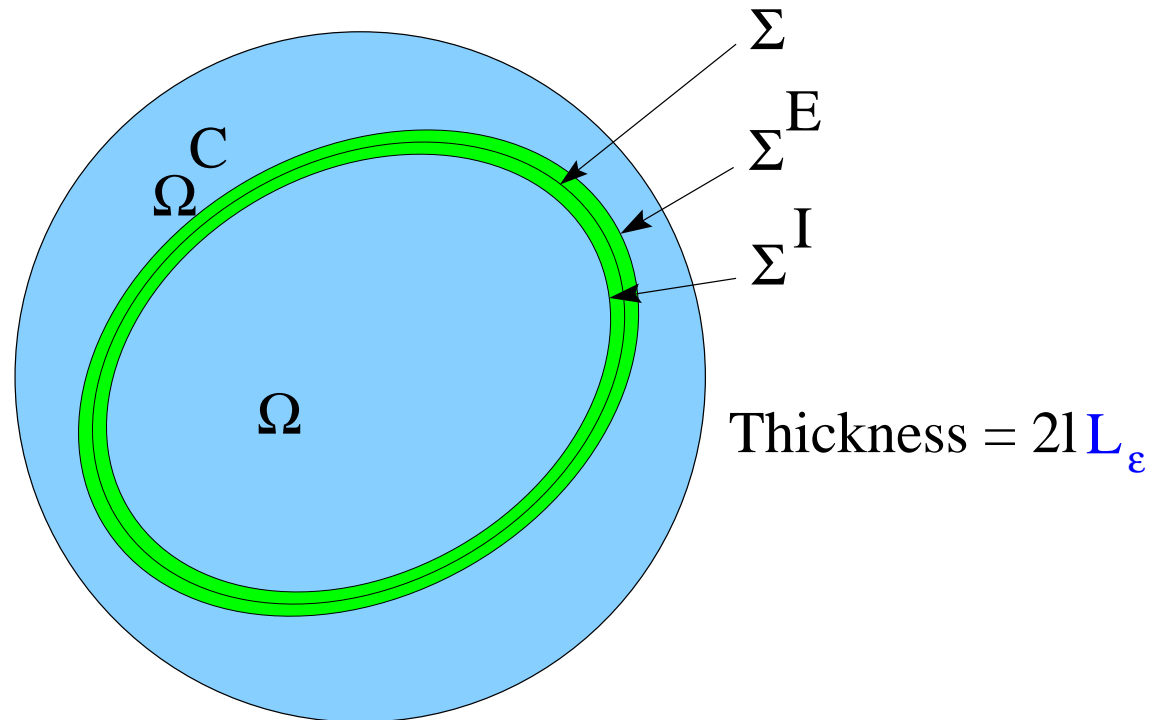
$$u_0(x) = \Lambda(g(x, v)) \quad \text{on } \partial\Omega.$$

Λ is a linear form on $L^\infty(V_-)$.

We obtain in any reasonable sense that

$$u_\varepsilon(x, v) = u_0(x) + O(\varepsilon).$$

Generalization to an **Extended Object** of small thickness (**Clear Layer**)



Geometry of the **Clear Layer** Ω^C of boundary $\left\{ \begin{array}{l} \Sigma^E = \Sigma + lL_\epsilon\nu(x), \\ \Sigma^I = \Sigma - lL_\epsilon\nu(x), \end{array} \right.$
where $\nu(x)$ is the outgoing normal to Σ at $x \in \Sigma$.

Local Generalized Diffusion Model

Assuming $L_\varepsilon^2 |\ln L_\varepsilon| \sim \varepsilon$, in the limit $\varepsilon \rightarrow 0$ we obtain in a joint work with **Kui Ren** the following **generalized diffusion model**

$$-\nabla \cdot D(x) \nabla U(x) + \sigma_a(x) U(x) = 0 \quad \text{in } \Omega \setminus \Sigma$$

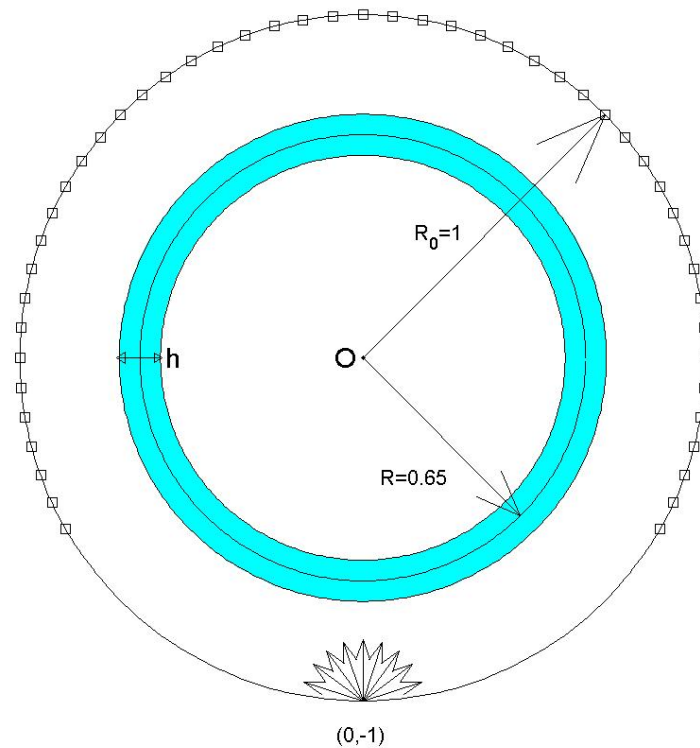
$$U(x) + 3L_3 \varepsilon D(x) \nu(x) \cdot \nabla U(x) = \Lambda(g(x, v)) \quad \text{on } \partial\Omega$$

$$[U](x) = 0 \quad \text{on } \Sigma$$

$$\boxed{[\nu \cdot D \nabla U](x) = -\nabla_\perp d^c \nabla_\perp U.}$$

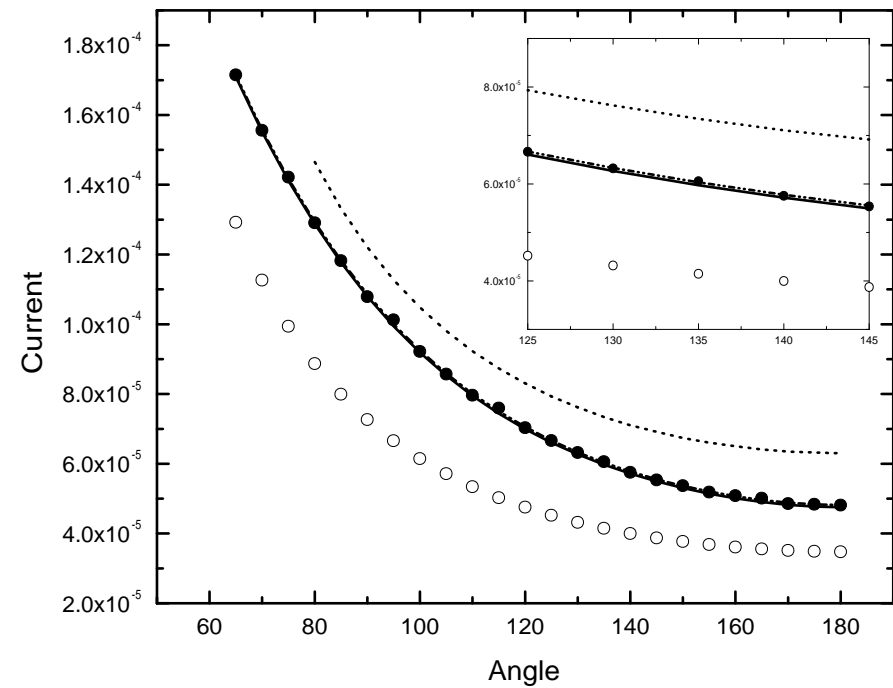
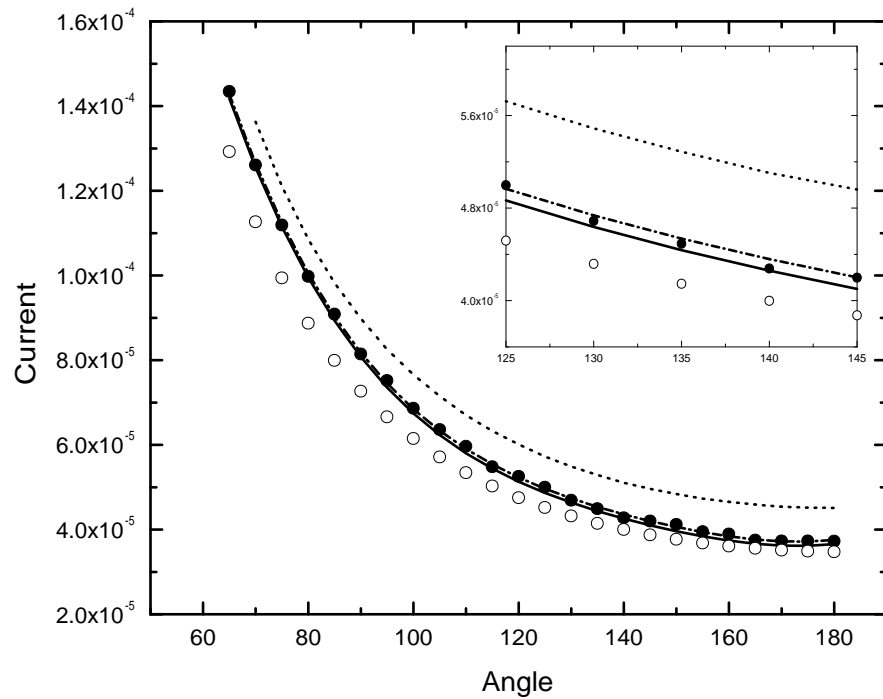
The clear layer is modeled as a tangential (supported on Σ) diffusion process with coefficient $d^c(\mathbf{x})$. The approximation (w.r.t. transport solution) is of order $\sqrt{\varepsilon}$ when Σ has **positive curvature** and can be as bad as $|\ln \varepsilon|^{-1}$ for **straight** clear layers.

Numerical simulations



Geometry of domain with circular/spherical clear layer.

Two-dimensional Numerical simulation



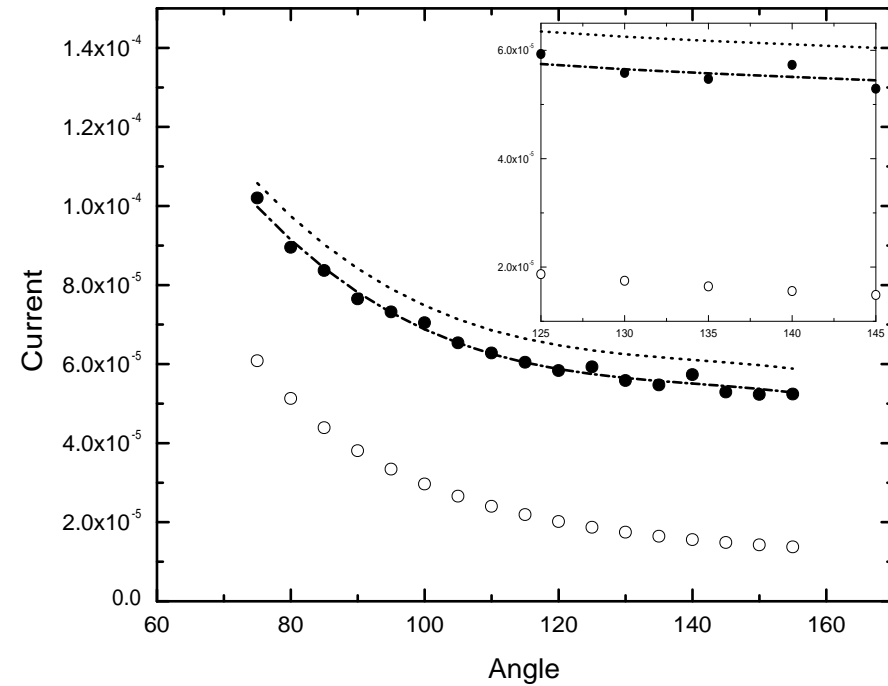
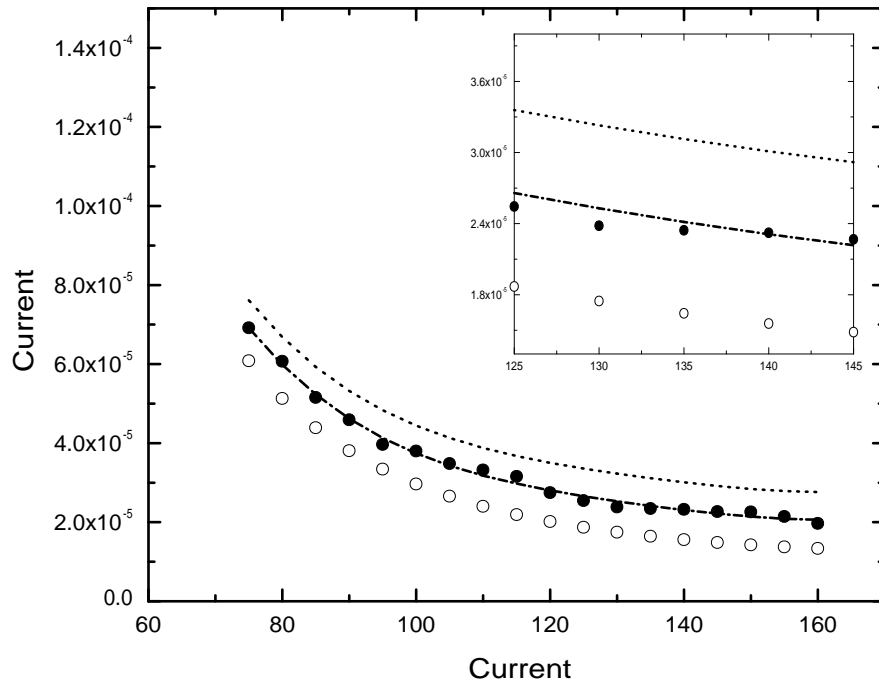
Outgoing current for clear layers of 2 and 5 mean free paths.

Two-dimensional Numerical simulation

h	0.01	0.02	0.03	0.04	0.05	0.06	0.07
d_{theory}^C	0.0124	0.0455	0.0971	0.166	0.253	0.355	0.475
$d_{\text{best fit}}^C$	0.0129	0.0465	0.0983	0.167	0.253	0.356	0.474
E_{GDM} (%)	1.17	1.56	1.43	1.09	0.81	0.56	0.60
E_{BF} (%)	0.73	0.65	0.57	0.49	0.46	0.47	0.46
E_{DI} (%)	3.3	10.2	17.7	24.5	30.2	35.3	39.8

Tangential diffusion coefficients and relative L^2 error between the **transport Monte Carlo** simulations and the various **diffusion models** for several thicknesses of the clear layer.

Three-dimensional Numerical simulation



Outgoing current for clear layers of 3 and 6 mean free paths.

Summary of Forward Modeling:

- We have a **macroscopic model** that captures particle propagation *both* in scattering and non-scattering regions, such as **embedded objects** and **clear layers**.
- The **generalized diffusion** model is computationally only slightly more expensive than the **classical diffusion** equation (essentially, one term is added in the variational formulation) and much less expensive than the **full phase-space transport** model.
- The **accuracy** of the macroscopic equation is sufficient to address the **inverse problem** where absorption and scattering cross sections are reconstructed from boundary measurements.

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Inverse Problem

- Optical Tomography uses **near-infrared photons** to image properties of **human tissues**.
- **Advantages:** **Non-invasive** (as are all “imaging” techniques); **Cheap** (that is, for a medical technique); Quite **harmless** (as light should be); and **Good Discrimination** properties between healthy and non-healthy tissues.
- **Disadvantages:** photons **scatter** a lot with underlying medium because they have low energy. This implies that the images have a **low spatial resolution**, and forward models are **computationally expensive**.
- Here we focus on reconstructing the **clear layer** and what it **encloses**. We also consider the similar problem in **Impedance tomography**.

Model problem in Impedance Tomography

The **potential** $u(\mathbf{x})$ solves the following equation:

$$\begin{aligned}
 \nabla \cdot \gamma \nabla u &= 0, && \text{in } \Omega \setminus \Sigma \\
 [u] &= 0 && \text{on } \Sigma \\
 [\mathbf{n} \cdot \gamma \nabla u] &= -\nabla_{\perp} \cdot d \nabla_{\perp} u && \text{on } \Sigma \\
 \mathbf{n} \cdot \gamma \nabla u &= g && \text{on } \partial\Omega \\
 \int_{\partial\Omega} u \, d\sigma &= 0.
 \end{aligned}$$

Assume that the above hypotheses are satisfied and that $g \in H_0^{-1/2}(\partial\Omega)$. Then the above system admits a **unique solution** $u \in H_{0,\Sigma}^1(\Omega)$ with trace $u|_{\partial\Omega} \in H_0^{1/2}(\partial\Omega)$. The **variational formulation** is

$$\int_{\Omega} \gamma \nabla u \cdot \nabla v \, d\mathbf{x} + \int_{\Sigma} d \nabla_{\perp} u \cdot \nabla_{\perp} v \, d\sigma = \int_{\partial\Omega} g v \, d\sigma.$$

Model problem in Optical Tomography

The **photon density** $u(\mathbf{x}; \omega)$ solves the following equation

$$\begin{aligned}
 i\omega u - \nabla \cdot \gamma \nabla u + au &= 0, && \text{in } \Omega \setminus \Sigma \\
 [u] &= 0 && \text{on } \Sigma \\
 [\mathbf{n} \cdot \gamma \nabla u] &= -\nabla_{\perp} \cdot d \nabla_{\perp} u && \text{on } \Sigma \\
 \mathbf{n} \cdot \gamma \nabla u &= g && \text{on } \partial\Omega.
 \end{aligned}$$

Assume that $a(\mathbf{x})$ is bounded when $\omega \neq 0$ and that $a(\mathbf{x})$ is uniformly bounded from below by a positive constant when $\omega = 0$, and that $g \in H^{-1/2}(\partial\Omega)$. Then the above system admits a **unique solution** $u \in H_{\Sigma}^1(\Omega)$ with trace $u|_{\partial\Omega} \in H^{1/2}(\partial\Omega)$. The **variational formulation** is:

$$\int_{\Omega} (i\omega + a)uv + \int_{\Omega} \gamma \nabla u \cdot \nabla v \, d\mathbf{x} + \int_{\Sigma} d \nabla_{\perp} u \cdot \nabla_{\perp} v \, d\sigma = \int_{\partial\Omega} gv \, d\sigma.$$

Assumptions and what we can reconstruct

- Main Assumption: The conductivity tensor γ is **known** on $\Omega \setminus \bar{D}$ such that $\Sigma = \partial D$.
- We reconstruct the interface $\Sigma = \partial D$ using a **factorization method**. The method is **“constructive”**.
- Next we find the **tangential diffusion** tensor $d(\mathbf{x})$ on Σ .
- Finally we reconstruct what we can (using **known theories**) on γ from the knowledge of the **Dirichlet-to-Neumann** map.

A few more assumptions (Impedance case)

We define the **Neumann-to-Dirichlet** operator Λ_Σ as

$$\Lambda_\Sigma : H_0^{-1/2}(\partial\Omega) \longrightarrow H_0^{1/2}(\partial\Omega), \quad g \longmapsto u|_{\partial\Omega}.$$

We define the “**background**” Neumann-to-Dirichlet operator Λ_0 as above with $\gamma(\mathbf{x})$ replaced by a known background $\gamma_0(\mathbf{x})$ and with $d(\mathbf{x})$ replaced by 0.

Our assumptions on the background $\gamma_0(\mathbf{x})$ is that it is the true conductivity tensor on $\Omega \setminus \overline{D}$ and a *lower-bound* to the true conductivity tensor on D :

$$\gamma_0(\mathbf{x}) \leq \gamma(\mathbf{x}) \quad \text{on } D, \quad \gamma_0(\mathbf{x}) = \gamma(\mathbf{x}) \quad \text{on } \Omega \setminus \overline{D}.$$

The main assumption is thus that we **assume** that everything is known in $\Omega \setminus \overline{D}$.

A typical result

Theorem. Let us assume that the tensor $\gamma(\mathbf{x})$ is of class $C^2(\Omega)$ for $n = 2, 3$, is **known** on $\Omega \setminus \bar{D}$, and is **proportional to identity** (i.e., $\gamma(\mathbf{x}) = \frac{1}{n} \text{Tr}(\gamma(\mathbf{x}))I$) on \bar{D} .

Then the **surface** $\Sigma = \partial D$, the **tangential diffusion** tensor $d(\mathbf{x})$, and the **conductivity tensor** $\gamma(\mathbf{x})$ are uniquely determined by the Cauchy data $\{u|_{\partial\Omega}, \mathbf{n} \cdot \gamma \nabla u|_{\partial\Omega}\}$ in $H^{1/2}(\partial\Omega) \times H^{-1/2}(\partial\Omega)$.

Moreover the method to recover Σ is constructive and based on a suitable **factorization** of $\Lambda_0 - \Lambda_\Sigma$.

The Factorization method

The idea is to reconstruct the **support of objects** *without* knowing what is inside.

Originally proposed by Colton and Kirsch and analyzed to detect obstacles in the **scattering context** by Kirsch [IP1998].

Analyzed in **impedance tomography** for objects with **different impedance** than the **background** by Brühl [SIMA01].

Factorization method idea

The idea is to **factor** the difference of NtD operators as

$$\Lambda_0 - \Lambda_\Sigma = L^*FL,$$

where L and L^* are defined on $\Omega \setminus \overline{D}$ and where F can be decomposed as B^*B with B^* **surjective**. This implies that

$$\mathcal{R}((\Lambda_0 - \Lambda_\Sigma)^{1/2}) = \mathcal{R}(L^*).$$

We then construct functions $\mathbf{y} \mapsto g_{\mathbf{y}}(\cdot)$ from the measured data that solve the **source-less** diffusion equation in $\Omega \setminus \overline{D}$ and are in the **Range** of L if and only if $\mathbf{y} \in D$.

This allows us to **constructively** image the interface Σ from the boundary measurements.

Details of the factorization

Let us define v and v^* as the **solutions** to:

$$\begin{array}{llll}
 \nabla \cdot \gamma \nabla v = 0, & \text{in } \Omega \setminus \overline{D} & \nabla \cdot \gamma \nabla v^* = 0, & \text{in } \Omega \setminus \overline{D} \\
 \mathbf{n} \cdot \gamma \nabla v = 0 & \text{on } \Sigma & \mathbf{n} \cdot \gamma \nabla v^* = -\phi & \text{on } \Sigma \\
 \mathbf{n} \cdot \gamma \nabla v = \phi & \text{on } \partial\Omega & \mathbf{n} \cdot \gamma \nabla v^* = 0 & \text{on } \partial\Omega \\
 \int_{\partial\Omega} v \, d\sigma = 0, & & \int_{\Sigma} v^* \, d\sigma = 0. &
 \end{array}$$

L maps $\phi \in H_0^{-1/2}(\partial\Omega)$ to $v|_{\Sigma} \in H_0^{1/2}(\Sigma)$ and its adjoint operator L^* maps $\phi \in H_0^{-1/2}(\Sigma)$ to $v|_{\partial\Omega}^* \in H_0^{1/2}(\partial\Omega)$. We have

$$(u, L^*v)_{\partial\Omega} \equiv \int_{\partial\Omega} u L^*v \, d\sigma = \int_{\Sigma} v Lu \, d\sigma \equiv (Lu, v)_{\Sigma}.$$

Construction of F

Let us define w as the solution to

$$\begin{aligned}
 \nabla \cdot \gamma \nabla w &= 0, && \text{in } \Omega \setminus \Sigma \\
 [w] &= \phi, && \text{on } \Sigma \\
 [\mathbf{n} \cdot \gamma \nabla w] &= -\nabla_{\perp} d \nabla_{\perp} w^{-} && \text{on } \Sigma \\
 \mathbf{n} \cdot \gamma \nabla w &= 0 && \text{on } \partial\Omega \\
 \int_{\partial\Omega} w \, d\sigma &= 0.
 \end{aligned}$$

The operator F_{Σ} maps $\phi \in H_0^{1/2}(\Sigma)$ to $\mathbf{n} \cdot \gamma \nabla w^{+} \in H_0^{-1/2}(\Sigma)$.

The **variational formulation** to the above problem is

$$\int_{\Omega} \gamma \nabla w \cdot \nabla w \, d\mathbf{x} + \int_{\Sigma} d \nabla_{\perp} w^{-} \cdot \nabla_{\perp} w^{-} \, d\sigma = \int_{\Sigma} \mathbf{n} \cdot \gamma \nabla w^{+} \phi \, d\sigma = \int_{\Sigma} F_{\Sigma} \phi \phi \, d\sigma.$$

F_0 is defined similarly with $\gamma(\mathbf{x})$ replaced by $\gamma_0(\mathbf{x})$ and $d(\mathbf{x}) \equiv 0$.

The operator F is defined as $F = F_0 - F_{\Sigma}$. It is **symmetric** and we have

$$\Lambda_0 - \Lambda_{\Sigma} = L^* F L.$$

Coercivity of F

After a few integrations by parts we obtain with $\delta w = w_\Sigma - w_0$:

$$\int_\Sigma F\phi \phi = \int_\Omega \gamma \nabla \delta w \cdot \nabla \delta w + \int_D (\gamma - \gamma_0) \nabla w_0 \cdot \nabla w_0 + \int_\Sigma d \nabla_\perp w_\Sigma^- \cdot \nabla_\perp w_\Sigma^-.$$

We can then show that F is **coercive** in the sense that

$$(F\phi, \phi) \geq \alpha \|\phi\|_{H_0^{1/2}(\Sigma)}^2,$$

for some $\alpha > 0$.

What makes the factorization useful (I)

In the case of a **jump** of the **diffusion coefficient** across the interface Σ , one can show that F is an **isomorphism** so that it can be written $F = B^*B$ with B also an **isomorphism**.

In the **clear layer** case, F may not be an isomorphism. It can still be decomposed. Let \mathcal{I} be the **canonical isomorphism** between $H_0^{-1/2}(\Sigma)$ and $H_0^{1/2}(\Sigma)$ and define

$$\mathcal{I} = \mathcal{J}^* \mathcal{J}, \quad \mathcal{J} : H_0^{-1/2}(\Sigma) \rightarrow L_0^2(\Sigma), \quad \mathcal{J}^* : L_0^2(\Sigma) \rightarrow H_0^{1/2}(\Sigma).$$

We can thus **recast the coercivity** of F as

$$(F\phi, \phi) = (F\mathcal{J}^*u, \mathcal{J}^*u) = (\mathcal{J}F\mathcal{J}^*u, u) \geq \alpha \|\phi\|_{H_0^{1/2}(\Sigma)}^2 = \alpha \|u\|_{L_0^2(\Sigma)}^2.$$

What makes the factorization useful (II)

Since

$$(\mathcal{J}F\mathcal{J}^*u, u) \geq \alpha \|u\|_{L_0^2(\Sigma)}^2,$$

$\mathcal{J}F\mathcal{J}^*$ is **symmetric and positive definite** as an operator on $L_0^2(\Sigma)$. So we can decompose the operator as

$$\mathcal{J}F\mathcal{J}^* = C^*C, \quad \text{with } C, C^* \text{ positive operators from } L_0^2(\Sigma) \text{ to } L_0^2(\Sigma).$$

So we have the **decomposition**

$$\boxed{F = B^*B}, \quad B = \mathcal{J}^{-1}C^* \text{ maps } H_0^{1/2}(\Sigma) \text{ to } L_0^2(\Sigma).$$

Since F is **coercive**, we deduce that $\|B\phi\|_{L_0^2(\Sigma)} \geq C\|\phi\|_{H_0^{1/2}(\Sigma)}$.

This implies that B^* is **surjective**.

Factorization: The Range Characterization

From the above calculations we obtain that

$$\Lambda_0 - \Lambda_\Sigma = L^*FL = L^*B^*(L^*B^*)^* = A^*A.$$

Since the Range of $(A^*A)^{1/2}$ is the Range of A^* , we deduce:

$$\mathcal{R}((\Lambda_0 - \Lambda_\Sigma)^{1/2}) = \mathcal{R}(L^*B^*) = \mathcal{R}(L^*)$$

since B^* is **surjective**. Now consider the **solution** of

$$\begin{aligned} \nabla \cdot \gamma_0 \nabla N(\cdot; \mathbf{y}) &= \delta(\cdot - \mathbf{y}), & \text{in } \Omega \\ \mathbf{n} \cdot \gamma_0 \nabla N(\cdot; \mathbf{y}) &= 0 & \text{on } \partial\Omega \quad \int_\Sigma N(\cdot; \mathbf{y}) \, d\sigma = 0. \end{aligned}$$

Then $\mathbf{n} \cdot \gamma \nabla N(\mathbf{x}; \mathbf{y})|_\Sigma \in H_0^{-1/2}(\Sigma)$ and $N(\mathbf{x}; \mathbf{y}) \in \mathcal{R}(L^*)$ **if and only if** $\mathbf{y} \in D$. Notice that this requires that $\gamma(\mathbf{x}) = \gamma_0(\mathbf{x})$ be **known** on $\Omega \setminus \overline{D}$.

How do we get the rest?

Now that Σ is known, we have on $\mathcal{R}(\Lambda_0 - \Lambda_\Sigma) \subset \mathcal{R}(L^*)$:

$$(L^*)^{-1}(\Lambda_0 - \Lambda_\Sigma) = FL.$$

L is dense in $H_0^{1/2}(\Sigma)$ since $\overline{\mathcal{R}(L)} = \mathcal{N}(L^*)^\perp = \{0\}^\perp = H_0^{1/2}(\Sigma)$ so we have access to the **full mapping** F in $\mathcal{L}(H_0^{1/2}(\Sigma), H_0^{-1/2}(\Sigma))$ and $F_\Sigma = F + F_0$.

The Range of $G_\Sigma = F_\Sigma L$ is **dense** since G_Σ^* is injective. This provides knowledge of the full Cauchy data:

$$\left\{ w|_\Sigma^- \in H_0^{1/2}(\Sigma); \quad \mathbf{n} \cdot \gamma \nabla w|_\Sigma^+ \in H_0^{-1/2}(\Sigma) \right\},$$

whence of the **Dirichlet to Neumann** operator

$$\Lambda_D = -\nabla_\perp \cdot d\nabla_\perp + \tilde{\Lambda}_D,$$

where $\tilde{\Lambda}_D$ is the **Dirichlet to Neumann map** of the domain D .

Reconstruction of $d(\mathbf{x})$.

Recall that

$$\Lambda_D = -\nabla_{\perp} \cdot d\nabla_{\perp} + \tilde{\Lambda}_D.$$

The second contribution $\tilde{\Lambda}_D$ is a bounded operator from $H_0^1(\Sigma)$ to $L_0^2(\Sigma)$. Let Σ be given locally by $x^n = 0$ in the coordinates (\mathbf{x}', x^n) . Since $\tilde{\Lambda}_D$ differentiates only **once**, it is clear that

$$\omega' \cdot d(\mathbf{x}')\omega' = \lim_{s \rightarrow \infty} \frac{-1}{s^2} e^{-is\omega' \cdot \mathbf{x}'} \Lambda_D e^{is\omega' \cdot \mathbf{x}'}, \quad \text{for all } \omega' \in S^{n-2}.$$

This **fully characterizes** the **symmetric tensor** $d(\mathbf{x}')$.

Reconstruction of $\gamma(\mathbf{x})$.

Once $d(\mathbf{x})$ is known, we have access to the Dirichlet to Neumann map $\tilde{\Lambda}_D$ of the domain D .

We then use known results to show that $\gamma(\mathbf{x})$ can **uniquely** be reconstructed if it is a sufficiently smooth (depending on space dimension) **scalar-valued** conductivity.

For **anisotropic tensors** in dimension $n = 2$ we have that γ_1 and γ_2 in $C^{2,\alpha}(D)$, $0 < \alpha < 1$, with boundary ∂D of class $C^{3,\alpha}$ with same data Λ_γ are such that there exists a $C^{3,\alpha}(D)$ diffeomorphism Φ with $\Phi|_{\partial\Omega} = I_{\partial\Omega}$, the identity operator on $\partial\Omega$, and

$$\gamma_2(x) = \frac{(D\Phi)^T \gamma_1(D\Phi)}{|D\Phi|} \circ \Phi^{-1}(x).$$

In **dimension $n \geq 3$** the same results holds provided that γ_1 , γ_2 , and ∂D (then Φ) are **real-analytic**.

Shape sensitivity analysis.

In a joint work with **Kui Ren**, we have developed a **shape-sensitivity-based** method to reconstruct the singular interface (clear layer) Σ . This is recast as a regularized nonlinear least square problem:

$$\mathcal{F}_\alpha(\Sigma) := \frac{1}{2} \|u - u_m^\delta\|_{L^2(\Gamma)}^2 + \alpha \int_\Sigma d\sigma(\mathbf{x}) \rightarrow \min_{\Sigma \in \Pi}.$$

Here and below, $\Gamma = \delta\Omega$. For a smooth vector field $\mathbf{V}(\mathbf{x})$ we define

$$\mathbf{F}_t(\mathbf{x}) = \mathbf{x} + t\mathbf{V}(\mathbf{x}), \quad \Sigma_t = \mathbf{F}_t(\Sigma),$$

and show that

$$d\mathcal{F}_\alpha(\Sigma) = (u - u_m^\delta, u')_{(\Gamma)} + \alpha(\kappa(\mathbf{x}), V_n)_{(\Sigma)},$$

where u' is the **shape derivative** of the current estimate $u = u(\Sigma)$.

Level-set based numerical simulation.

We show that $d\mathcal{F}_\alpha(\Sigma) \leq 0$ when \mathbf{V} is chosen such that

$$V_n = d\kappa \nabla_{\perp} u \cdot \nabla_{\perp} w + \mathbf{n} \cdot \nabla u^+ \mathbf{n} \cdot D \nabla w^+ - \mathbf{n} \cdot \nabla u^- \mathbf{n} \cdot D \nabla w^- - \alpha \kappa,$$

where w solves an adjoint equation.

Combined with a [level-set](#) approach, it allows us to construct velocity fields and to numerically move a guessed interface (assuming that $d(\mathbf{x})$ is *known*) so as to lower the discrepancy with the measured data.

The method was first proposed by F. Santosa to image the interface between two areas with known (and different) diffusion coefficients.

Simulations show how **noise** in the data **degrades** the reconstruction.

Ellipse 0% noise

Ellipse 5% noise

Star 0% noise

Star 2% noise

Conclusions.

Assuming the conductivity is **known** between $\partial\Omega$ and Σ and a **lower bound** is known on Ω , we can reconstruct the **singular interface** Σ , the **tangential diffusion** tensor $d(\mathbf{x})$, and a **scalar-valued conductivity** on the region enclosed by Σ .

The method to obtain Σ is **constructive**.

This means that we can **image** Σ and **through** Σ . This a positive result. The extension to Optical Tomography is straightforward.

Numerical simulations (based on **shape derivatives** and the level set method) show reconstructions of the interface from boundary measurements.

References.

- [1] G.Bal, Transport through diffusive and non-diffusive regions, embedded objects, and clear layers, *SIAM J. Appl. Math.*, **62**(5), pp. 1677–1697, 2002
- [2] G.Bal and K.Ren, Generalized diffusion model in optical tomography with clear layers, *J. Opt. Soc. Amer. A*, **20**(12), pp. 2355-2364, 2003
- [3] A.Kirsch, Characterization of the shape of a scattering obstacle using the spectral data of the far field operator, *Inverse Problems*, **14**, pp. 1489-1512, 1998
- [4] M.Brühl, Explicit characterization of inclusions in electrical impedance tomography, *SIAM J. Math. Anal.*, **32**, pp. 1327-1341, 2001
- [5] G.Bal, Reconstructions in impedance and optical tomography with singular interfaces, *Inverse Problems*, **21**(1), pp. 113-132, 2005
- [6] G.Bal and K.Ren, Reconstruction of singular surfaces by shape sensitivity analysis and level set method, 2005