

Numerical methods for EIT

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About me...









Numerical methods for EIT

Outline

- 1. The Calderón problem and linearization
- 2. The CGO-method for reconstruction in 2D
- 3. The CGO-method for reconstruction in 3D
- 4. The Calderón problem with partial data

1. The Calderón problem and linearization

The use of electricity in treatment and monitoring of patients:

• Electrocardiography (EKG)



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- Electrical Impedance Tomography









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- Fricke and Morse reported in the article "The electric capacity of tumours of the breast" (1926) that the electrical properties of breast tumours differ from healthy tissue
- Barber-Brown (1989):

Tissue	Conductivity (mS/cm)
Blood	6.7
Liver	2.8
Skeletal muscle	8.0 (long.), 0.6 (trans.)
Cardiac muscle	6.3(long.), 2.3 (trans.)
Lung (expiration-inspiration)	1.0 - 0.4
Fat	0.36
Bone	0.06

Measurement setup EIT





Mathematical model for EIT

Smooth bounded domain $\Omega \subset \mathbb{R}^d$, d = 2, 3, conductivity coefficient

$$0 < c \le \sigma \le C < \infty; \qquad \sigma \equiv 1 \text{ near } \partial \Omega.$$

Voltage potential u in Ω generated by boundary voltage potential f

$$abla \cdot \sigma \nabla u = 0 \text{ in } \Omega,$$

 $u|_{\partial \Omega} = f.$

Current field: $J = \sigma \nabla u$. Normal component of current field at $\partial \Omega$:

$$\boldsymbol{g} = \boldsymbol{\nu} \cdot \boldsymbol{J} = \sigma \partial_{\boldsymbol{\nu}} \boldsymbol{u}|_{\partial \Omega}.$$

Dirichlet to Neumann (voltage to current) map

$$\Lambda_{\sigma} \colon f \mapsto g.$$



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$$\Lambda_{\sigma} \colon H^{1/2}(\partial \Omega) \to H^{-1/2}(\partial \Omega)$$
$$f \mapsto g.$$

Weakly defined for $h \in H^{1/2}(\partial \Omega)$ by

$$\langle \Lambda_{\sigma} f, h \rangle = \int_{\partial \Omega} (\Lambda_{\sigma} f) \overline{h} \, ds(x) = \int_{\Omega} \sigma \nabla u \cdot \overline{\nabla v} dx, \quad v \in H^{1}(\Omega): \ v|_{\partial \Omega} = h.$$

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Note:

- Λ_{σ} bounded operator $H^{1/2}(\partial\Omega) \rightarrow H^{-1/2}(\partial\Omega)$
- Λ_{σ} is unbounded, selfadjoint in $L^{2}(\partial\Omega)$
- $\Lambda_{\sigma} \Lambda_1$ is compact in $L^2(\partial \Omega)$

Forward problem:

 $\Lambda : \sigma \mapsto \Lambda_{\sigma}$

From interior conductivity to boundary fields.

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Calderón problem is ill-posed:

• Large change in conductivity yields small change in data

Small change in data yields large change in reconstruction

Example with $f(\theta) = \cos(\theta)$

Current flow $J = \sigma \nabla u$:





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Boundary normal current $g = \sigma \partial_{\nu} u$:



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Example with $f(\theta) = \cos(4\theta)$

Current flow $J = \sigma \nabla u$:



Homogeneous conductivity



Perturbed conductivity

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Boundary currents



Short and incomplete history

1980 Calderón: Problem posed, uniqueness for linearized problem, and linear, approximate reconstruction algorithm

3D

- 1987 Sylvester and Uhlmann: Uniqueness for smooth conductivities. Implicit reconstruction algorithm
- 1987-88 Novikov, Nachman-Sylvester-Uhlmann, Nachman: Uniqueness for conductivities with 2 derivatives and explicit high frequency reconstruction algorithm. Multidimensional D-bar equation.
 - 1990 Alessandrini: Stability
 - 2003 Brown-Torres, Päivärinta-Panchenko-Uhlmann: Uniqueness for conductivities with 3/2 derivatives.
 - 2006 Cornean-Knudsen-Siltanen: Low frequency reconstruction algorithm
 - 2010 Bikowski-Knudsen-Mueller: Numerical implementation of simplified reconstruction algorithm
- 2011-14 Debary Hansen- Knudsen: Implementation of more accurate numerical reconstruction method
 - 2012 Haberman Tataru: Uniqueness for Lipschitz conductivities

2D

- 1996 Nachman: Uniqueness and reconstruction for $W^{2,p}(\Omega)$ conductivities.
- 1997 Liu: Stabilty for $W^{2,p}(\Omega)$ conductivities
- 1997 Brown-Torres: Uniqueness for $W^{1,p}(\Omega)$ conductivities
- 2001 Barceló-Barceló-Ruiz: Stability for $C^{1+\epsilon}$ conductivities
- 2001 Knudsen-Tamasan: Reconstruction for $C^{1+\epsilon}$ conductivities
- 2005 Astala-Päivärinta: Uniqueness and reconstruction for $L^{\infty}(\Omega)$
- 2009 Knudsen-Lassas-Mueller-Siltanen: Regularized 7-method
- 2010 Clop-Faraco-Ruiz: Stability for discontinuous conductivities

+ many more

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Replace non-linear operator $\Lambda : \sigma \mapsto \Lambda_{\sigma}$ by linear operator and solve linear inverse problem.

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 Optimization: Minimize over γ

$$\Phi(\gamma) = \|\Lambda_{\gamma} - \Lambda_{\sigma}\|_{Y} + \alpha \|\gamma\|_{X}$$

for suitable (semi-)norms X, Y.

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• Bayesian inversion:

$$\pi(\boldsymbol{x}|\boldsymbol{y}) = \frac{\pi(\boldsymbol{y}|\boldsymbol{x})\pi_{\mathrm{pr}}(\boldsymbol{x})}{\pi(\boldsymbol{y})}$$

Numerical methods for $x_{for \in I}\sigma$ and $y = \Lambda_{\sigma}$.

Linearization

Green's formula yields

$$\langle (\Lambda_{\sigma_1} - \Lambda_{\sigma_0}) f_1, f_0 \rangle = \int_{\Omega} (\sigma_1 - \sigma_0) \nabla u_1 \cdot \overline{\nabla u_0} dx, \\ \nabla \cdot \sigma_j \nabla u_j = 0 \text{ in } \Omega, \quad u_j |_{\partial \Omega} = f_j, \ j = 0, 1.$$

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For $\sigma_0 = 1$

$$\langle (\Lambda_{1+\delta\sigma} - \Lambda_1) f_1, f_0 \rangle \approx \langle (d\Lambda[1]\delta\sigma) f_1, f_0 \rangle = \int_{\Omega} \delta\sigma \nabla v_1 \cdot \overline{\nabla v_0} dx$$

with $\Delta v_j = 0$, $v_j|_{\partial\Omega} = f_j$.

Numerical methods for EIT

The linearized problem

Concerns the inversion of the mapping

 $\delta \sigma \mapsto (d\Lambda[1])(\delta \sigma).$

We want to compute $\delta\sigma$ by knowing:

$$\int_{\Omega} \delta \sigma \nabla \mathbf{v}_1 \cdot \overline{\nabla \mathbf{v}_0} d\mathbf{x}$$

for all harmonic functions v_0 , v_1 . Questions:

- Uniqueness?
- Stable reconstruction?

Problem: find σ from knowing

$$\mathcal{K}\sigma(x) = \int_{\Omega} \sigma(y) k(x,y) dy.$$

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1. Calderón problem: unknown diffuse kernel

$$k((i,j), \mathbf{y}) = \nabla u_i \cdot \overline{\nabla v_j}, \quad \nabla \cdot \sigma \nabla u = \mathbf{0}, \ \Delta \mathbf{v} = \mathbf{0}.$$

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3. Computerized Tomography: known localized kernel $k(\theta, r, y) = \delta(y \cdot \theta - r).$

Exponentially growing harmonics

Fix real vector $\xi \in \mathbb{R}^n$ and complex vector $\zeta \in \mathbb{C}^n$ such that

$$\zeta \cdot \zeta = (\xi + \zeta) \cdot (\xi + \zeta) = \mathbf{0}.$$

Harmonic functions in \mathbb{R}^n .

$$v_1(x,\zeta) = e^{ix\cdot\zeta}, \qquad v_0(x,\zeta) = e^{ix\cdot(\xi+\overline{\zeta})}$$

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Then

$$\nabla v_1 \cdot \overline{\nabla v_0} = \zeta \cdot (\xi + \zeta) e^{-ix \cdot \xi} = -\frac{1}{2} |\xi|^2 e^{-ix \cdot \xi}$$

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and

$$\begin{split} \langle d\Lambda_1[\delta\sigma] e^{ix\cdot\zeta}, e^{ix\cdot(\xi+\overline{\zeta})} \rangle &= -\frac{1}{2} |\xi|^2 \int_{\Omega} \delta\sigma e^{-ix\cdot\xi} dx \\ &= -\frac{1}{2} (2\pi)^{n/2} |\xi|^2 \widehat{\delta\sigma}(\xi) \\ \Leftrightarrow \qquad \widehat{\delta\sigma}(\xi) = -\frac{2}{(2\pi)^{n/2} |\xi|^2} \langle d\Lambda_1[\delta\sigma] e^{ix\cdot\zeta}, e^{ix\cdot(\xi+\overline{\zeta})} \rangle. \end{split}$$

Numerical methods for EIT

Uniqueness and stable reconstruction

$$\widehat{\delta\sigma}(\xi) = -\frac{2}{(2\pi)^{n/2}|\xi|^2} \langle d\Lambda_1[\delta\sigma] e^{i\mathbf{x}\cdot\zeta}, e^{i\mathbf{x}\cdot(\xi+\overline{\zeta})} \rangle.$$

• Uniqueness: Injectivity of Fourier transform.

Uniqueness and stable reconstruction

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- Reconstruction:

$$\delta\sigma(\mathbf{x}) = -\frac{2}{(2\pi)^n} \int_{\mathbb{R}^n} \frac{\langle d\Lambda_1[\delta\sigma] e^{i\mathbf{x}\cdot\zeta}, e^{i\mathbf{x}\cdot(\xi+\zeta)} \rangle}{|\xi|^2} e^{i\mathbf{x}\cdot\xi} d\xi.$$

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$$\delta\sigma(\mathbf{x}) = -\frac{2}{(2\pi)^n} \int_{\mathbb{R}^n} \frac{\langle d\Lambda_1[\delta\sigma] e^{i\mathbf{x}\cdot\zeta}, e^{i\mathbf{x}\cdot(\xi+\zeta)} \rangle}{|\xi|^2} e^{i\mathbf{x}\cdot\xi} d\xi.$$

Stabilization: Noise amplified exponential harmonics. Remedy: Avoid high frequencies by low-pass filtering:

$$\delta\sigma_{R}(\mathbf{x}) = -\frac{2}{(2\pi)^{n}} \int_{\mathbb{R}^{n}} \frac{\langle d\Lambda_{1}[\delta\sigma] \mathbf{e}^{i\mathbf{x}\cdot\zeta}, \mathbf{e}^{i\mathbf{x}\cdot(\xi+\overline{\zeta})} \rangle}{|\xi|^{2}} \mathbf{e}^{i\mathbf{x}\cdot\xi} \chi_{R}(\xi) \ d\xi.$$

Regularization scheme if *R* is chosen correctly.

Numerical methods for EIT

Calderón's reconstruction method

Treat non-linear data

$$\mathbf{t}^{\exp}(\xi,\zeta) := \langle (\Lambda_{\sigma} - \Lambda_{1}) \boldsymbol{e}^{i\boldsymbol{x}\cdot\zeta}, \boldsymbol{e}^{i\boldsymbol{x}\cdot(\xi+\overline{\zeta})} \rangle = \int_{\Omega} \delta\sigma \nabla \boldsymbol{u} \cdot \nabla \boldsymbol{e}^{-i\boldsymbol{x}\cdot(\xi+\zeta)} d\boldsymbol{x}$$

as linear data in previous formula

$$\sigma^{\operatorname{Cal}}(x) = 1 - \frac{2}{(2\pi)^n} \int_{\mathbb{R}^n} \frac{\mathbf{t}^{\exp}(\xi,\zeta)}{|\xi|^2} e^{ix\cdot\xi} \chi_{\mathsf{R}}(\xi) \ \mathsf{d}\xi.$$

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Estimate:

$$egin{aligned} \|\sigma^{ ext{Cal}}(x) - \eta_\gamma st \sigma\|_{L^\infty} &\leq \|m{R}(k)\hat\eta(k/\gamma)\|_{L^1(\mathbb{R}^2)} \ &\leq C\|\sigma-1\|^{1+lpha}_{L^\infty(\Omega)}(\log(\|\sigma-1\|_{L^\infty(\Omega)}))^2. \end{aligned}$$



Concentric reconstruction (linear)



Numerical methods for EIT





Figure: Increasing Fourier truncation for Calderón's method



Conclusion, linearized reconstruction

- Easy to implement and fast: based on FFT
- Recovers (with no regularization) the support of perturbation $\delta\sigma$ (cf [von Harrach Seo, 2010] and [Knudsen Lassas Mueller Siltanen, 2007])
- Recovers well low contrast perturbations
- Regularized algorithm recovers smooth approximatrion
- Can rigorous mathematics allow better reconstructions?