Monotonicity Methods in Electrical Impedance Tomography

Bastian von Harrach

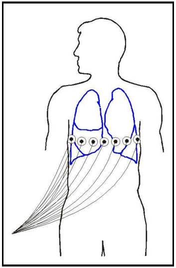
harrach@ma.tum.de

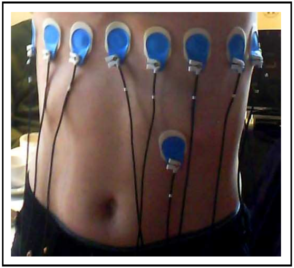
Department of Mathematics - M1, Technische Universität München, Germany

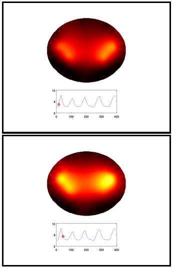
Joint work with Marcel Ullrich

ICIAM 2011
Vancouver, BC, Canada, July 18–22, 2011.

Electrical impedance tomography







- Apply electric currents on subject's boundary
- Measure necessary voltages

⇝ Reconstruct conductivity inside subject.

Mathematical Model

Forward operator of EIT:

$$\Lambda: \ \sigma \mapsto \Lambda(\sigma), \quad \text{"conductivity"} \mapsto \text{"measurements"}$$

- Conductivity: $\sigma \in L^\infty_+(\Omega)$
- Continuum model: $\Lambda(\sigma)$: Neumann-Dirichlet-operator

$$\Lambda(\sigma): \ g \mapsto u|_{\partial\Omega}, \quad \text{"applied current"} \mapsto \text{"measured voltage"}$$

$$\nabla \cdot (\sigma \nabla u) = 0 \quad \text{in } \Omega, \quad \sigma \partial_\nu u|_{\partial\Omega} = g \quad \text{on } \partial\Omega.$$

- Linear elliptic PDE theory:

$$\Lambda(\sigma): L^2_\diamond(\partial\Omega) \to L^2_\diamond(\partial\Omega) \text{ linear, compact, self-adjoint}$$

Inverse problem

Non-linear forward operator of EIT

$$\Lambda: \ \sigma \mapsto \Lambda(\sigma), \quad L^\infty_+(\Omega) \to \mathcal{L}(L^2_\diamond(\partial\Omega))$$

Inverse problem of EIT:

$$\Lambda(\sigma) \mapsto \sigma?$$

- Uniqueness ("Calderón problem"): Is Λ injective?
- Convergent numerical methods to reconstruct σ?

Reconstruction

Convergent numerical methods to reconstruct σ?

- Newton iteration: almost no theory

  Dobson (1992): (Local) convergence for regularized EIT equation.

  Lechleiter/Rieder(2008): (Local) convergence for discretized setting.

- D-bar method: convergent 2D-implementation for $\sigma \in C^2$

  Knudsen, Lassas, Mueller, Siltanen (2008)

In practice:

- large jumps in conductivity
- large interest in detecting shapes / inclusions / anomalies

---

Inclusion/shape detection problem:

$$\Lambda(\sigma) \mapsto \mathrm{supp}(\sigma - \sigma_0)?, \quad \sigma_0\text{: reference conductivity.}$$

Shape detection

Promising approach: Factorization method *(Kirsch 1998)*

- *FM for EIT (1999–): Brühl, Hakula, Hanke, H., Hyvönen, Kirsch, Lechleiter, Nachman, Päivärinta, Pursiainen, Schappel, Schmitt, Seo, Teirilä*

Typical result:

$$z \notin \mathrm{supp}(\sigma - \sigma_0) \quad \text{iff} \quad \lim_{\alpha \to 0} I_\alpha(z) = \infty.$$

($I_\alpha(z)$: indicator function)

Unsolved problems since 1998:

- Convergent regularization strategies for "infinity test"?
- Theory needs definiteness assumption, e.g., $\sigma \geq \sigma_0$ everywhere

In this talk: A monotonicity based sampling method.

Monotony

$$\int_\Omega (\sigma_1 - \sigma_2)|\nabla u_1|^2 \,\mathrm{d}x \leq (g, (\Lambda(\sigma_2) - \Lambda(\sigma_1))g)$$

u_1 solution corresponding to σ_1 and boundary current g.

Simple consequence:

$$\sigma_1 \leq \sigma_2 \quad \Longrightarrow \quad \Lambda(\sigma_1) \geq \Lambda(\sigma_2)$$

Monotony based imaging

- True conductivity: $\sigma = 1 + \chi_D$, D: unknown inclusion

$\rightsquigarrow$ $\Lambda(\sigma)$: measured data

- Test conductivity: $\kappa = 1 + \chi_B$, B: small ball

$\rightsquigarrow$ $\Lambda(\kappa)$ can be simulated for different balls B

Monotony:

$$B \subseteq D \quad \Longrightarrow \quad \Lambda(\sigma) \geq \Lambda(\kappa)$$

Monotony based reconstruction algo. for EIT *(Tamburrino/Rubinacci 02)*

- For all balls B, calculate $\Lambda(\kappa)$ and test whether $\Lambda(\sigma) \geq \Lambda(\kappa)$

$\rightsquigarrow$ Result: upper bound of D.

Only an upper bound? Converse montony relation?

Converse montony relation

Theorem *(H./Ullrich, 2010)*
$\Omega \setminus \overline{D}$ connected. $\sigma = 1 + \chi_D$, $\kappa = 1 + \chi_B$.

$$B \not\subseteq D \quad \Longrightarrow \quad \Lambda(\kappa) \not\geq \Lambda(\sigma).$$

$\rightsquigarrow$ Monotony method detects exact shape.

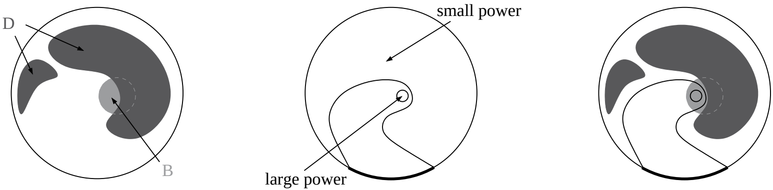
(Extensions possible for non-connected complement, inhomogeneous inclusions or background, continuous transitions between inclusion and background,. . .)

Converse montony relation

Proof $\quad (\sigma = 1 + \chi_D,\ \kappa = 1 + \chi_B)$

$$\int_\Omega (\kappa - \sigma)|\nabla u_\kappa|^2 \, \mathrm{d}x \leq (g, (\Lambda(\sigma) - \Lambda(\kappa))g)$$

Apply localized potentials (H 2008) to control power term $|\nabla u_\kappa|^2$.



$\rightsquigarrow \exists g : \ (g, (\Lambda(\sigma) - \Lambda(\kappa))g) \geq 0 \quad \Longrightarrow \quad \Lambda(\sigma) \not\leq \Lambda(\kappa)$

Fast implementation

- Testing $\Lambda(\sigma) \geq \Lambda(\kappa)$ is expensive. One forward problem per κ.
- Using linear approx. of $\Lambda(\kappa)$ still fulfills monotony relation (still exact, no linearization error!)

Theorem *(H./Ullrich, 2010)*

$\Omega \setminus \overline{D}$ connected. $\sigma = 1 + \chi_D$, $\kappa = 1 + k\chi_B$ (here: $0 < k \leq 1/2$)

$$B \subseteq D \quad \Longleftrightarrow \quad \Lambda(\mathbb{1}) + k\Lambda'(\mathbb{1})\chi_B \geq \Lambda(\sigma).$$

$\rightsquigarrow$ Fast implementation, requires only homogeneous forward solution

- Comp. cost equivalent to linearized methods or FM

(Again, extensions possible for non-connected complement, inhomogeneous inclusions or background, continuous transitions between inclusion and background,...)

Indefinite inclusions

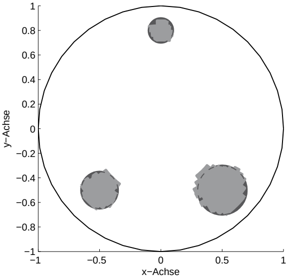
Indefinite inclusions: $\sigma = 2 + \chi_{D^+} - \chi_{D^-}$.

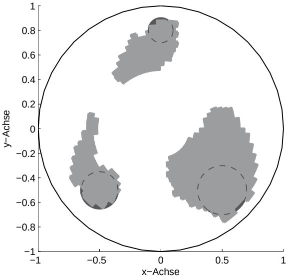
With $\kappa^+ = 2 + \chi_B$. $\kappa^- = 2 - \chi_B$:

$$D^+ \cup D^- \subseteq B \quad \Longleftrightarrow \quad \Lambda(\kappa^-) \leq \Lambda(\sigma) \leq \Lambda(\kappa^+).$$

- Indefinite inclusions can be treated by step-wise shrinking of larger test domains.

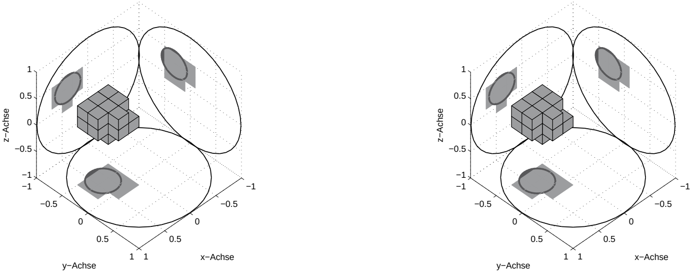
Numerical results





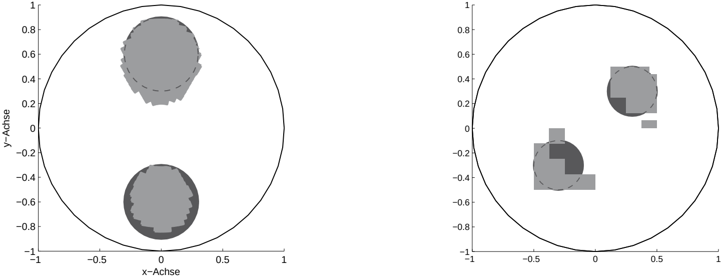
Reconstructions with exact data and with 0.1% noise.

Numerical results



Reconstructions with exact data and with 0.1% noise.

Numerical results



Reconstructions for smooth transitions between inclusion and background and for the indefinite case.

Summary

New results on the monotonicity method of Tamburrino and Rubinacci

- Method yields the exact shape not just an upper bound
- Method can be efficiently implemented by linearization (while still reconstructing the exact shape)

Advantages

- Rigorous treatment of indefinite inclusions
- Convergent regularization implementation of testing criteria seems possible

For practical applications:

- Enhance linearized/iterative methods by exact shape reconstruction *(H./Seo SIMA 2010, H./Seo/Woo IEEE TMI 2010)*