

Monotonicity methods for medical imaging

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http://numerical.solutions

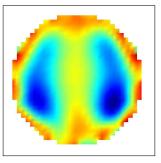
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Electrical impedance tomography







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

Calderón problem



Can we recover $\sigma \in L^{\infty}_{+}(\Omega)$ in

$$\nabla \cdot (\boldsymbol{\sigma} \nabla u) = 0, \quad x \in \Omega \subset \mathbb{R}^d$$
 (1)

from all possible Dirichlet and Neumann boundary values

$$\{(u|_{\partial\Omega},\sigma\partial_{\nu}u|_{\partial\Omega}): u \text{ solves (1)}\}?$$

Equivalent: Recover σ from Neumann-to-Dirichlet-Operator

$$\Lambda(\sigma): L^2_{\diamond}(\partial\Omega) \to L^2_{\diamond}(\partial\Omega), \quad g \mapsto u|_{\partial\Omega},$$

where u solves (1) with $\sigma \partial_{\nu} u|_{\partial \Omega} = g$.



Generic approaches for inverting $\sigma \mapsto \Lambda(\sigma)$

Penalty-based regularization: Minimize Tikhonov functional

$$\|\Lambda_{\text{meas}} - \Lambda(\sigma)\|^2 + \alpha \|\sigma - \sigma_0\|^2 \rightarrow \text{min!}$$

 σ_0 : Initial guess or known reference state (e.g. exhaled state)

Deep learning based methods:

Given training data $\{(\sigma_n, \Lambda(\sigma_n)): n = 1, ..., N\}$ minimize

$$\sum_{n=1}^{N} \| \sigma_n - f(\Lambda(\sigma_n)) \|^2 \to \min!$$

over all functions $f \in \mathbb{DL}$ described by DL-network.

Advantages: Very flexible, additional data/unknowns easily added Disadvantages: Almost no rigorous theory (convergence, resolution, ...)

Is there any specific problem structure that we can use to derive convergent algorithms?

Ikehata-Kang-Seo-Sheen Monotonicity



For two conductivities $\sigma_0, \sigma_1 \in L^{\infty}(\Omega)$:

$$\sigma_0 \le \sigma_1 \implies \Lambda(\sigma_0) \ge \Lambda(\sigma_1)$$

This follows from (Kang/Seo/Sheen 1997, Ikehata 1998)

$$\int_{\Omega} (\sigma_1 - \sigma_0) |\nabla u_0|^2 \ge \int_{\partial \Omega} g(\Lambda(\sigma_0) - \Lambda(\sigma_1)) g \ge \int_{\Omega} \frac{\sigma_0}{\sigma_1} (\sigma_1 - \sigma_0) |\nabla u_0|^2$$

for all solutions u_0 of

$$\nabla \cdot (\sigma_0 \nabla u_0) = 0, \quad \sigma_0 \partial_{\nu} u_0|_{\partial \Omega} = g.$$



The monotonicity method for inclusion detection in EIT

Monotonicity method



Sample inclusion detection problem (for ease of presentation)

- $\sigma_0 = 1$
- $\sigma = 1 + \chi_D$
- ▶ D open, $\overline{D} \subseteq \Omega$, $\Omega \setminus \overline{D}$ connected

All of the following also holds for

- \bullet σ_0 pcw. analytic and known,
- $\sigma = \sigma_0 + \kappa \chi_D$ with $\kappa \in L^{\infty}_+(D)$,
- ▶ in any dimension $n \ge 2$,
- for partial boundary data on open subset $\Gamma \subseteq \partial \Omega$.

Monotonicity method



Sample inclusion detection problem

•
$$\sigma_0 = 1$$
, $\sigma = 1 + \chi_D$, D open, $\overline{D} \subseteq \Omega$, $\Omega \setminus \overline{D}$ connected

Monotonicity

Monotonicity-based inclusion detection (Tamburrino/Rubinacci 2002):

$$B \subseteq D \implies 1 + \chi_B \le \sigma \implies \Lambda(1 + \chi_B) \ge \Lambda(\sigma)$$

Algorithm:

- ▶ Mark all balls *B* with $\Lambda(1 + \chi_B) \ge \Lambda(\sigma)$
- Result: upper bound of D.

Only an upper bound? Converse monotonicity relation?

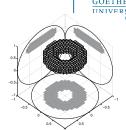
Monotonicity method (for simple test example)

Theorem (*H./Ullrich*, 2013)

$$B \subseteq D \iff \Lambda(1 + \chi_B) \ge \Lambda(\sigma).$$

For faster implementation:

$$B \subseteq D \iff \Lambda(1) + \frac{1}{2}\Lambda'(1)\chi_B \ge \Lambda(\sigma).$$



Shape can be reconstructed by linearized monotonicity tests.

Idea of proof: Combine monotonicity inequality:

$$\int_{\Omega} (\sigma_1 - \sigma_0) |\nabla u_0|^2 \ge \int_{\partial \Omega} g(\Lambda(\sigma_0) - \Lambda(\sigma_1)) g \ge \int_{\Omega} \frac{\sigma_0}{\sigma_1} (\sigma_1 - \sigma_0) |\nabla u_0|^2$$

with localized potentials (H., 2008):

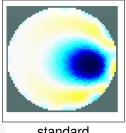
$$\int_{D_1} \left| \nabla u_0^{(k)} \right|^2 dx \to \infty \quad \text{and} \quad \int_{D_2} \left| \nabla u_0^{(k)} \right|^2 dx \to 0.$$

Monotonicity-based regularization

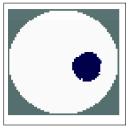


For real data: Monotonicity for regularizing residuum-based methods

- Rigorous convergence of reconstructed shape (H./Mach, 2016)
- Comparison with heuristic standard for tank data (H./Mach, 2018)







monoton.-regularized

- EIDORS: http://eidors3d.sourceforge.net (Adler/Lionheart)
- EIDORS standard solver: heuristic linearized method with Tikhonov regularization
- Dataset: iirc_data_2006 (Woo et al.): 2cm insulated inclusion in 20cm tank
 - using interpolated data on active electrodes (H., Inverse Problems 2015)



Monotonicity-based Uniqueness and Lipschitz-stability

Uniqueness



Monotonicity & localized potentials yield uniqueness results:

Non-linear Calderón problem: (Kohn/Vogelius 1985, H./Seo 2010) If $\sigma_1 \in L^\infty_+(\Omega)$ fulfills (UCP) and $\sigma_2 - \sigma_1$ is pcw. analytic then

$$\Lambda(\sigma_1) - \Lambda(\sigma_2)$$
 implies $\sigma_1 = \sigma_2$.

Linearized Calderón problem: (H./Seo 2010) If $\sigma_1 \in L^{\infty}_+(\Omega)$ fulfills (UCP) and $\kappa \in L^{\infty}(\Omega)$ is pcw. analytic then

$$\Lambda'(\sigma_1)\kappa = 0$$
 implies $\kappa = 0$.

Linearized & discretized Calderón problem: (Lechleiter/Rieder 2008)
With enough electrodes, the linearized Calderón problem with
CEM is uniquely solvable in fin.-dim. subspaces of pcw. analytic
functions (e.g., pcw. polynomials of fixed degree on fixed partition).





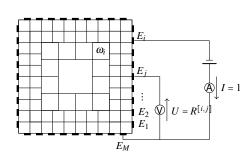
Complete Electrode Model

$$\nabla \cdot (\sigma \nabla u) = 0 \quad \text{in } \Omega$$

$$u|_{E_m} + z\sigma \partial_{\nu} u|_{E_m} = \text{const.} =: U_m$$

$$\int_{E_m} \sigma \partial_{\nu} u|_{E_m} \, \mathrm{d} s = J_m$$

$$\sigma \partial_{\nu} u = 0 \quad \text{else}$$



Current-to-Voltage operator

$$R_M(\sigma): \mathbb{R}^M_{\diamond} \to \mathbb{R}^M_{\diamond}, \quad (J_1, \dots, J_M) \mapsto (U_1, \dots, U_M).$$

What constraints on σ can make the inverse problem $R_M(\sigma) \mapsto \sigma$ well-posed?



Uniqueness and Lipschitz-stability for fixed resolution

Assumptions:

- Increasing number of electrodes fulfilling Hyvönen conditions
- F: finite-dimensional subset of pcw.-analytic functions (e.g., pcw. constant on fixed a-priori known partition)
- ► Known background conductivity: $\exists U$ nbr.hood of $\partial \Omega$, $\sigma_0 \in C^{\infty}$, so that $\sigma|_U = \sigma_0|_U$ for all $\sigma \in \mathcal{F}$
- A-prior known bounds

$$\mathcal{F}_{[a,b]} := \{ \sigma \in \mathcal{F} : a \le \sigma(x) \le b \text{ for all } x \in \Omega \}$$

Theorem. (H, 2019) $\exists N \in \mathbb{N}, c > 0$:

$$\|R_M(\sigma_1)-R_M(\sigma_2)\|_{\mathcal{L}(\mathbb{R}^M_{\diamond})} \geq c \|\sigma_1-\sigma_2\|_{L^{\infty}(\Omega)} \quad \forall \, \sigma_1,\sigma_2 \in \mathcal{F}_{[a,b]}, M \geq N.$$



Proof (main ideas)

► Monotonicity (H/Ullrich, 2015)

$$\langle (R'(\sigma_2)(\sigma_1 - \sigma_2))J, J \rangle_M = \int_{\Omega} (\sigma_2 - \sigma_1) |\nabla u_{\sigma_2}^{(J)}|^2 dx$$

$$\leq \langle (R_M(\sigma_1) - R_M(\sigma_2))J, J \rangle_M.$$

Lower bound on Lipschitz stability

$$\|R_M(\sigma_1) - R_M(\sigma_2)\| \geq \|\sigma_1 - \sigma_2\| \inf_{\substack{(\tau_1, \tau_2, \kappa) \\ \in \mathcal{F}_{[a,b]} \times \mathcal{F}_{[a,b]} \times \mathcal{F}_{[a,b]} \times \mathcal{K} \\ \|J\| = 1}} \sup_{\substack{J \in \mathbb{R}_0^M \\ \|J\| = 1}} f_M(\tau_1, \tau_2, \kappa, J),$$

$$f_M(\tau_1, \tau_2, \kappa, J) := \max \left\{ \left\langle \left(R'_M(\tau_1) \kappa \right) J, J \right\rangle, -\left\langle \left(R'_M(\tau_2) \kappa \right) J, J \right\rangle \right\},$$

Relation to NtD-operators, localized potentials & compactness

$$\inf_{\substack{(\tau_1,\tau_2,\kappa)\\ \in \mathcal{F}_{[a,b]}\times \mathcal{F}_{[a,b]}\times \mathcal{K} \\ \|J\|=1}} \sup_{J\in\mathbb{R}_{\diamond}^{M}} f_{M}(\tau_1,\tau_2,\kappa,J) > 0$$

Conclusions



Ikehata-Kang-Seo-Sheen Monotonicity yields

- fundamental relation between measurements and unknowns,
- convergent inclusion detection methods,
- rigorous regularizers for residuum-based methods,
- theoretical uniqueness and Lipschitz stability results.

Approach can be extended

- ▶ to partial boundary data, independently of dimension $n \ge 2$,
- to stochastic settings,
- at least partially to closely related problems (diffuse optical tomography, magnetostatics, inverse scattering, eddy-current equations, p-Laplacian, fractional diffusion, ...)