Monotonicity-based regularization of inverse coefficient problems

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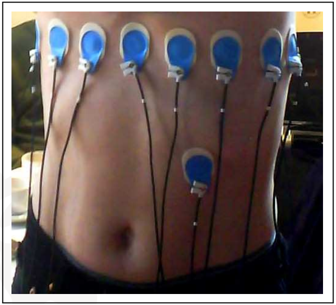
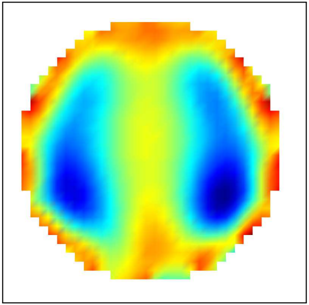
Electrical impedance tomography (EIT)





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

⇝ Reconstruct conductivity inside subject.

Mathematical Model

Electrical potential $u(x)$ solves

$$\nabla \cdot (\sigma(x) \nabla u(x)) = 0 \quad x \in \Omega$$

$\Omega \subset \mathbb{R}^n$: imaged body, $n \geq 2$
$\sigma(x)$: conductivity
$u(x)$: electrical potential

Idealistic model for boundary measurements (continuum model):

$\sigma \partial_\nu u(x)|_{\partial\Omega}$: applied electric current
$u(x)|_{\partial\Omega}$: measured boundary voltage (potential)

Calderón problem

Can we recover $\sigma \in L^\infty_+(\Omega)$ in

$$\nabla \cdot (\sigma \nabla u) = 0, \quad x \in \Omega \qquad (1)$$

from all possible Dirichlet and Neumann boundary values

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

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

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

Generic iterative solvers for non-linear inverse problems:

- Linearize and regularize:

$$\Lambda_{\text{meas}} \approx \Lambda(\sigma) \approx \Lambda(\sigma_0) + \Lambda'(\sigma_0)(\sigma - \sigma_0).$$

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

  $\rightsquigarrow$ Linear inverse problem for σ

  (Solve using linear regularization method, repeat for Newton-type algorithm.)

- Regularize and linearize:

  E.g., minimize non-linear Tikhonov functional

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

Advantages of generic solvers:

- Very flexible, additional data/unknowns easily incorporated
- Problem-specific regularization can be applied

  (e.g., total variation penalization, stochastic priors, etc.)

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

Problems with generic iterative solvers

- High computational cost
  - Evaluations of $\Lambda(\cdot)$ and $\Lambda'(\cdot)$ require PDE solutions.
  - PDE solutions too expensive for real-time imaging
- Convergence unclear

  (Validity of TCC/Scherzer-condition is a long-standing open problem for EIT.)
  - Convergence against true solution for exact meas. Λ_{meas}?

    (in the limit of infinite computation time)
  - Convergence against true solution for noisy meas. $\Lambda^{\delta}_{\text{meas}}$?

    (in the limit of $\delta \to 0$ and infinite computation time)
  - Global convergence? Resolution estimates for realistic noise?
- Influence of modelling errors
  - Evaluations of $\Lambda(\cdot)$ affected by large modelling errors

    (boundary geometry, electrode position, etc.)

Linearized methods

Popular approach in practice:

- Measure difference data $\Lambda_{\text{meas}} \approx \Lambda(\sigma) - \Lambda(\sigma_0)$.

  (e.g. $\Lambda(\sigma_0)$ measurement at exhaled state)

- Calculate $\sigma - \sigma_0$ from Λ_{meas} by single linearization step.

Standard linearized method

e.g. NOSER (Cheney et al., 1990), GREIT (Adler et al., 2009)

$$\text{Solve } \Lambda'(\sigma_0)\kappa = \Lambda_{\text{meas}}, \text{ then } \kappa \approx \sigma - \sigma_0.$$

After discretization and regularization:

$$\|\mathbf{S}\kappa - \mathbf{V}\|^2 + \alpha \|\kappa\|^2 \to \text{min!}$$

$\mathbf{S}$: sensitivity matrix, $\mathbf{V}$: vector of EIT measurements.

Linearization and shape reconstruction

Theorem (**H.**/Seo, SIMA 2010)
Let κ, σ, σ_0 pcw. analytic.

$$\Lambda'(\sigma_0)\kappa = \Lambda(\sigma) - \Lambda(\sigma_0) \quad \Longrightarrow \quad \mathrm{supp}_{\partial\Omega}\kappa = \mathrm{supp}_{\partial\Omega}(\sigma - \sigma_0)$$

$\mathrm{supp}_{\partial\Omega}$: outer support ($=\mathrm{supp}$ + parts unreachable from $\partial\Omega$)

- Linearized EIT equation contains correct shape information.
  (in the continuous version for noise-free measurements on infinitely many electrodes)
- Practitioners use heuristic regularization of linearized EIT equ.
  (in the discretized version for noisy measurements on finitely many electrodes)

Can we find a regularization that rigorously guarantees convergence of reconstructed shapes?

Monotonicity based imaging

- Monotonicity:

$$\tau \leq \sigma \quad \Longrightarrow \quad \Lambda(\tau) \geq \Lambda(\sigma)$$

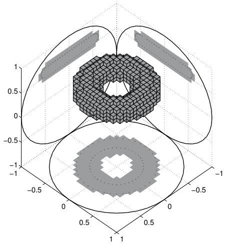
- Idea: Simulate $\Lambda(\tau)$ for test cond. τ and compare with $\Lambda(\sigma)$.
  (Tamburrino/Rubinacci 02, Lionheart, Soleimani, Ventre, ...)
- Inclusion detection: For $\sigma = 1 + \chi_D$ with unknown D,
  use $\tau = 1 + \chi_B$, with small ball B.

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

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

Only an upper bound? Converse monotonicity relation?

Monotonicity method (for simple test example)



Theorem *(**H.**/Ullrich, SIMA 2013)*

$\Omega \setminus \overline{D}$ connected. $\sigma = 1 + \chi_D$.

$$B \subseteq D \quad \Longleftrightarrow \quad \Lambda(1 + \chi_B) \geq \Lambda(\sigma).$$

For faster implementation:

$$B \subseteq D \quad \Longleftrightarrow \quad \Lambda(1) + \tfrac{1}{2}\Lambda'(1)\chi_B \geq \Lambda(\sigma).$$

Proof: Monotonicity & localized potentials

Shape can be reconstructed by linearized monotonicity tests.

Idea: Use monotonicity tests for regularizing linearized EIT equation.

Monotonicity method

Quantitative, pixel-based variant of monotonicity method:

(for $\Omega \setminus \overline{D}$ connected. $\sigma = 1 + \chi_D$)

- Pixel partition $\Omega = \bigcup_{k=1}^{m} P_k$
- Monotonicity tests

$$\beta_k \in [0, \infty] \text{ max. values s.t. } \beta_k \Lambda'(1)\chi_{P_k} \geq \Lambda(\sigma) - \Lambda(1)$$

- By theory of monotonicity method:

$$\beta_k \text{ fulfills } \begin{cases} \beta_k = 0 & \text{if } P_k \nsubseteq D \\ \beta_k \geq \frac{1}{2} & \text{if } P_k \subseteq D \end{cases}$$

Raise conductivity in each pixel until monotonicity test fails.

- Plot of β_k shows inclusions for perfect data but is very noise-sensitive since it ignores residuum information.

Monotonicity-based regularization

- Standard linearized methods for EIT: Minimize

$$\|\Lambda'(1)\kappa - (\Lambda(\sigma) - \Lambda(1))\|^2 + \alpha \|\kappa\|^2 \to \text{min!}$$

Choice of norms heuristic. No convergence theory!

- Monotonicity-based regularization: Minimize

$$\|\Lambda'(1)\kappa - (\Lambda(\sigma) - \Lambda(1))\|_F \to \text{min!}$$

under the constraint $\kappa|_{P_k} = \text{const.}$, $0 \leq \kappa|_{P_k} \leq \min\{\frac{1}{2}, \beta_k\}$.

($\|\cdot\|_F$: Frobenius norm of Galerkin projektion to finite-dimensional space)

Theorem (**H.**/Mach, submitted)

- There exists unique minimizer $\hat{\kappa}$ and

$$P_k \subseteq \operatorname{supp} \hat{\kappa} \iff P_k \subseteq \operatorname{supp}(\sigma - 1).$$

- Minimizer fulfills $\hat{\kappa} = \sum_{k=1}^{m} \min\{1/2, \beta_k\} \chi_{P_k}$

Monotonicity-based regularization

For noisy measurements $\Lambda^{\delta}_{\text{meas}} \approx \Lambda(\sigma) - \Lambda(1)$:

- Use regularized monotonicity tests

$$\beta_k^{\delta} \in [0,\infty] \text{ max. values s.t. } \beta_k^{\delta} \Lambda'(1)\chi_{P_k} \geq \Lambda^{\delta}_{\text{meas}} - \delta I$$

($\delta > 0$: noise level in $\mathcal{L}(L^2_\diamond(\partial\Omega))$-norm)

- Minimize

$$\|\Lambda'(1)\kappa^{\delta} - \Lambda^{\delta}_{\text{meas}}\|_{\text{F}} \to \text{min!}$$

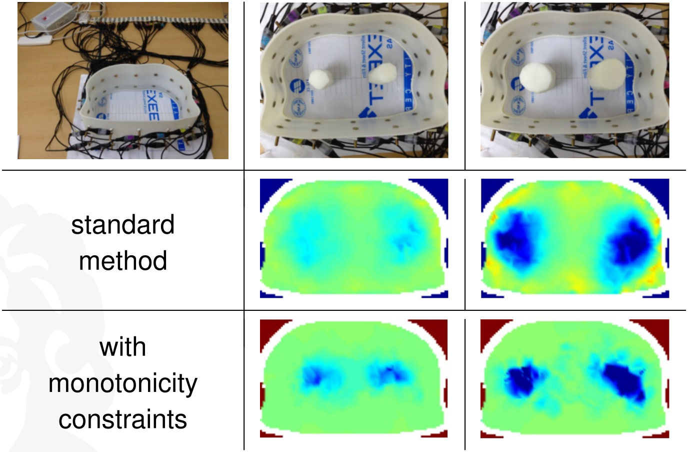
under the constraint $\kappa^{\delta}|_{P_k} = \text{const.},\ 0 \leq \kappa^{\delta}|_{P_k} \leq \min\{\frac{1}{2}, \beta_k^{\delta}\}$.

Theorem (**H.**/Mach, submitted)

- There exist minimizers κ^{δ} and $\kappa^{\delta} \to \hat{\kappa}$ for $\delta \to 0$.

Monotonicity-regularized solutions converge against correct shape.

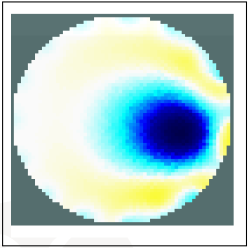
Phantom experiment



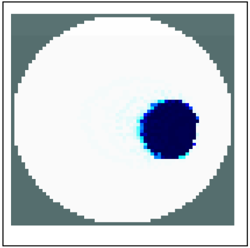
Enhancing standard methods by monotonicity-based constraints

(Zhou/**H.**/Seo, 2016)

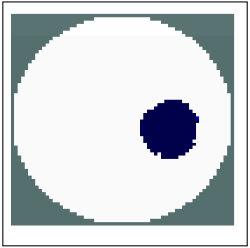
Benchmark example



standard



monoton.-regularized
(Matlab quadprog)



monoton.-regularized
(cvx package)

Monotonicity-regularization vs. community standard

(**H.**/Mach)

- EIT community standard: GREIT in EIDORS
- EIDORS: `http://eidors3d.sourceforge.net` (Adler/Lionheart)
- GREIT: Graz consensus Reconstruction algorithm for EIT (Adler et al.)
- Dataset: `iirc_data_2006` (Woo et al.): 2cm insulated inclusion in 20cm tank
  - using interpolated data on active electrodes (**H.**, Inverse Problems 2015)

Conclusions

EIT is a highly ill-posed, non-linear inverse problem.

- Convergence of generic solvers unclear.
- Practitioners use single linearization step with heuristic regularization and no theoretical justification.

Monotonicity-based regularization of linearized EIT equation

- uses that shape reconstr. in EIT is (essentially) a linear problem,
- yields solutions that rigorously converge against correct shape,
- combines rigorous theory of monotonicity method with practical robustness of residuum-based methods.

Approach (monotonicity + localized potentials) can be extended

- to partial boundary data, independently of dimension $n \geq 2$
- to other linear elliptic problems *(diffuse optical tomography, magnetostatics)*
- at least partially to closely related problems

  (eddy-current equations, p-Laplacian)