

Towards global convergence for inverse coefficient problems

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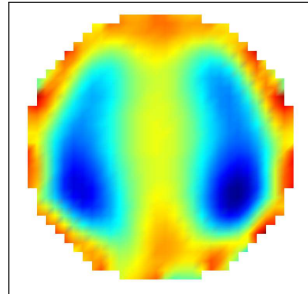
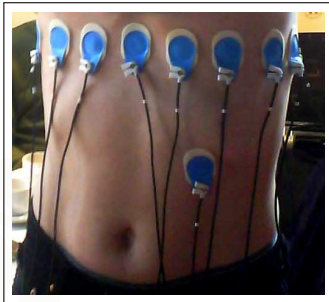
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29th Nordic Congress of Mathematicians with EMS
Aalborg University, Denmark, July 3–7, 2023.

Electrical impedance tomography (EIT)

Electrical impedance tomography (EIT)



- ▶ 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

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

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**

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

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

Challenges in idealized EIT

Mathematical idealization of EIT $\leadsto$ Calderón problem

- ▶ infinitely many unknowns $\sigma \in L_+^\infty(\Omega)$
- ▶ infinitely many measurements $\Lambda(\sigma) \in \mathcal{L}(L_\diamond^2(\partial\Omega))$
- ▶ nonlinear forward map $\sigma \mapsto \Lambda(\sigma)$

Mathematical challenges

- ▶ Uniqueness? Does $\Lambda(\sigma)$ determine σ ?
- ▶ Stability? $\Lambda^{-1} : \Lambda(\sigma) \mapsto \sigma$ continuous?
- ▶ Convergence (local/global)? How to determine σ from $\Lambda(\sigma)$?

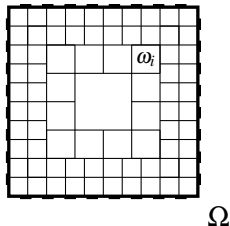
Consequences for practical EIT?

EIT in practice

- ▶ Finitely many unknowns, σ pcw. const. on given resolution $\Omega = \bigcup_{i=1}^n \omega_i$
- ▶ Finitely many measurements

$$\int_{\partial\Omega} g_j \Lambda(\sigma) g_k \, ds$$

for given currents $g_1, \dots, g_m \in L^2_{\diamond}(\partial\Omega)$



Finite-dimensional inverse problem: Determine

$$\sigma = \begin{pmatrix} \sigma_1 \\ \vdots \\ \sigma_n \end{pmatrix} \in \mathbb{R}_+^n \quad \text{from } F(\sigma) = \left(\int_{\partial\Omega} g_j \Lambda(\sigma) g_k \, ds \right)_{j,k=1}^m \in \mathbb{R}^{m \times m}.$$

Mathematical challenges for practical EIT

Inverse problem: Determine $\sigma \in \mathbb{R}_+^n$ from $Y = F(\sigma) \in \mathbb{R}^{m \times m}$.

For a fixed desired resolution:

- ▶ How many measurements uniquely determine σ ?
- ▶ Stability / error estimates for noisy data $Y^\delta \approx F(\sigma)$?
- ▶ Numerical algorithm to determine $\sigma \in \mathbb{R}_+^n$ from $Y^\delta \approx F(\sigma)$?
- ▶ Global/local convergence of algorithm?

Next slides: The problem of local convergence

Simple example: EIT with 2 unknowns & 6 bndry. currents

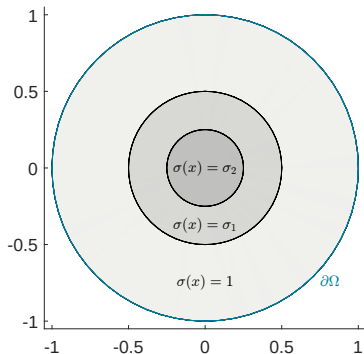
Ω : unit circle

$$F: \mathbb{R}_+^2 \rightarrow \mathbb{R}^{6 \times 6}$$

$$F \begin{pmatrix} \sigma_1 \\ \sigma_2 \end{pmatrix} := \left(\int_{\partial\Omega} g_j \Lambda(\sigma) g_k \right)_{j,k=1}^6$$

with trigonometric currents

$$\{g_1, \dots, g_6\} = \{\sin(\varphi), \dots, \cos(3\varphi)\}$$

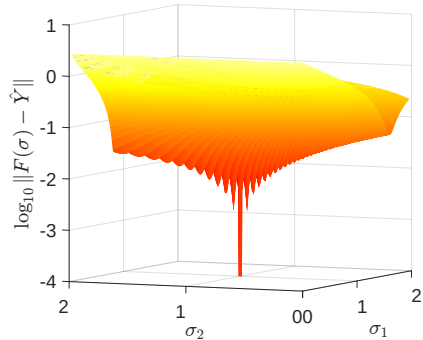
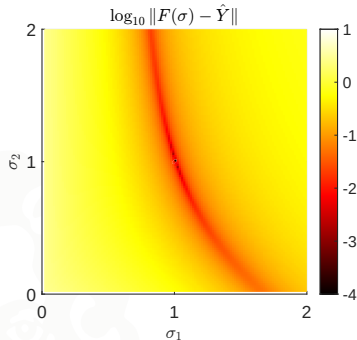


Inverse problem: Reconstruct $\hat{\sigma} \in \mathbb{R}_+^2$ from $\hat{Y} = F(\hat{\sigma}) \in \mathbb{R}^{6 \times 6}$

Natural approach: Least squares data fitting

$$\text{minimize} \quad \|F(\sigma) - \hat{Y}\|_F^2 \quad (+ \text{Regularization})$$

Problem of local minima

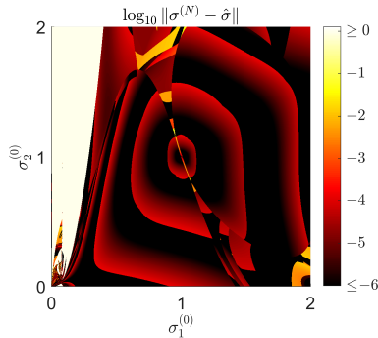


Numerical results indicate

- ▶ $\hat{Y} = F(\hat{\sigma})$ uniquely determines $\hat{\sigma} \dots$
- ▶ $\dots$ but residuum is highly non-convex, many local minima

Impossible to find global minimizer?

Problem of local convergence



- Error of Matlab's `lsqnonlin` depends on initial values

Are globally convergent algorithms impossible?

Monotonicity and Convexity

The Monotonicity Lemma

Lemma. (First appearance: Kang/Seo/Sheen 1997, Ikehata 1998)

$$\int_{\partial\Omega} g(\Lambda(\sigma_1) - \Lambda(\sigma_2))g \, ds \geq \int_{\Omega} (\sigma_2 - \sigma_1) |\nabla u_{\sigma_2}^g|^2 \, dx.$$

for all $\sigma_1, \sigma_2 \in L_+^\infty(\Omega)$, $g \in L_\diamond^2(\partial\Omega)$.

- Monotonicity w.r.t. Loewner order:

$$\sigma_1 \leq \sigma_2 \implies \Lambda(\sigma_1) \geq \Lambda(\sigma_2)$$

↪ Inclusion detection method (Tamburrino/Rubinacci 2002)

- Localized potentials:

$$\exists (g_k)_{k \in \mathbb{N}} : \int_{D_1} |\nabla u_{\sigma}^{g_k}|^2 \, dx \rightarrow \infty, \quad \int_{D_2} |\nabla u_{\sigma}^{g_k}|^2 \, dx \rightarrow 0.$$

↪ Converse monotonicity holds for inclusion detection.

↪ Monotonicity method yields exact shape (H./Ullrich 2013).

Monotonicity and Convexity

Lemma.

$$\begin{aligned} \int_{\partial\Omega} g(\Lambda(\sigma_1) - \Lambda(\sigma_2))g \, ds &\geq \int_{\Omega} (\sigma_2 - \sigma_1) |\nabla u_{\sigma_2}^g|^2 \, dx \\ &= \int_{\partial\Omega} g\Lambda'(\sigma_2)(\sigma_1 - \sigma_2)g \, ds. \end{aligned}$$

for all $\sigma_1, \sigma_2 \in L_+^\infty(\Omega)$, $g \in L_\diamond^2(\partial\Omega)$.

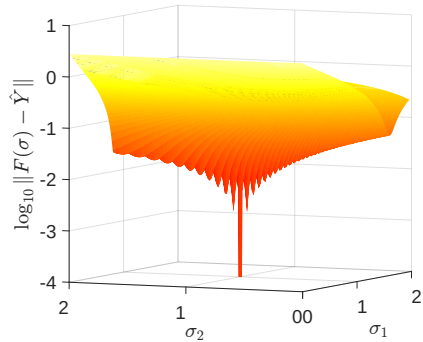
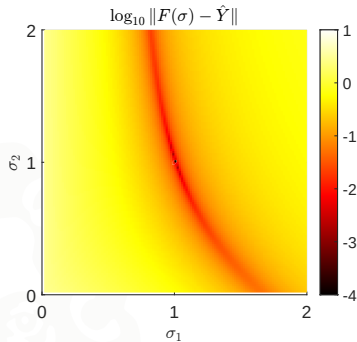
↷ For all $\sigma_1, \sigma_2 \in L_+^\infty(\Omega)$: $\Lambda(\sigma_1) - \Lambda(\sigma_2) \geq \Lambda'(\sigma_2)(\sigma_1 - \sigma_2)$.

↷ **Convexity:** For all $\sigma_1, \sigma_2 \in L_+^\infty(\Omega)$, $t \in [0, 1]$

$$\Lambda((1-t)\sigma_1 + t\sigma_2) \leq (1-t)\Lambda(\sigma_1) + t\Lambda(\sigma_2).$$

The "monotonicity lemma" also implies convexity.

Convex or not?

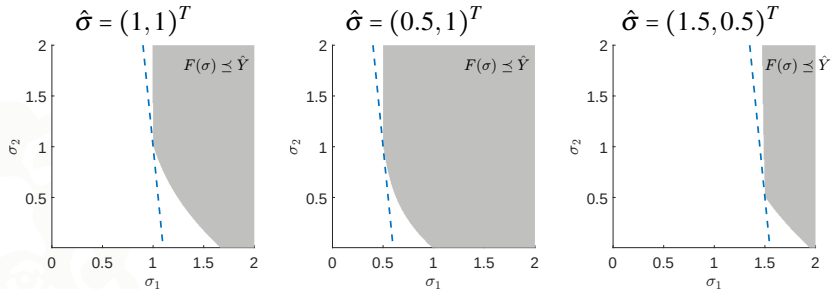


- ▶ Standard data-fitting yields non-convex residuum functionals
- ▶ But the NtD is convex w.r.t. Loewner order...

Can we find convex reformulation of the Calderón problem?

Convexity for the simple example

Inverse problem: Reconstruct $\hat{\sigma} \in \mathbb{R}_+^2$ from $\hat{Y} = F(\hat{\sigma}) \in \mathbb{R}^{6 \times 6}$

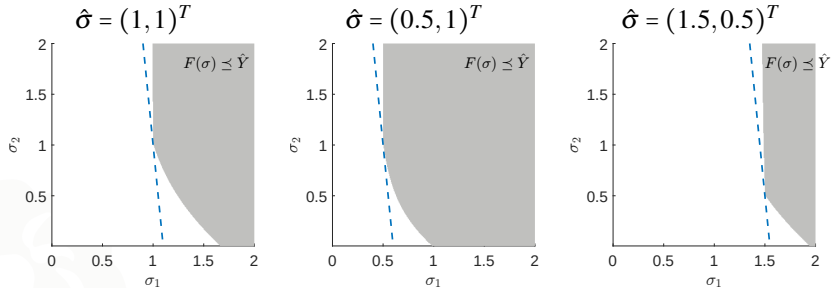


Observation.

$\hat{\sigma}$ is the lower left corner of the convex set $F(\sigma) \preceq \hat{Y}$.

("≤": Loewner / semidefiniteness order)

Mathematical formulation



Conjecture. $\exists c \in \mathbb{R}^n$ so that true solution $\hat{\sigma}$ minimizes

$$c^T \sigma = \sum_{i=1}^n c_i \sigma_i \rightarrow \min! \quad \text{s.t.} \quad \sigma \in [a, b]^n, F(\sigma) \leq \hat{Y}.$$

For a similar but simpler Robin problem:

- ▶ Conjecture holds with $c = \mathbb{1}$ (*H., Optim. Lett. 2021*)
- ▶ Global Newton convergence is possible (*H., Numer. Math. 2021*)

Convex reformulation for EIT

Theorem. (H., SIMA, to appear)

If sufficiently many measurements are taken, then:

- ▶ EIT forward mapping $F : [a, b]^n \rightarrow \mathbb{S}_m \subset \mathbb{R}^{m \times m}$ is injective.
- ▶ Derivative $F'(\sigma)$ is injective for all $\sigma \in [a, b]^n$.
- ▶ There exists $c \in \mathbb{R}_+^n$ so that for all $\hat{\sigma} \in [a, b]^n$, $\hat{Y} = \Lambda(\hat{\sigma})$:

$\hat{\sigma}$ is the unique solution of the convex problem

$$\text{minimize } c^T \sigma = \sum_{i=1}^n c_i \sigma_i \quad \text{s.t.} \quad \sigma \in [a, b]^n, F(\sigma) \leq \hat{Y}.$$

The Calderón problem with finitely many unknowns is equivalent to convex semidefinite optimization

Stability and error estimates

Theorem (continued). (H., SIMA, to appear)

There exists $\lambda > 0$ so that

- ▶ for all $\hat{\sigma} \in [a, b]^n$, and $\hat{Y} := \Lambda(\hat{\sigma})$,
- ▶ and all $\delta > 0$, and $Y^\delta \in \mathbb{S}_m \subset \mathbb{R}^{m \times m}$, with $\|Y^\delta - \hat{Y}\| \leq \delta$,

the convex semidefinite optimization problem

$$\text{minimize } c^T \sigma = \sum_{i=1}^n c_i \sigma_i \quad \text{s.t.} \quad \sigma \in [a, b]^n, F(\sigma) \leq Y^\delta + \delta I.$$

possesses a minimizer σ^δ . Every such minimizer fulfills

$$\|\sigma^\delta - \hat{\sigma}\|_{c, \infty} \leq \frac{n-1}{\lambda} \delta.$$

($\|\cdot\|_{c, \infty}$: *c-weighted maximum norm*)

Error estimates for noisy data $Y^\delta \approx \hat{Y}$ also hold.

Conclusions 1/2

For elliptic coefficient inverse problems

- ▶ least-squares residuum functionals may be highly non-convex
- ▶ local minima are usually useless

Possible remedy

- ▶ utilize monotonicity & convexity with respect to Loewner order
- ▶ utilize localized potentials to control directional derivatives

Equivalent convex reformulations are possible

- ▶ globally convergent solution algorithms are possible
- ▶ error estimates for noisy data are possible
- ▶ For similar but simpler Robin problem
 - ▶ explicit characterizations of achievable resolution
 - ▶ explicit error estimates for noisy data

Conclusions 2/2 *(now getting very subjective)*

Some future challenges in inverse problems in PDEs:

We need to progress and extend. . .

FROM: **Uniqueness** results for infinite-dimensional DtN/NtD
To: **Resolution** attainable from finitely many measurements

FROM: **Stability** results
To: **Error estimates** (with computable constants)

FROM: **Local convergence** and non-convex residuum functionals
To: **Global convergence** and convex functionals

Loewner monotonicity & convexity can help with these challenges.