

The Calderón problem with corrupted data

Pedro Caro

ikerbasque
Basque Foundation for Science

(b)cam
basque center for applied mathematics

Joint works with:

Andoni García

Ru-Yu Lai, Yi-Hsuan Lin, Ting Zhou

Cristóbal Meroño

Web seminar:

Control en tiempos de crisis

July 13, 2020

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

The inverse Calderón problem

The **inverse Calderón problem** aims at determining the **conductivity** of an inhomogeneous conductive medium from **non-invasive measurements**.

The formulation

If f is an **electric potential** prescribed on ∂D , the **electric potential** u inside of D satisfies

$$\begin{cases} \nabla \cdot (\gamma \nabla u) = 0 & \text{in } D, \\ u|_{\partial D} = f. \end{cases}$$

- ▶ $\gamma \partial_\nu u|_{\partial D}$ is the **outgoing electric current density** through ∂D .
- ▶ Measurements: the **Dirichlet-to-Neumann map**

$$\Lambda_\gamma : f \mapsto \gamma \partial_\nu u|_{\partial D}$$

The **inverse Calderón problem** is

- ▶ to decide if γ is **uniquely determined** by Λ_γ ,
- ▶ and **to calculate** γ in terms of Λ_γ if γ is determined by Λ_γ .

Discussing the model

This problem originates as a theoretical model in electrical prospecting.

- ▶ The aim is to determine the conductivity **conductivity** by means of **steady state electrical measurements** on ∂D .

Ideally, Λ_γ is determined through measurements effected on ∂D .

The model assumes to have access (to the graph of the DN map):

- ▶ to **infinite many pieces of data**
- ▶ and to **infinite-precision measurements**.

This is unjustified (data do not lie on the graph of the DN map):

- ▶ only a **finite number of measurements are available**
- ▶ the **data is corrupted** by measurement errors

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

Boundary reconstruction (smooth setting)

In 1988 [Sylvester–Uhlmann](#) show that, whenever D and γ are smooth, the DN map Λ_γ can be locally identified with a first order pseudodifferential operator, and its symbol can be expanded as:

$$\sum_{j=0}^{\infty} \partial_\nu^j \gamma.$$

Then, to reconstruct $\partial_\nu^j \gamma|_{\partial D}$ we only need to recover the symbol of a pseudodifferential operator —this is well known.

$$P = \sum_{|\alpha| \leq m} a_\alpha(x) (-i)^{|\alpha|} \partial_x^\alpha \quad \Rightarrow \quad e^{-ix \cdot \xi} P(e^{ix \cdot \xi}) = \sum_{|\alpha| \leq m} a_\alpha(x) \xi^\alpha$$

The **plane waves** $e^{ix \cdot \xi}$ are the tools.

Boundary reconstruction (non-regular setting)

In 2001 [Brown](#) used solutions with **highly oscillatory Dirichlet data** concentrating around a point $P \in \partial D$ to recover

$$\gamma(P).$$

To visualize these solutions think of $P = 0 \in \partial D$ and

$$D \subset \{x \in \mathbb{R}^d : x_d > 0\}.$$

Then, the Dirichlet data of the solutions looks like

$$M^{(d-1)/2} N^{-1/2} \chi(Mx) e^{N(i\xi - e_d) \cdot x}.$$

In 2006 [Brown–Salo](#) modified the method to recover:

$$\partial_\nu \gamma(P).$$

The tools are **wave packets**

$$f_{t,\lambda}(x) = t^{d/2} \chi(t(x - x_0)) e^{it^\lambda(x - x_0) \cdot \xi_0}.$$

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

The Calderón problem with noisy data

Recall that the goal is to reconstruct γ from the DN map

$$\int_{\partial D} \Lambda_\gamma f g = \int_{\partial D} \gamma \partial_\nu u g$$

where

$$\begin{cases} \nabla \cdot (\gamma \nabla u) = 0 & \text{in } D, \\ u|_{\partial D} = f. \end{cases}$$

In order to avoid the infinite-precision assumption of Calderón's formulation, we assume data to be the DN map plus a **random error**:

$$\mathcal{N}_\gamma(f, g) = \int_{\partial D} \Lambda_\gamma f g + \mathcal{E}(f, g),$$

where we want $\mathcal{E}(f, g)$ to denote a centred complex Gaussian whose variance depends on f and g .

Comments on the expectation

Note that

$$\mathbb{E} \mathcal{N}_\gamma(f, g) = \int_{\partial D} \Lambda_\gamma f g.$$

Therefore, the noise can be filtered having access to many independent outcomes:

$$\frac{1}{N} \sum_{n=1}^N \mathcal{N}_\gamma(f, g)(\omega_n) \xrightarrow{N \rightarrow \infty} \int_{\partial D} \Lambda_\gamma f g.$$

- ▶ A few repetitions of the same measurement **do not oscillate enough** to filter out the noise by averaging.
- ▶ We want to avoid averaging and show that **a single realization** of \mathcal{N}_γ is enough to reconstruct γ .

Comments on the variance

The variance

$$\mathbb{E} \left| \mathcal{N}_\gamma(f, g) - \int_{\partial D} \Lambda_\gamma f g \right|^2$$

depends on f and g .

- ▶ The *variable* variance aims at modelling measurement devices which decalibrates as the *strength* of the electric potential and the outgoing current increases.

Different approaches

There seem to be two different approaches.

- ▶ Deterministic regularization [[Tikhonov](#)]: The noise is deterministic and small.
- ▶ Statistical point of view: [[Sudakov–Halfin, Franklin](#)] No smallness assumption for the noise. [[Abraham–Nickl](#)] The level of noise is small.

Our approach is stochastic with no restriction on the size of the noise. It seems to be a new approach for the Calderón problem.

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

Reconstruction of $\gamma|_{\partial D}$

Theorem (C, Garcia)

For every $P \in \partial D$, there exists an explicit sequence $\{f_N : N \in \mathbb{N}\}$ such that

$$\lim_{N \rightarrow \infty} \mathcal{N}_\gamma(f_N, \overline{f_N}) = \gamma(P)$$

almost surely.

Rate of convergence for $\gamma|_{\partial D}$

Theorem (C, Garcia)

For every $P \in \partial D$, there exist an explicit sequence $\{f_N : N \in \mathbb{N}\}$ and a constant $C > 0$ such that, for every $\epsilon > 0$, we have

$$\mathbb{P}\{|\mathcal{N}_\gamma(f_N, \bar{f}_N) - \gamma(P)| \leq CN^{-2/3}\} \geq 1 - \epsilon \quad \forall N \geq c\epsilon^{-3}.$$

Reconstruction of $\partial_\nu \gamma|_{\partial D}$

The DN map of the reference medium with conductivity identically one is denoted by Λ .

Theorem (C, Garcia)

For every $P \in \partial D$, there exists an explicit family $\{f_t : t \geq 1\}$ such that, if

$$Y_N = \frac{1}{N^4} \int_{N^4}^{2N^4} \left[\mathcal{N}_\gamma(f_{t^2}, \overline{f_{t^2}}/\gamma) - \int_{\partial D} \Lambda f_{t^2} \overline{f_{t^2}} \right] dt,$$

one has that

$$\lim_{N \rightarrow \infty} Y_N = \frac{\partial_{\nu_P} \gamma(P) + i\tau_P \cdot \nabla \gamma(P)}{\gamma(P)}$$

almost surely. Here ν_P is the outward unit normal vector to ∂D at P and τ_P denotes any unitary tangential vector at P .

Why the need of Y_N ?

Recall that Λ_γ is a first order pseudodifferential operator with symbol

$$\sum_{j=0}^{\infty} \partial_\nu^j \gamma.$$

Since $\mathcal{N}_\gamma(f_{t^2}, \overline{f_{t^2}}) \rightarrow \gamma(P)$, then

$$\mathcal{N}_\gamma(f_{t^2}, \overline{f_{t^2}/\gamma}) \rightarrow 1.$$

Consequently,

$$\mathcal{N}_\gamma(f_{t^2}, \overline{f_{t^2}/\gamma}) - \int_{\partial D} \Lambda f_{t^2} \overline{f_{t^2}} \rightarrow \frac{\partial_{\nu_P} \gamma(P)}{\gamma(P)}.$$

Rate of convergence for $\partial_\nu \gamma|_{\partial D}$

Theorem (C, Garcia)

Consider $P \in \partial D$ and $\{f_t : t \geq 1\}$ the family of the previous theorem.
For every $N \in \mathbb{N}$, set

$$Y_N = \frac{1}{N^4} \int_{N^4}^{2N^4} \left[\mathcal{N}_\gamma(f_{t^2}, \overline{f_{t^2}}/\gamma) - \int_{\partial D} \Lambda_{f_{t^2}} \overline{f_{t^2}} \right] dt.$$

Then, there exists a constant $C > 0$ such that, for every $\epsilon > 0$, we have

$$\mathbb{P} \left\{ \left| Y_N - \frac{\partial_{\nu_P} \gamma(P) + i\tau_P \cdot \nabla \gamma(P)}{\gamma(P)} \right| \leq CN^{-2/3} \right\} \geq 1 - \epsilon \quad \forall N > c\epsilon^{-3}.$$

Comments on the results

- ▶ The main contributions are to filter the measurement errors almost surely and provide a *highly probable* rate of convergence.
- ▶ For the first two theorems **no average is needed** because

$$\|f_N\|_{L^2(\partial D)} = \mathcal{O}(N^{-1/2}).$$

- ▶ For the other two theorems we **require an average in \sqrt{N}** since

$$\|f_N\|_{L^2(\partial D)} = \mathcal{O}(1).$$

The strong law of large numbers

The underlying principle is the **Strong Law of Large Numbers**:

If $\{X_n\}$ is a sequence of independent random variables with means $\{\mu_n\}$ and variances $\{\sigma_n^2\}$ such that

$$\sum_{n=1}^{\infty} \frac{\sigma_n^2}{n^2} < \infty,$$

then

$$\frac{1}{N} \sum_{n=1}^N (X_n - \mu_n) \rightarrow 0$$

almost surely.

Recall

$$\mathcal{N}_\gamma(f, g) = \int_{\partial D} \Lambda_\gamma f g + \mathcal{E}(f, g).$$

The idea is to see that there is enough uncorrelation for

$$\mathcal{E}(f_t, \bar{f}_t).$$

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

White noise

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space and \mathcal{H} be a Hilbert space. A linear map $\mathbb{W} : \mathcal{H} \rightarrow L^2(\Omega, \mathcal{F}, \mathbb{P})$ is said to be a **complex Gaussian white noise** if, for every $f \in \mathcal{H}$, $\mathbb{W}f$ is a centred complex Gaussian variable and

$$\mathbb{E}(\overline{\mathbb{W}f} \mathbb{W}g) = (f|g)_{\mathcal{H}}, \text{ for all } f, g \in \mathcal{H}.$$

Here $(\cdot|\cdot)_{\mathcal{H}}$ denotes the inner product of \mathcal{H} .

Existence of white noise

If \mathcal{H} is a separable Hilbert space and $(\Omega, \mathcal{F}, \mathbb{P})$ is a probability space so that there exists a sequence $\{X_n : n \in \mathbb{N}\}$ of independent complex Gaussian so that

$$\mathbb{E}X_n = 0, \quad \mathbb{E}(\overline{X_n}X_n) = 1,$$

then, there always exists a complex Gaussian white noise for $(\Omega, \mathcal{F}, \mathbb{P})$ and \mathcal{H} .

It is enough to consider an orthonormal basis $\{e_n : n \in \mathbb{N}\}$ of \mathcal{H} , and define

$$\mathbb{W}f = \sum_{n \in \mathbb{N}} (e_n | f)_{\mathcal{H}} X_n,$$

where the convergence takes place in $L^2(\Omega, \mathcal{F}, \mathbb{P})$.

The model for the error

We define the **error** \mathcal{E} from a complex Gaussian white noise \mathbb{W} in the Hilbert space $\mathcal{H} = L^2(\partial D) \otimes L^2(\partial D)$ as follows:

$$\mathcal{E}(f, g) = \mathbb{W}(f \otimes g).$$

Recall that

$$(f_1 \otimes g_1 | f_2 \otimes g_2)_{\mathcal{H}} = (f_1 | f_2)(g_1 | g_2),$$

with $(\phi | \psi) = \int_{\partial D} \phi \bar{\psi}$.

This makes the error \mathcal{E} take the form

$$\mathcal{N}_{\gamma}(f, g) = \int_{\partial D} \Lambda_{\gamma} f g + \sum_{\alpha \in \mathbb{N}^2} (f | e_{\alpha_1})(g | e_{\alpha_2}) X_{\alpha}$$

with $X_{\alpha} = \mathbb{W}(e_{\alpha_1} \otimes e_{\alpha_2})$ and $\{e_n : n \in \mathbb{N}\}$ an o.n.b. of $L^2(\partial D)$.

- ▶ $\mathcal{N}_{\gamma}(f, g)$ is complex Gaussian
- ▶ $\mathbb{E} \mathcal{N}_{\gamma}(f, g) = \int_{\partial D} \Lambda_{\gamma} f g$
- ▶ $\mathbb{E} |\mathcal{N}_{\gamma}(f, g) - \int_{\partial D} \Lambda_{\gamma} f g|^2 = \|f\|_{L^2(\partial D)}^2 \|g\|_{L^2(\partial D)}^2$

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

Maxwell's equations

In collaboration with [Lai](#), [Lin](#) and [Zhou](#), we extended the results for the time-harmonic Maxwell system:

$$\nabla \times E - i\omega\mu H = 0 \text{ in } D,$$

$$\nabla \times H + i\omega\gamma E = 0 \text{ in } D.$$

In this situation the boundary data is given by the map:

$$\nu \times E|_{\partial D} \mapsto \nu \times H|_{\partial D}.$$

We reconstructed $\mu|_{\partial D}$ and $\gamma|_{\partial D}$ from noisy data modelling the error in

$$\mathcal{H} = L^2(\partial D)^3 \otimes L^2(\partial D)^3 \quad \text{and} \quad \mathcal{H} = H^{-1}(\partial D)^3 \otimes H^{-1}(\partial D)^3.$$

- ▶ **Need of averaging** to reconstruct $\mu|_{\partial D}$ and $\gamma|_{\partial D}$ when the error is modelled in $\mathcal{H} = L^2(\partial D)^3 \otimes L^2(\partial D)^3$.
- ▶ **No need of averaging** when the error is modelled in $\mathcal{H} = H^{-1}(\partial D)^3 \otimes H^{-1}(\partial D)^3$.

The problem of observability with noise

To understand the role of the choice of \mathcal{H} in the error \mathcal{E} , we introduce the problem of recovering an **observable** P from certain **measurements** \mathcal{N}_P that contain some random errors.

- ▶ The observable P is a pseudodifferential operator

$$Pf(x) = \frac{1}{(2\pi)^{d/2}} \int_{\mathbb{R}^d} e^{ix \cdot \xi} a(x, \xi) \widehat{f}(\xi) d\xi,$$

with a classical symbol a of order $m \in \mathbb{R}$.

- ▶ The measurements

$$\mathcal{N}_P(f, g) = \int_{\mathbb{R}^d} \bar{f} P g + \mathcal{E}_\beta(\bar{f}, g),$$

with $\mathcal{H} = H^\beta(\mathbb{R}^d) \otimes H^\beta(\mathbb{R}^d)$.

Different β s correspond to different variances of \mathcal{E}_β .

- ▶ If $\beta = 0$ the oscillations of f and g do not affect the size of the error, only their masses.
- ▶ For $\beta > 0$ the noise increase with the oscillations of f and g .
- ▶ For $\beta < 0$ the oscillations reduce the size of the noise.

The observational limit of wave packets

Assume

$$a \sim \sum_{j=1}^{\infty} a_j,$$

with a_j being a classical symbol of order $m_j \in \mathbb{R}$, for $m_j < m_{j-1} < \dots < m_1 = m$, which is *homogeneous in the variable ξ* . In collaboration with Meroño, showed how to use wave packets to reconstruct

$$a_1, \dots, a_{j_\beta}, a_{j_\beta+1}, \dots, a_{k_\beta}$$

when the observable P is so that

$$m = m_1 > \dots > m_{j_\beta} > 2\beta \geq m_{j_\beta} > \dots > m_{k_\beta} > 2\beta - 1/2.$$

- ▶ For a_1, \dots, a_{j_β} no averaging is needed.
- ▶ For $a_{j_\beta+1}, \dots, a_{k_\beta}$ averaging is required.

Furthermore, it is not possible to use wave packets to reconstruct

$$a_{k_\beta+1}, a_{k_\beta+2}, \dots$$

in presence of the error. **The signal is lost in the noise.**

A particular case to keep in mind

- ▶ If the observable P is a **differential operator of order m** , we can recover the full operator P from $\mathcal{N}_{\beta,P}$ with $\beta < 1/4$.
- ▶ Even with an error \mathcal{E}_β that gets amplified with oscillations, one can obtain the full observable.

Outline

The inverse Calderón problem

Boundary reconstruction

The Calderón problem with noise

Boundary reconstruction with noisy data

Modelling the error

Extensions

Conclusion

To take home

- ▶ The Calderón problem is a theoretical model that arises in electrical prospecting.
- ▶ Implementing the model presents non-trivial challenges since it assumes **infinite-precision measurements** and **infinite many pieces of data**.
- ▶ We consider the problem of **data corruption** in the boundary reconstruction. Our approach is stochastic and provides reconstruction almost surely.
- ▶ We also show a **highly probable rate of convergence**.
- ▶ The key underlying principle is the Strong Law of Large Numbers.
- ▶ The results can be extended to Maxwell's equations.
- ▶ There is a freedom in the choice of modelling the error. Different choices respond to oscillations in very different ways.
- ▶ Wave packets are useful but have limitations in the problem of observability with noise.