

Direct Electrical Impedance Tomography for Nonsmooth Conductivities

Jennifer Mueller

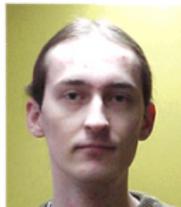
Department of Mathematics
and School of Biomedical Engineering
Colorado State University

June 20, 2011

Collaborators on this work



Kari Astala
University of Helsinki



Allan Perämäki
Helsinki University of Technology

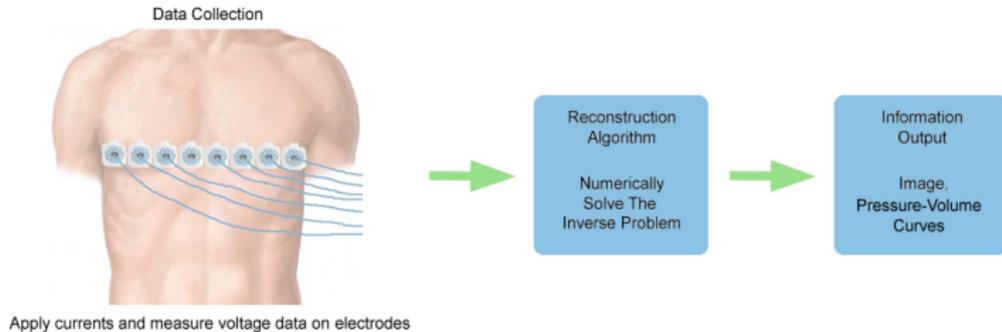


Lassi Päivärinta
University of Helsinki, Finland



Samuli Siltanen
University of Helsinki, Finland

The EIT Problem



Medical Applications in 2-D:

- Monitoring ventilation and perfusion in ARDS patients
- Detection of pneumothorax
- Diagnosis of pulmonary edema and pulmonary embolus

The 2-D EIT Problem

Given a bounded domain $\Omega \in \mathbb{R}^2$, determine the conductivity $\sigma(\mathbf{z})$ where

$$\begin{aligned}\nabla \cdot (\sigma(\mathbf{z})\nabla u) &= 0 \text{ in } \Omega, \\ u &= f \text{ on } \partial\Omega\end{aligned}$$

from knowledge of the Dirichlet-to-Neumann map

$$\Lambda_\sigma f = \sigma \frac{\partial u}{\partial \nu} \Big|_{\partial\Omega}$$

The approach presented here is based on the constructive proof of Astala and Päivärinta [Ann. of Math. **163** (2006)].

CGO Solutions

The method is based on the existence of exponentially growing solutions to the **conductivity and resistivity** equations

$$\nabla \cdot (\sigma(\mathbf{z}) \nabla u_1(\mathbf{z}, k)) = 0, \quad u_1 \sim e^{ikz} \text{ when } |\mathbf{z}| \rightarrow \infty$$

$$\nabla \cdot \left(\frac{1}{\sigma(\mathbf{z})} \nabla u_2(\mathbf{z}, k) \right) = 0, \quad u_2 \sim ie^{ikz} \text{ when } |\mathbf{z}| \rightarrow \infty$$

The exponential behaviour of the CGO solutions is used for **nonlinear Fourier analysis** for the inverse problem.

k can be thought of as a frequency-domain variable.

CGO Solutions

Defining

$$f_\mu(z, k) = u_1(z, k) + iu_2(z, k)$$

and

$$\mu(z) = \frac{1 - \sigma(z)}{1 + \sigma(z)}$$

one can show $f_\mu(z, k)$ satisfies the **Beltrami equation**

$$\bar{\partial}_z f_\mu = \mu \overline{\partial_z f_\mu}$$

and the solutions can be written as

$$f_\mu(z, k) = e^{ikz}(1 + \omega(z, k)), \quad \text{with} \quad \omega(z, k) = \mathcal{O}\left(\frac{1}{z}\right) \text{ as } |z| \rightarrow \infty.$$

Computing CGO Solutions (FP)

A computation shows that ω satisfies the equation

$$\bar{\partial}_z \omega - \nu \overline{\partial_z \omega} - \alpha \bar{\omega} - \alpha = 0. \quad (1)$$

Here $e_k(z) := \exp(i(kz + \bar{k}\bar{z}))$ and

$$\nu(z, k) \equiv e_{-k}(z)\mu(z), \quad (2)$$

$$\alpha(z, k) \equiv -i\bar{k}e_{-k}(z)\mu(z), \quad (3)$$

We will make a substitution, defining $u \in L^p(\Omega)$ such that

$$\bar{u} = -\bar{\partial}_z \omega.$$

Computing CGO Solutions (FP)

Then $\omega = -P\bar{u}$ and $\partial\omega = -S\bar{u}$, where

$$Pf(z) = -\frac{1}{\pi} \int_{\mathbb{C}} \frac{f(\lambda)}{\lambda - z} dm(\lambda), \quad Sg(z) = -\frac{1}{\pi} \int_{\mathbb{C}} \frac{g(\lambda)}{(\lambda - z)^2} dm(\lambda).$$

Then (1) becomes

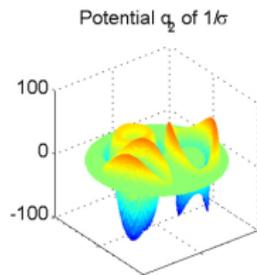
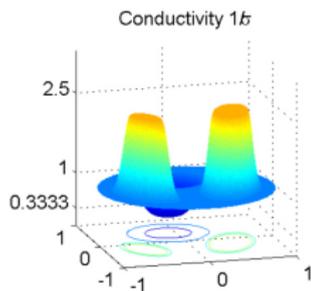
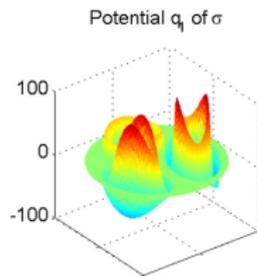
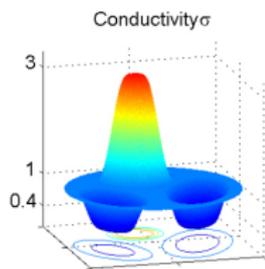
$$u + (-\bar{\nu}S - \bar{\alpha}P)\bar{u} = -\bar{\alpha}$$

or

$$(I + A\rho)u = -\bar{\alpha}, \quad \text{with } \rho f = \bar{f} \text{ and } A = -\bar{\nu}S - \bar{\alpha}P$$

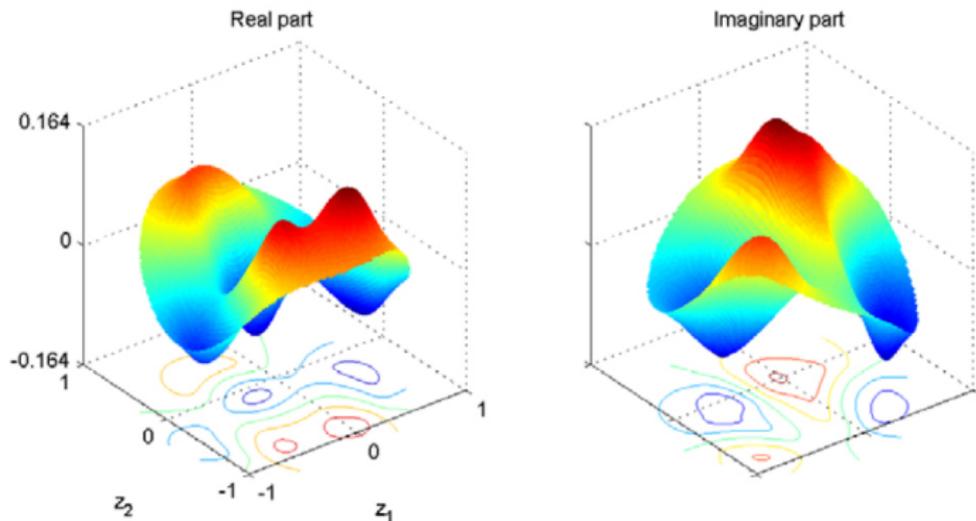
This is equation is then discretized and solved with GRMES using a preconditioner.

An Example for the CGO Solutions



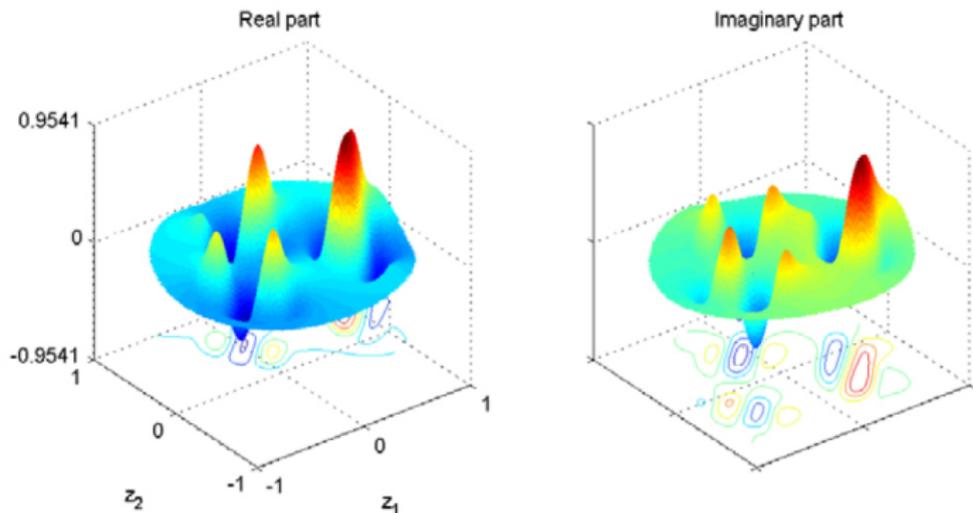
An example conductivity and corresponding resistivity

Computing CGO Solutions



Real and imaginary parts of $\omega(z, 1)$

Computing CGO Solutions



Real and imaginary parts of $\omega(z, -4.9497 - 4.9497i)$

Overview of the reconstruction algorithm

The reconstruction procedure consists of these three steps:

- (i) **Recover traces** of CGO solutions at the boundary $\partial\Omega$ from the DN map by solving a boundary integral equation given by Astala and Päivärinta.
- (ii) **Compute approximate values of CGO solutions inside the unit disc using the low-pass transport matrix.**
- (iii) **Reconstruct the conductivity.** The approximate conductivity is computed from the recovered values of the CGO solutions inside Ω using differentiation and simple algebra.

A Boundary Integral Formula for CGO Solutions

Defining

$$M_\mu(z, k) = 1 + \omega(z, k),$$

the following **boundary integral equation** holds:

$$M_\mu(\cdot, k)|_{\partial\Omega} + 1 = (\mathcal{P}_\mu^k + \mathcal{P}_0)M_\mu(\cdot, k)|_{\partial\Omega}, \quad (4)$$

where \mathcal{P}_μ^k and \mathcal{P}_0 are **projection operators** to be discussed.

Numerical solution of (4) is done by

- writing real and imaginary parts separately
- replacing all the operators by their $(4N + 2) \times (4N + 2)$ matrix approximations
- solving the resulting finite linear system for $|k| \leq R$ where $R > 0$ depends on the noise level.

The Hilbert Transform

Define the μ – Hilbert transform $\mathcal{H}_\mu : H^{1/2}(\partial\Omega) \rightarrow H^{1/2}(\partial\Omega)$ by

$$\mathcal{H}_\mu : u_1|_{\partial\Omega} \longrightarrow u_2|_{\partial\Omega}$$

To extend this to complex-valued functions in $H^{1/2}(\partial\Omega)$, define

$$\mathcal{H}_\mu(iu) = i\mathcal{H}_{-\mu}(u)$$

Theorem [AP]: The Dirichlet-to-Neumann map Λ_σ uniquely determines \mathcal{H}_μ , $\mathcal{H}_{-\mu}$, and $\Lambda_{\sigma^{-1}}$.

The Projection Maps

Define an averaging operator

$$\mathcal{L}\phi := |\partial\Omega|^{-1} \int_{\partial\Omega} \phi \, ds.$$

The operator $\mathcal{P}_\mu : H^{1/2}(\partial\Omega) \rightarrow H^{1/2}(\partial\Omega)$ is defined by

$$\mathcal{P}_\mu g = \frac{1}{2}(I + i\mathcal{H}_\mu)g + \frac{1}{2}\mathcal{L}g,$$

where g may be complex-valued. Further, denote

$$\mathcal{P}_\mu^k g := e^{-ikz} \mathcal{P}_\mu(e^{ikz} g)$$

Boundary Data

For $n = 1, \dots, 2N$, define a set of **trigonometric basis functions**:

$$\phi_n(\theta) = \begin{cases} \pi^{-1/2} \cos((n+1)\theta/2), & \text{for odd } n, \\ \pi^{-1/2} \sin(n\theta/2), & \text{for even } n. \end{cases}$$

Any function $g \in L^2(\partial\Omega)$ representing **current density** on the boundary can then be approximated by

$$g(\theta) \approx \sum_{n=1}^{2N} \langle g, \phi_n \rangle \phi_n(\theta),$$

where the inner product is defined for real-valued functions $f, g \in L^2(\partial\Omega)$ by

$$\langle f, g \rangle := \int_0^{2\pi} f(\theta)g(\theta) d\theta.$$

Boundary Data

Now define the $2N \times 2N$ matrix approximation $[R_{mn}]$ to the ND map by

$$R_{mn} = \langle u_n|_{\partial\Omega}, \phi_m \rangle$$

where $u_n|_{\partial\Omega}$ is the solution to the Neumann problem with $g = \phi_n$. Define

$$\tilde{L}_\sigma := [R_{mn}]^{-1};$$

Now we can approximate \mathcal{H}_μ acting on real-valued, zero-mean functions expanded in the trig basis by

$$\tilde{H}_\mu := D_T^{-1} L_\sigma.$$

Step 2: The Low-Pass Transport Matrix

Useful Facts:

- The function f_μ is harmonic outside the unit disc since μ is supported inside Ω .
- We know the trace of f_μ on $\partial\Omega$.
- Thus, the Fourier coefficients of f_μ can be used to expand f_μ as a power series outside Ω .

The **transport matrix** is the matrix in a 2×2 linear system that connects the CGO solutions inside Ω to their values outside Ω .

Step 2: The Low-Pass Transport Matrix

For any $z_0 \in \mathbb{R}^2 \setminus \bar{\Omega}$, set $\nu_{z_0}^{(R)}(k) = 0$ if $|k| \geq R$, and if $|k| < R$

$$\nu_{z_0}^{(R)}(k) := \frac{-f_\mu(z_0, k) + \overline{f_{-\mu}(z_0, k)}}{f_\mu(z_0, k) + f_{-\mu}(z_0, k)}$$

We solve the truncated Beltrami equations

$$\begin{aligned}\bar{\partial}_k \alpha^{(R)} &= \nu_{z_0}^{(R)}(k) \overline{\partial_k \alpha^{(R)}}, & \alpha^{(R)}(z, z_0, k) &= e^{ik(z-z_0)+k\phi(k)}, \\ \bar{\partial}_k \beta^{(R)} &= \nu_{z_0}^{(R)}(k) \overline{\partial_k \beta^{(R)}}, & \beta^{(R)}(z, z_0, k) &= ie^{ik(z-z_0)+k\tilde{\phi}(k)},\end{aligned}$$

where $\phi(k) \rightarrow 0$ as $k \rightarrow \infty$. We also have the conditions

$$\alpha^{(R)}(z, z_0, 0) = 1 \quad \text{and} \quad \beta^{(R)}(z, z_0, 0) = i.$$

Step 2: The Low-Pass Transport Matrix

For any $z_0 \in \mathbb{R}^2 \setminus \bar{\Omega}$, set $\nu_{z_0}^{(R)}(k) = 0$ if $|k| \geq R$, and if $|k| < R$

$$\nu_{z_0}^{(R)}(k) := \frac{-f_\mu(z_0, k) + \overline{f_{-\mu}(z_0, k)}}{f_\mu(z_0, k) + f_{-\mu}(z_0, k)}$$

We solve the truncated Beltrami equations

$$\begin{aligned}\bar{\partial}_k \alpha^{(R)} &= \nu_{z_0}^{(R)}(k) \overline{\partial_k \alpha^{(R)}}, & \alpha^{(R)}(z, z_0, k) &= e^{ik(z-z_0)+k\phi(k)}, \\ \bar{\partial}_k \beta^{(R)} &= \nu_{z_0}^{(R)}(k) \overline{\partial_k \beta^{(R)}}, & \beta^{(R)}(z, z_0, k) &= ie^{ik(z-z_0)+k\tilde{\phi}(k)},\end{aligned}$$

where $\phi(k) \rightarrow 0$ as $k \rightarrow \infty$. We also have the conditions

$$\alpha^{(R)}(z, z_0, 0) = 1 \quad \text{and} \quad \beta^{(R)}(z, z_0, 0) = i.$$

Step 2: The Low-Pass Transport Matrix

Fix any nonzero $k_0 \in \mathbb{C}$ and choose any point z inside the unit disc. We can now use the **approximate transport matrix**

$$T^{(R)} = T_{z, z_0, k_0}^{(R)} := \begin{pmatrix} a_1^{(R)} & a_2^{(R)} \\ b_1^{(R)} & b_2^{(R)} \end{pmatrix} \quad (6)$$

to compute

$$\begin{aligned} u_1^{(R)}(z, k_0) &= a_1^{(R)} u_1(z_0, k_0) + a_2^{(R)} u_2(z_0, k_0), \\ u_2^{(R)}(z, k_0) &= b_1^{(R)} u_1(z_0, k_0) + b_2^{(R)} u_2(z_0, k_0), \end{aligned} \quad (7)$$

where $\alpha^{(R)} = a_1^{(R)} + ia_2^{(R)}$ and $\beta^{(R)} = b_1^{(R)} + ib_2^{(R)}$.

Step 3: Reconstructing the Conductivity

From [AP] for any fixed $k_0 \in \mathbb{C}$, $\mu(z)$ is related to f_μ by

$$\mu(z) = \frac{\bar{\partial} f_\mu(z, k_0)}{\partial f_\mu(z, k_0)}.$$

Thus, the conductivity $\sigma(z)$ can be recovered by

$$\sigma(z) = -i \frac{\bar{\partial}(\Im f)}{\bar{\partial}(\Re f)}$$

This can be computed independently for each z in the ROI.

Example: Heart-and-Lungs Phantom

Ideal Conductivity	From ideal data	From 0.01% noise
--------------------	-----------------	------------------

Background :	1.0		
--------------	-----	--	--

~ 1.2

~ 1.2

Lungs :	0.7		
---------	-----	--	--

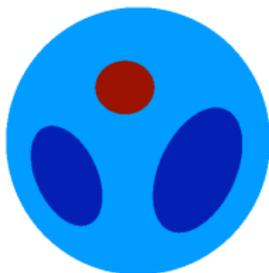
0.637

0.637

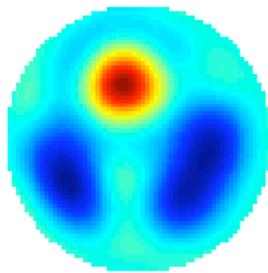
Heart :	2.0		
---------	-----	--	--

1.997

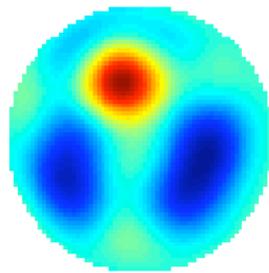
1.870



Relative error:
Dynamic range:



11.6%
105%



12.7%
95%

Example: Heart-and-Lungs + Spine

Ideal Conductivity	From ideal data
--------------------	-----------------

Background :	1.0
--------------	-----

~ 1.1

Spine :	0.2
---------	-----

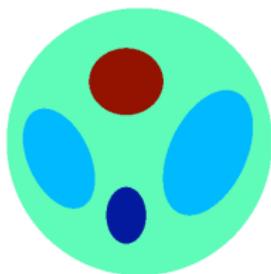
0.373 (*min*)

Lungs :	0.7
---------	-----

~ 0.7

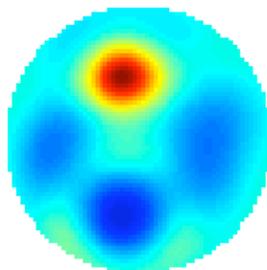
Heart :	2.0
---------	-----

2.273 (*max*)



Relative error:

Dynamic range:



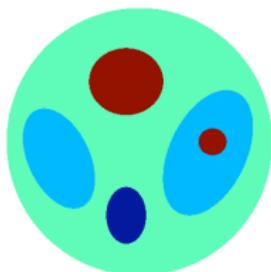
16.3%

106%

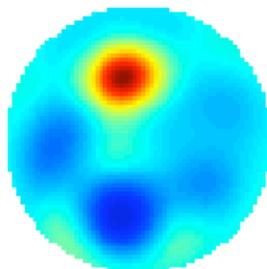
Example: Heart-and-Lungs + Spine + Tumor

Ideal Conductivity	From ideal data
--------------------	-----------------

Background :	1.0	~ 1.1
Spine :	0.2	0.378 (<i>min</i>)
Lungs :	0.7	~ 0.7
Heart :	2.0	2.332 (<i>max</i>)



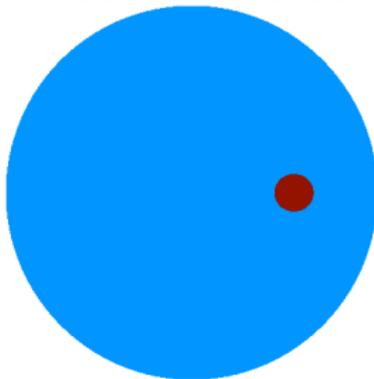
Relative error:
Dynamic range:



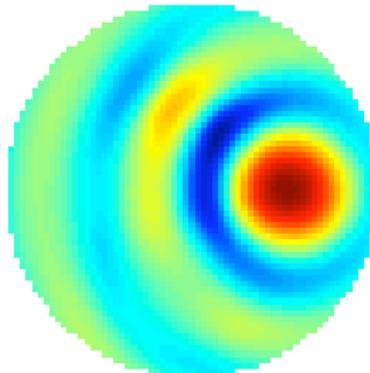
16.7%
109%

Subtract the previous images:

Ideal Difference



Reconstruction



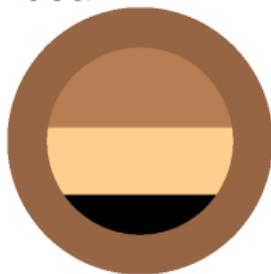
Example 3: Layered Medium

Top Layer: 1.2

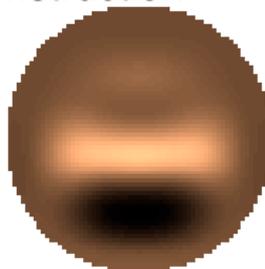
Middle Layer: 2.0

Bottom Layer: 0.3

Ideal

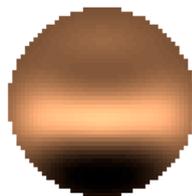


Reconstruction



Relative error

21.7%



24.7%

Dynamic range: 134%