

A New Method for the Inverse Potential Problem Based on the Topological Derivative Concept

Antonio André Novotny¹, Alfredo Canelas² & Antoine Laurain³

¹Laboratório Nacional de Computação Científica, LNCC/MCTI
Av. Getúlio Vargas 333, 25651-075 Petrópolis - RJ, Brasil

²Instituto de Estructuras y Transporte, Facultad de Ingeniería,
Av. Julio Herrera y Reissig 565, C.P. 11.300, Montevideo, Uruguay

³Institut für Mathematik, Technical University Berlin,
Street 36, A-8010 Berlin, Germany

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- 2 Topological Derivative Concept
- 3 Applications of the Topological Derivative
- 4 Second-Order Topological Derivative
- 5 Inverse Potential Problem
 - Problem Formulation
 - Topological Derivative Calculation
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- 6 Conclusions



Motivation

$$\inf_{\Omega \in \mathcal{E}} \psi(\Omega)$$

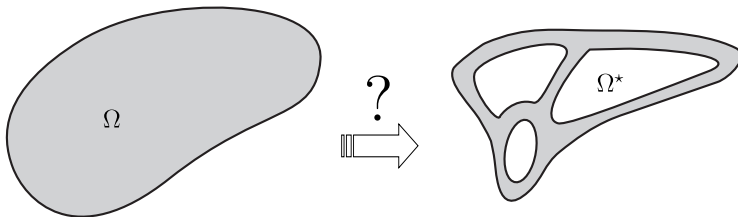
- $\psi(\Omega)$: shape functional
- Ω : geometrical domain
- \mathcal{E} : set of admissible domains



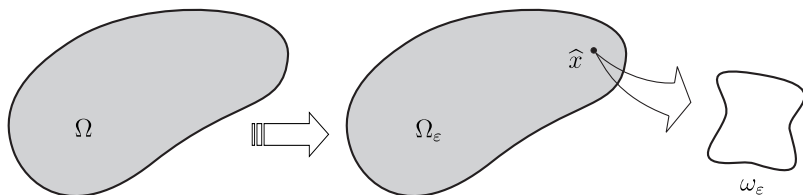
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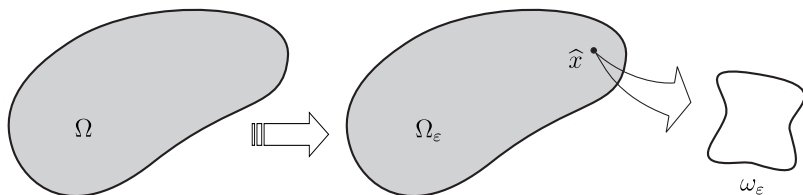
Topological Derivative Concept



Sokolowski & Zochowski, 1999



Topological Derivative Concept



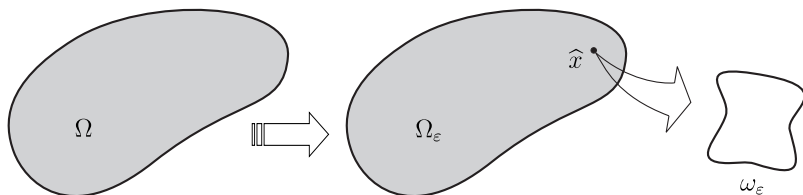
Sokolowski & Zochowski, 1999

$$\psi(\Omega_\varepsilon(\hat{x})) = \psi(\Omega) + f(\varepsilon)\mathcal{T}(\hat{x}) + o(f(\varepsilon)) ,$$

where $\Omega_\varepsilon(\hat{x}) = \Omega \setminus \overline{\omega_\varepsilon(\hat{x})}$ and $f(\varepsilon) \rightarrow 0$, when $\varepsilon \rightarrow 0$.



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$$\mathcal{T}(\hat{x}) = \lim_{\varepsilon \rightarrow 0} \frac{\psi(\Omega_\varepsilon(\hat{x})) - \psi(\Omega)}{f(\varepsilon)} .$$

In general, $f(\varepsilon) = |\omega_\varepsilon|$. It depends on the boundary condition on $\partial\omega_\varepsilon$.



Applications of the Topological Derivative

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The topological sensitivity analysis gives the topological asymptotic expansion of a shape functional with respect to a singular domain perturbation, like the insertion of holes, inclusions or cracks. The first term of this expansion, called topological derivative, is now of common use for resolution of several problems, such as:



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- Mechanical Modeling: fracture and damage mechanics



Topology Optimization

Energy-Based Topological Derivative in Linear Elasticity

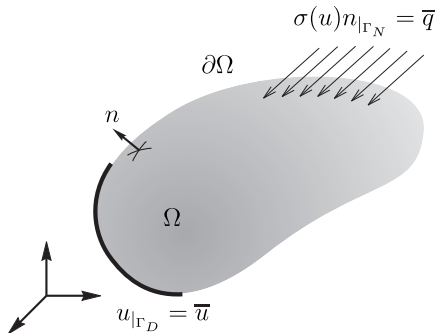


Figure : unperturbed problem defined in the domain Ω .



Topology Optimization

$$\psi(\Omega) := \mathcal{J}_\Omega(u) = \frac{1}{2} \int_\Omega \sigma(u) \cdot \nabla u^s - \int_{\Gamma_N} \bar{q} \cdot u ,$$

$$\left\{ \begin{array}{ll} \text{Find } u, \text{ such that} \\ -\operatorname{div} \sigma(u) &= 0 \quad \text{in } \Omega , \\ \sigma(u) &= \mathbb{C} \nabla u^s \\ u &= \bar{u} \quad \text{on } \Gamma_D , \\ \sigma(u)n &= \bar{q} \quad \text{on } \Gamma_N . \end{array} \right.$$

$$\mathbb{C} = \frac{E}{1 + \nu} \left(\mathbb{I} + \frac{\nu}{1 - 2\nu} \mathbf{I} \otimes \mathbf{I} \right) ,$$



Topology Optimization

Topological Derivative Calculation

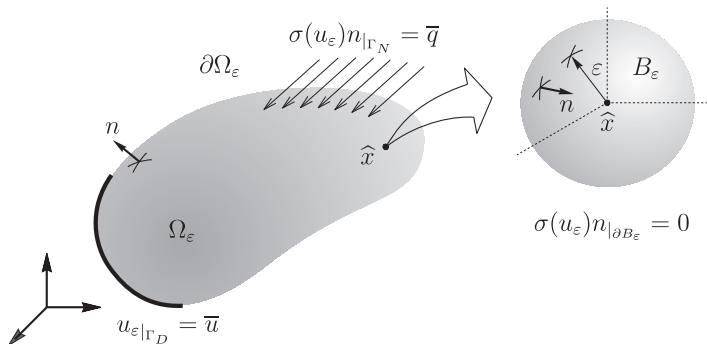


Figure : perturbed problem defined in the domain Ω_ε .



Topological Asymptotic Expansion

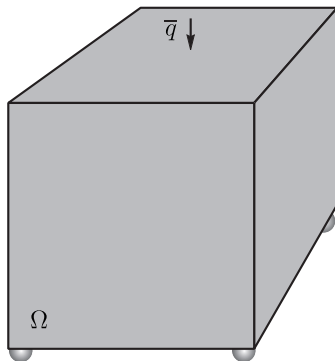
$$\psi(\Omega_\varepsilon(\hat{x})) = \psi(\Omega) - \pi\varepsilon^3 \mathbb{P} \sigma(u(\hat{x})) \cdot \nabla u^s(\hat{x}) + o(\varepsilon^3) ,$$

$$\mathbb{P} = \frac{3}{4} \frac{1-\nu}{7-5\nu} \left(10\mathbb{I} - \frac{1-5\nu}{1-2\nu} \mathbf{I} \otimes \mathbf{I} \right)$$



Topology Optimization

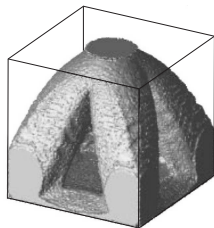
A *benchmark* example in 3D



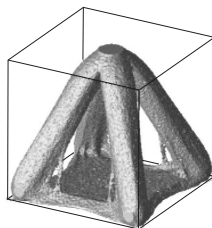
$$\Psi_{\Omega}(u) := -\mathcal{J}_{\Omega}(u) + \beta |\Omega| \quad , \quad \mathcal{T} = \mathbb{P}\sigma(u) \cdot \nabla u^s - \beta \quad .$$



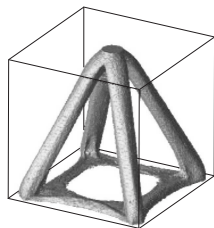
Topology Optimization



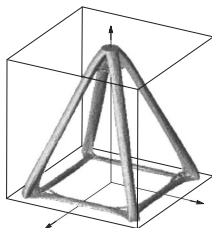
(a) iteration 13



(b) iteration 35



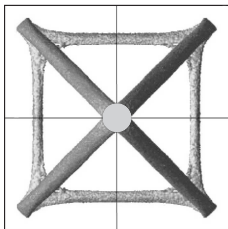
(c) iteration 52



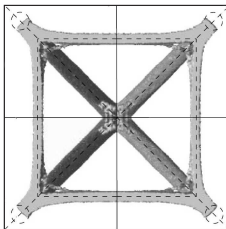
(d) iteration 76



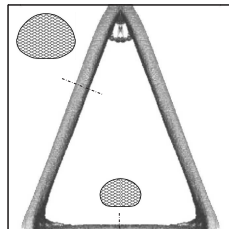
Topology Optimization



(a) top



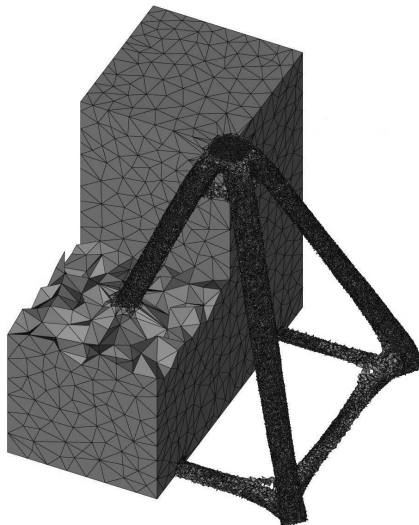
(b) bottom



(c) lateral



Topology Optimization



Second-Order Topological Derivative

$$\psi(\Omega_\varepsilon(\widehat{x})) = \psi(\Omega) + f(\varepsilon)\mathcal{T}(\widehat{x}) + f_2(\varepsilon)\mathcal{T}^2(\widehat{x}) + \mathcal{R}(f_2(\varepsilon)) ,$$



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where $f(\varepsilon) \rightarrow 0$ and $f_2(\varepsilon) \rightarrow 0$ with $\varepsilon \rightarrow 0$, and

$$\lim_{\varepsilon \rightarrow 0} \frac{f_2(\varepsilon)}{f(\varepsilon)} = 0 , \quad \lim_{\varepsilon \rightarrow 0} \frac{\mathcal{R}(f_2(\varepsilon))}{f_2(\varepsilon)} = 0 .$$



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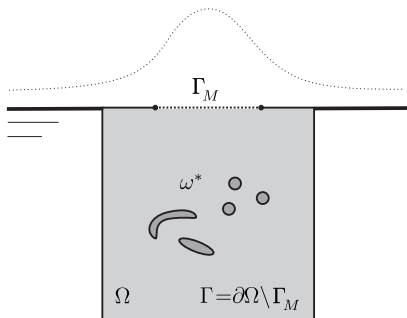
second order topological derivative

$$\mathcal{T}^2(\hat{x}) := \lim_{\varepsilon \rightarrow 0} \frac{\psi(\Omega_\varepsilon(\hat{x})) - \psi(\Omega) - f(\varepsilon)\mathcal{T}(\hat{x})}{f_2(\varepsilon)} .$$



Inverse Potential Problem

Problem Formulation: Gravimetry Inverse Problem



$$\left\{ \begin{array}{l} \text{Find } b^*, \text{ such that} \\ -\Delta u = b^* \quad \text{in } \Omega, \\ u = u^* \\ -\partial_n u = q^* \end{array} \right\} \quad \text{on } \Gamma_M.$$

$$b^* = \gamma \chi_{\omega^*} \in PC_\gamma(\Omega) \text{ ,}$$

$$PC_\gamma(\Omega) := \{b \in L^\infty(\Omega) : b = \gamma \chi_\omega, \omega \subset \Omega \text{ is measurable}\},$$



Inverse Potential Problem

$$u[b^*](x) = \int_{\Omega} K(x, y) b^*(y) dy ,$$

$$K(x, y) = \begin{cases} \frac{1}{4\pi|x-y|} & \text{for } n = 3 , \\ -\frac{1}{2\pi} \ln |x-y| & \text{for } n = 2 . \end{cases}$$



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$$u^* := u[b^*]|_{\Gamma_M} \text{ and } q^* := -\partial_n u[b^*]|_{\Gamma_M} .$$



Difficulties

- The problem is over determined and highly ill-posed;
- Additional measurements do not provide extra information;
- Lack of uniqueness if the intensity γ and the region ω^* are unknown.



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▷ We assume that the intensity γ is known



Inverse Potential Problem

Theorem (Uniqueness Result)

Let ω_1 and ω_2 be two star-shaped domains with respect to their centers of gravity. If $u_1 = u_2$ and $\partial_n u_1 = \partial_n u_2$ on Γ_M , with $|\Gamma_M| \neq 0$, then $\omega_1 = \omega_2$.

V. Isakov. Inverse Source Problems. American Mathematical Society, Providence, Rhode Island, 1990.



Inverse Potential Problem

Kohn-Vogelius Criterion

$$\min_{b \in PC_\gamma(\Omega)} J(b) := \frac{1}{2} \int_{\Omega} (u^D[b] - u^N[b])^2 ,$$



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Inverse Potential Problem

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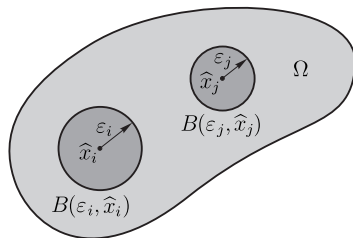
$$\min_{b \in PC_\gamma(\Omega)} J(b) := \frac{1}{2} \int_{\Omega} (u^D[b] - u^N[b])^2 ,$$

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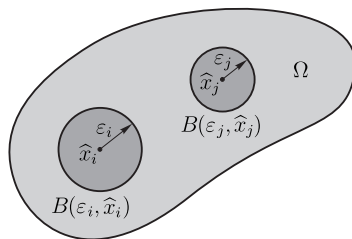
$$u^T[b] = \int_{\Omega} K(x, y) b(y) dy .$$



Inverse Potential Problem



Inverse Potential Problem



$$b_{\mathbf{e}, \hat{\mathbf{x}}} = b + \gamma \sum_{i \in \mathcal{I}} \chi_{B(\varepsilon_i, \hat{x}_i)} .$$

$$\varpi_{\mathbf{e}, \hat{\mathbf{x}}} = \cup_{i \in \mathcal{I}} B(\varepsilon_i, \hat{x}_i) , \quad \text{with } \mathcal{I} = \{1, \dots, m\}$$

$$\mathbf{e} := \{\varepsilon_i\}_{i \in \mathcal{I}} \quad \hat{\mathbf{x}} := \{\hat{x}_i\}_{i \in \mathcal{I}} , \quad \text{with } \varepsilon_i > 0 , \quad \hat{x}_i \in \Omega$$



Inverse Potential Problem

$$J(b_{\mathbf{e}, \hat{\mathbf{x}}}) = J(b) - \int_{\Omega} (u^D[b] - u^N[b]) \sum_{i \in \mathcal{I}} a_i h_i + \frac{1}{2} \int_{\Omega} \left(\sum_{i \in \mathcal{I}} a_i h_i \right)^2$$

where $a_i := |B(\varepsilon_i, \hat{\mathbf{x}}_i)|$ and

$$\begin{cases} -\Delta h_i &= 0 & \text{in } \Omega, \\ -\partial_n h_i &= g_i & \text{on } \Gamma_M, \\ h_i &= 0 & \text{on } \Gamma, \end{cases}$$

with $g_i = \partial_n v_i$ on Γ_M and

$$\begin{cases} -\Delta v_i &= \gamma \delta(\mathbf{x} - \hat{\mathbf{x}}_i) & \text{in } \Omega, \\ v_i &= 0 & \text{on } \Gamma_M, \\ v_i &= \gamma K(\mathbf{x}, \hat{\mathbf{x}}_i) & \text{on } \Gamma. \end{cases}$$



Inverse Potential Problem

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Minimization with respect to a_i yields

$$H_{ij} a_j = f_i$$

$$H_{ij} = \int_{\Omega} h_i h_j \quad \text{and} \quad f_i = \int_{\Omega} (u^D - u^N) h_i ,$$



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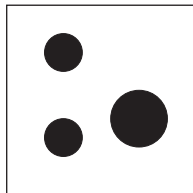
$$H_{ij} = \int_{\Omega} h_i h_j \quad \text{and} \quad f_i = \int_{\Omega} (u^D - u^N) h_i ,$$

$$J(b_{\mathbf{e},\hat{\mathbf{x}}}) = J(b) - \frac{1}{2} a_i f_i$$



Inverse Potential Problem

Example 1: Looking for three anomalies



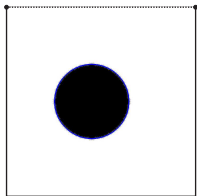
target



Inverse Potential Problem



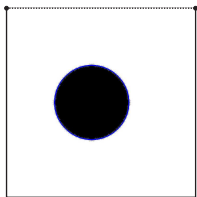
Inverse Potential Problem



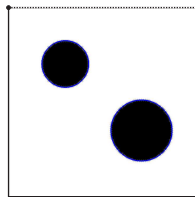
(a) one ball



Inverse Potential Problem



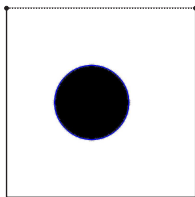
(a) one ball



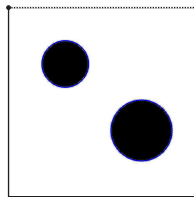
(b) two balls



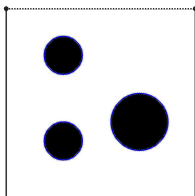
Inverse Potential Problem



(a) one ball



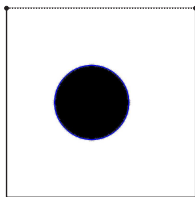
(b) two balls



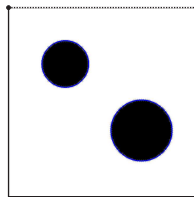
(c) three balls



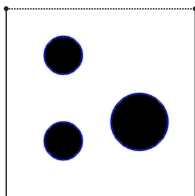
Inverse Potential Problem



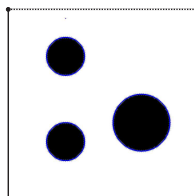
(a) one ball



(b) two balls



(c) three balls

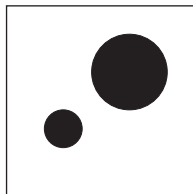


(d) four balls



Inverse Potential Problem

Example 2: Partial boundary measurement



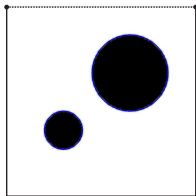
target



Inverse Potential Problem



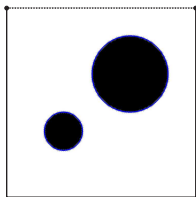
Inverse Potential Problem



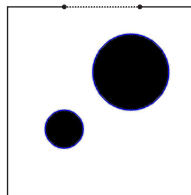
(a) $|\Gamma_M| = 1.0$



Inverse Potential Problem



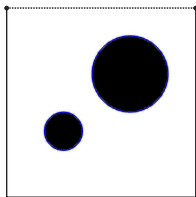
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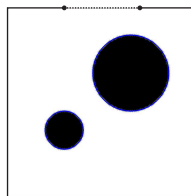
(b) $|\Gamma_M| = 0.4$



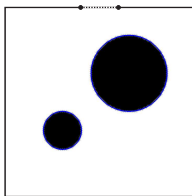
Inverse Potential Problem



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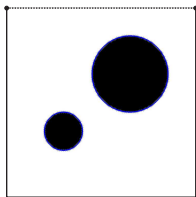
(b) $|\Gamma_M| = 0.4$



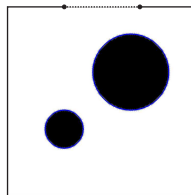
(c) $|\Gamma_M| = 0.2$



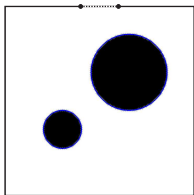
Inverse Potential Problem



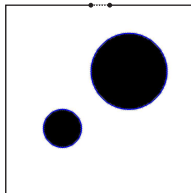
(a) $|\Gamma_M| = 1.0$



(b) $|\Gamma_M| = 0.4$



(c) $|\Gamma_M| = 0.2$

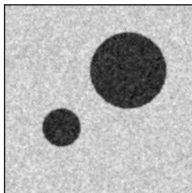


(d) $|\Gamma_M| = 0.1$



Inverse Potential Problem

Example 3: Noisy data



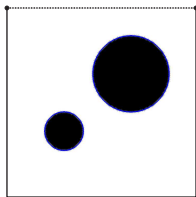
target



Inverse Potential Problem



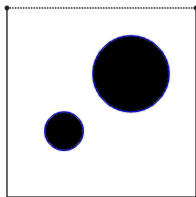
Inverse Potential Problem



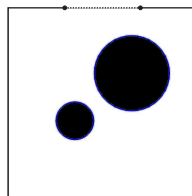
(a) $|\Gamma_M| = 1.0$



Inverse Potential Problem



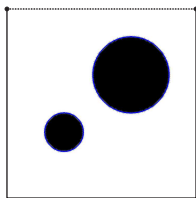
(a) $|\Gamma_M| = 1.0$



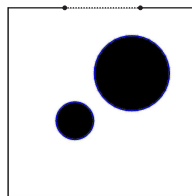
(b) $|\Gamma_M| = 0.4$



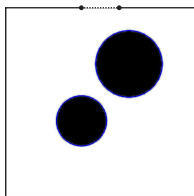
Inverse Potential Problem



(a) $|\Gamma_M| = 1.0$



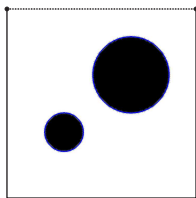
(b) $|\Gamma_M| = 0.4$



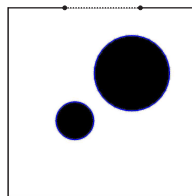
(c) $|\Gamma_M| = 0.2$



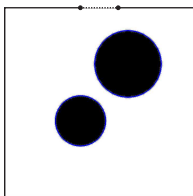
Inverse Potential Problem



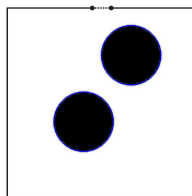
(a) $|\Gamma_M| = 1.0$



(b) $|\Gamma_M| = 0.4$



(c) $|\Gamma_M| = 0.2$



(d) $|\Gamma_M| = 0.1$



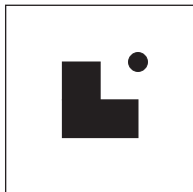
Inverse Potential Problem

Example 4: Shape and topology reconstruction



Inverse Potential Problem

Example 4: Shape and topology reconstruction

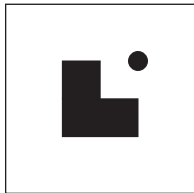


(a) target

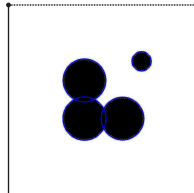


Inverse Potential Problem

Example 4: Shape and topology reconstruction



(a) target



(b) result



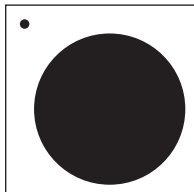
Inverse Potential Problem

Example 5: Two anomalies far from each other



Inverse Potential Problem

Example 5: Two anomalies far from each other

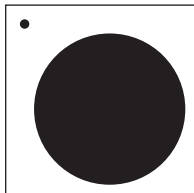


(a) target

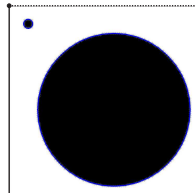


Inverse Potential Problem

Example 5: Two anomalies far from each other



(a) target



(b) result



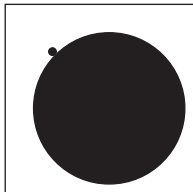
Inverse Potential Problem

Example 6: Two anomalies close to each other



Inverse Potential Problem

Example 6: Two anomalies close to each other

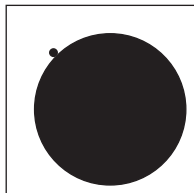


(a) target

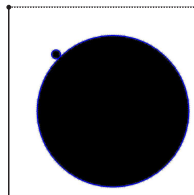


Inverse Potential Problem

Example 6: Two anomalies close to each other



(a) target



(b) result



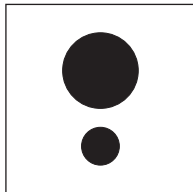
Inverse Potential Problem

Example 7: Hidden object



Inverse Potential Problem

Example 7: Hidden object

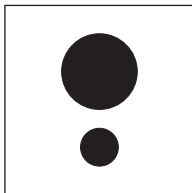


(a) target

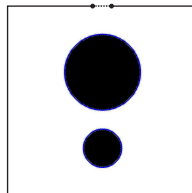


Inverse Potential Problem

Example 7: Hidden object



(a) target



(b) result



Conclusions

- The number of unknown anomalies can be found after some trials.
- Due to the combinatorial nature of the search procedure, the problem is tractable only in the case of small number of unknown measures.
- Completely hidden anomalies can be detected from very few information (single partial boundary measurement).
- Corrupted measurements with a high level of noise can be reconstructed with acceptable precision.
- The characterization of the biggest set $PC_\gamma(\Omega)$ seems to be an open problem.



Muito Obrigado!



A.A. Novotny (joint with A. Canelas and A. Laurain). A Non-Iterative Method for the Inverse Potential Problem Based on the Topological Derivative. Oberwolfach Seminars vol. 47. Geometries, Shapes and Topologies in PDE-based Applications. Edited by M. Hintermüller, G. Leugering, J. Sokolowski. To appear.



M. Hintermüller, A. Laurain, A.A. Novotny, Second-order topological expansion for electrical impedance tomography, *Advances in Computational Mathematics* 36(2):235–265, 2012.



A.A. Novotny & J. Sokołowski. *Topological Derivatives in Shape Optimization*. Mechanics and Mathematics Interaction Series. 432p. Springer, 2013.