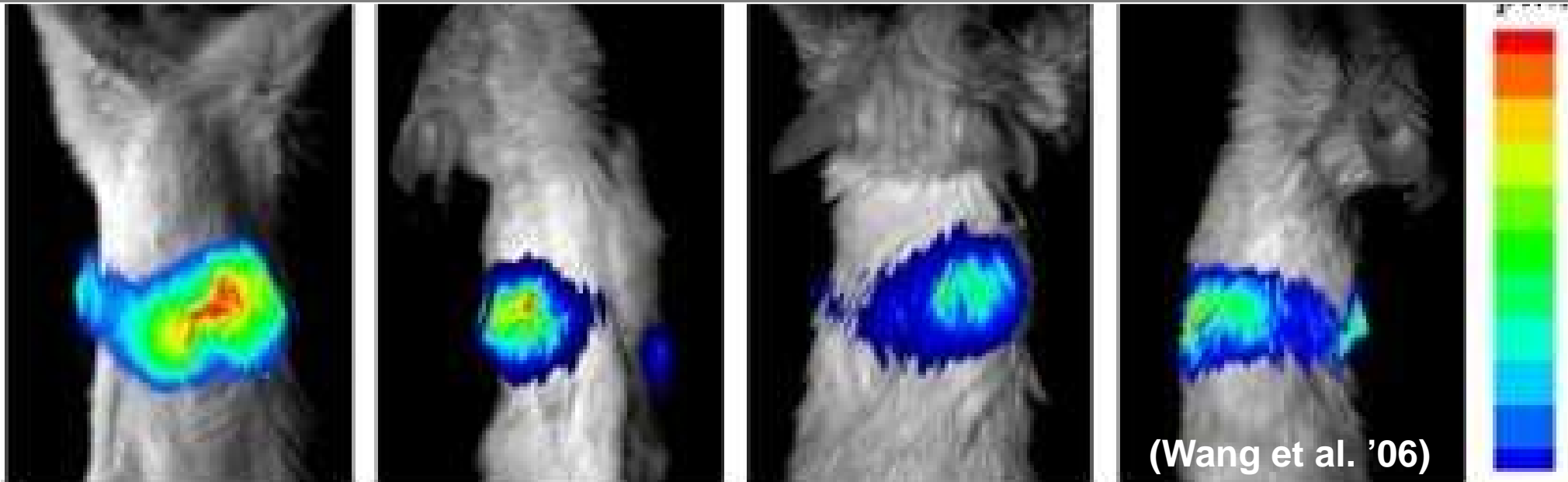


Geometric Reconstruction in Bioluminescence Tomography (BLT)

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Overview

Mathematical model

Inverse problem: formulation & uniqueness

Inverse problem: reformulation & stabilization

Gradient of the minimization functional

Numerical experiments in 2D

Summary

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▷ model

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The (stationary) radiative transfer equation (RTE) (Boltzmann transport equation)

Let $u(x, \theta)$ be the **photon flux** (radiance) in direction $\theta \in S^2$ about $x \in \Omega \subset \mathbb{R}^3$. Then,

$$\theta \cdot \nabla u(x, \theta) + \mu(x)u(x, \theta) = \mu_s(x) \int_{S^2} \eta(\theta \cdot \theta') u(x, \theta') d\theta' + q(x, \theta)$$

$$u(x, \theta) = g^-(x, \theta), \quad x \in \partial\Omega, \quad \mathbf{n}(x) \cdot \theta \leq 0$$

$$g(x) = \frac{1}{4\pi} \int_{S^2} \mathbf{n}(x) \cdot \theta u(x, \theta) d\theta, \quad x \in \partial\Omega$$

where $\mu = \mu_s + \mu_a$ and

μ_s / μ_a scattering/absorption coefficients

η scattering kernel ($\int_{S^2} \eta(\theta \cdot \theta') d\theta' = 1$)

q source term

$\mu_s = 0$: RTE yields integral eqs. of transmission and emission tomography
(F. Natterer & F. Wübbeling, Math. Methods in Image Reconstr., SIAM, '01)

Diffusion approximation: setting

Assume that

$$u(x, \theta) = u_0(x) + 3\theta \cdot u_1(x)$$

where

$$u_0(x) = \frac{1}{4\pi} \int_{S^2} u(x, \theta) d\theta \in \mathbb{R} \quad \text{and} \quad u_1(x) = \frac{1}{4\pi} \int_{S^2} \theta u(x, \theta) d\theta \in \mathbb{R}^3.$$

By the Funk-Hecke theorem,

$$\int_{S^2} \theta \eta(\theta \cdot \theta') d\theta = \bar{\eta} \theta'$$

where $\bar{\eta} = \int_{S^2} \theta' \cdot \theta \eta(\theta \cdot \theta') d\theta$ is the scattering anisotropy.

Diffusion approximation: derivation

- Integrate RTE over S^2 ,
- multiply RTE by θ , integrate again, and
- assume $g^-(x, \theta) = g^-(x)$.

Then,

$$-\nabla \cdot (D \nabla u_0) + \mu_a u_0 = q_0 := \frac{1}{4\pi} \int_{S^2} q(\cdot, \theta) d\theta,$$

$$u_0 + 2D \partial_{\mathbf{n}} u_0 = g^- \quad \text{on } \partial\Omega,$$

$$D \partial_{\mathbf{n}} u_0 = -g \quad \text{on } \partial\Omega,$$

where

$$D = \frac{1}{3(\mu - \bar{\eta} \mu_s)}$$

is the diffusion coefficient (reduced scattering coefficient).

Diffusion approximation: final equation

- Change of notation: $u = u_0$, $q = q_0$, $\mu = \mu_a$, and $g = -g$.
- The photon density u obeys the BVP

$$\begin{aligned} -\nabla \cdot (D\nabla u) + \mu u &= q \quad \text{in } \Omega, \\ u + 2D\partial_{\mathbf{n}}u &= g^- \quad \text{on } \partial\Omega. \end{aligned}$$

- The measurements are given by

$$D\partial_{\mathbf{n}}u = g \quad \text{on } \partial\Omega.$$

- Assume $g^- = 0$ (no photons penetrate the object from outside).

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Inverse problem of BLT (in the diffusive regime)

Define the (linear) forward operator

$$\begin{aligned} A: L^2(\Omega) &\rightarrow H^{-\frac{1}{2}}(\partial\Omega), \\ q &\mapsto D\partial_{\mathbf{n}}u, \end{aligned}$$

where u solves the BVP with $g^- = 0$:

$$\begin{aligned} -\nabla \cdot (D\nabla u) + \mu u &= q \quad \text{in } \Omega, \\ u + 2D\partial_{\mathbf{n}}u &= 0 \quad \text{on } \partial\Omega. \end{aligned}$$

BLT Problem: Given $g \in \mathcal{R}(A)$, find a source $q \in L^2(\Omega)$ satisfying

$$Aq = g.$$

Null Space of A

Lemma (Wang, Li & Jiang '04, Kreutzmann '13):

There is an isomorphism $\Phi: H^1(\Omega) \rightarrow H^1(\Omega)'$ such that

$$\mathcal{N}(A) = \Phi(H_0^1(\Omega)) \cap L^2(\Omega).$$

If $D \in W^{1,\infty}$ then

$$\mathcal{N}(A) = \Phi(H_0^1(\Omega) \cap H^2(\Omega)).$$

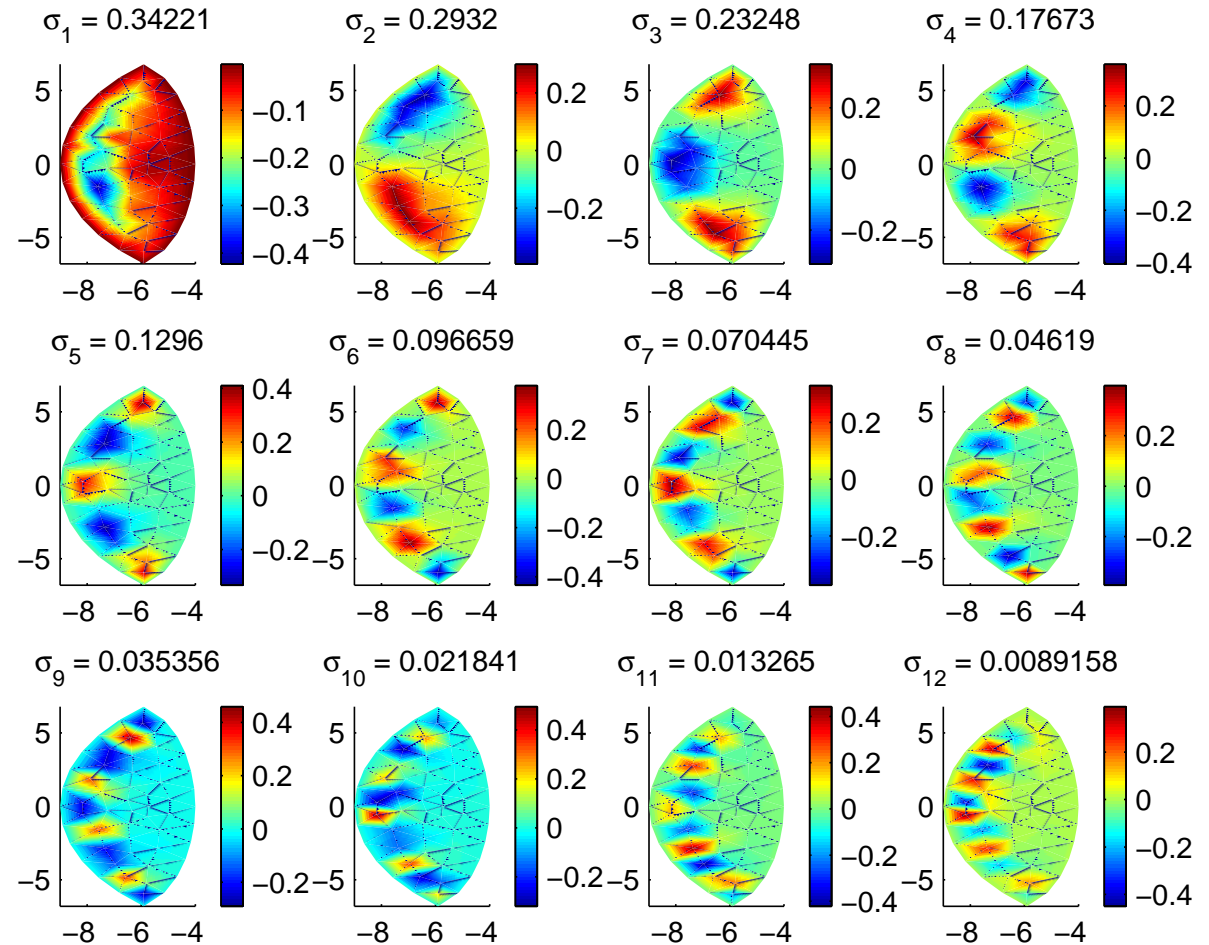
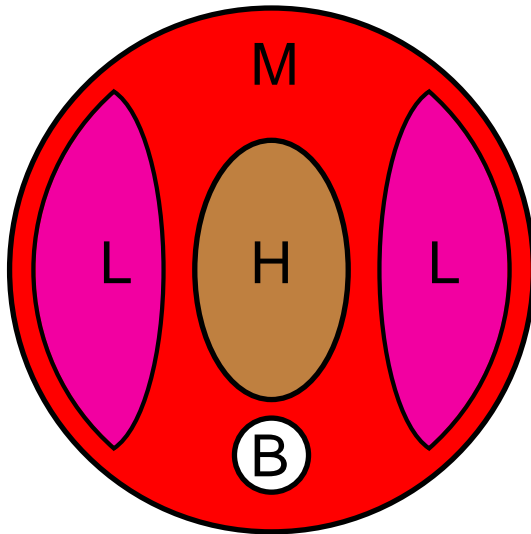
Proof: Define

$$\Phi: H^1(\Omega) \rightarrow H^1(\Omega)', \quad u \mapsto (\Phi u)(v) = a(u, v)$$

where

$$a(u, v) = \int_{\Omega} (D \nabla u \cdot \nabla v + \mu uv) dx + \frac{1}{2} \int_{\partial\Omega} uv \, ds.$$

Singular Functions of $A: L^2(\Omega_0) \rightarrow L^2(\partial\Omega)$



Can we restore uniqueness by *a priori* information?

Consider, for instance,

$$q = \lambda \chi_S \quad \text{where } \lambda \geq 0 \text{ is a constant and } S \subset \Omega.$$

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Consider, for instance,

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Lemma (Wang, Li & Jiang '04):

There exist $z \in \Omega$, $\lambda_1 \neq \lambda_2$ and $r_1 \neq r_2$ such that

$$A(\lambda_1 \chi_{B_1}) = A(\lambda_2 \chi_{B_2})$$

with $B_k = B_{r_k}(z)$.

Mathematical model

Inverse problem:
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Inverse problem:
reformulation &
▷ stabilization

Reformulation
Tikhonov-like
regularization

Existence of a
minimizer & stability

Regularization
property

Gradient of the mini-
mization functional

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ments in 2D

Summary

Inverse problem: reformulation & stabilization

Reformulation

Ansatz: $q = \sum_{i=1}^I \lambda_i \chi_{S_i}$ where $S_i \subset \Omega$, $\lambda_i \in [\underline{\lambda}_i, \bar{\lambda}_i] = \Lambda_i$, and $I \in \mathbb{N}$.

For the ease of presentation: $I = 1$.

Define the **nonlinear** operator

$$\begin{aligned} F: \Lambda \times \mathcal{L} &\rightarrow L^2(\partial\Omega), \\ (\lambda, S) &\mapsto D\partial_{\mathbf{n}}u|_{\partial\Omega} \end{aligned}$$

where \mathcal{L} is the set of all measurable subsets of Ω .

Note: $F(\lambda, S) = \lambda A \chi_S$

BLT Problem: Given measurements g , find an intensity $\lambda \in \Lambda$ and a domain $S \in \mathcal{L}$ such that

$$F(\lambda, S) = g.$$

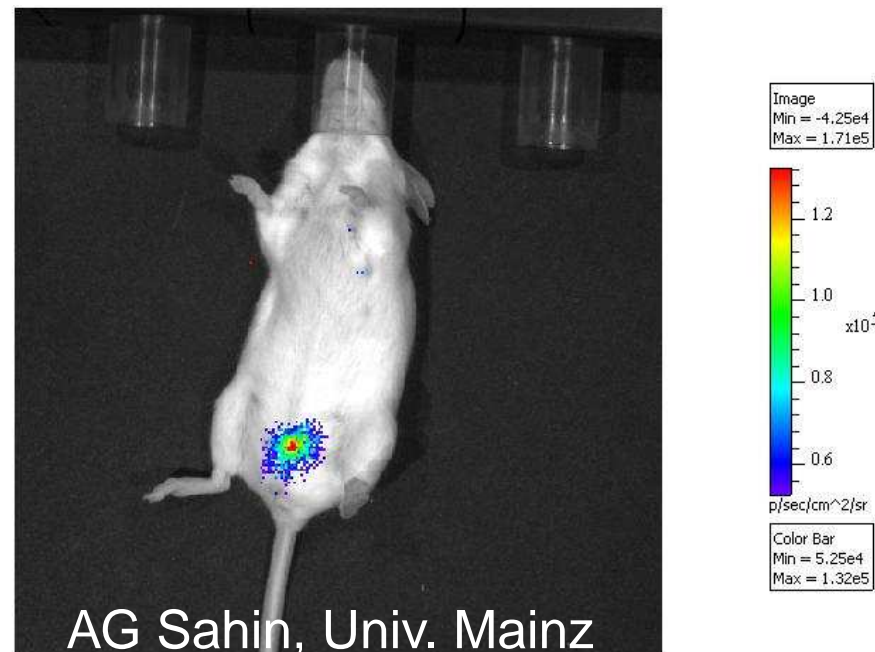
Tikhonov-like regularization

$$\text{Minimize } J_\alpha(\lambda, S) = \frac{1}{2} \|F(\lambda, S) - g\|_{L^2}^2 + \alpha \text{Per}(S) \text{ over } \Lambda \times \mathcal{L}$$

where $\alpha > 0$ is the regularization parameter and $\text{Per}(S)$ is the perimeter of S :

$$\text{Per}(S) = |D(\chi_S)|,$$

with $|D(\cdot)|$ denoting the BV-semi-norm (Ramlau & Ring '07, '10).



Existence of a minimizer & stability

Theorem: For all $\alpha > 0$ and $g \in L^2(\partial\Omega)$ there exists a minimizer $(\lambda^*, S^*) \in \Lambda \times \mathcal{L}$, that is,

$$J_\alpha(\lambda^*, S^*) \leq J_\alpha(\lambda, S) \quad \text{for all } (\lambda, S) \in \Lambda \times \mathcal{L}.$$

Theorem: Let $g_n \rightarrow g$ in L^2 as $n \rightarrow \infty$ and let (λ^n, S^n) minimize

$$J_\alpha^n(\lambda, S) = \frac{1}{2} \|F(\lambda, S) - g_n\|_{L^2}^2 + \alpha \text{Per}(S) \quad \text{over } \Lambda \times \mathcal{L}.$$

Then there exists a subsequence $\{(\lambda^{n_k}, S^{n_k})\}_k$ converging to a minimizer $(\lambda^*, S^*) \in \Lambda \times \mathcal{L}$ of J_α in the sense that

$$\|\lambda^{n_k} \chi_{S^{n_k}} - \lambda^* \chi_{S^*}\|_{L^2} \rightarrow 0 \quad \text{as } k \rightarrow \infty.$$

Furthermore, every convergent subsequence of $\{(\lambda^n, S^n)\}_n$ converges to a minimizer of J_α .

Regularization property

Theorem: Let g be in $\text{range}(F)$ and let $\delta \mapsto \alpha(\delta)$ where

$$\alpha(\delta) \rightarrow 0 \quad \text{and} \quad \frac{\delta^2}{\alpha(\delta)} \rightarrow 0 \quad \text{as } \delta \rightarrow 0.$$

In addition, let $\{\delta_n\}_n$ be a positive null sequence and $\{g_n\}_n$ such that

$$\|g_n - g\|_{L^2} \leq \delta_n.$$

Then, the sequence $\{(\lambda^n, S^n)\}$ of minimizers of $J_{\alpha(\delta_n)}^n$ possesses a subsequence converging to a solution (λ^+, S^+) where

$$S^+ = \arg \min \{ \text{Per}(S) : S \in \mathcal{L} \text{ s.t. } \exists \lambda \in \Lambda \text{ with } F(\lambda, S) = g \}.$$

Furthermore, every convergent subsequence of $\{(\lambda^n, S^n)\}_n$ converges to a pair $(\lambda^\dagger, S^\dagger)$ with above property.

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Gradient of the
minimization
▷ functional

Domain derivative:
general definition

Domain derivative
of $F(\lambda, \cdot) : \mathcal{S} \rightarrow$
 $L^2(\partial\Omega)$

Domain derivative of
 $\text{Per} : \mathcal{S} \rightarrow \mathbb{R}$

Derivative of
 $J_\alpha : \Lambda \times \mathcal{S} \rightarrow \mathbb{R}$

Approximate vari-
ational principle
(Ekeland 1974)

Numerical experi-
ments in 2D

Summary

Gradient of the minimization functional

Domain derivative: general definition

Let $\Gamma \in \mathcal{S} = \{\tilde{\Gamma} \subset \Omega : \partial \tilde{\Gamma} \in C^2\}$ and let $h \in C_0^2(\Omega, \mathbb{R}^d)$. Define

$$\Gamma_h = \{x + h(x) : x \in \Gamma\}.$$

If h is small enough, say if $\|h\|_{C^2} < 1/2$, then $\Gamma_h \in \mathcal{S}$.

By the **domain derivative** of $\Phi: \mathcal{S} \rightarrow Y$ about Γ we understand $\Phi'(\Gamma) \in \mathcal{L}(C^2, Y)$ satisfying

$$\|\Phi(\Gamma_h) - \Phi(\Gamma) - \Phi'(\Gamma)h\|_Y = o(\|h\|_{C^2})$$

where Y is a normed space.

Domain derivative of $F(\lambda, \cdot): \mathcal{S} \rightarrow L^2(\partial\Omega)$

Reminder: $F(\lambda, S) = \lambda A\chi_S$

Lemma: We have that

$$\partial_S F(\lambda, S)h = u'|_{\partial\Omega}$$

where $u' \in H^1(\Omega \setminus \partial S)$ solves the transmission bvp

$$\begin{aligned} -\nabla \cdot (D\nabla u') + \mu u' &= 0 && \text{in } \Omega \setminus \partial S, \\ 2D\partial_{\mathbf{n}} u' + u' &= 0 && \text{on } \partial\Omega, \\ [u']_{\pm} &= 0 && \text{on } \partial S, \\ [D\partial_{\mathbf{n}} u']_{\pm} &= -\lambda h \cdot \mathbf{n} && \text{on } \partial S. \end{aligned}$$

Proof: similar to Hettlich's habilitation thesis 1999.

Domain derivative of $\text{Per}: \mathcal{S} \rightarrow \mathbb{R}$

Lemma (Simon 1980):

We have that

$$\partial_S \text{Per}(S)h = \int_{\partial S} H_{\partial S}(h \cdot \mathbf{n}) \, ds$$

where $H_{\partial S}$ denotes the mean curvature of ∂S .

Derivative of $J_\alpha: \Lambda \times \mathcal{S} \rightarrow \mathbb{R}$

$$J_\alpha(\lambda, S) = \frac{1}{2} \|F(\lambda, S) - g\|_{L^2}^2 + \alpha \text{Per}(S)$$

$$\partial_\lambda F(\lambda, S)k = kA\chi_S = F(k, S)$$

Theorem: We have that

$$J'_\alpha(\lambda, S)(k, h) = \langle F(\lambda, S) - g, F(k, S) + u' \rangle_{L^2(\partial\Omega)} + \alpha \int_{\partial S} H_{\partial S}(h \cdot \mathbf{n}) \, ds$$

for $k \in \mathbb{R}$, $h \in C_0^2(\Omega, \mathbb{R}^3)$.

Proof:

$$J'_\alpha(\lambda, S)(k, h) = \partial_\lambda J_\alpha(\lambda, S)k + \partial_S J_\alpha(\lambda, S)h$$

Approximate variational principle (Ekeland 1974)

There exist smooth almost critical points of J_α near to any of its minimizers.

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There exist smooth almost critical points of J_α near to any of its minimizers.

Theorem: Let (λ^*, S^*) be a minimizer of J_α where λ^* is an inner point of Λ . Then, for any $\varepsilon > 0$ sufficiently small there is a $(\lambda^\varepsilon, S^\varepsilon) \in \Lambda \times \mathcal{S}$ with

$$J_\alpha(\lambda^\varepsilon, S^\varepsilon) - J_\alpha(\lambda^*, S^*) \leq \varepsilon,$$

$$\|\lambda^\varepsilon \chi_{S^\varepsilon} - \lambda^* \chi_{S^*}\|_{L^1} \leq \varepsilon,$$

$$\|J'_\alpha(\lambda^\varepsilon, S^\varepsilon)\|_{\mathbb{R} \times C^2 \rightarrow \mathbb{R}} \leq \varepsilon.$$

Approximate variational principle (Ekeland 1974)

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$$J_\alpha(\lambda^\varepsilon, S^\varepsilon) - J_\alpha(\lambda^*, S^*) \leq \varepsilon,$$

$$\|\lambda^\varepsilon \chi_{S^\varepsilon} - \lambda^* \chi_{S^*}\|_{L^1} \leq \varepsilon,$$

$$\|J'_\alpha(\lambda^\varepsilon, S^\varepsilon)\|_{\mathbb{R} \times C^2 \rightarrow \mathbb{R}} \leq \varepsilon.$$

Proof: Key ingredient is

To any bounded measurable $\Gamma \subset \mathbb{R}^d$ with finite perimeter exists a sequence $\{\Gamma^n\}_n$ of C^∞ -domains such that

$$\int_{\mathbb{R}^d} |\chi_{\Gamma^n} - \chi_\Gamma| dx \rightarrow 0 \quad \text{and} \quad \text{Per}(\Gamma^n) \rightarrow \text{Per}(\Gamma) \quad \text{as } n \rightarrow \infty.$$

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Gradient of the mini-
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Numerical
experiments in
▷ 2D

Star-shaped do-
mains

Algorithm: *Projected
Gradient Method*

The model

H^3 -Reconstructions

L^2 -Reconstructions

Summary

Numerical experiments in 2D

Star-shaped domains

- For the numerical experiments we consider a star-shaped domain only:

$$S = \{x \in \mathbb{R}^2 : x = m + t \theta(\vartheta) r(\vartheta), 0 \leq t \leq 1, 0 \leq \vartheta \leq 2\pi\}$$

where m is the center (assumed to be known) and $r: [0, 2\pi] \rightarrow [0, \infty[$ parameterizes the boundary of S .

- All previous results hold in this setting as well if we work in a space of smooth parameterizations, say, $r \in H_p^3(0, 2\pi) \subset C_p^2(0, 2\pi)$.
- $(\lambda, S) \rightsquigarrow (\lambda, r) \in \Lambda \times \mathcal{R}_{ad}$ where $\mathcal{R}_{ad} = \{r \in H_p^3(0, 2\pi) : r \geq 0\}$.
- Gradient equation: $\langle \text{grad} J_\alpha(\lambda, r), (k, h) \rangle_{\mathbb{R} \times H^3} = J'_\alpha(\lambda, r)(k, h)$.
- We have implemented star-shaped domains using trigonometric polynomials.

Algorithm: *Projected Gradient Method*

(S0) Choose $(\lambda^0, r^0) \in \mathcal{C} := \Lambda \times \mathcal{R}_{ad}$, $k := 0$

(S1) Iterate (S2)-(S4) until 😊

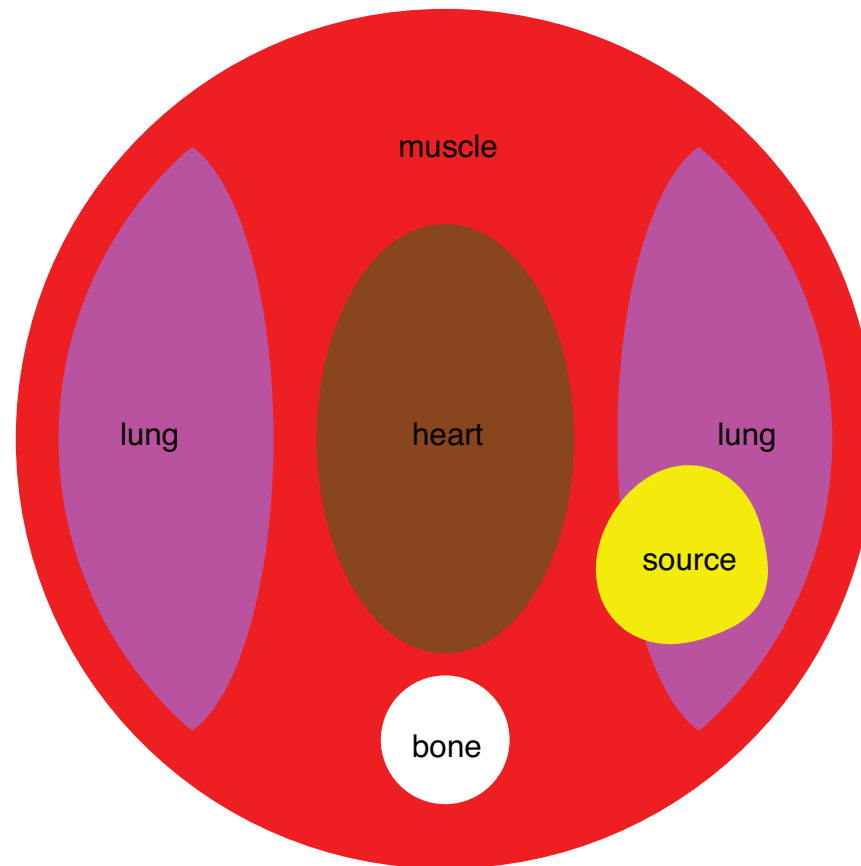
(S2) Set $\nabla_k := -\text{grad} J_\alpha(\lambda^k, r^k)$.

(S3) Choose σ_k by a projected step size rule such that

$$J_\alpha\left(P_{\mathcal{C}}((\lambda^k, r^k) + \sigma_k \nabla_k)\right) < J_\alpha(\lambda^k, r^k).$$

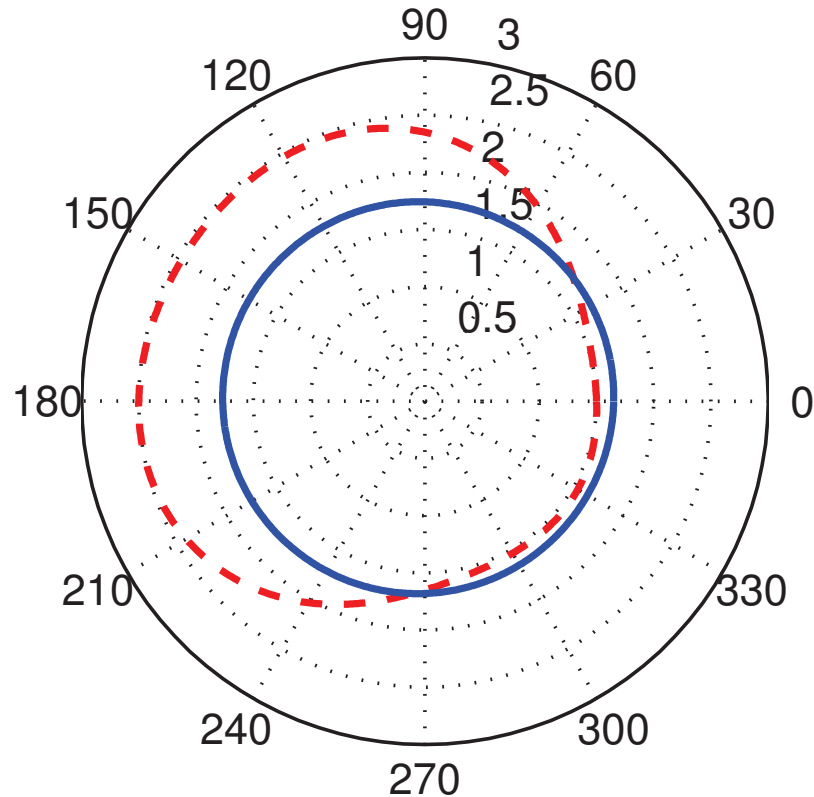
(S4) Set $(\lambda^{k+1}, r^{k+1}) := P_{\mathcal{C}}((\lambda^k, r^k) + \sigma_k \nabla_k)$.

The model

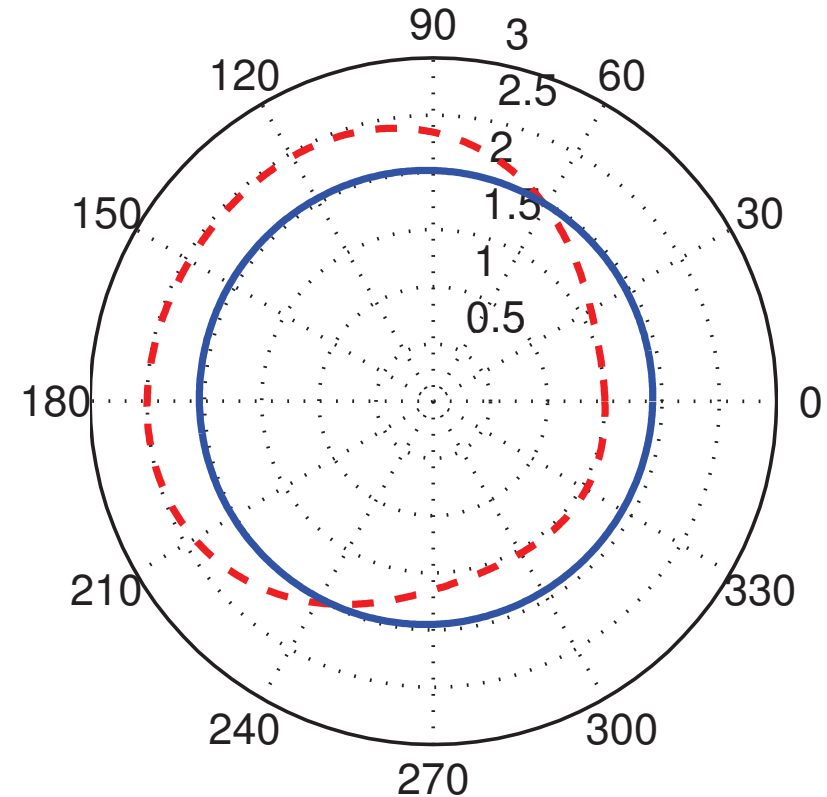


H^3 -Reconstructions

$\lambda = 0.97843$ for $\alpha = 0.00763$



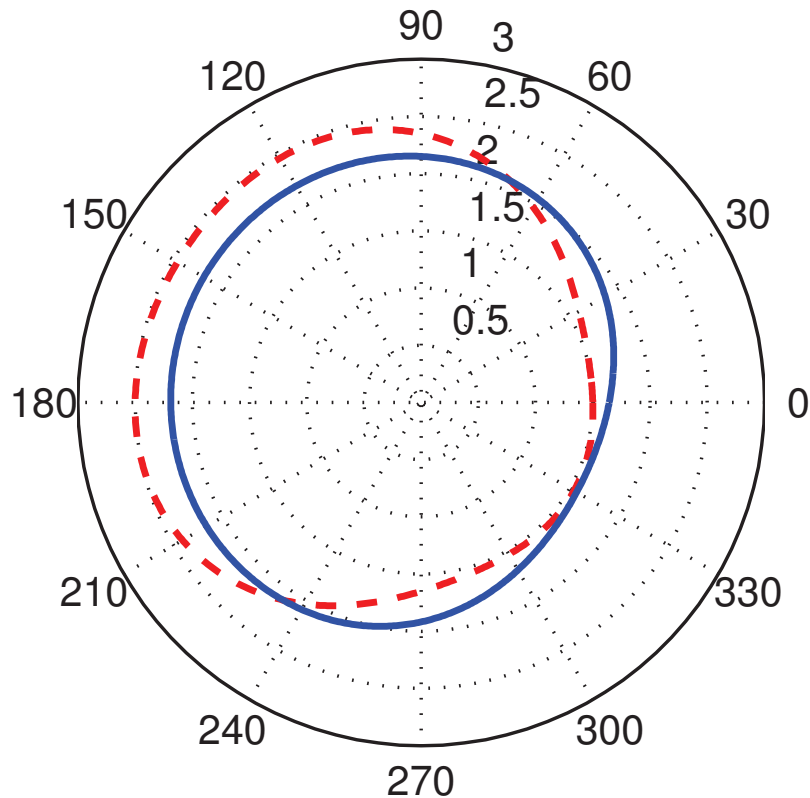
$\lambda = 0.702$ for $\alpha = 0.00762$



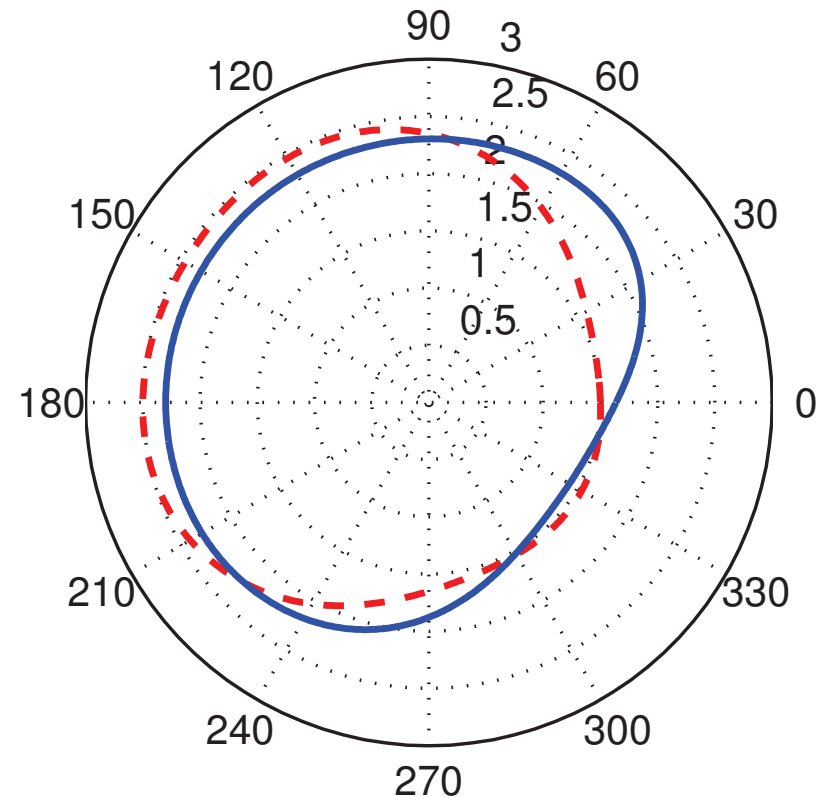
Reconstructions (blue) and source (red).
Left: 69 iterations, right: $k = 17$ iterations

L^2 -Reconstructions

$\lambda = 0.84033$ for $\alpha = 0.0079$



$\lambda = 0.77183$ for $\alpha = 0.008$



Reconstructions (blue) and source (red).

Left: 37 iterations, right: noisy data (rel. 3%), 24 iterations

L^2 -Reconstruction with variable center

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What to remember
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Summary

What to remember from this talk

- Bioluminescence tomography images cells *in vivo*. From a mathematical point of view it is an inverse source problem which suffers from non-uniqueness (diffusion approximation) and ill-posedness.
- To overcome these difficulties the sources are modeled as "hot spots" leading to a nonlinear problem which is stabilized by a Tikhonov-like regularization penalizing the perimeter of the hot spots.
- The approximate variational principle justifies the restriction to hot spots with smooth boundaries.
- For star-shaped domains in 2D a projected steepest decent solver has been implemented and tested.