

Fluorescence Ultrasound Modulated Optical Tomography (fUMOT) in the Diffusive Regime

Yang Yang

Computational Math, Science and Engineering (CMSE)
Michigan State University

joint work with:

Wei Li, Louisiana State University

Yimin Zhong, University of California Irvine

Conference on Modern Challenges in Imaging: in the Footsteps
of Allan MacLeod Cormack

MS1: Applied Math in Tomography, Tufts University, August 5, 2015

Outline

- 1 Introduction to fUMOT
- 2 Diffusive Model
- 3 Results

Optical Tomography

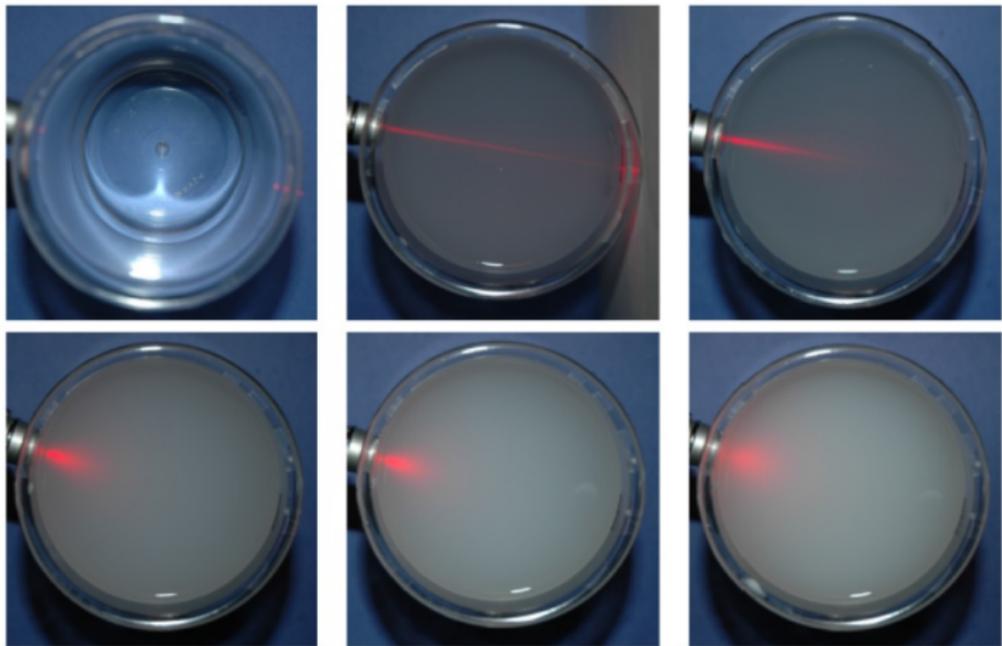


Figure: Credit: Nina Schotland

Fluorescence + Optical Tomography (fOT)

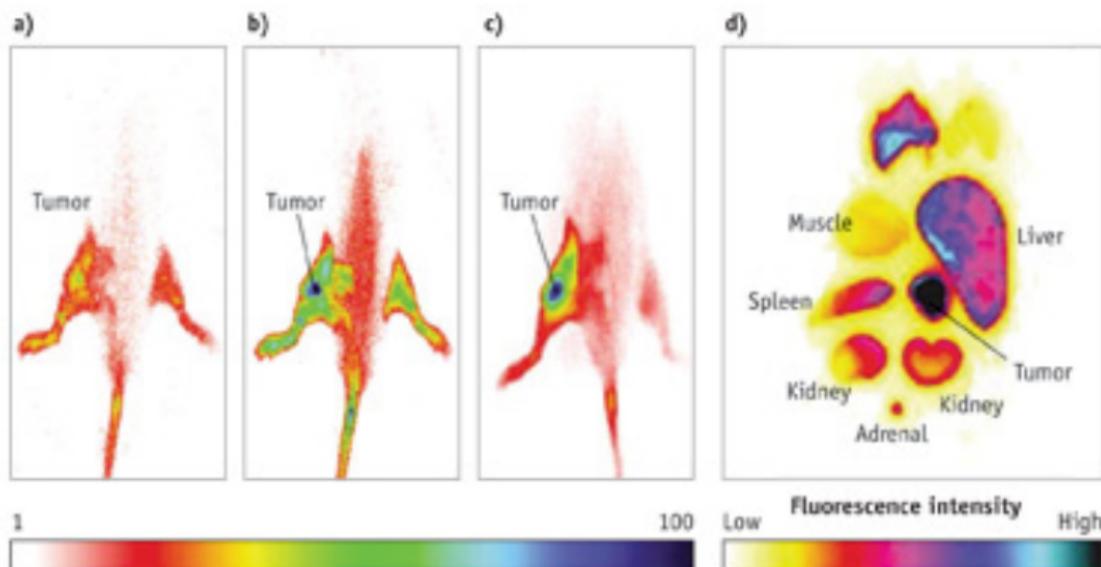


Figure: Fluorescence Optical Tomography (fOT). Image from Yang Pu et al, "Cancer detection/fluorescence imaging: 'smart beacons' target cancer tumors", *BioOpticsWorld.com.*, 2013.

Fluorescence + Ultrasound Modulation + Optical Tomography (fUMOT)

S: **excitation** light source,

D: detector

solid curve: **excitation** photon path

dotted curve: emitted **fluorescence** photon path

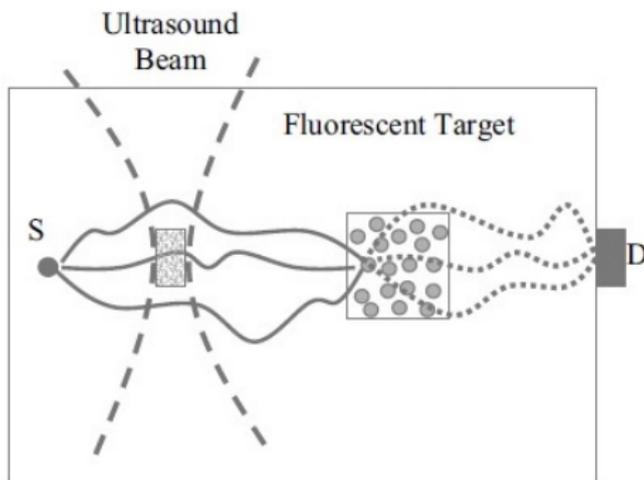


Figure: Fluorescence Ultrasound Modulated Optical Tomography (fUMOT). Image from B. Yuan et al, "Mechanisms of the ultrasonic modulation of fluorescence in turbid media", *J. Appl. Phys.* 2008; 104: 103102

Incomplete literature

- **Fluorescence Optical Tomography (FOT):** Arridge, Arridge-Schotland, Stefanov-Uhlmann, ...
- **Ultrasound Modulated Optical Tomography (UMOT):** Ammari-Bossy-Garnier-Nguyen-Seppecher, Bal, Bal-Moskow, Bal-Schotland, Chung-Schotland, ...

Outline

- 1 Introduction to fUMOT
- 2 Diffusive Model
- 3 Results

fOT Model

Diffusive regime for fOT (Ren-Zhao 2013):

$u(\mathbf{x})$: excitation photon density, $w(\mathbf{x})$: emission photon density

fOT Model

Diffusive regime for fOT (Ren-Zhao 2013):

$u(\mathbf{x})$: excitation photon density, $w(\mathbf{x})$: emission photon density

- excitation process (subscripted by x):

$$\begin{cases} -\nabla \cdot D_x \nabla u + (\sigma_{x,a} + \sigma_{x,f})u = 0 & \text{in } \Omega \\ u = g & \text{on } \partial\Omega. \end{cases}$$

$D_x(\mathbf{x})$: diffusion coeffi.

$g(\mathbf{x})$: boundary illumination

$\sigma_{x,a}(\mathbf{x})$: absorption coeffi. of medium

$\sigma_{x,f}(\mathbf{x})$: absorption coeffi. of fluore

fOT Model

Diffusive regime for fOT (Ren-Zhao 2013):

$u(\mathbf{x})$: excitation photon density, $w(\mathbf{x})$: emission photon density

- excitation process (subscripted by x):

$$\begin{cases} -\nabla \cdot D_x \nabla u + (\sigma_{x,a} + \sigma_{x,f})u = 0 & \text{in } \Omega \\ u = g & \text{on } \partial\Omega. \end{cases}$$

$D_x(\mathbf{x})$: diffusion coeffi.

$g(\mathbf{x})$: boundary illumination

$\sigma_{x,a}(\mathbf{x})$: absorption coeffi. of medium

$\sigma_{x,f}(\mathbf{x})$: absorption coeffi. of fluore

- emission process (subscripted by m):

$$\begin{cases} -\nabla \cdot D_m \nabla w + (\sigma_{m,a} + \sigma_{m,f})w = \eta \sigma_{x,f} u & \text{in } \Omega \\ w = 0 & \text{on } \partial\Omega. \end{cases}$$

$D_m(\mathbf{x})$: diffusion coeffi.

$\eta(\mathbf{x})$: quantum efficiency coeffi.

$\sigma_{m,a}(\mathbf{x})$: absorption coeffi. of medium

$\sigma_{m,f}(\mathbf{x})$: absorption coeffi. of fluore

Ultrasound Modulation Model

Ultrasound modulation with plane waves:

- weak acoustic field:

$$p(t, \mathbf{x}) = A \cos(\omega t) \cos(\mathbf{q} \cdot \mathbf{x} + \phi).$$

Ultrasound Modulation Model

Ultrasound modulation with plane waves:

- weak acoustic field:

$$p(t, \mathbf{x}) = A \cos(\omega t) \cos(\mathbf{q} \cdot \mathbf{x} + \phi).$$

- modulation effect on optical coefficients (Bal-Schotland 2009):

$$D_x^\epsilon(\mathbf{x}) = (1 + \epsilon \gamma_x \cos(\mathbf{q} \cdot \mathbf{x} + \phi)) D_x(\mathbf{x}), \quad \gamma_x = (2n_x - 1),$$

$$D_m^\epsilon(\mathbf{x}) = (1 + \epsilon \gamma_m \cos(\mathbf{q} \cdot \mathbf{x} + \phi)) D_m(\mathbf{x}), \quad \gamma_m = (2n_m - 1),$$

$$\sigma_{x,a}^\epsilon(\mathbf{x}) = (1 + \epsilon \beta_x \cos(\mathbf{q} \cdot \mathbf{x} + \phi)) \sigma_{x,a}(\mathbf{x}), \quad \beta_x = (2n_x + 1),$$

$$\sigma_{m,a}^\epsilon(\mathbf{x}) = (1 + \epsilon \beta_m \cos(\mathbf{q} \cdot \mathbf{x} + \phi)) \sigma_{m,a}(\mathbf{x}), \quad \beta_m = (2n_m + 1),$$

$$\sigma_{x,f}^\epsilon(\mathbf{x}) = (1 + \epsilon \beta_f \cos(\mathbf{q} \cdot \mathbf{x} + \phi)) \sigma_{x,f}(\mathbf{x}), \quad \beta_f = (2n_f + 1).$$

fUMOT Model

For $\epsilon > 0$ small,

- **excitation process** (subscripted by x):

$$\begin{cases} -\nabla \cdot D_x^\epsilon \nabla u^\epsilon + (\sigma_{x,a}^\epsilon + \sigma_{x,f}^\epsilon) u^\epsilon = 0 & \text{in } \Omega \\ u^\epsilon = g & \text{on } \partial\Omega. \end{cases}$$

- **emission process** (subscripted by m):

$$\begin{cases} -\nabla \cdot D_m^\epsilon \nabla w^\epsilon + (\sigma_{m,a}^\epsilon + \sigma_{m,f}^\epsilon) w^\epsilon = \eta \sigma_{x,f}^\epsilon u^\epsilon & \text{in } \Omega \\ w^\epsilon = 0 & \text{on } \partial\Omega. \end{cases}$$

fUMOT Model

For $\epsilon > 0$ small,

- **excitation process** (subscripted by x):

$$\begin{cases} -\nabla \cdot D_x^\epsilon \nabla u^\epsilon + (\sigma_{x,a}^\epsilon + \sigma_{x,f}^\epsilon) u^\epsilon = 0 & \text{in } \Omega \\ u^\epsilon = g & \text{on } \partial\Omega. \end{cases}$$

- **emission process** (subscripted by m):

$$\begin{cases} -\nabla \cdot D_m^\epsilon \nabla w^\epsilon + (\sigma_{m,a}^\epsilon + \sigma_{m,f}^\epsilon) w^\epsilon = \eta \sigma_{x,f}^\epsilon u^\epsilon & \text{in } \Omega \\ w^\epsilon = 0 & \text{on } \partial\Omega. \end{cases}$$

Measurement: boundary photon currents $(D_x^\epsilon \partial_\nu u^\epsilon, D_x^\epsilon \partial_\nu w^\epsilon)|_{\partial\Omega}$.

fUMOT Model

For $\epsilon > 0$ small,

- **excitation process** (subscripted by x):

$$\begin{cases} -\nabla \cdot D_x^\epsilon \nabla u^\epsilon + (\sigma_{x,a}^\epsilon + \sigma_{x,f}^\epsilon) u^\epsilon = 0 & \text{in } \Omega \\ u^\epsilon = g & \text{on } \partial\Omega. \end{cases}$$

- **emission process** (subscripted by m):

$$\begin{cases} -\nabla \cdot D_m^\epsilon \nabla w^\epsilon + (\sigma_{m,a}^\epsilon + \sigma_{m,f}^\epsilon) w^\epsilon = \eta \sigma_{x,f}^\epsilon u^\epsilon & \text{in } \Omega \\ w^\epsilon = 0 & \text{on } \partial\Omega. \end{cases}$$

Measurement: boundary photon currents $(D_x^\epsilon \partial_\nu u^\epsilon, D_x^\epsilon \partial_\nu w^\epsilon)|_{\partial\Omega}$.

Inverse Problem: recover $(\sigma_{x,f}, \eta)$.

fUMOT Model

For $\epsilon > 0$ small,

- **excitation process** (subscripted by x):

$$\begin{cases} -\nabla \cdot D_x^\epsilon \nabla u^\epsilon + (\sigma_{x,a}^\epsilon + \sigma_{x,f}^\epsilon) u^\epsilon = 0 & \text{in } \Omega \\ u^\epsilon = g & \text{on } \partial\Omega. \end{cases}$$

- **emission process** (subscripted by m):

$$\begin{cases} -\nabla \cdot D_m^\epsilon \nabla w^\epsilon + (\sigma_{m,a}^\epsilon + \sigma_{m,f}^\epsilon) w^\epsilon = \eta \sigma_{x,f}^\epsilon u^\epsilon & \text{in } \Omega \\ w^\epsilon = 0 & \text{on } \partial\Omega. \end{cases}$$

Measurement: boundary photon currents $(D_x^\epsilon \partial_\nu u^\epsilon, D_x^\epsilon \partial_\nu w^\epsilon)|_{\partial\Omega}$.

Inverse Problem: recover $(\sigma_{x,f}, \eta)$.

Our strategy: recover $\sigma_{x,f}$ from the excitation process, then η from the emission process.

Outline

- 1 Introduction to fUMOT
- 2 Diffusive Model
- 3 Results

Derivation of Internal Data: I

For fixed boundary illumination g ,

$$\int_{\Omega} (D_x^\epsilon - D_x^{-\epsilon}) \nabla u^\epsilon \cdot \nabla u^{-\epsilon} + (\sigma_x^\epsilon - \sigma_x^{-\epsilon}) u^\epsilon u^{-\epsilon} dx = \int_{\partial\Omega} (D_x^\epsilon \partial_\nu u^\epsilon) u^{-\epsilon} - (D_x^{-\epsilon} \partial_\nu u^{-\epsilon}) u^\epsilon dx$$

Derivation of Internal Data: I

For fixed boundary illumination g ,

$$\int_{\Omega} (D_x^\epsilon - D_x^{-\epsilon}) \nabla u^\epsilon \cdot \nabla u^{-\epsilon} + (\sigma_x^\epsilon - \sigma_x^{-\epsilon}) u^\epsilon u^{-\epsilon} dx = \int_{\partial\Omega} (D_x^\epsilon \partial_\nu u^\epsilon) u^{-\epsilon} - (D_x^{-\epsilon} \partial_\nu u^{-\epsilon}) u^\epsilon dx$$

RHS is known. LHS has leading coefficient

$$J_1(\mathbf{q}, \phi) = \int_{\Omega} (\gamma_x D_x |\nabla u|^2 + (\beta_x \sigma_{x,a} + \beta_f \sigma_{x,f}) |u|^2) \cos(\mathbf{q} \cdot \mathbf{x} + \phi) dx.$$

Derivation of Internal Data: I

For fixed boundary illumination g ,

$$\int_{\Omega} (D_x^\epsilon - D_x^{-\epsilon}) \nabla u^\epsilon \cdot \nabla u^{-\epsilon} + (\sigma_x^\epsilon - \sigma_x^{-\epsilon}) u^\epsilon u^{-\epsilon} dx = \int_{\partial\Omega} (D_x^\epsilon \partial_\nu u^\epsilon) u^{-\epsilon} - (D_x^{-\epsilon} \partial_\nu u^{-\epsilon}) u^\epsilon dx$$

RHS is known. LHS has leading coefficient

$$J_1(\mathbf{q}, \phi) = \int_{\Omega} (\gamma_x D_x |\nabla u|^2 + (\beta_x \sigma_{x,a} + \beta_f \sigma_{x,f}) |u|^2) \cos(\mathbf{q} \cdot \mathbf{x} + \phi) dx.$$

Varying \mathbf{q} and ϕ gives the Fourier transform of

$$Q(\mathbf{x}) := \gamma_x D_x |\nabla u|^2 + (\beta_x \sigma_{x,a} + \beta_f \sigma_{x,f}) |u|^2 \quad \text{in } \Omega,$$

where u is the unperturbed solution (i.e., $\epsilon = 0$).

Derivation of Internal Data: I

For fixed boundary illumination g ,

$$\int_{\Omega} (D_x^\epsilon - D_x^{-\epsilon}) \nabla u^\epsilon \cdot \nabla u^{-\epsilon} + (\sigma_x^\epsilon - \sigma_x^{-\epsilon}) u^\epsilon u^{-\epsilon} dx = \int_{\partial\Omega} (D_x^\epsilon \partial_\nu u^\epsilon) u^{-\epsilon} - (D_x^{-\epsilon} \partial_\nu u^{-\epsilon}) u^\epsilon dx$$

RHS is known. LHS has leading coefficient

$$J_1(\mathbf{q}, \phi) = \int_{\Omega} (\gamma_x D_x |\nabla u|^2 + (\beta_x \sigma_{x,a} + \beta_f \sigma_{x,f}) |u|^2) \cos(\mathbf{q} \cdot \mathbf{x} + \phi) dx.$$

Varying \mathbf{q} and ϕ gives the Fourier transform of

$$Q(\mathbf{x}) := \gamma_x D_x |\nabla u|^2 + (\beta_x \sigma_{x,a} + \beta_f \sigma_{x,f}) |u|^2 \quad \text{in } \Omega,$$

where u is the unperturbed solution (i.e., $\epsilon = 0$).

Observation: if u can be recovered from Q , so can $\sigma_{x,f}$.

Inverse Problems Recast

Inverse Problem Recast: recover u from Q .

Recall

$$\begin{cases} -\nabla \cdot D_x \nabla u + (\sigma_{x,a} + \sigma_{x,f})u & = 0 & \text{in } \Omega \\ u & = g & \text{on } \partial\Omega. \end{cases}$$

and the internal data is

$$Q(\mathbf{x}) := \gamma_x D_x |\nabla u|^2 + (\beta_x \sigma_{x,a} + \beta_f \sigma_{x,f}) |u|^2 \quad \text{in } \Omega.$$

Inverse Problems Recast

Inverse Problem Recast: recover u from Q .

Recall

$$\begin{cases} -\nabla \cdot D_x \nabla u + (\sigma_{x,a} + \sigma_{x,f})u & = 0 & \text{in } \Omega \\ u & = g & \text{on } \partial\Omega. \end{cases}$$

and the internal data is

$$Q(\mathbf{x}) := \gamma_x D_x |\nabla u|^2 + (\beta_x \sigma_{x,a} + \beta_f \sigma_{x,f}) |u|^2 \quad \text{in } \Omega.$$

- $\beta_f = 0$: solving a Hamilton-Jacobi equation to find u ;
- $\beta_f \neq 0$: eliminating $\sigma_{x,f}$ through substitution.

Recovery of $\sigma_{x,f}$: uniqueness

- $\beta_f \neq 0$ (conti.ed):

set $\theta := \frac{\beta_f - \gamma_x}{\beta_f + \gamma_x}$ and $\Psi := u^{\frac{2}{1+\theta}}$

$$\left\{ \begin{array}{l} \nabla \cdot D_x \nabla \Psi = \underbrace{-\frac{2}{1+\theta} \sigma_{x,a} \left(\frac{\beta_x}{\beta_f} - 1 \right)}_{:=b} \Psi + \underbrace{\frac{2}{1+\theta} \frac{Q}{\beta_f}}_{:=c} |\Psi|^{-(1+\theta)} \Psi \\ \Psi = g^{\frac{2}{1+\theta}} \end{array} \right.$$

Theorem (Li-Y.-Zhong, 2018)

The semi-linear elliptic BVP has a unique positive weak solution $\Psi \in H^1(\Omega)$ in either of the following cases:

Case (1): $-1 \neq \theta < 0$, $b \geq 0$ and $c \geq 0$;

Case (2): $\theta \geq 0$, $b \geq 0$ and $c \leq 0$.

Recovery of $\sigma_{x,f}$: stability and reconstruction

Theorem (Li-Y.-Zhong, 2018)

In either Case (1) or Case (2), one has the stability estimate

$$\|\sigma_{x,f} - \tilde{\sigma}_{x,f}\|_{L^1(\Omega)} \leq C \left(\|Q - \tilde{Q}\|_{L^1(\Omega)} + \|Q - \tilde{Q}\|_{L^2(\Omega)}^2 \right)$$

We further give three iterative algorithms with convergence proofs to reconstruct $\sigma_{x,f}$.

Remark: uniqueness and stability may fail if θ , b , c violate the conditions.

Recovery of η

Sketch of procedures:

- 1 derive an integral identity from the emission process;

Recovery of η

Sketch of procedures:

- 1 derive an integral identity from the emission process;
- 2 derive an internal functional S from the leading order term of the identity;

Recovery of η

Sketch of procedures:

- 1 derive an integral identity from the emission process;
- 2 derive an internal functional S from the leading order term of the identity;
- 3 rewrite the equations for u and w to obtain a Fredholm type equation

$$\mathcal{T}\eta = S;$$

Recovery of η

Sketch of procedures:

- 1 derive an integral identity from the emission process;
- 2 derive an internal functional S from the leading order term of the identity;
- 3 rewrite the equations for u and w to obtain a Fredholm type equation

$$\mathcal{T}\eta = S;$$

- 4 if 0 is not an eigenvalue of \mathcal{T} , then uniqueness, stability and reconstruction are immediate.

Numerical examples

Domain: $[-0.5, 0.5]^2$; excitation source: $g(x, y) = e^{2x} + e^{-2y}$..

The domain is triangulated into 37008 triangles and uses 4-th order Lagrange finite element method to solve the equations.

$$D_x \equiv 0.1, \quad D_m = 0.1 + 0.02 \cos(2x) \cos(2y),$$
$$\sigma_{x,a} \equiv 0.1, \quad \sigma_{m,a} = 0.1 + 0.02 \cos(4x^2 + 4y^2).$$

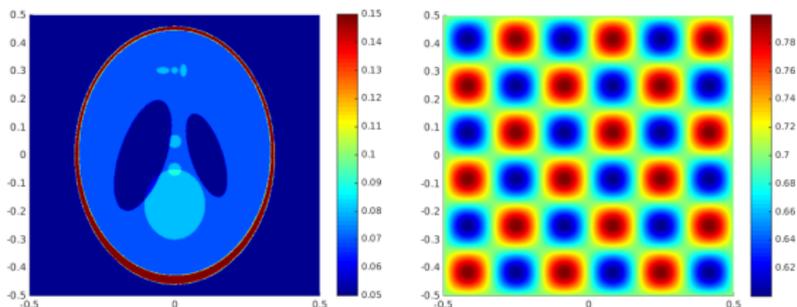


Figure: Left: The absorption coefficient $\sigma_{x,f}$ of fluorophores. Right: The quantum efficiency coefficient η .

Numerical examples- Case I-1

$\gamma_x = -2.6$, $\gamma_m = -2.4$, $\beta_x = -0.6$, $\beta_m = -0.4$, $\beta_f = -0.8$ and $\tau = 3.25$. $\mu = -0.25$ and $\theta = -\frac{9}{17}$.

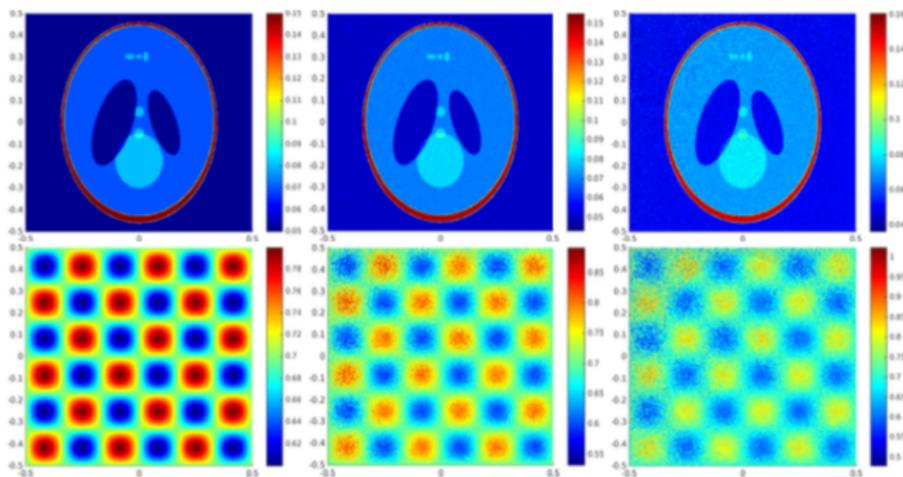


Figure 2: The reconstruction of $\sigma_{x,f}$ and η in Example I. First row, from left to right, 0%, 1%, 2% random noises are added to the internal data Q and the relative L^1 errors of reconstructed $\sigma_{x,f}$ are 0.000132%, 3.88%, 7.76% respectively. Second row, from left to right, assuming the knowledge of $\sigma_{x,f}$ from the first row, 0%, 1%, 2% random noises are added to the internal data S . The relative L^2 errors of reconstructed η are 0.00313%, 5.60%, 11.7% respectively.

Numerical examples- Case I-2

$\gamma_x = -1.4$, $\gamma_m = 0.0$, $\beta_x = 0.6$, $\beta_m = 2.0$, $\beta_f = 0.4$ and $\tau = -3.5$.
 $\mu = 0.5$ and $\theta = -\frac{9}{5}$.

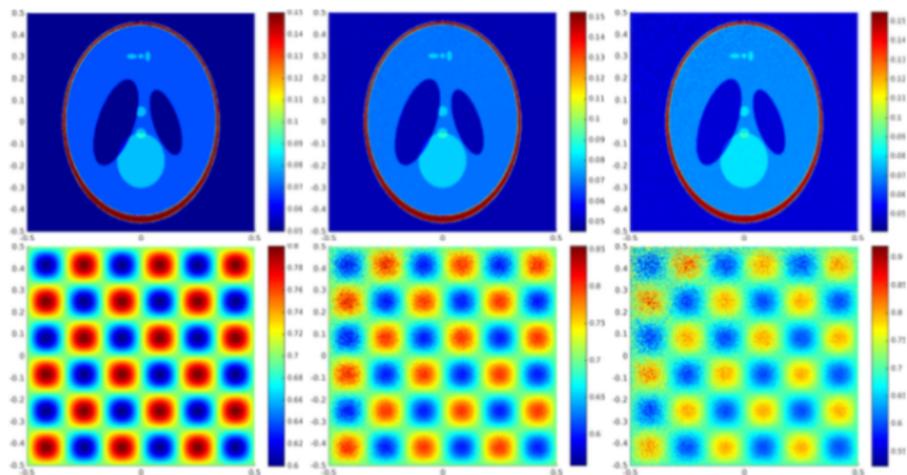


Figure 3: The reconstruction of $\sigma_{x,f}$ and η in Example II. First row, from left to right, 0%, 1%, 2% random noises are added to the internal data Q and the relative L^1 errors of reconstructed $\sigma_{x,f}$ are 0.0086%, 2.62%, 5.27% respectively. Second row, from left to right, assuming the knowledge of $\sigma_{x,f}$ from the first row, 0%, 1%, 2% random noises are added to the internal data S . The relative L^2 errors of reconstructed η are 0.0150%, 4.23%, 8.89% respectively.

Numerical examples- Case II

$\gamma_x = 0.2$, $\gamma_m = 0.6$, $\beta_x = 2.2$, $\beta_m = 2.6$, $\beta_f = -0.3$ and $\tau = -\frac{2}{3}$.
 $\mu = -\frac{25}{8}$ and $\theta = 5$.

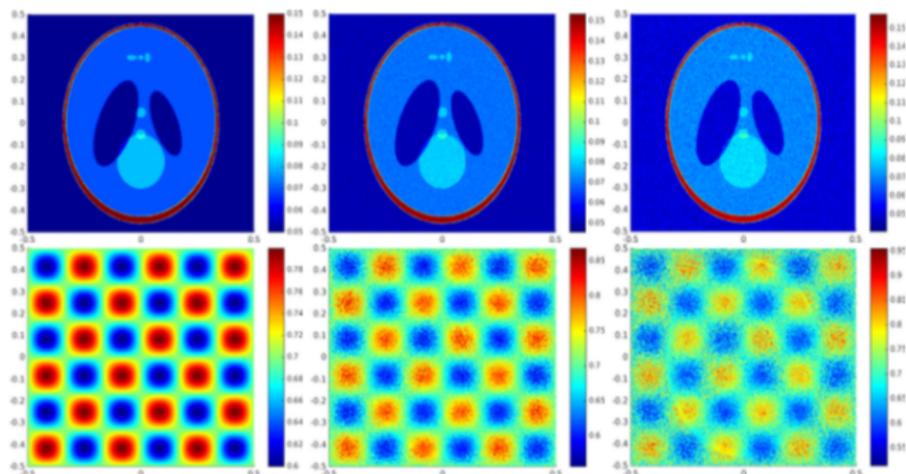


Figure 4: The reconstruction of $\sigma_{x,f}$ and η in Example III. First row, from left to right, 0%, 1%, 2% random noises are added to the internal data Q and the relative L^1 errors of reconstructed $\sigma_{x,f}$ are 0.00147%, 3.68%, 7.38% respectively. Second row, from left to right, assuming the knowledge of $\sigma_{x,f}$ from the first row, 0%, 1%, 2% random noises are added to the internal data S . The relative L^2 errors of reconstructed η are 0.00392%, 4.65%, 9.48% respectively.

Thank you for the attention!

