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UNIVERSITY OF EASTERN FINLAND

Imaging with Light and Sound

Wave Physics and Imaging Applications, University of Helsinki, May 20, 2022

Tanja Tarvainen, Department of Applied Physics, University of Eastern Finland

Finnish Centre of Excellence in Inverse Modelling and Imaging 2018-2025

COMPUTATIONAL PHYSICS AND INVERSE PROBLEMS GROUP

Professors, associate professors

- Jari Kaipio
- Marko Vauhkonen
- Ville Kolehmainen
- Tanja Tarvainen
- Aku Seppänen

Senior scientists

- Timo Lähivaara
- Aki Pulkkinen

Postdoctoral researchers: Anna Kaasinen, Jarkko Leskinen, Meghdoot Mozumder, Matti Niskanen, Jussi Toivanen, Antti Voss

PhD students: Muhammad Arif, Matti Hanhela, Marzieh Hosseini, Niko Hänninen, Jonna Kangasniemi, Mahnaz Khalili, Eero Koponen, Matti Kortelainen, Petri Kuusela, Kimmo Laitinen, Piia Lesonen, Tomi Nissinen, Mikko Räsänen, Teemu Sahlström, Teemu Salminen, Miika Suhonen, Elias Vänskä, Ville-Veikko Wettenhovi, Rahul Yadav

Technical personnel: Asko Hänninen, Tuomo Savolainen

RESEARCH

Methodological competence

- Bayesian inverse problems
- Numerical methods for physical problems
- Computational modelling of measurements, unknowns and uncertainties
- Uncertainty quantification
- Developing solutions for problems arising from challenging real world applications

$$\pi(x|y) = \frac{\pi(x)\pi(y|x)}{\pi(y)}$$

Applications

- **Biomedical inverse problems**

  Hybrid medical imaging, optical imaging, imaging using coupled physics, biomedical electrical impedance tomography, ultrasound tomography and therapy

- **Industrial inverse problems**

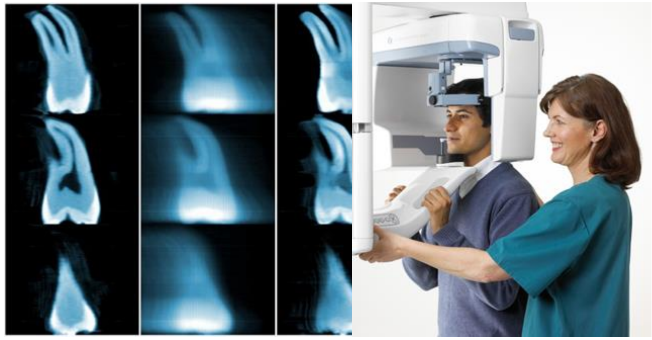
  Process tomography, non-destructive testing, thermal tomography

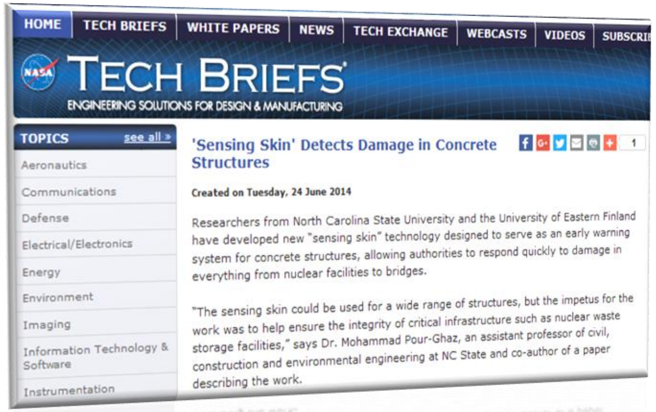
- **Inverse problems in geosciences and in atmospheric sciences**

  Seismic imaging, remote sensing, atmospheric inverse problems

- **Miscellaneous distributed parameter estimation problems**

  Acoustic and electromagnetic modelling





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'Sensing Skin' Detects Damage in Concrete Structures

Created on Tuesday, 24 June 2014

Researchers from North Carolina State University and the University of Eastern Finland have developed new "sensing skin" technology designed to serve as an early warning system for concrete structures, allowing authorities to respond quickly to damage in everything from nuclear facilities to bridges.

"The sensing skin could be used for a wide range of structures, but the impetus for the work was to help ensure the integrity of critical infrastructure such as nuclear waste storage facilities," says Dr. Mohammad Pour-Ghaz, an assistant professor of civil, construction and environmental engineering at NC State and co-author of a paper describing the work.

INFRASTRUCTURE

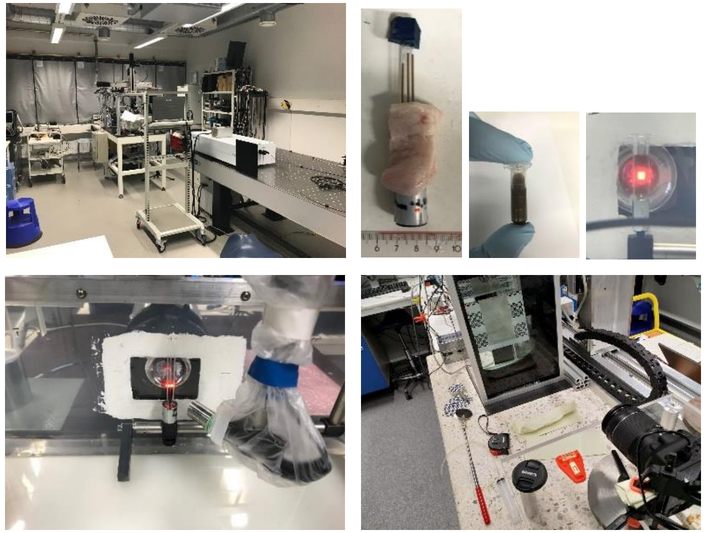
Electrical tomography laboratory

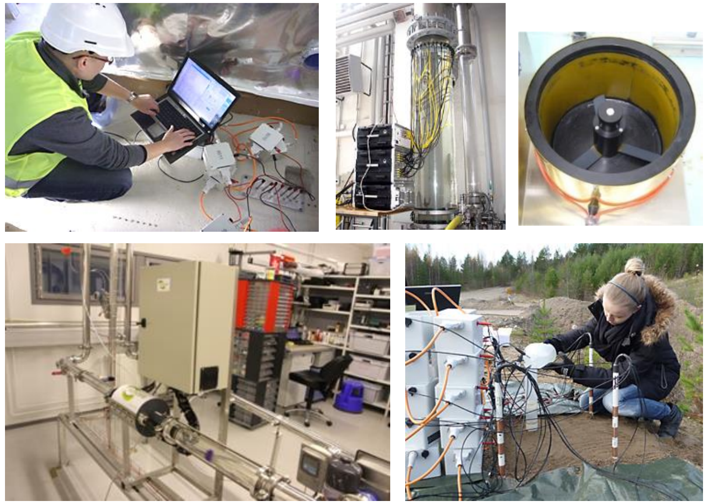
- Process tomography, non-destructive testing, medical imaging
- Eight EIT/ECT imaging systems
- Electromagnetic flow tomography system

Biomedical optical imaging and ultrasound laboratory (OPUS)

- Part of FinnLight FIRI
- Prototype instrumentation for optical, photoacoustic and acousto-optic imaging
- Ultrasound instrumentation
- https://youtu.be/3uW0oSzCd8s

Other infrastructure available through collaborators (Kuopio university hospital etc.)





TEAM TANJA TARVAINEN

Team members

- Professor Tanja Tarvainen
- Senior scientist Aki Pulkkinen
- Laboratory engineer Jarkko Leskinen
- Postdoc Meghdoot Mozumder
- PhD students: Niko Hänninen, Jonna Kangasniemi, Eero Koponen, Teemu Sahlström, Miika Suhonen
- MSc students

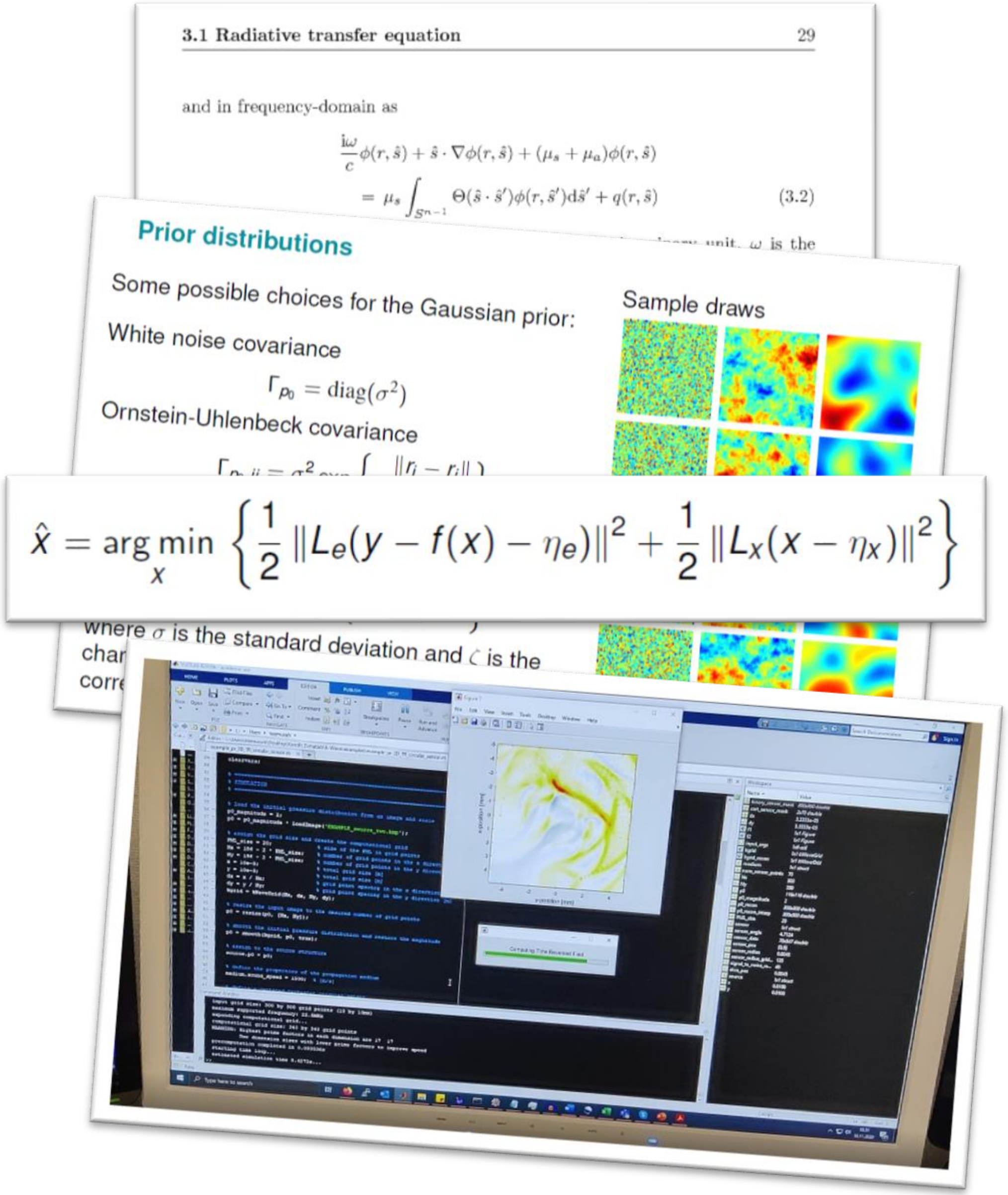
Research interests

Computational inverse problems

- Bayesian methods to ill-posed inverse problems
- Quantitative tomography
- Model reduction and uncertainty quantification

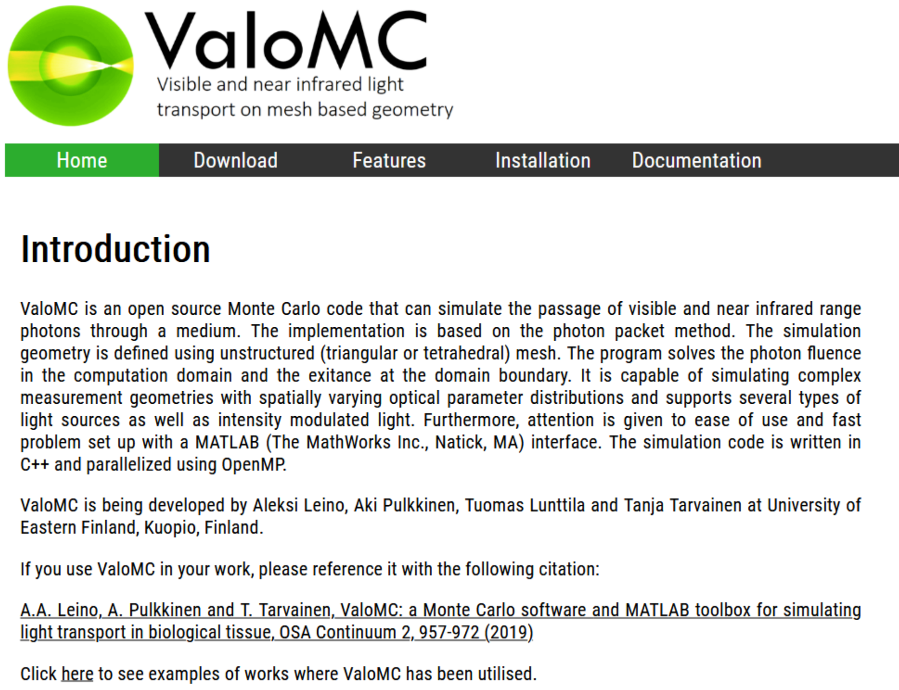
Experimental system development

- Prototype systems for optical and coupled physics imaging



Radiative transfer

- Modelling light transport in tissue
- Numerical solution of the radiative transfer equation and its approximations
- Monte Carlo simulation of light transport
- Inverse problems (imaging) utilising the radiative transfer equation



ValoMC
Visible and near infrared light transport on mesh based geometry

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Introduction

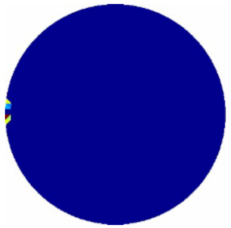
ValoMC is an open source Monte Carlo code that can simulate the passage of visible and near infrared range photons through a medium. The implementation is based on the photon packet method. The simulation geometry is defined using unstructured (triangular or tetrahedral) mesh. The program solves the photon fluence in the computation domain and the exitance at the domain boundary. It is capable of simulating complex measurement geometries with spatially varying optical parameter distributions and supports several types of light sources as well as intensity modulated light. Furthermore, attention is given to ease of use and fast problem set up with a MATLAB (The MathWorks Inc., Natick, MA) interface. The simulation code is written in C++ and parallelized using OpenMP.

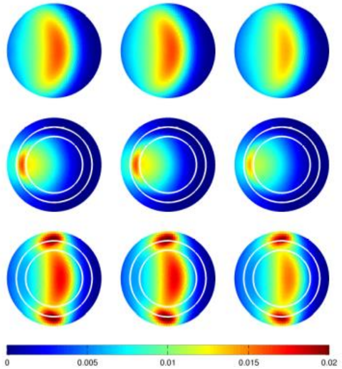
ValoMC is being developed by Aleksi Leino, Aki Pulkkinen, Tuomas Lunttila and Tanja Tarvainen at University of Eastern Finland, Kuopio, Finland.

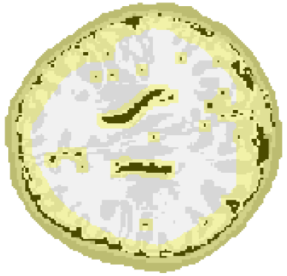
If you use ValoMC in your work, please reference it with the following citation:

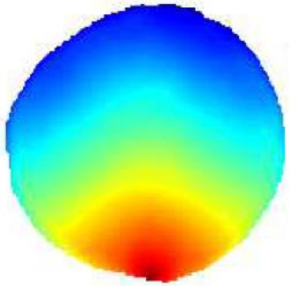
A.A. Leino, A. Pulkkinen and T. Tarvainen, ValoMC: a Monte Carlo software and MATLAB toolbox for simulating light transport in biological tissue, OSA Continuum 2, 957-972 (2019)

Click here to see examples of works where ValoMC has been utilised.



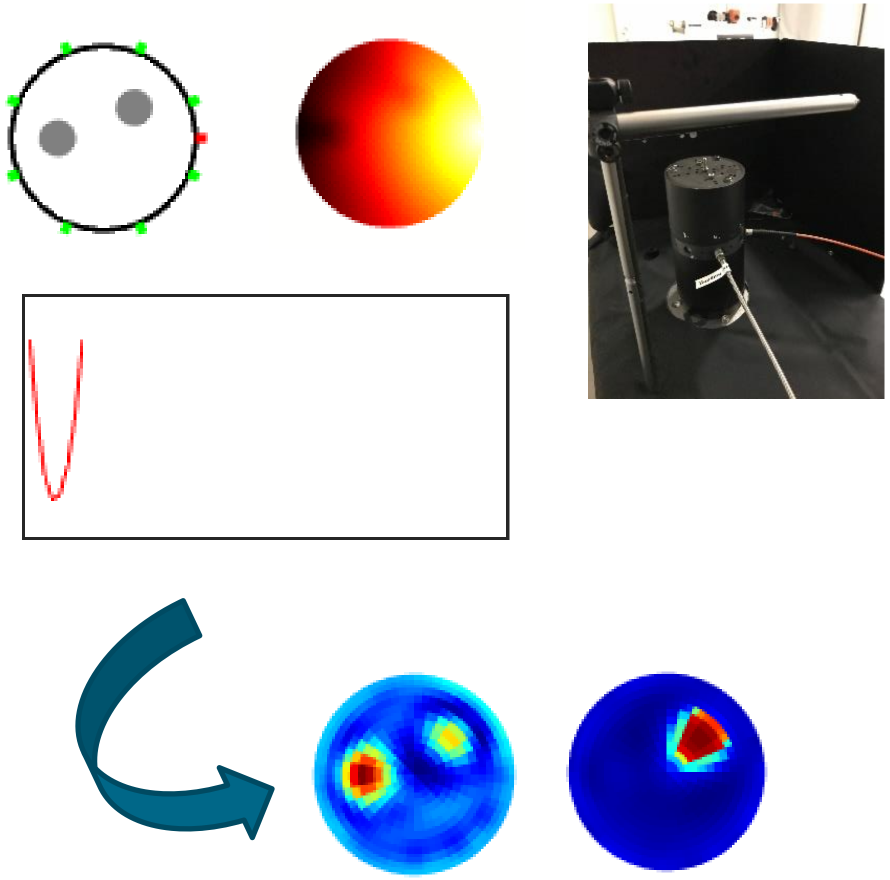






Diffuse optical tomography

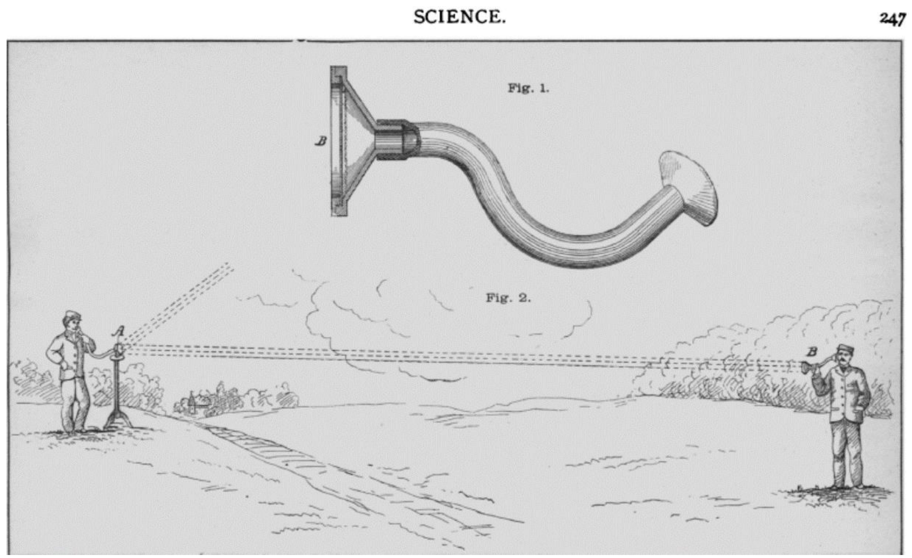
- Tomographic imaging based on light
  - Light is introduced to the target on the boundary
  - Amount of transmitted light is measured
  - Image of target optical properties is reconstructed form these measurements
  - Highly ill-posed inverse problem
- Novelty: optical contrast
- Disadvantage: low resolution
- Potential applications: breast cancer imaging, functional brain studies, infant brain oxygenation monitoring, etc.



PHOTOACOUSTIC TOMOGRAPHY

Photoacoustic effect

- Photoacoustic effect was first reported by Alexander Graham Bell in 1880
- Generated audio waves using chopped sunlight
- Photoacoustic effect: formation of sound waves following absorption of pulsed light
- Is widely utilised in various analysis and imaging modalities

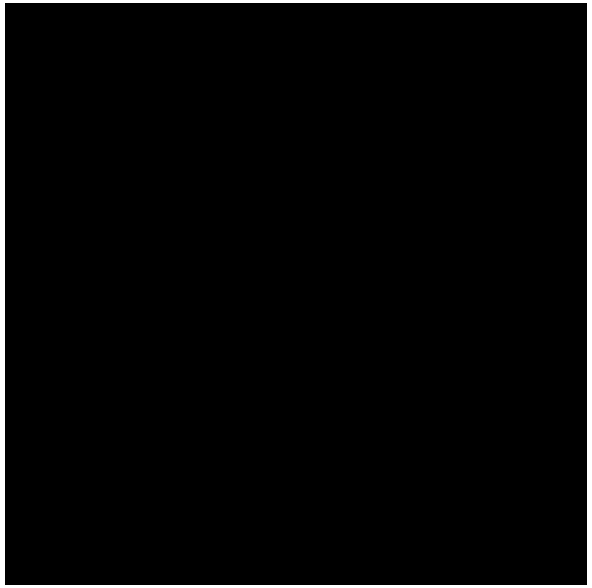


A.G. Bell, The Production of Sound by Radiant Energy, *Science*, 2(48):242-253, 1881

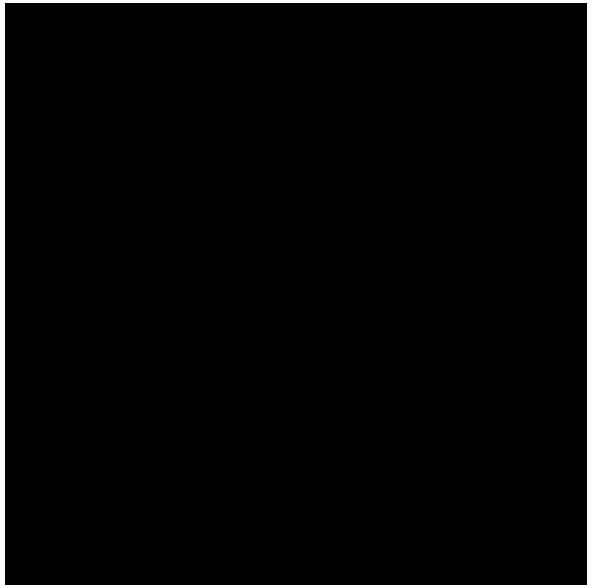
Photoacoustic tomography

- Tissue is illuminated by a short pulse (ns scale) of light
- As light propagates within the tissue, it is absorbed by light absorbing molecules

Propagation of a photon fluence pulse in a medium

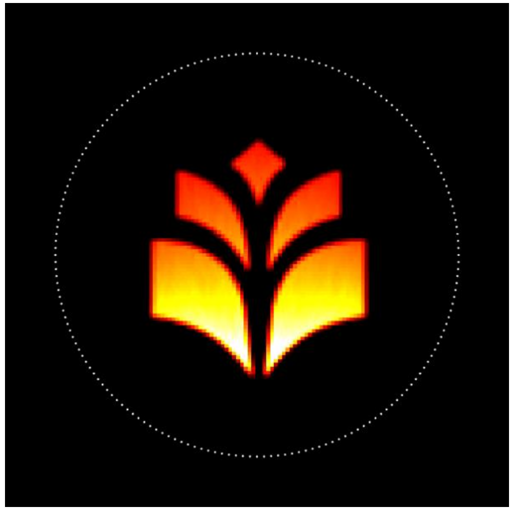


Absorbed optical energy density

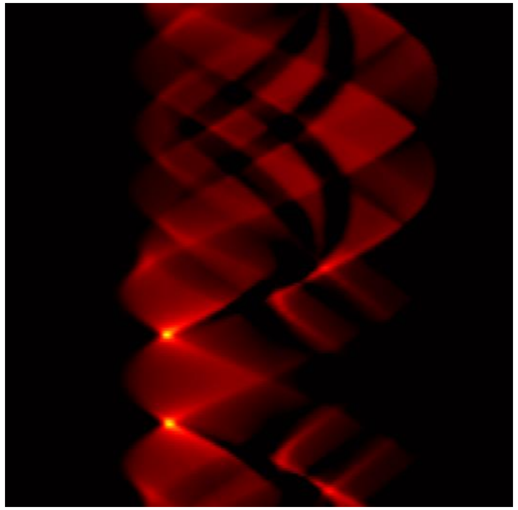


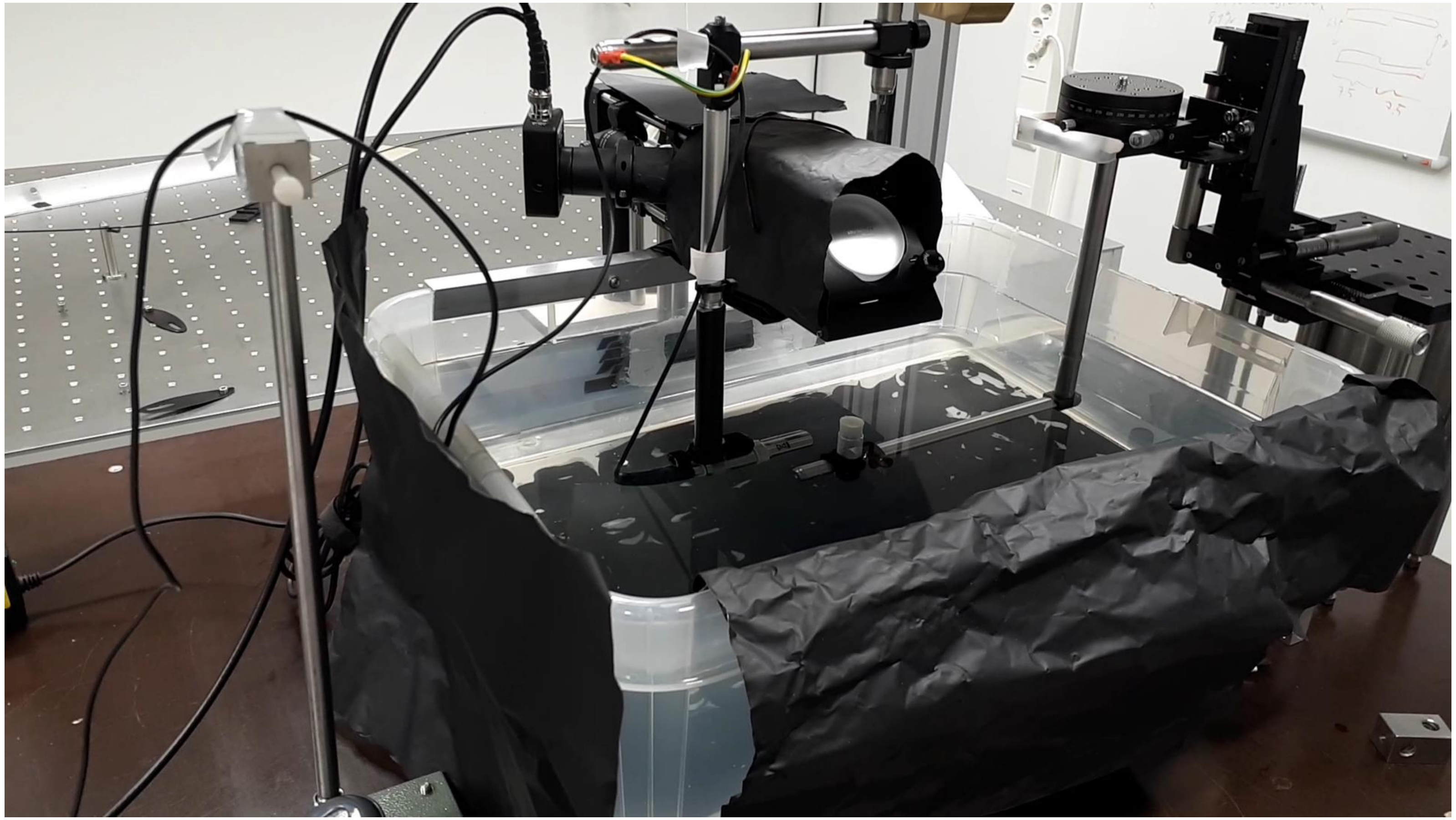
- The absorbed energy causes pressure rise
- This pressure increase propagates though the tissue as an acoustic wave
- It can be detected on the surface of the tissue using ultrasound sensors

Propagation of an acoustic wave

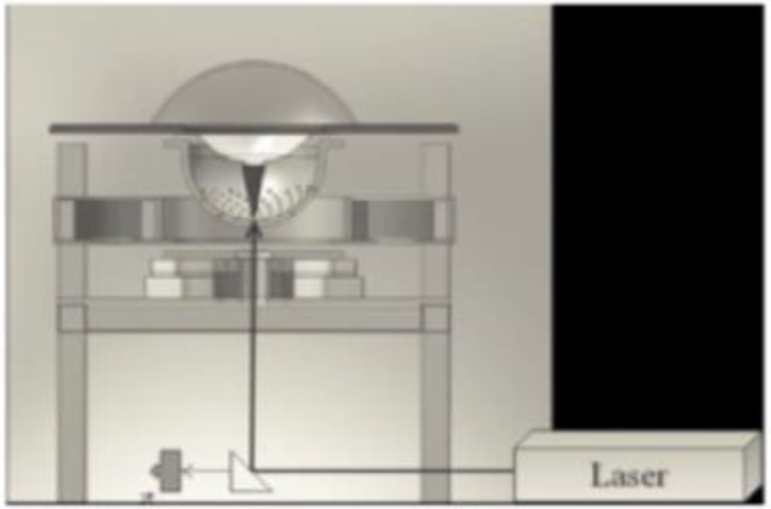


Measured data

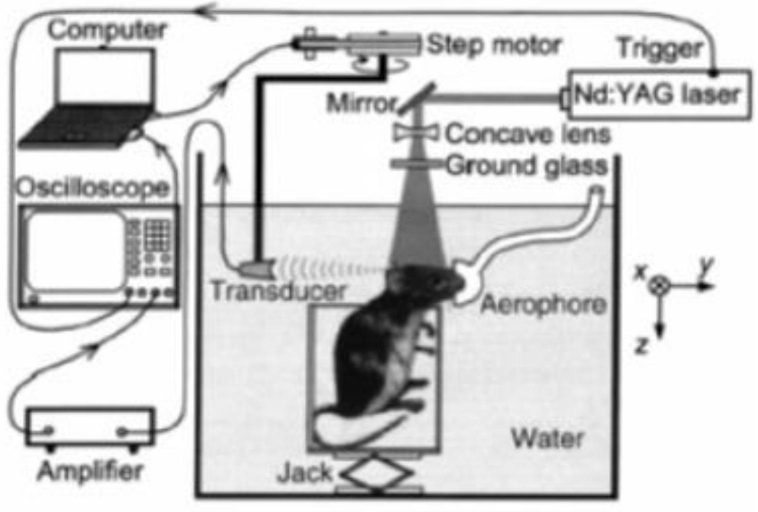




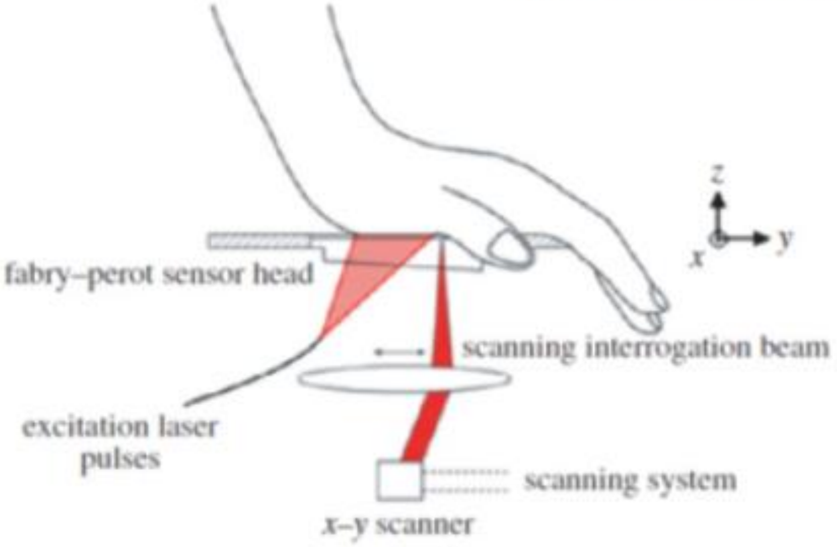
Daoudi et al, *Biomed Opt Express*, 2014



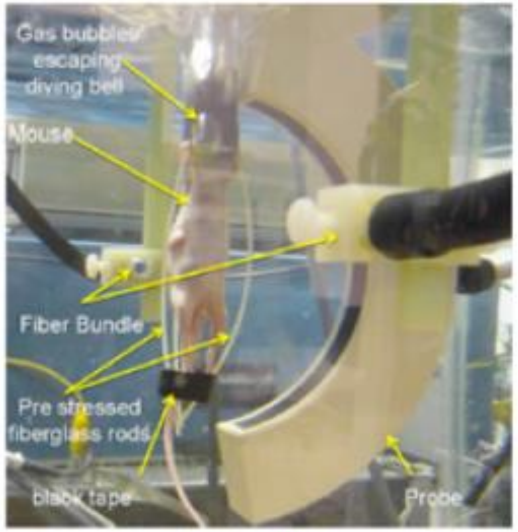
Brecht et al, *J Biomed Opt*, 2009



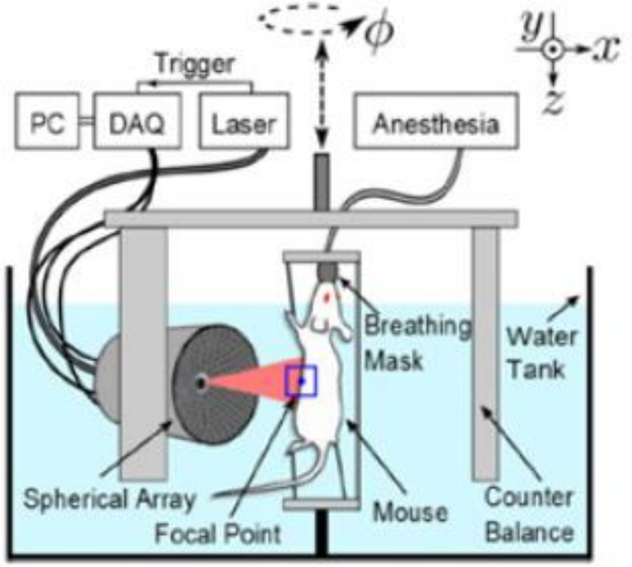
Wang et al, *Nature Biotechnology*, 2003



Beard, *Interfrace Focus*, 2011



Kruger et al, *Med Phys*, 2010

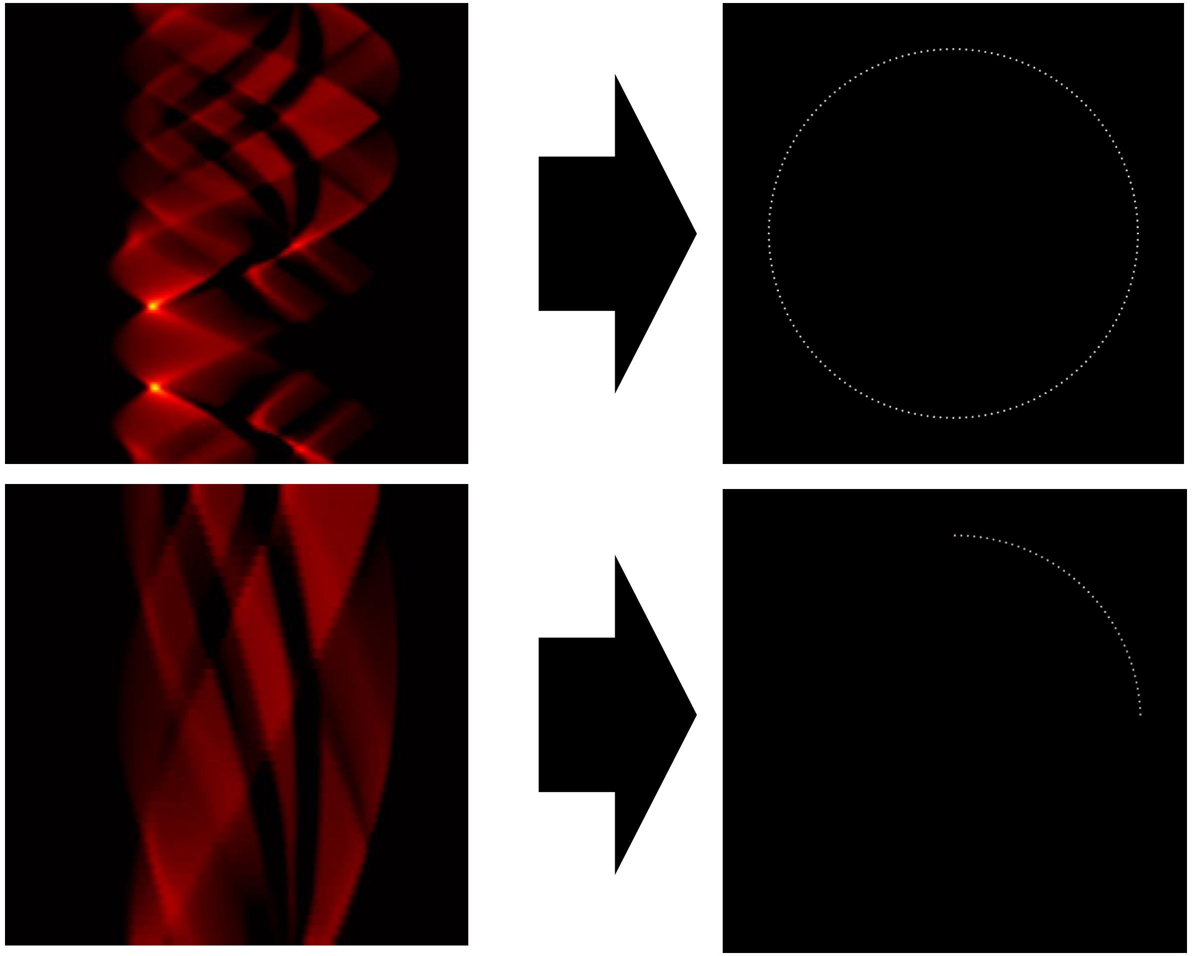


Fehm et al, *Optica*, 2016

- Initial pressure is reconstructed from the measured pressure waves

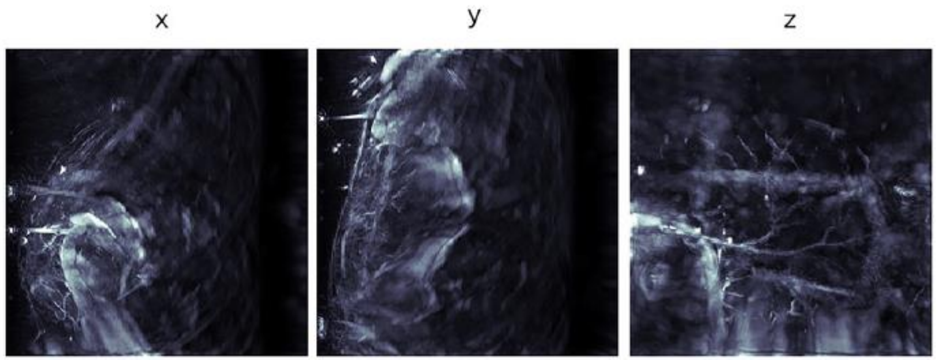
Full-view (360°) measurements

Limited-view (45°) measurements



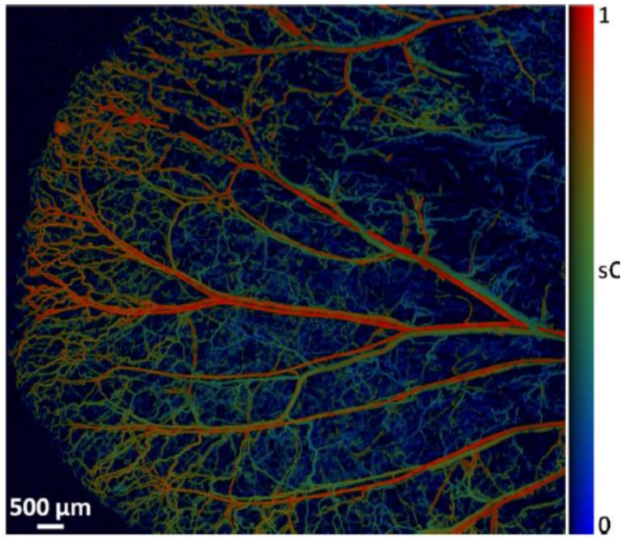
Photoacoustic imaging combines benefits of optical and acoustic methods

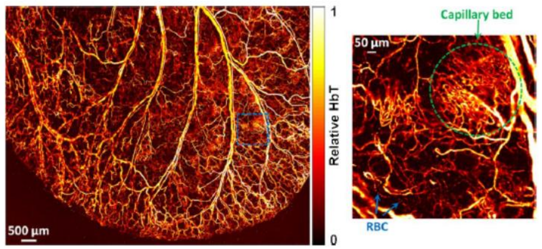
- Contrast through optical absorption
  - Tissue chromophores: oxygenated and deoxygenated haemoglobin, water, lipids, melanin
  - Contrast agents
- Resolution by ultrasound
  - Low scattering in soft biological tissue



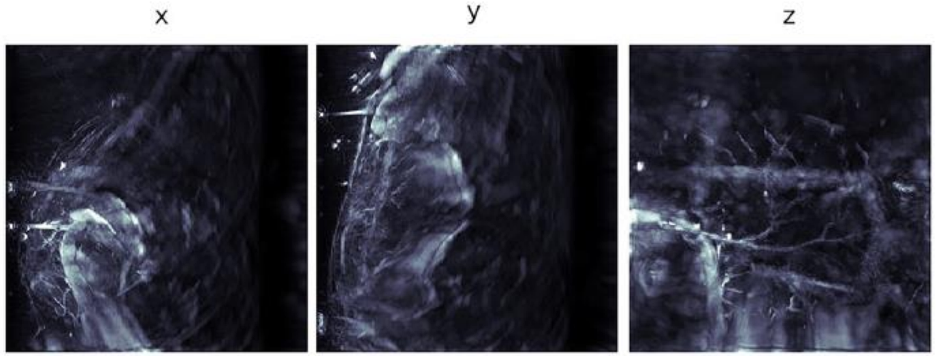
J Tick et. al. Three dimensional photoacoustic tomography in Bayesian framework, *J Acoust. Soc. Am.*, 2018.

- Can be used for imaging biological samples from micrometres photoacoustic microscopy to few centimetres photoacoustic tomography
- Applications of photoacoustic tomography
  - Imaging tissue vasculature
  - Imaging of breast cancer
  - Small animal imaging





Hu et al, Second-generation optical-resolution photoacoustic microscopy with improved sensitivity and speed, *Optics Letters*, 2011



J Tick et. al. Three dimensional photoacoustic tomography in Bayesian framework, *J Acoust. Soc. Am.*, 2018.

Inverse problems

Inverse problem

- Using a set of (indirect) observations to determine the factors that caused them

Ill-posedness

- The solution may not be unique and/or
- The solution may not depend continuously on the observation
  - Even small errors in measurements or modelling can cause large errors in the solution

Inverse problem in photoacoustic tomography

Two-inverse problems

- **Acoustic inverse problem**: Estimate the initial pressure from measured ultrasound waves
- **Optical inverse problem**: estimate the optical parameters from the initial pressure

Bayesian approach

- All parameters are modelled as random variables
- Combines the information obtained through the measurements, the forward model, and the prior model for unknown parameters
- Facilitates representing and taking into account the uncertainties in parameters, models, and geometries

Steps

- Derive the solution (posterior distribution)
- Formulate as a minimisation problem (point estimates)

$$\arg\min_{x} \left\{ \frac{1}{2} \| L_e (y - A(x) - \eta_e) \|^2 + \frac{1}{2} \| L_x (x - \eta_x) \|^2 \right\}$$

- Solve using methods of computational optimisation

Inverse problem in a Bayesian perspective

$$\arg\min_x \left\{ \boxed{\frac{1}{2}\|L_e(y - A(x) - \eta_e)\|^2} + \boxed{\frac{1}{2}\|L_x(x - \eta_x)\|^2} \right\}$$

Data likelihood

- $y \in \mathbb{R}^m$ measurement data
- $x \in \mathbb{R}^n$ unknown parameters
- Noise model $e \sim \mathcal{N}(\eta_e, \Gamma_e)$, $\Gamma_e^{-1} = L_e^{\mathrm{T}} L_e$
- $A: \mathbb{R}^n \to \mathbb{R}^m$ (discretised) forward model

Prior

- $x \in \mathbb{R}^n$ unknown parameters
- Prior model x$\sim\mathcal{N}(\eta_x, \Gamma_x)$, $\Gamma_x^{-1} = L_x^{\mathrm{T}} L_x$

Inverse problem in a Bayesian perspective

$$\arg\min_x \left\{ \frac{1}{2}\|\boxed{L_e}\boxed{(y} - A(\boxed{x}) - \boxed{\eta_e})\|^2 + \frac{1}{2}\|L_x(\boxed{x} - \eta_x)\|^2 \right\}$$

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Inverse problem in a Bayesian perspective

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Inverse problem in a Bayesian perspective

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Forward model

- Solution of the inverse problem requires solution of the forward model describing the physics of the imaging situation
- Modelling light and ultrasound propagation in biological tissue
- Computing the (measurement) data

Light transport

- Radiative transfer equation (RTE)

$$\hat{s} \cdot \nabla \phi(r, \hat{s}) + (\mu_s + \mu_a)\phi(r, \hat{s}) = \mu_s \int_{S^{n-1}} \Theta(\hat{s} \cdot \hat{s}')\phi(r, \hat{s}')\mathrm{d}\hat{s}', \quad r \in \Omega$$

$$\phi(r, \hat{s}) = \begin{cases} \phi_0(r, \hat{s}), & r \in \epsilon_j, \quad \hat{s} \cdot \hat{n} < 0 \\ 0, & r \in \partial\Omega \backslash \epsilon_j, \quad \hat{s} \cdot \hat{n} < 0 \end{cases}$$

where $\phi(r, \hat{s})$ is radiance, μ_a is absorption, μ_s is scattering, $\Theta(\hat{s} \cdot \hat{s}')$ is scattering phase function and $\phi_0(r, \hat{s})$ is light source in position r and direction $\hat{s}$

  - Numerical approximation based on, for example, finite element method with a modified test basis, discontinuous Galerkin, etc.

- Monte Carlo

  - Based on random sampling of photon paths as they propagate in a scattering medium

- RTE and Monte Carlo simulate light propagation accurately in a scattering medium
- However, they are computationally challenging
- Different approximative models have been utilised
  - Diffusion approximation

$$-\nabla \cdot \kappa(r)\nabla\Phi(r) + \mu_a(r)\Phi(r) = 0 \qquad r \in \Omega$$

$$\Phi(r) + \frac{1}{2\gamma_n}\kappa(r)A\frac{\partial\Phi(r)}{\partial\hat{n}} = \begin{cases} \frac{I_s}{\gamma_n}, & r \in \epsilon_i \\ 0, & r \in \partial\Omega \setminus \epsilon_i \end{cases}$$

where $\Phi(r) = \int_{S^{n-1}} \phi(r,\hat{s})\mathrm{d}\hat{s}$ is photon fluence and
$\kappa = (d(\mu_a + \mu_s(1-g)))^{-1}$ is diffusion coefficient

Photoacoustic effect

- Absorbed optical energy density and initial pressure

$$H(r) = \mu_a(r)\Phi(r)$$
$$p_0(r) = p(r, t = 0) = G(r)H(r)$$

where $G(r)$ is the Grüneisen parameter

Wave propagation

- In soft biological tissue, acoustic wave equation

$$\begin{cases} \left(\frac{\partial^2}{\partial t^2} - v^2(r)\nabla^2\right) p(r,t) = 0 \\ p(r, t=0) = p_0(r) \\ \frac{\partial}{\partial t} p(r, t=0) = 0 \end{cases}$$

where p is the time-varying pressure and $p_0(r)$ is the initial pressure distribution

  - Numerical approximations based on, for example, finite difference or *k*-space time-domain methods
- More research is required on
  - Acoustically heterogeneous medium
  - Elastic wave equation

Inverse problem in a Bayesian perspective

$$\arg\min_x \left\{ \frac{1}{2} \|L_e(y - A(x) - \eta_e)\|^2 + \frac{1}{2} \|\boxed{L_x}(x - \boxed{\eta_x})\|^2 \right\}$$

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Prior

- $x \in \mathbb{R}^n$ unknown parameters
- Prior model x$\sim \mathcal{N}(\eta_x, \Gamma_x)$, $\Gamma_x^{-1} = L_x^{\mathrm{T}} L_x$

Prior distribution

- Describes our prior knowledge on the unknown parameters
- Some examples of Gaussian $x \sim \mathcal{N}(\eta_x, \Gamma_x)$, $\Gamma_x^{-1} = L_x^{\mathrm{T}} L_x$ prior

White noise covariance

$$\Gamma_{p_0} = \mathrm{diag}(\sigma^2)$$

Ornstein-Uhlenbeck covariance

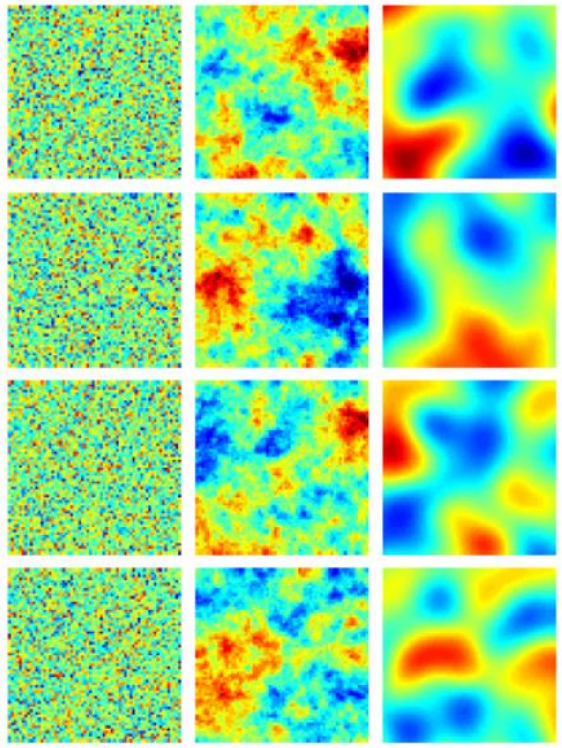
$$\Gamma_{p_0,ij} = \sigma^2 \exp\left\{-\frac{\|r_i - r_j\|}{\zeta}\right\}$$

Squared exponential covariance

$$\Gamma_{p_0,ij} = \sigma^2 \exp\left\{-\frac{\|r_i - r_j\|^2}{2\zeta^2}\right\}$$

where σ is the standard deviation and ζ is the characteristic length scale (controls spatial correlation)

Sample draws



Inverse problem in a Bayesian perspective

$$\arg\min_{x}\left\{\frac{1}{2}||L_e(y - A(x) - \eta_e)||^2 + \frac{1}{2}||L_x(x - \eta_x)||^2\right\}$$

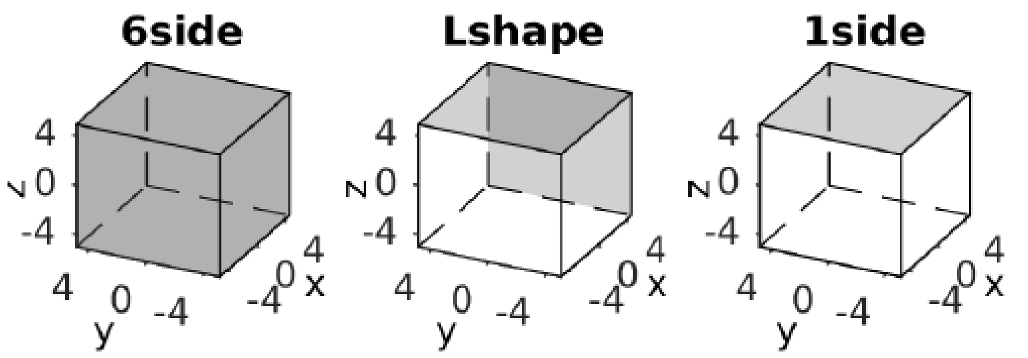
- The minimisation problem is solved using methods of computational optimisation
  - For example Gauss-Newton method
  - Need computation of the Jacobians (and approximations of the Hessian matrix)

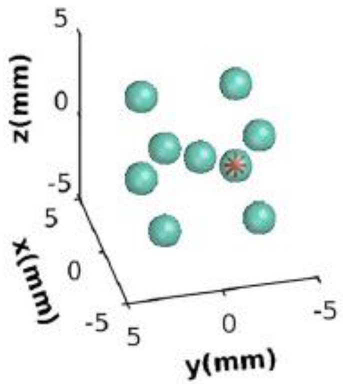
Example: Bayesian approach to photoacoustic tomography

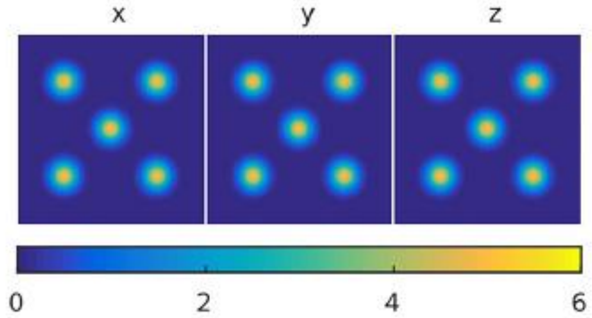
- Tick J, Pulkkinen A, Tarvainen T, Image reconstruction with uncertainty quantification in photoacoustic tomography, *The Journal of the Acoustical Society of America*, 139:1951-1961, 2016.
- Tick J, Pulkkinen A, Lucka F, Ellwood R, Cox BT, Kaipio JP, Arridge SR, Tarvainen T, Three dimensional photoacoustic tomography in Bayesian framework, *The Journal of the Acoustical Society of America*, 144(4):2061-2071, 2018

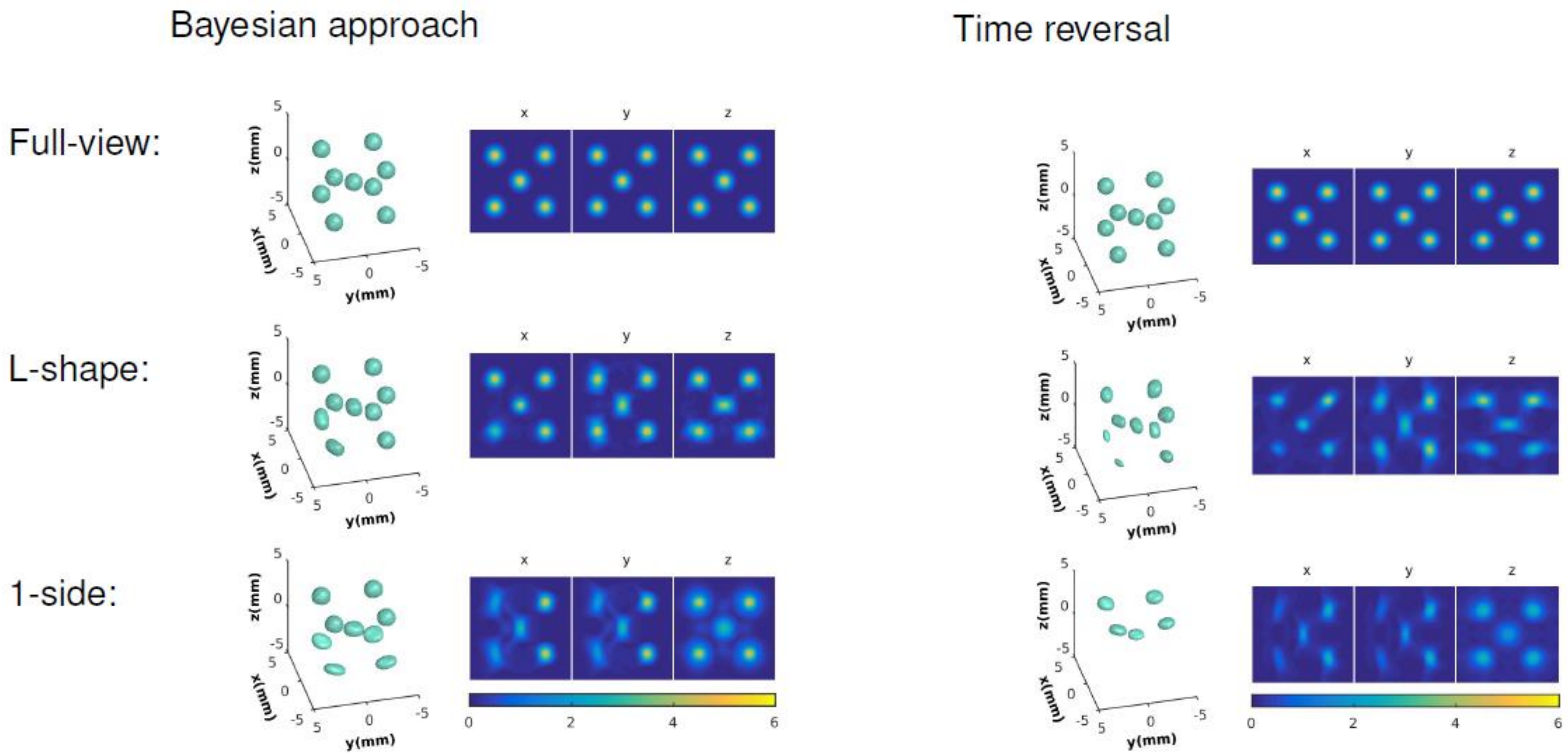
Numerical simulations

- A cube with a side length 10mm
- Three types of detector geometries were considered: full view (6-side), L-shaped, one-side
- Initial pressure of nine spheres embedded in a uniform background



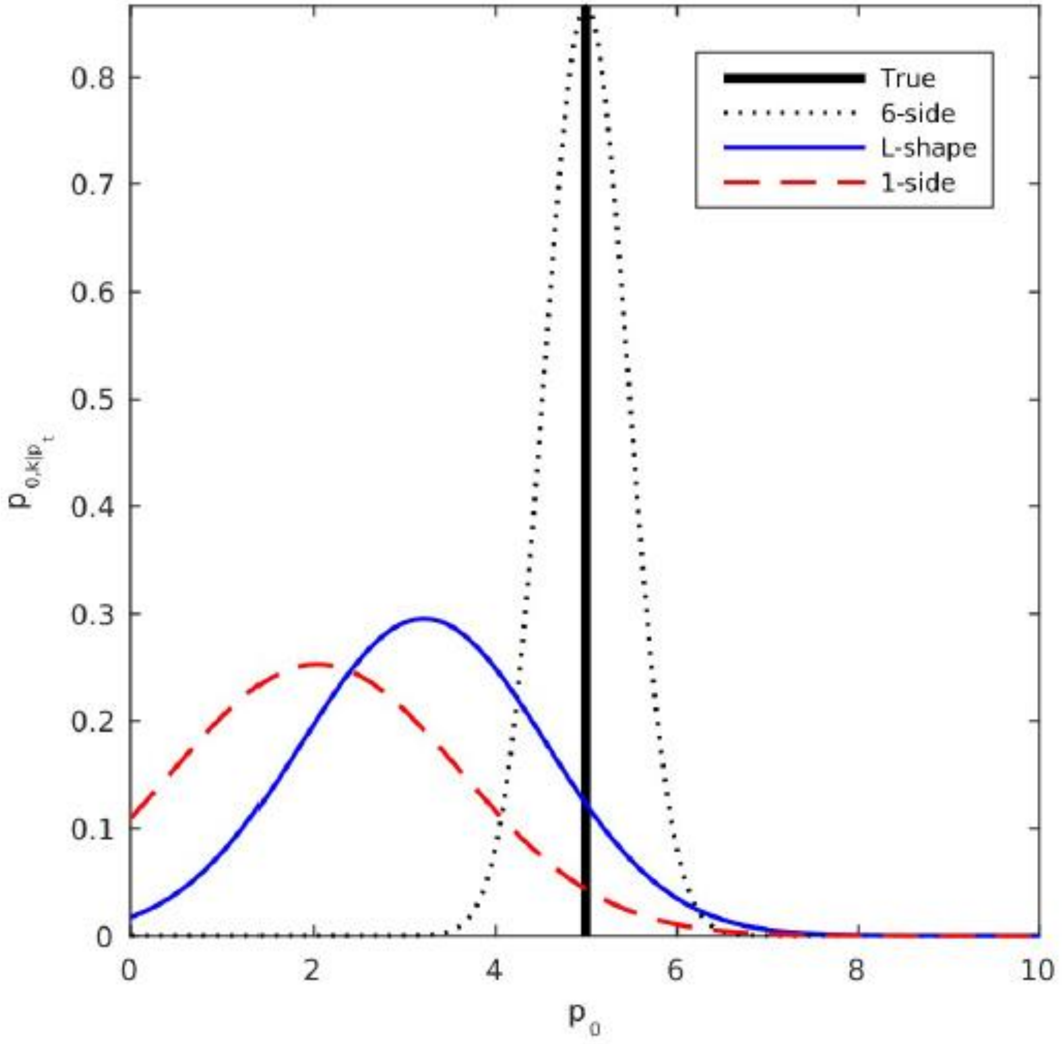






Relative errors (%)

	full-view	L-shape	1-side
Bayesian approach	3.8	24.9	48.4
Time-reversal	4.0	61.5	79.9

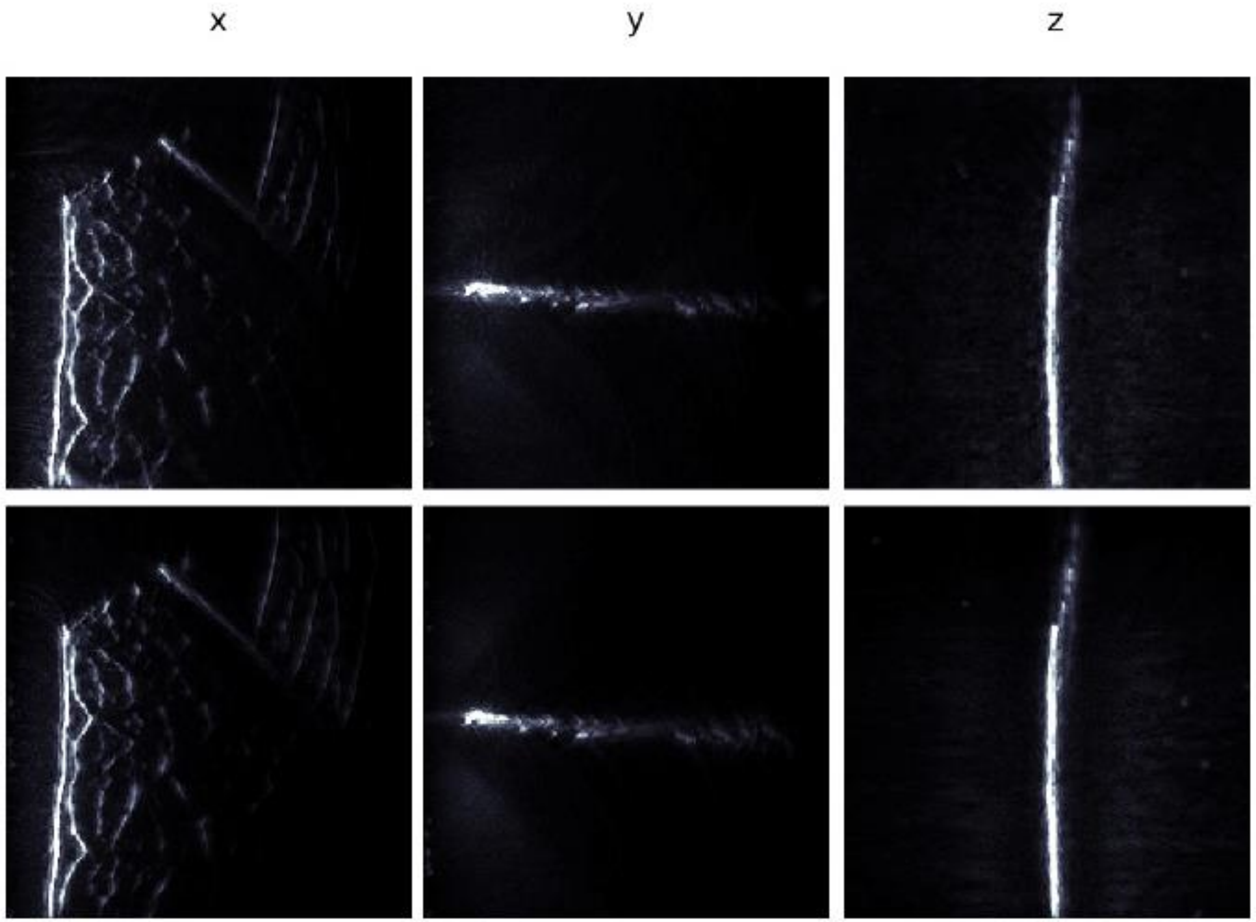

True
6-side
L-shape
1-side
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
2
4
6
8
10
$p_{0,k|p_t}$
p_0

Experiments

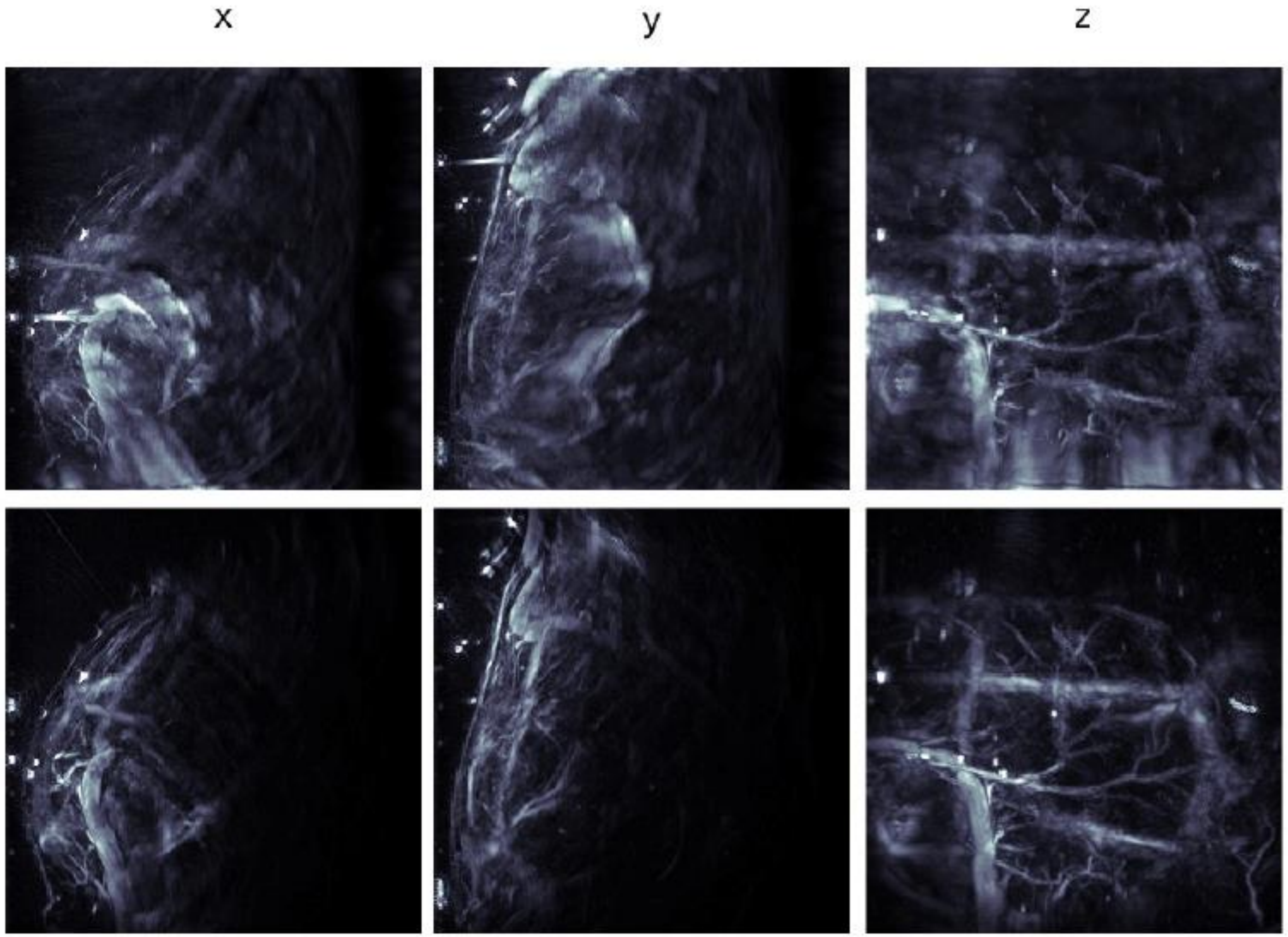
- Photoacoustic tomography system of University College London

  Zhang E, Laufer J, Beard P, Backward-mode multiwavelength photoacoustic scanner using a planar Fabry-Perot polymer film ultrasound sensor for high-resolution three-dimensional imaging of biological tissues, *Applied Optics*, 47:561-577, 2008)

Leaf phantom



Mouse head



Example: Modelling of uncertainties in photoacoustic tomography

- Sahlström T, Pulkkinen A, Tick J, Leskinen J, Tarvainen T, Modelling of errors due to uncertainties in ultrasound sensor locations in photoacoustic tomography, *IEEE Transactions on Medical Imaging*, 39(6):2140-2150, 2020.

Modelling of uncertainties

- We studied modelling of uncertainties related to modelling of sensor positions in photoacoustic tomography
- Bayesian approximation error modelling was used for modelling the errors
  - Modelling errors and uncertainties are modelled as Gaussian distributed
  - Their statistics is included in the solution of the inverse problem as a noise model

Inverse problem in a Bayesian perspective

$$\arg\min_x \left\{ \frac{1}{2} \| \boxed{L_e} (y - A(x) - \boxed{\eta_e}) \|^2 + \frac{1}{2} \| L_x (x - \eta_x) \|^2 \right\}$$

Data likelihood

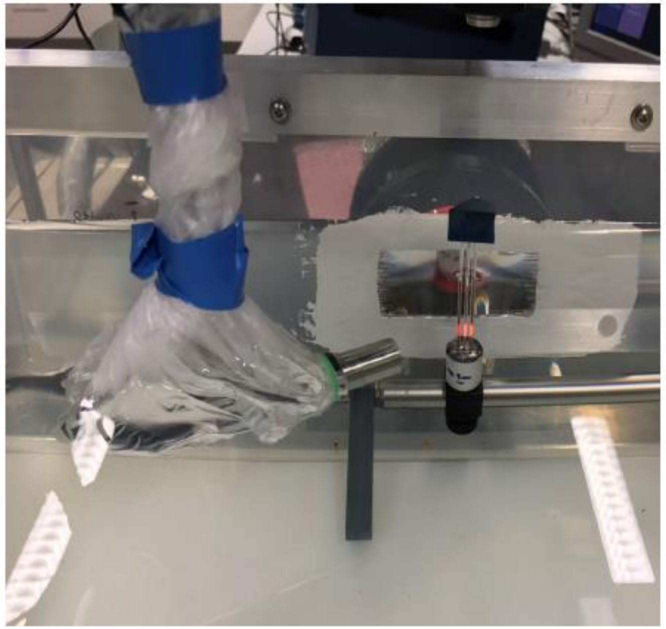
- $y \in \mathbb{R}^m$ measurement data
- $x \in \mathbb{R}^n$ unknown parameters
- Noise model $e \sim \mathcal{N}(\eta_e, \Gamma_e)$, $\Gamma_e^{-1} = L_e^\mathrm{T} L_e$
- $A: \mathbb{R}^n \to \mathbb{R}^m$ (discretised) forward model

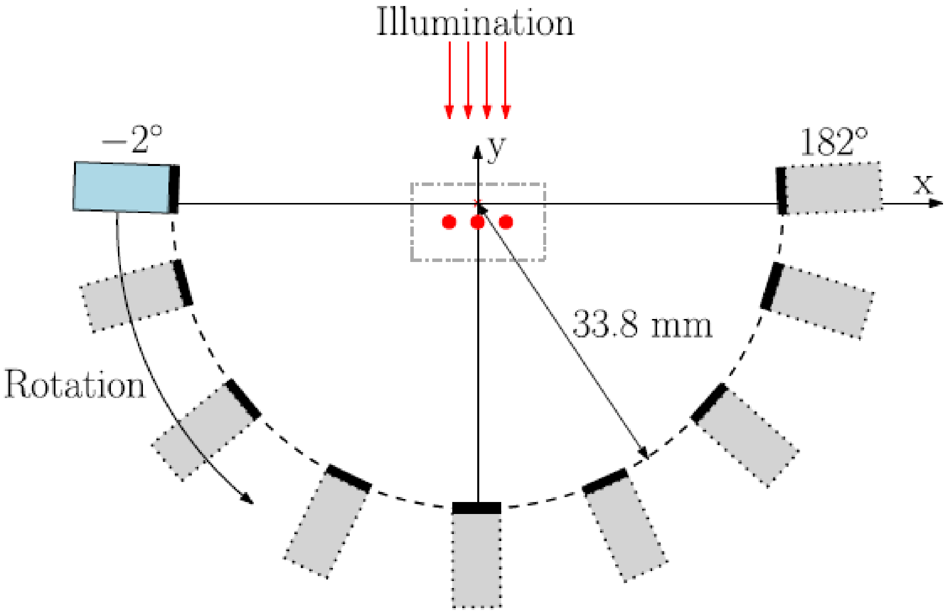
Prior

- $x \in \mathbb{R}^n$ unknown parameters
- Prior model x$\sim\mathcal{N}(\eta_x, \Gamma_x)$, $\Gamma_x^{-1} = L_x^\mathrm{T} L_x$

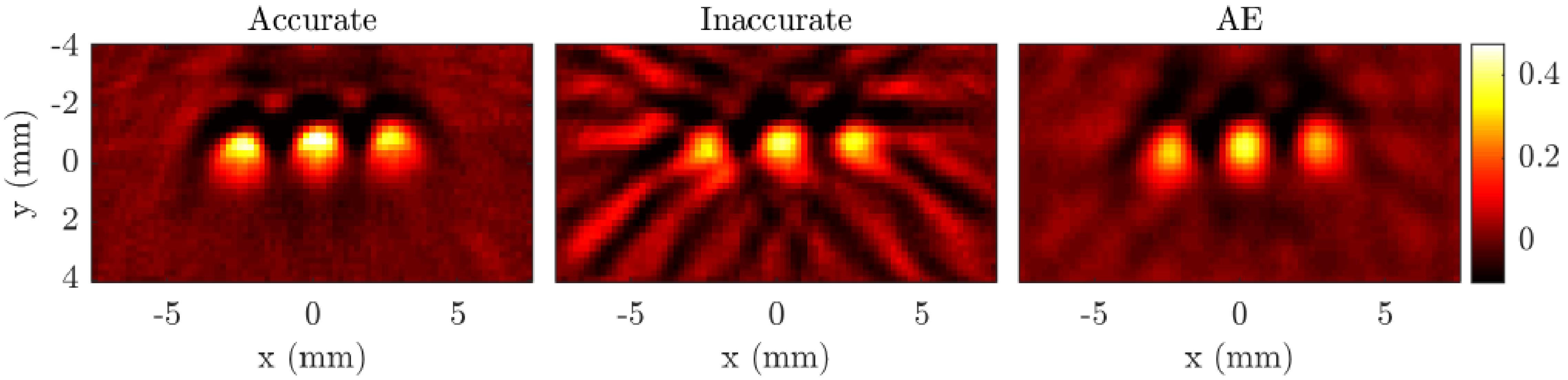
- University of Eastern Finland PAT system using LED illuminations

  Leskinen J, Pulkkinen A, Tick J, Tarvainen T, Photoacoustic tomography setup using LED illumination, *In Proc. SPIE 11077*, 110770Q, 2019.)





- Uncertainty: $\pm 188\mu m$ in the radial direction
- Mean of the posterior distribution computed in three cases
  - Accurately modelled sensor locations
  - Inaccurately modelled sensor locations
  - Inaccurately modelled sensor locations with Bayesian approximation error modelling



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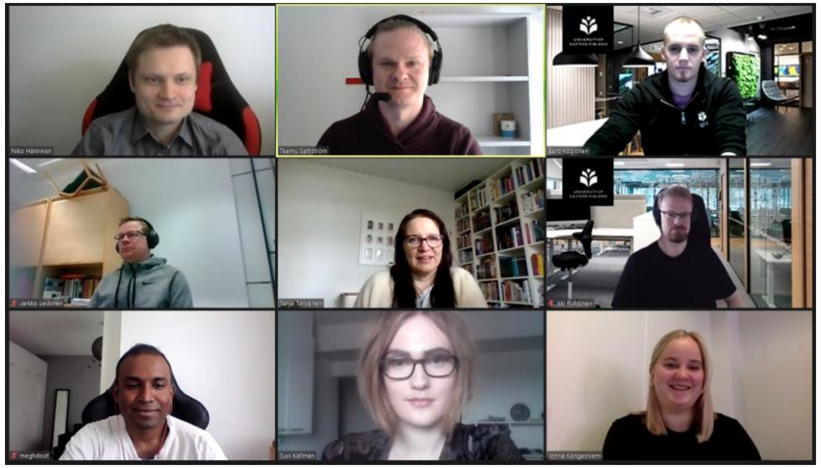
- Biomedical optical imaging and ultrasound laboratory (OPUS): https://sites.uef.fi/opus/
- Tanja Tarvainen: https://uefconnect.uef.fi/en/person/tanja.tarvainen/



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