

Bayesian estimation of acoustic aberrations in high intensity focused ultrasound treatment

Bamdad Hosseini¹, Charles Mougnot², Samuel Pichardo³, Elodie Constancier⁴, James M. Drake⁴, John M. Stockie¹

¹Simon Fraser University

²Philips Healthcare

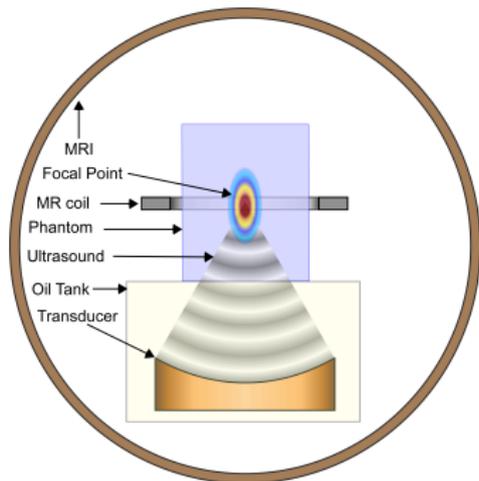
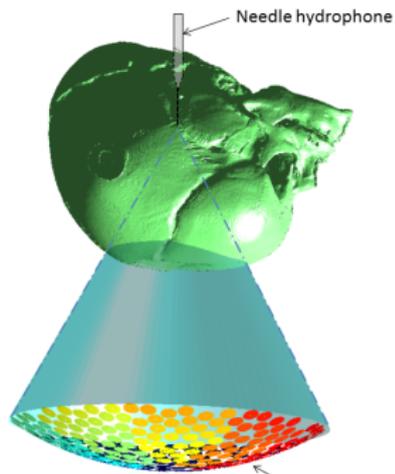
³Thunder Bay Regional Research Institute

⁴Hospital for Sick Children

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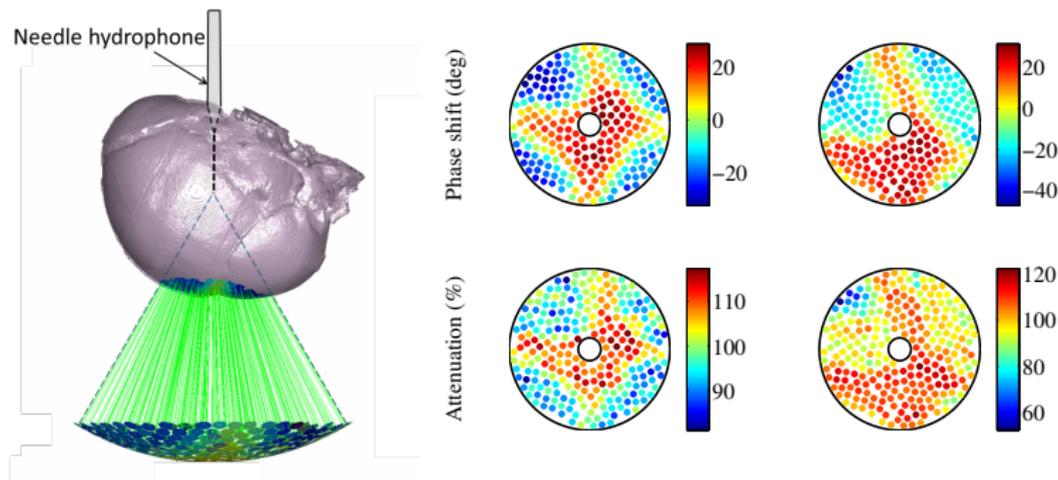
What is HIFU?

- High intensity focused ultrasound (HIFU).
- A focused beam of acoustic waves converging in a small volume.
- The generated heat ablates diseased tissue.



What are the challenges?

- Clinical success in treatment of prostate cancer, liver tumours, uterine fibroids, etc.
- Treatment of brain tumours remains a challenge.
- Strong aberrations due to skull bone \rightarrow defocused beam.
- Estimate aberrations \rightarrow compensate phase shift \rightarrow refocus.

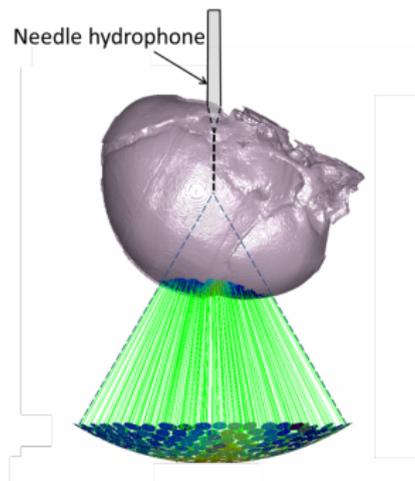


An approximate forward model

The pressure field due to a single piezoelectric element:

$$p(\mathbf{x}) = p_0 \exp\left(i\left[\omega t + \frac{\omega}{c_0}|\mathbf{x}|\right]\right) \times \mu \quad \mu = \zeta \exp(i\phi t).$$

- p_0 signal amplitude.
- ω frequency.
- c_0 speed of sound.
- μ aberration due to tissue
- ζ is attenuation
- ϕ phase shift



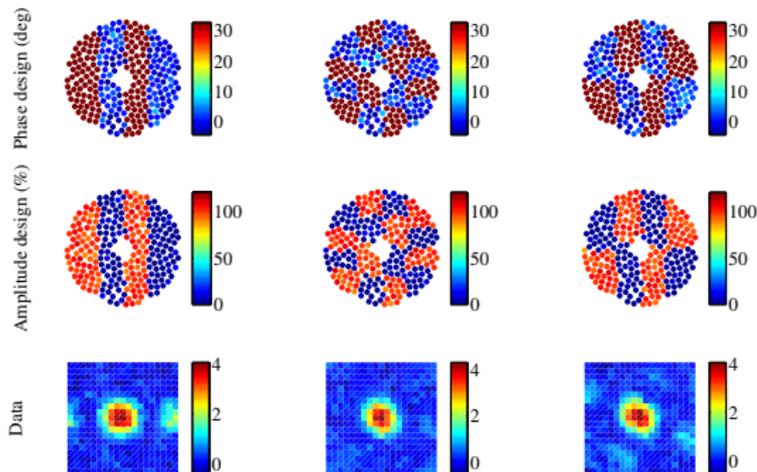
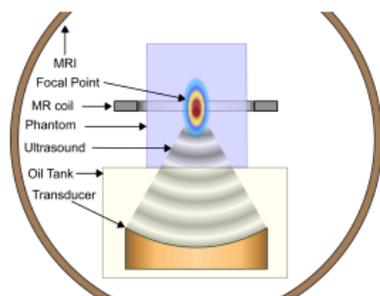
Energy based measurements

- Assemble in to a linear forward map:

$$\mathbf{p} = \mathbf{FZa}$$

- \mathbf{F} free field matrix (Green's function).
- \mathbf{Z} input phase and amplitude (experimental design).
- \mathbf{a} aberration due to tissue.
- Measure the amplitude of pressure

$$\mathbf{d} = \text{diag}(\mathbf{p})\mathbf{p}^*.$$



The inverse problem

- Estimate the vector of aberrations \mathbf{a} given the data \mathbf{d} and matrices \mathbf{F} and \mathbf{Z} .
- Use Bayes' rule¹:

$$\pi(\mathbf{a}|\mathbf{d}) \propto \pi(\mathbf{d}|\mathbf{a})\pi_0(\mathbf{a}).$$

- $\pi(\mathbf{d}|\mathbf{a})$ likelihood.
- $\pi_0(\mathbf{a})$ prior.
- $\pi(\mathbf{a}|\mathbf{d})$ posterior.

¹J. Kaipio and E. Somersalo. *Statistical and Computational Inverse Problems*. Springer Science and Business Media, New York, 2005.

The likelihood

$$\pi(\mathbf{a}|\mathbf{d}) \propto \pi(\mathbf{d}|\mathbf{a})\pi_0(\mathbf{a}).$$

- Additive noise model

$$\mathcal{G}(\mathbf{a}) := \text{diag}(\mathbf{FZa})(\mathbf{FZa})^* \quad \mathbf{d} = \mathcal{G}(\mathbf{a}) + \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{\Sigma}).$$

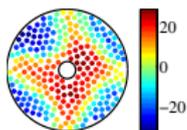
- Likelihood:

$$\pi(\mathbf{d}|\mathbf{a}) \propto \exp\left(-\frac{1}{2} \left\| \boldsymbol{\Sigma}^{-1/2}(\mathbf{d} - \mathcal{G}(\mathbf{a})) \right\|_2^2\right)$$

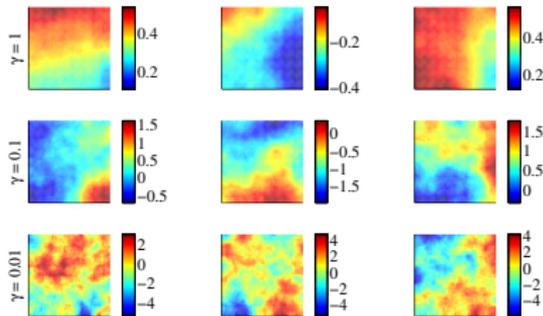
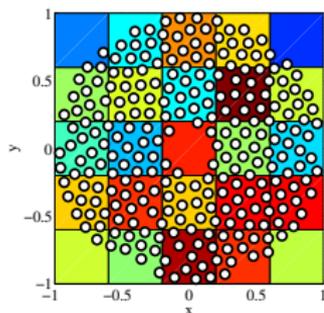
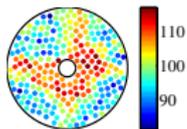
Choosing the prior π_0

$$\pi(\mathbf{a}|\mathbf{d}) \propto \pi(\mathbf{d}|\mathbf{a})\pi_0(\mathbf{a}).$$

Phase shift (deg)



Attenuation (%)



- Measured aberrations hint at an underlying continuous field.
- Construct $\pi_0(\mathbf{a})$ by pointwise evaluation of a Gaussian random field:

$$\mathcal{N}(0, (\mathcal{I} - \gamma\Delta)^{-2})$$

- $(\mathcal{I} - \gamma\Delta)^{-2}$ biharmonic operator with Neumann boundary condition.

Sampling from π_0

- Pick $\sigma > 0$.
- Discretize $(\mathcal{I} - \Delta)^{-2}$.
- Sample

$$\begin{aligned}\mathbf{u} &\sim \mathcal{N}(0, (\mathcal{I} - \gamma\Delta)^{-2}), & \alpha_1 &\sim N(0, \sigma) \\ \mathbf{v} &\sim \mathcal{N}(0, (\mathcal{I} - \gamma\Delta)^{-2}), & \alpha_2 &\sim N(0, \sigma)\end{aligned}$$

- Set $\mathbf{a} = \text{diag}(\alpha_1^2 \mathbf{u}) \exp(i\alpha_2^2 \mathbf{v})$.

Sampling from the posterior $\pi(\mathbf{a}|\mathbf{d})$

- Forward problem is nonlinear \rightarrow posterior $\pi(\mathbf{a}|\mathbf{d})$ is not Gaussian.
- Markov Chain Monte Carlo.
- Requires sampling from the prior π_0 and evaluating likelihood $\pi(\mathbf{d}|\mathbf{a})$.

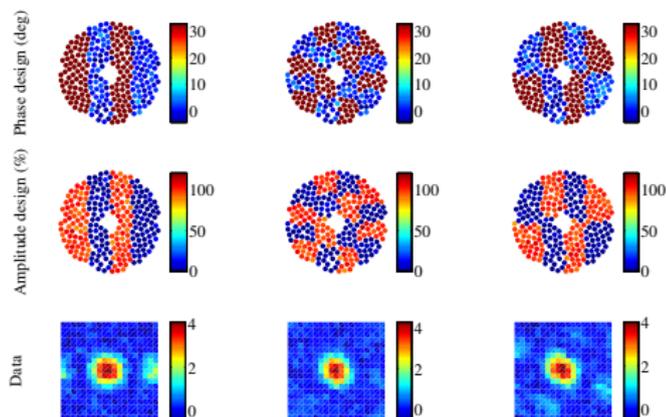
$$\pi(\mathbf{d}|\mathbf{a}) \propto \exp\left(-\frac{1}{2} \left\| \boldsymbol{\Sigma}^{-1/2}(\mathbf{d} - \mathcal{G}(\mathbf{a})) \right\|_2^2\right).$$

- Differentiable in real arguments, not differentiable in the complex arguments.
- MALA + Random walk block sampler² (at every step):
 - (1) Fix \mathbf{v} and α_2 and sample \mathbf{u} and α_1 using Metropolis adjusted Langevin algorithm (uses gradient information).
 - (2) Fix \mathbf{u} and α_1 and sample \mathbf{v} and α_2 using preconditioned Crank-Nicolson random walk algorithm.

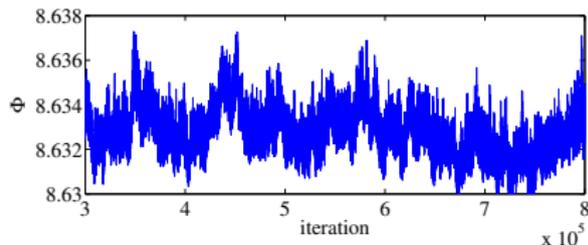
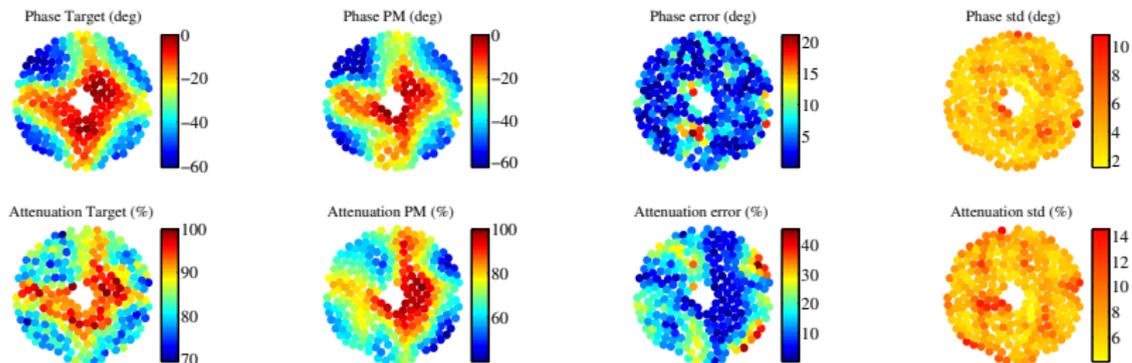
²S. L. Cotter et al. "MCMC methods for functions: modifying old algorithms to make them faster". In: *Statistical Science* 28.3 (2013), pp. 424–446.

Synthetic experiment

- Philips Sonalleve device with 256 piezoelectric elements.
- 512 unknowns.
- Discretize the continuous field on a 8×8 mesh (64 dimensional parameter space).
- 16 sonication tests.
- 19×19 voxel MRI window for each sonication test.
- $SNR = 5$.
- 3×10^5 burn-in + 5×10^5 steps of MCMC.

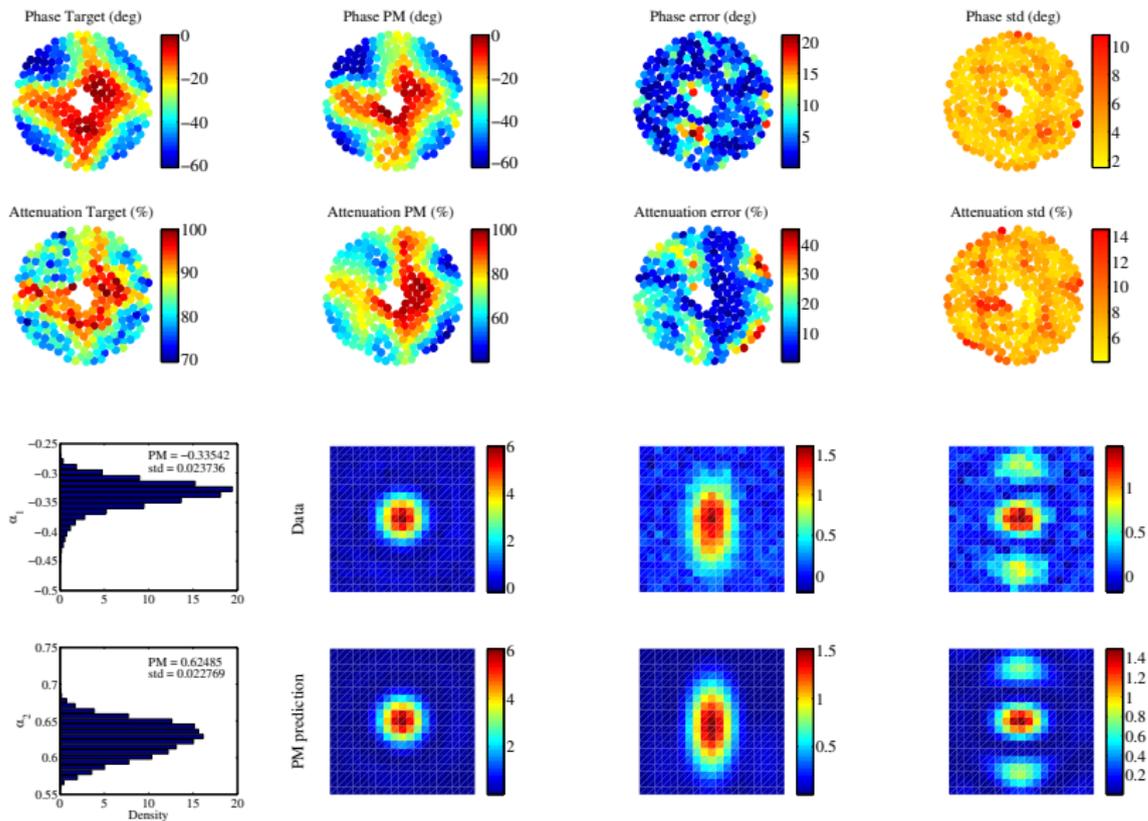


Synthetic experiment

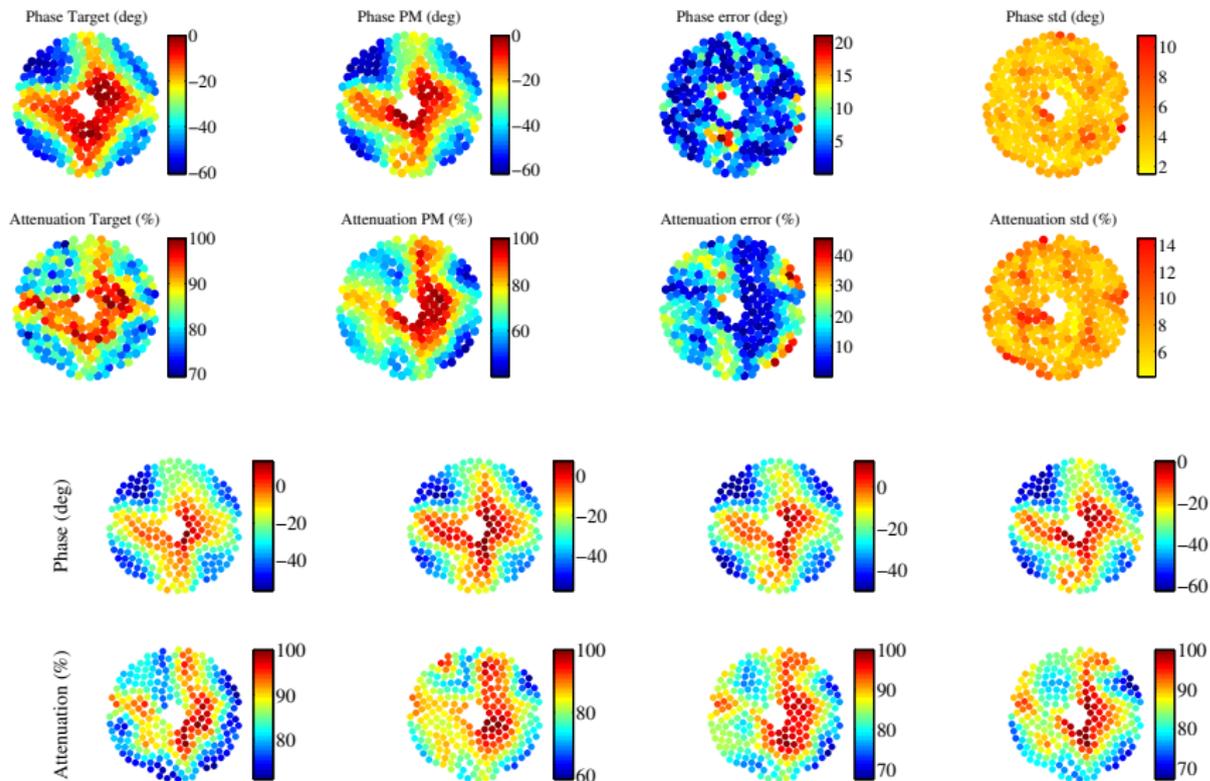


$$\Phi := -\frac{1}{2} \left\| \Sigma^{-1/2} (\mathbf{d} - \mathcal{G}(\mathbf{a})) \right\|_2^2$$

Synthetic experiment



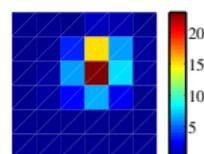
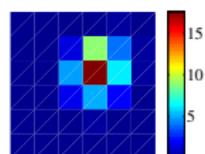
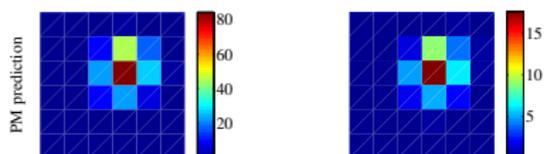
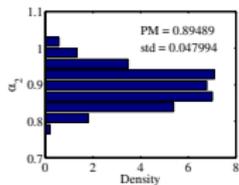
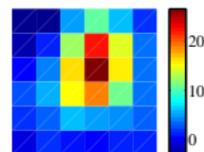
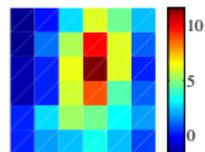
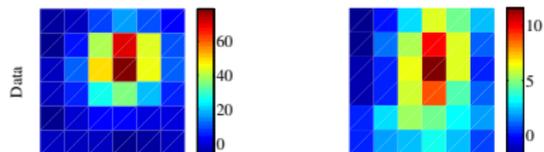
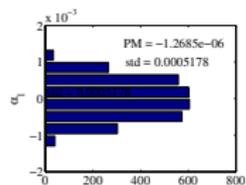
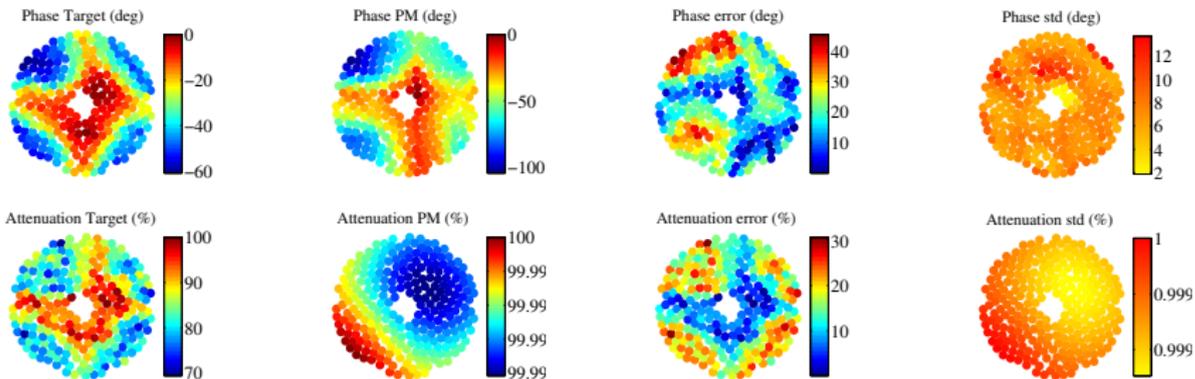
Synthetic experiment



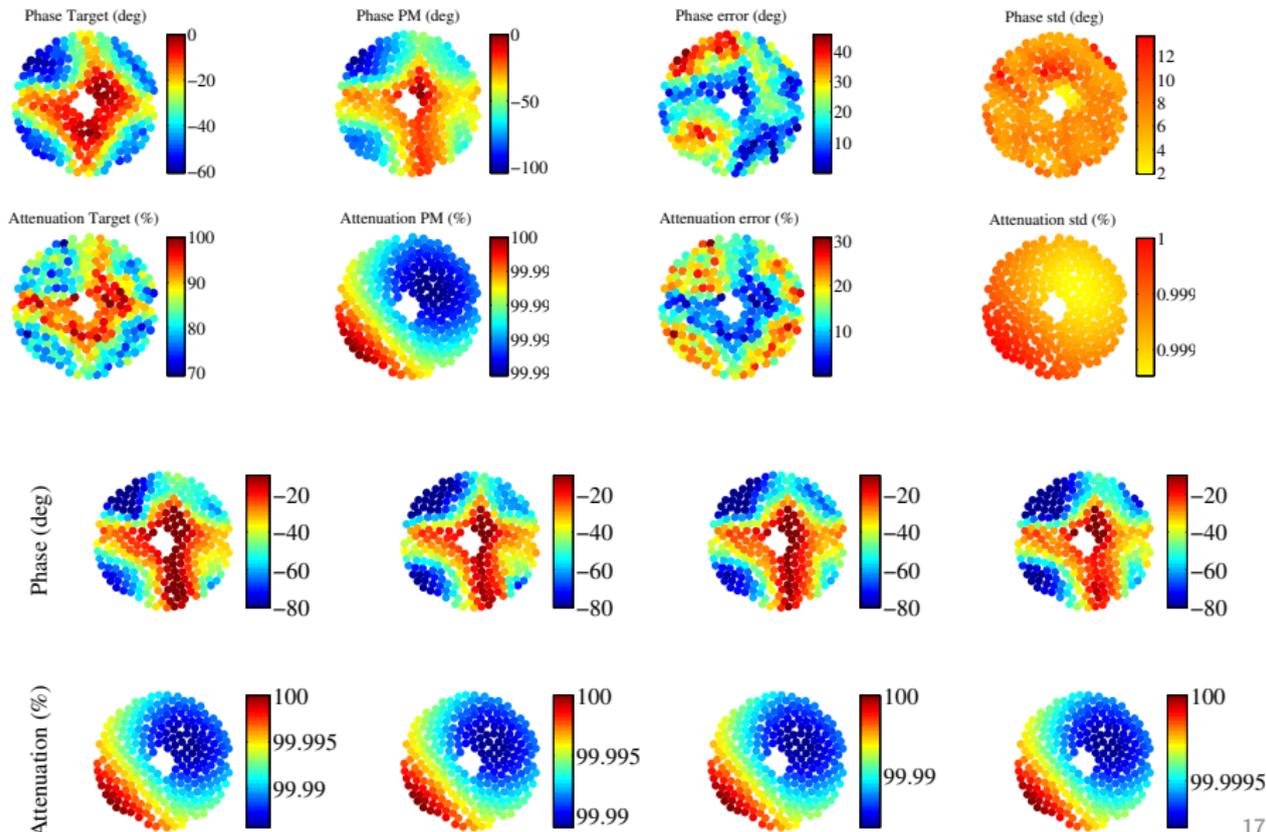
Physical experiment

- The same Philips Sonalleve device.
- Artificial aberrator.
- Discretize the Gaussian field on a 8×8 grid.
- 32 sonication tests.
- 7×7 voxel MRI window for each test.
- 3×10^5 burn-in + 5×10^5 steps of MCMC.

Physical experiment



Physical experiment



Selling points

For the practitioner:

- The “state of the art”³ uses 256 sonication tests as compared to 32 tests used here.
- Patient spends less time in the MRI machine.
- Save energy.
- flexible design of experiments (choice of matrix \mathbf{Z}).

For the mathematician:

- Well-posed inverse problem.
- Estimate uncertainty.
- Compute in 2-4 hours on a laptop.
- Experimental design.

³E. Herbert et al. “Energy-based adaptive focusing of waves: application to noninvasive aberration correction of ultrasonic wavefields”. In: *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control* 56.11 (2009), pp. 2388–2399.

Challenges and future directions

Challenges:

- Large discrepancy between the model and physical process
- Calibration of \mathbf{F} .
- Better data.
- Regularizing the likelihood.
- Better sampling algorithm.

Future direction:

- Phase retrieval techniques⁴.
- Matrix completion to estimate the free-field \mathbf{F} .
- Design of experiments.

⁴E. J. Cándes et al. “Phase retrieval via matrix completion”. In: *SIAM Review* 57.2 (2015), pp. 225–251.

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MCMC performance

