Uncertainty in Acoustic Sensor Networks

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February 2, 2018

The Problem



- 16 Receivers
- 26 Frequencies
- 1 Goal: Reconstruct acoustic pressure everywhere, with uncertainty

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Our Idea: Pseudo-Sources



Pressure due to point source at \mathbf{s} with amplitude A is

$$u(\mathbf{x}) \propto \frac{A}{\omega \|\mathbf{x} - \mathbf{s}\|}$$

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Idea: Describe pressure field in terms of point sources.

Pseudo-Source Lattice



Pseudo source *i* emits on frequency ω_j with amplitude A_{ij} Observe (noisy) pressure Y_{kj} on frequency ω_j at fixed location $\mathbf{x} = \mathbf{r}_k$

Bayesian Inference using Gaussian "Bodge"

After reshaping A_{ij} and Y_{kj} into vectors **c** and **y**;

Prior Likelihood $\mathbf{c} \sim \mathit{N}(oldsymbol{\mu}, \sigma_{a}^{2} \mathit{I})$ $\mathbf{y} | \mathbf{c} \sim \mathit{N}(\mathit{D}\mathbf{c}, \sigma^{2} \mathit{I})$

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Posterior:

 $\mathbf{c}|\mathbf{y} \sim \mathit{N}(oldsymbol{\mu}', \Sigma)$

where

$$\Sigma = \left(\frac{1}{\sigma^2}D^T D + \frac{1}{\sigma_a^2}I\right)^{-1}$$
$$\mu' = \Sigma \left(\frac{1}{\sigma^2}D^T \mathbf{y} + \frac{1}{\sigma_a^2}\mu\right)$$

Interpretation as a Gaussian Process

Mean function for ω_j field:

$$\mu_j(\mathbf{x}) = \frac{1}{\omega_j} \sum_{i=1}^{S} \frac{\mu'_{ij}}{\|\mathbf{x} - \mathbf{s}_i\|}$$

Kernel for ω_j field:

$$k_j(\mathbf{x}, \mathbf{x}') = \frac{1}{\omega_j^2} \sum_{i=1}^{S} \sum_{k=1}^{S} \frac{\operatorname{Cov}(A_{ij}, A_{kj})}{\|\mathbf{x} - \mathbf{s}_i\| \|\mathbf{x}' - \mathbf{s}_k\|}$$

Results



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Results



Acoustic Pressure 4pm

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Results



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Squared-Exponential Kernel (No Physics!)



Onwards

Now:

- Improvement on standard GP
- Includes some physics
- Not completely physical

Future:

- Completely physical representation
 - Lose Gaussian process structure

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- Spatial Statistics?
- Incorporate environment
 - Modelling, PDEs

Thanks!

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