Bayesian Approaches in Acoustic Source Localization and Imaging

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Abstract

- Background: Acoustic source localization and power reconstruction from limited noisy measurements on microphones.
- Challenges: Ill-posed inverse problem, low spatial resolution at low frequencies, time-consuming for large imaging.
- Motivation: Super resolution, robustness to noises, large dynamic range, efficient imaging on vehicle surface in wind tunnel.
- Contribution: Beamforming, deconvolution, Bayesian approach with sparsity prior, Variational Bayesian Approximation.

1. Forward models of acoustic propagation

- Assumptions:
  - Sources: monopole, uncorrelated;
  - Background noise: i.i.d AGWN ($\sim N(0, \sigma^2)$);
  - Sensors: omni-directional, unit gain;
  - Wind tunnel: simple reverberations (refraction, reflection).

- Wind tunnel
- Microphone array
- Object
- Ground

2. State-of-the-art methods

- Beamforming [3]: Simple, fast, but low resolution.
- $y = \begin{bmatrix} y_1 & y_2 & \ldots & y_N \end{bmatrix} \in \mathbb{C}^{N \times 1}$; Beamforming power at grid n;
- Low spatial resolution (W Cincinnati) at low frequency (200Hz).
- $\text{beam} = \text{orientation and magnitude}$; Spatially variant PSF.

- Deconvolution and regularization [4, 1]: High resolution.
- $y = \begin{bmatrix} y_1 & y_2 & \ldots & y_N \end{bmatrix} \in \mathbb{C}^{N \times 1}$; Beamforming power at grid n;
- Sparsity priors on correlated sources;
- Model errors $e - \text{Beamforming}$.


- Bayesian Principle:
  to jointly infer $(x, \theta)$ from measurements $y$ using useful prior models to obtain the most probably sparse solution of $x$.

- Bayesian framework of JMAP estimation:
  $y = Cx + \sigma^2_2 l + \xi$
  $(x, \theta) = \arg \max (p(x, \theta | y))$
  $p(x, \theta | y)$ Full Bayes laws
  $\theta = \{\theta_1, \theta_2\} = \{[\alpha, \sigma_2^2] \}$: Hyper-parameters
  - Robust forward model [5]: random uncertainty $\xi \sim N(0, \sigma^2)$ caused by unknown acoustic multi-propagation (refraction, reflection, etc.).
  - Sparsity enforcing prior from Generalized Gaussian family $p(x | \theta) \propto \exp(\gamma |x|^\alpha) P_s(x | \theta)$.

4. Proposed Variational Bayesian Approximation (VBA) [6]

- Y = HX + e
  $y = \begin{bmatrix} y_1 & y_2 & \ldots & y_N \end{bmatrix} \in \mathbb{C}^{N \times 1}$; Beamforming power at grid n;
  - Prior models $p(x | \theta)$ perform as regularization.
  - Non-quadratic optimization on joint estimation of $x, \theta$.

5. Simulation at 2500Hz and SNR=0dB

- Efficient imaging for monopole and extended sources.
- 64 sensors, 33x33 pixels; 4.5 m distance; 10dB span; 101 pixels; 3.5 m sound reflection.

6. Wind tunnel experiments at 2500Hz

- Mapping acoustic power on vehicle.
- 64 sensors; 5cm discretization; 31x101 pixels; 4.5 m distance; 10dB span; 101 pixels; 3.5 m sound reflection.

7. Perspectives

- Forward model of full-wave acoustic propagation.
- Sparsity priors on constant sources.
- Real-time realization using GPU Parallelization.

References