Bayesian approach with sparse enforcing prior for acoustic sources localization and imaging

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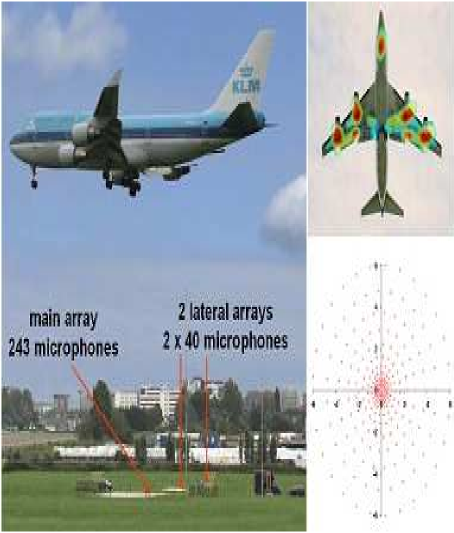
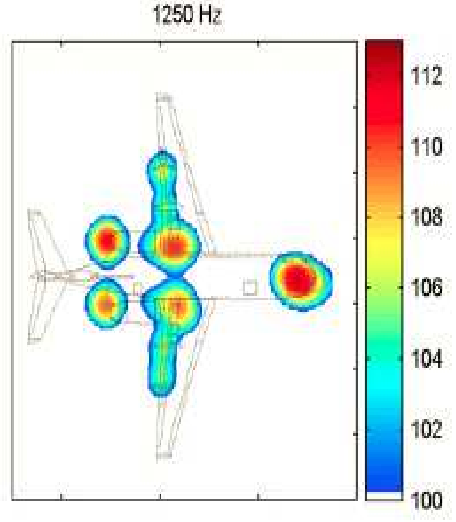
Content

- Acoustic sources localization and imaging applications
- Forward models
- Beam forming and Deconvolution based models
- Regularization methods
- Proposed Bayesian inference method
- Results on simulated and real data
- Conclusions

Acoustic sources localization and imaging

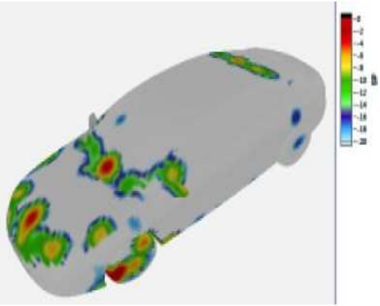




Flyover meausrements at airport   Acoustic imaging of noise sources (dB)

Courtesy of National Aerospace Laboratory (NLA) Holland [Vander 2009]

Acoustic sources localization and imaging

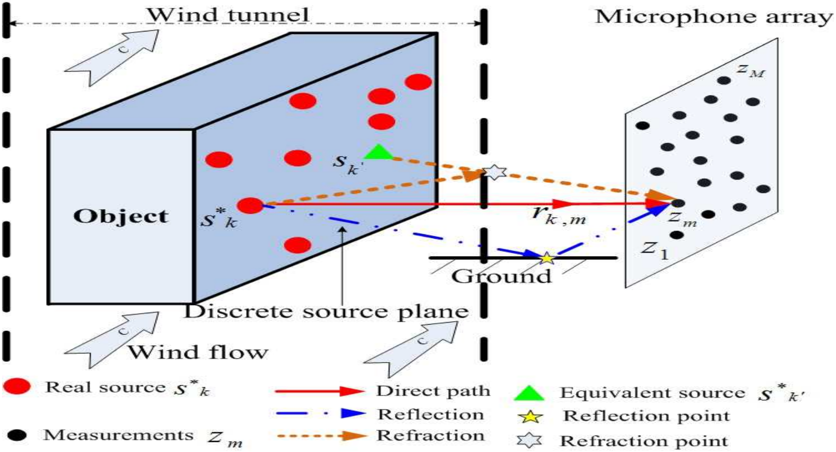


Previous work developed by Renault France [Adam 2010].

Motivation:

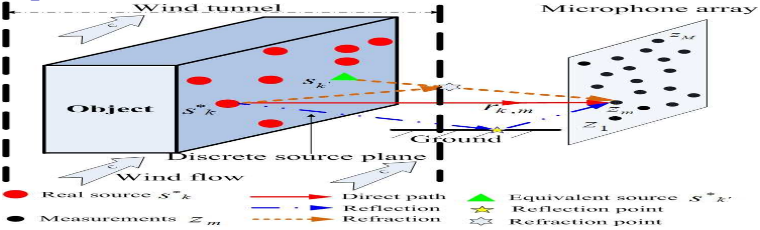
- Higher spatial resolution for low frequencies.
- Robust to measurement errors.
- Wide dynamic range of source powers.
- Fast acoustic imaging for industry application.

Propagation forward models



- Assumptions: Ponctual sources, ideal sensors, no reverberation
- Measured data: z
- Unknowns: sources number K, positions P^* & amplitudes s^*

Propagation forward model



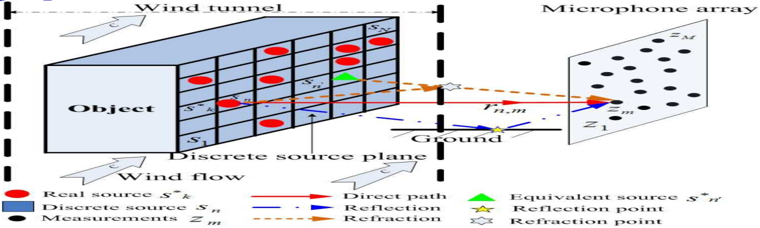
$$z_m(f) = \sum_{k=1}^{K} a_{m,k}(\boldsymbol{p}_k^*, f)\, s_k^*(f) + e_m(f)$$

$$\Downarrow$$

$$\mathbf{z}(f) = \mathbf{A}(\mathbf{P}^*, f)\, \mathbf{s}^*(f) + \boldsymbol{e}(f)$$

- $a_{m,k}(\boldsymbol{p}_k^*, f) = \frac{1}{r_{m,k}} \exp\left(-\jmath 2\pi\, f\, \tau_{m,k}\right)$: signal propagation;
- $\mathbf{A}(\mathbf{P}^*, f) = [a_{m,k}(\boldsymbol{p}_k^*, f)]_{M\times K}$: signal propagation matrix;
- $\boldsymbol{p}_k^* \in \mathbf{P}^*$: kth source position.
- **Non-linear** for $\mathbf{P}^*$; Hard to jointly solve $\mathbf{P}^*$ and $\mathbf{s}^*$.

Imaging forward model



Assumption: $\mathbf{s}^* \subset \mathbf{s}$ N grids $\mathbf{s}$; $\mathbf{P}^* \subset \mathbf{P}$ discrete positions $\mathbf{P}$.

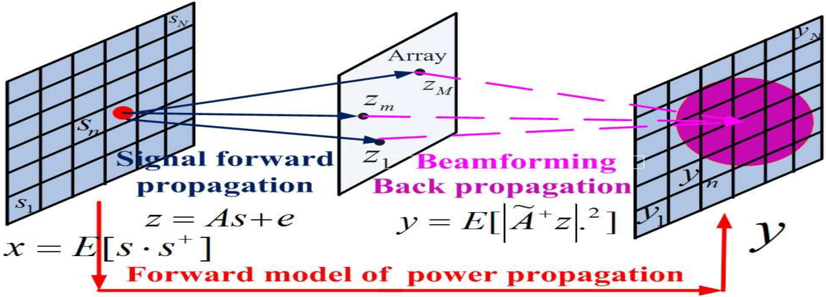
$$\mathbf{z}(f) = \mathbf{A}(\mathbf{P}^*, f)\, \mathbf{s}^*(f) + \boldsymbol{e}(f)$$

$$\Downarrow \text{ Discretization}$$

$$\mathbf{z}(f) = \mathbf{A}(\mathbf{P}\,,\; f)\; \mathbf{s}\,(f) + \boldsymbol{e}(f)$$

- $\mathbf{a}_{m,n}(\boldsymbol{p}_n, f) = \frac{1}{r_{m,n}} \exp\left(-\jmath 2\pi\, f\, \tau_{m,n}\right)$
- $\mathbf{A}(\mathbf{P}, f) = [\mathbf{a}_{m,n}(\boldsymbol{p}_n, f)]_{M\times N}$: discrete propagation matrix;
- $\mathbf{s} = \left[0, s_1^*, 0, \cdots, s_K^*, 0, \cdots\right]^T$: **Spatially K-sparsity**;
- **Linear** for $\mathbf{s}$; but **under-determined** due to $M \leq N$.

Beamforming and Deconvolution based methods



$$\boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2\,1_a$$

$\boldsymbol{C} = (|\tilde{\mathbf{A}}^\dagger\,\mathbf{A}|.^2)$

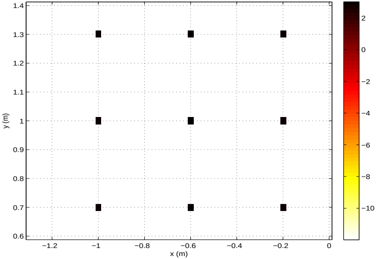
- $\tilde{\mathbf{A}} = \{\tilde{\mathbf{a}}_n\}_N$: Beamforming steering matrix, $\tilde{\mathbf{A}} : M \times N$;
- $\tilde{\mathbf{a}}_n = \frac{\mathbf{a}_n}{||\mathbf{a}_n||^2}$: Beamforming steering vector of $\mathbf{A} : M \times N$.

σ_e^2: Power of measurement errors $\mathbf{e}$ (i.i.d white noise).
Linear and **determined** equations ($\boldsymbol{C}:\ N \times N$) for source **powers** $\boldsymbol{x}$.

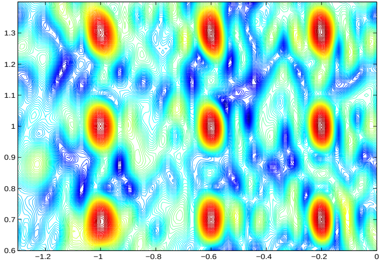
Beamforming: low spatial resolution

$$\boldsymbol{z} = \boldsymbol{A}\boldsymbol{s} \longrightarrow \boldsymbol{y} = \mathbb{E}[|\tilde{\mathbf{A}}^{\dagger}\,\mathbf{z}|.^{2}] \longrightarrow \boldsymbol{y} = \boldsymbol{C}\boldsymbol{x} + \sigma_{\epsilon}^{2}\,1_{a}$$

- **Low spatial resolution (30cm) at low frequency (2500Hz).**
- spatially variant PSF convolution

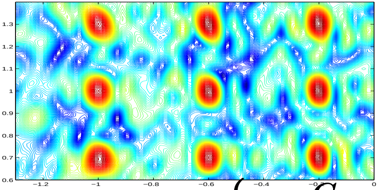


Source power $\boldsymbol{x}$

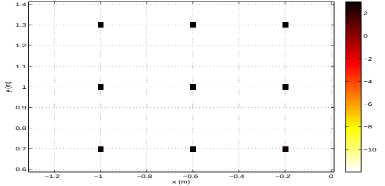


Beamforming power $\boldsymbol{y}$

Deconvolution methods for power propagation model



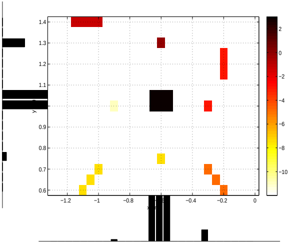
? $\Longrightarrow$



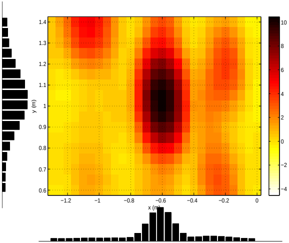
$$\begin{cases} \boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2\, 1_a \\ \widehat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \left\{ ||\boldsymbol{y} - \boldsymbol{C}\,\boldsymbol{x}||_2^2 + \alpha \mathcal{F}(\boldsymbol{x}) \right\} \\ \quad \text{s.t. } \boldsymbol{x} \geq 0 \text{ and } \textbf{sparse} \end{cases}$$

- **Iterative**: CLEAN used by [Stoica 2003], Parameter selection;
- **Breakthrough**: Deconvolution Approach for Mapping Acoustic Sources (**DAMAS**) proposed by [Brooks 2005]; Sensitive
- **Robustness**: Diagonal Removal DAMAS (DR-DAMAS) [Brooks 2005]; Over suppression
- $\mathcal{F}(\boldsymbol{x}) = ||\mathbf{w}\,\boldsymbol{x}||_l$ with $0 \leq l \leq 1$, weight vector $\mathbf{w}$:
  - $l = 0$: **Real sparsity**, but hard to solve;
  - $l = 1$: **Sparsity**, **well solved** by LASSO algorithm; DAMAS with sparsity constraint (**SC-DAMAS**) [Yardi 2008];
- α: to be tuned carefully;

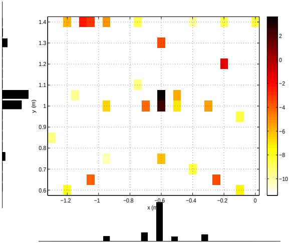
Deconvolution and regularization results



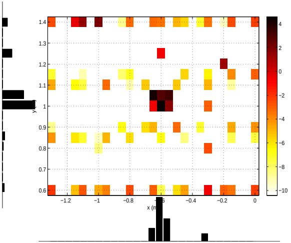
(a) Source powers $\boldsymbol{s}$



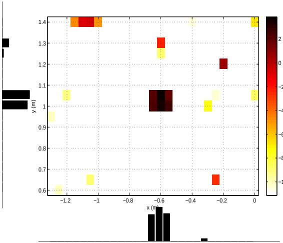
(b) Beamforming $\boldsymbol{y}$



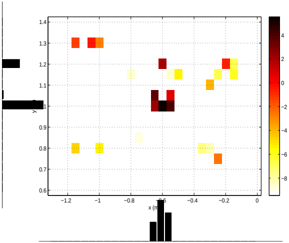
(c) CLEAN



(d) DAMAS



(e) DR-DAMAS



(f) SC-DAMAS

Deconvolution: High spatial resolution, but sensitive to errors

Regularization: High spatial resolution, robust to errors, but α selection.

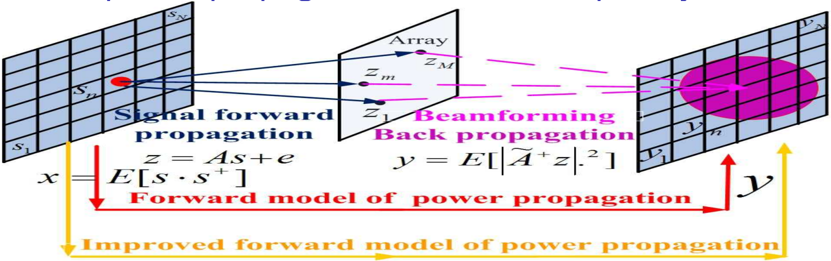
General performance of classical methods

Methods	CBF[1]	CLEAN	DAMAS	DR-DAMAS	SC-DAMAS
Resolutions	Low	Normal	Normal	Normal	High
Dynamic Range	Narrow	Normal	Normal	Normal	Normal
Noise	Robust	Sensitive	Sensitive	Normal	Normal
Parameter[2] number	No	Required	No	No	Required
Computation	Least	Normal	Normal	Normal	High

[1] Conventional Beamforming

[2] Parameter to be tuned

Improved power propagation model and sparsity



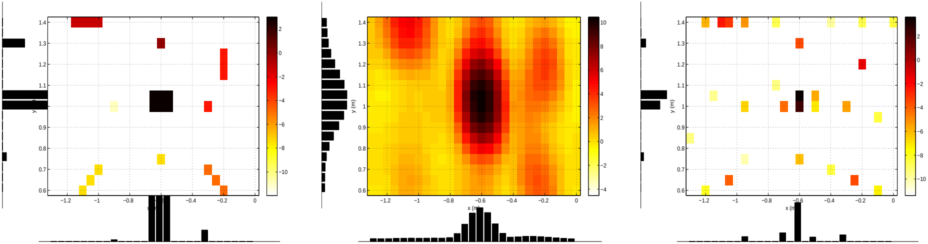
$$\boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2\,1_a \longrightarrow \boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2\,1_a + \boldsymbol{\xi}$$

Contribution: improve robustness using model uncertainty $\boldsymbol{\xi}$ caused by unknown effects: multi-path propagation and prior information of sparsity

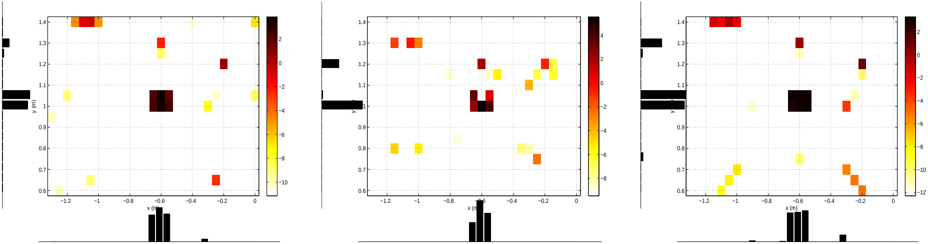
$$\begin{cases} (\widehat{\boldsymbol{x}}, \widehat{\sigma^2}) = \arg \min\limits_{(\boldsymbol{x}, \sigma_e^2)} \{ ||\boldsymbol{y} - \boldsymbol{C}\,\boldsymbol{x} - \sigma_e^2\,1_a||_2^2 \} \\ \text{s.t.} \quad \|\boldsymbol{x}\|_1 = \beta, \quad \boldsymbol{x} \succeq 0, \quad \sigma_e^2 \geq 0 \end{cases},$$

- $(\widehat{\boldsymbol{x}}, \widehat{\sigma^2})$ jointly estimated; Sparse solution on $\boldsymbol{x}$
- $\hat{\beta}$: **sparsity parameter** on **total source powers** $\|\boldsymbol{x}\|_1$;
- **Sensitive** to β

Robust DAMAS with sparsity constraint (SC-RDAMAS) [Chu et al. 2013 APACJounal]



(a) Source powers $\mathbf{s}$ (b) Beamforming $\boldsymbol{y}$ (c) CLEAN



(d) DR-DAMAS (e) SC-DAMAS (f) **SC-RDAMAS**

Higher resolution; **Robust** to measurement errors; but **Sensitive** to sparsity parameter.

Bayesian approach with a sparse prior [Chu et al. 2012 JSVJournal]

- Bayesian approach infers $(\mathbf{x}, \boldsymbol{\theta})$ from $\boldsymbol{y}$ using $p(\boldsymbol{x}, \boldsymbol{\theta}|\boldsymbol{y})$

$$p(\boldsymbol{x}, \boldsymbol{\theta}|\boldsymbol{y}) \propto \underbrace{p(\boldsymbol{y}|\boldsymbol{x}, \boldsymbol{\theta}_1)}_{Likelihood} \underbrace{p(\boldsymbol{x}|\boldsymbol{\theta}_2)}_{Prior} \quad \underbrace{p(\boldsymbol{\theta})}_{Hyper-prior}$$

$$\boldsymbol{\theta} = [\boldsymbol{\theta}_1, \boldsymbol{\theta}_2]$$

- Likelihood

$$\boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2 1_N + \boldsymbol{\xi}$$

$$p(\boldsymbol{y}|\boldsymbol{x}, \boldsymbol{\theta}_1) \propto \exp\left[-\frac{1}{2\sigma_\xi^2}\|\boldsymbol{y} - \boldsymbol{C}\,\boldsymbol{x} - \sigma_e^2\, 1_a\|^2\right]$$

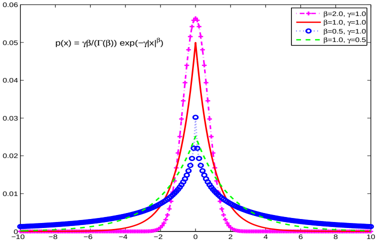
$$\boldsymbol{\theta}_1 = [\sigma_e^2, \sigma_\xi^2] : \text{Hyper-parameters}$$

- $p(\boldsymbol{x}|\boldsymbol{\theta}_2)$ Sparsity enforcing
- $p(\boldsymbol{\theta})$ Conjugate priors

Sparsity enforcing prior on source powers

- Sparsity enforcing prior in Generalized Gaussian family

$$p(\boldsymbol{x}|\boldsymbol{\theta}_2) \propto exp(-\gamma\,|x_n|^\beta),\;\; \boldsymbol{\theta}_2 = [\gamma, \beta]$$



$\beta = 1$ (fixed) enforces sparsity distribution: sharp peak;
$0 \leq \gamma \leq 1$ (to be estimated) enlarges dynamic range: long tail.

- $p(\boldsymbol{\theta})$: Positive priors using Jeffrey priors:
$p(\gamma) \sim \frac{1}{\gamma}\,,\; p(\sigma_\xi^2) \sim \frac{1}{\sigma_\xi^2}\,,\; p(\sigma_e^2) \sim \frac{1}{\sigma_e^2},\;\; \boldsymbol{\theta} = [\gamma, \sigma_e^2, \sigma_\xi^2]$

Joint Maximum A Posteriori (JMAP) [Chu et al. 2012 JSVJournal]

$$
\left\{
\begin{aligned}
(\widehat{\boldsymbol{x}}, \hat{\boldsymbol{\theta}}) &= \arg\max_{(\boldsymbol{x},\boldsymbol{\theta})} \left\{ p(\boldsymbol{x},\boldsymbol{\theta}|\boldsymbol{y}) \propto p(\boldsymbol{y}|\boldsymbol{x},\boldsymbol{\theta}_1)\, p(\boldsymbol{x}|\boldsymbol{\theta}_2)\, p(\boldsymbol{\theta}) \right\} \\
&= \arg\min_{(\boldsymbol{x},\boldsymbol{\theta})} \left\{ \mathcal{J}(\boldsymbol{x},\boldsymbol{\theta}) \right\}, \text{with}\, \mathcal{J}(\boldsymbol{x},\boldsymbol{\theta}) = -\ln p(\boldsymbol{x},\boldsymbol{\theta}|\boldsymbol{y}) \\
\mathcal{J}(\boldsymbol{x},\boldsymbol{\theta}) &= \underbrace{\frac{1}{2\sigma_\xi^2} \|\boldsymbol{y} - \boldsymbol{C}\,\boldsymbol{x} - \sigma_e^2\, 1_a\|^2}_{Likelihood:\, data\, fitting} + \underbrace{\gamma\, \|\boldsymbol{x}\|_{\beta=1}}_{Sparse\, prior} + \underbrace{\frac{N}{2}\, \ln \sigma_\xi^2 - N\, \ln \gamma}_{Hyper-parameter\, prior} \\
&\text{s.t. } \boldsymbol{x} \succeq 0,\ \sigma_e^2 \geq 0,\ \sigma_\xi^2 \geq 0,\ \gamma \geq 0;\ \boldsymbol{\theta} = [\sigma_e^2, \sigma_\xi^2, \gamma]
\end{aligned}
\right.
$$

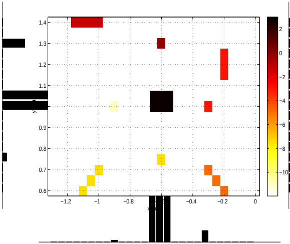
Advantages

- Super spatial resolution: sparse prior;
- Wide dynamic range: γ estimation;
- robustness to errors: σ_e^2, σ_ξ^2 estimations

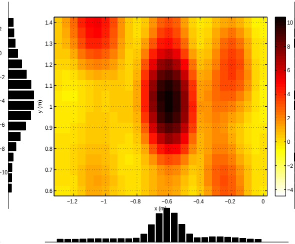
Limitations

- Non-quadratic optimization: $\boldsymbol{x}$ and $\boldsymbol{\theta}$;
- High computational costs $O(N^2)$: $\boldsymbol{C}\,\boldsymbol{x}$, $N \times N$ dimension.

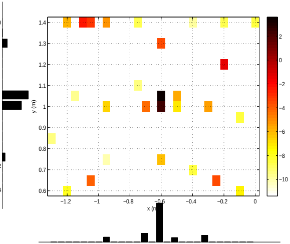
JMAP) optimization [Chu et al. 2012 JSVJournal]



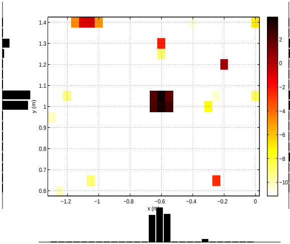
(a) Source powers $\boldsymbol{x}$.



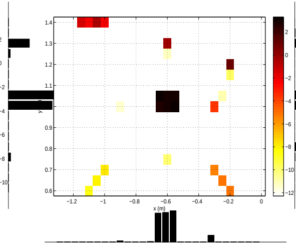
(b) Beamforming $\boldsymbol{y}$



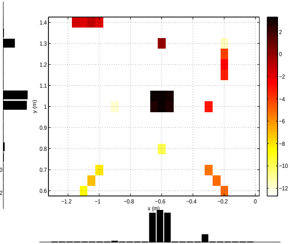
(c) CLEAN .



(d) DR-DAMAS.



(e) **SC-RDAMAS**.



(f) **JMAP**.

Higher resolution, robust, wide dynamics, parameter-independent, but time-consuming

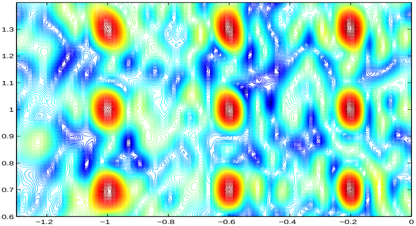
Method comparisons

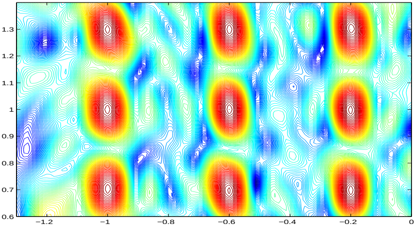
Methods	CBF	DR-DAMAS	SC-DAMAS	SC-RDAMAS	JMAP
Resolutions	Low	Normal	High	Higher	Higher
Dynamics[3]	Narrow	Normal	Normal	Wide	Wide
Noise	Robust	Normal	Normal	Robust	Robust
Parameter	No	No	Required	Required	No
Cost	Least	Normal	Higher	Higher	Higher

[3] Dynamic range

Invariant convolution model of power propagation [Chu et al. ICA2013a]

$$\boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2 1_a + \boldsymbol{\xi} \longrightarrow \boldsymbol{y} = \mathbf{H}\,\boldsymbol{x} + \boldsymbol{\epsilon} = \mathbf{h} * \boldsymbol{x} + \boldsymbol{\eta}$$





$\boldsymbol{C}$: spatially **variant** in **near-field** $\mathbf{H}$: spatially **invariant** in **far-field**

Operation	Expression[4]	Complexity	Speed gain
Matrix multiplication	$\boldsymbol{C}\,\boldsymbol{x}$	$O(N^2)$	1
2D invariant convolution	$\mathbf{h} * \boldsymbol{x}$	$O({N_h}^2\,N)$	$N/{N_h}^2$
1D separable convolution	$\mathbf{h}_1 * \mathbf{h}_2 * \boldsymbol{x}$	$O(2\,N_h\,N)$	$N/(2\,N_h)$

[4] $\mathbf{h}$: $N_h \times N_h$ matrix; $\mathbf{h}_1$, $\mathbf{h}_2$: N_h length vector;

Short summary of the works

$\mathbf{z}(f) = \mathbf{A}(\mathbf{P}^*, f)\, \mathbf{s}^*(f) + \boldsymbol{e}(f)$: Given $\mathbf{z}$ find $(\mathbf{P}^*, \,, \mathbf{s}^*)$

$\Downarrow$ Discretization

$\mathbf{z}(f) = \mathbf{A}(\mathbf{P}\,,\, f)\; \mathbf{s}\,(f)\; + \boldsymbol{e}(f)$: Given $(\mathbf{z}, \mathbf{A})$ find $\mathbf{s}$ (sparse) .

$\Downarrow$ Beamforming power

$\boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2\, 1_a$: Given $(\boldsymbol{y}, \boldsymbol{C})$ find $\boldsymbol{x}$ (sparse) by deconvolution/regularization.

$\Downarrow$ Model uncertainty $\boldsymbol{\xi}$

$\boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} + \sigma_e^2\, 1_a + \boldsymbol{\xi}$: Given $(\boldsymbol{y}, \boldsymbol{C})$ find $(\boldsymbol{x},\, \sigma_e^2\,)$ by proposed SC-RDAMAS.
Given $(\boldsymbol{y}, \boldsymbol{C})$ find $(\boldsymbol{x},\, \sigma_e^2, \sigma_\xi^2, \gamma\,)$ by proposed Bayesian JMAP.

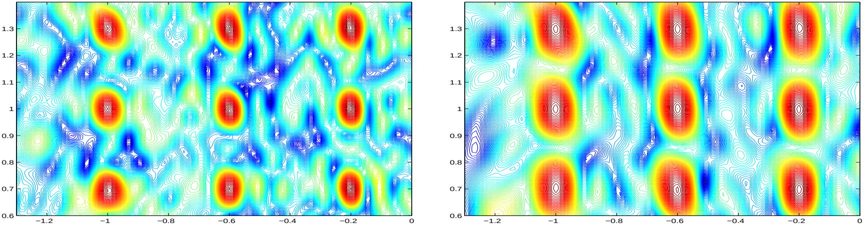
$\Downarrow$ Invariant convolution model $\boldsymbol{C}\,\boldsymbol{x} \approx \mathbf{h} * \boldsymbol{x} \approx \mathbf{h}_1 * \mathbf{h}_2 * \boldsymbol{x}$

$\boldsymbol{y} = \mathbf{H}\,\boldsymbol{x} + \boldsymbol{\epsilon}$: Given $(\boldsymbol{y}, \boldsymbol{C})$ to find $(\boldsymbol{x},\, \sigma_{\boldsymbol{\epsilon}}^2\,)$ by proposed Bayesian JMAP: fast, but low quality

$\Downarrow$ $\boldsymbol{\epsilon}$: Model errors are spatially variant noises

To be continued...

Spatialy variant noise model and Students-t priors [Chu et al. ICA2013a]



C: spatially **variant** in **near-field** $\quad$ $\mathbf{H}$: spatially **invariant** in **far-field**

$$\boldsymbol{y} = \mathbf{H}\,\boldsymbol{x} + \boldsymbol{\epsilon}$$

- $\boldsymbol{\epsilon}$: Model errors are spatially variant noises:

$$p(\epsilon_i|\nu_i) = \mathcal{N}(\epsilon_i|0,\, 1/\nu_i) \quad p(\nu_i) = \mathcal{G}(\nu_i|a_\nu, b_\nu)\,,$$

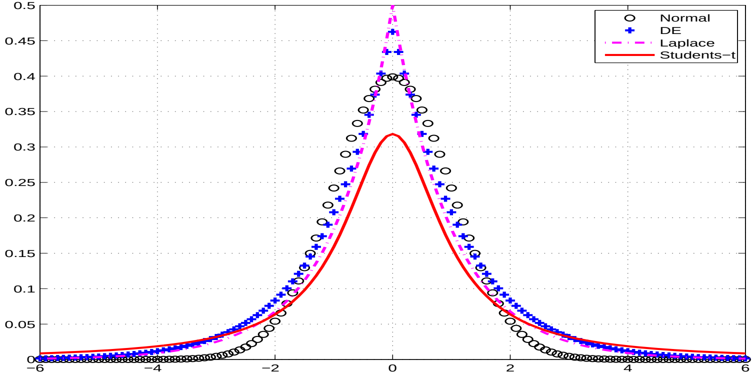
- Non-stationary prior $p(\boldsymbol{\epsilon})$:

$$p(\epsilon_i) = \int_{\nu_i} p(\epsilon_i|\nu_i)p(\nu_i)\, d\nu_i = S_t(\epsilon_i)$$

Sparsity enforcing via Students-t priors [Chu et al. ICA2013a]

$$\boldsymbol{y} = \mathbf{H}\,\boldsymbol{x} + \boldsymbol{\epsilon}$$

$\boldsymbol{x}$: Sparsity enforcing prior from Student-t family (Cauchy):



$$p(x_j) = \int p(x_i|\gamma_j)p(\gamma_j)\,d\gamma_j = S_t(x_j)$$

Non stationary noise model and sparsity enforcing via Students-t priors [Chu et al. ICA2013a]

$$\boldsymbol{y} = \boldsymbol{H}\,\boldsymbol{x} + \boldsymbol{\epsilon}$$

- Non stationary noise model via S_t

$$p(\boldsymbol{y}|\boldsymbol{x}) = \mathcal{N}(\boldsymbol{y}|\boldsymbol{H}\boldsymbol{x}, \boldsymbol{\Sigma}_\epsilon),\ \boldsymbol{\Sigma}_\epsilon = \text{diag}\left[\boldsymbol{\nu}\right],\ p(\boldsymbol{\nu}) = \prod_{m=1}^{M} \mathcal{G}(\nu_m|a_\gamma, b_\gamma)$$

- Sparsity enforcing prior via S_t prior

$$p(\boldsymbol{x}|\gamma) = \mathcal{N}(\boldsymbol{x}|\boldsymbol{0},\ \boldsymbol{\Sigma}_\gamma^{-1})\ \boldsymbol{\Sigma}_\epsilon = \text{diag}\left[\boldsymbol{\gamma}\right] p(\gamma) = \prod_{n=1}^{N} \mathcal{G}(\gamma_n|a_\gamma, b_\gamma)\,,$$

- Joint posterior law

$$p(\boldsymbol{x}, \boldsymbol{\gamma}, \boldsymbol{\nu}|\boldsymbol{y}) \propto \underbrace{\mathcal{N}(\boldsymbol{y}|\mathbf{H}\,\boldsymbol{x}\,, \boldsymbol{\Sigma}_\nu^{-1})}_{Likelihood} \underbrace{\prod_{n=1}^{N} \mathcal{G}(\nu_n|a_\nu, b_\nu)}_{Hyper-prior} \underbrace{\mathcal{N}(\boldsymbol{x}|0, \boldsymbol{\Sigma}_\gamma^{-1})}_{Prior} \underbrace{\prod_{n=1}^{N} \mathcal{G}(\gamma_n|a_\gamma, b_\gamma)}_{Hyper-prior}$$

- JMAP could solve $3N$-dimensional variables by alternate optimization
- JMAP is a point estimator. How to quantify estimation uncertainty???

Bayesian VBA via Students-t priors [Chu et al. ICA2013a]

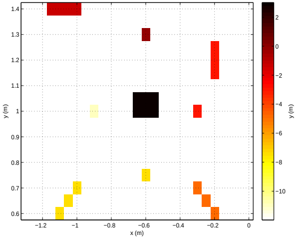
$$\left\{\begin{array}{c} \text{To find } \boldsymbol{x},\ \boldsymbol{\theta}=[\boldsymbol{\gamma},\boldsymbol{\nu}] \text{ from } \boldsymbol{y} \\ p(\boldsymbol{x},\boldsymbol{\theta}|\boldsymbol{y}) \approx \hat{q}(\boldsymbol{x},\boldsymbol{\theta}) = \underbrace{\arg\min_{q(\boldsymbol{x},\boldsymbol{\theta})} \left\{ \int_{(\boldsymbol{x},\boldsymbol{\theta})} q(\boldsymbol{x},\boldsymbol{\theta}) \ln \frac{q(\boldsymbol{x},\boldsymbol{\theta})}{p(\boldsymbol{x},\boldsymbol{\theta}|\boldsymbol{y})} \, d(\boldsymbol{x},\boldsymbol{\theta}) \right\}}_{\text{Minimizing K-L divergence}} \\ \hat{q}(\boldsymbol{x},\boldsymbol{\theta}) = \hat{q}_1(\boldsymbol{x})\,\hat{q}_2(\boldsymbol{\gamma})\,\hat{q}_3(\boldsymbol{\nu}), \end{array}\right.$$

- Analytical solutions: Conjugate priors:

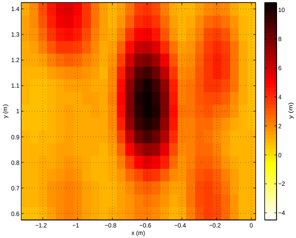
$$\left\{\begin{array}{l} \hat{q}_1(\boldsymbol{x}) = \mathcal{N}(\boldsymbol{x}|\hat{\boldsymbol{\mu}}_x, \hat{\boldsymbol{\Sigma}}_x) \\ \hat{q}_2(\boldsymbol{\gamma}) = \prod_{n=1}^{N} \mathcal{G}(\gamma_n|\hat{a}_\gamma, \hat{b}_\gamma^n) \\ \hat{q}_3(\boldsymbol{\nu}) = \prod_{n=1}^{N} \mathcal{G}(\nu_n|\hat{a}_\nu, \hat{b}_\nu^n) \end{array}\right. ,$$

- VBA jointly obtains $(\hat{\boldsymbol{\mu}}_x, \hat{\boldsymbol{\Sigma}}_x, \hat{\gamma}, \hat{\nu})$ for quantifying **estimation uncertainty** (confidential interval) ; **Outperforms** JMAP.

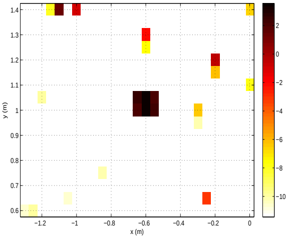
Simulation in colored (spatially **non-stationary**) noises



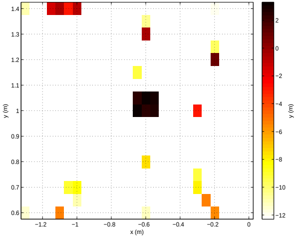
(a) Source powers $\boldsymbol{x}$.



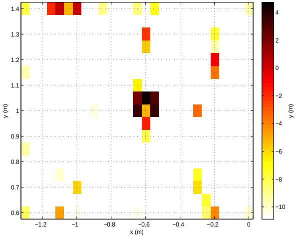
(b) Beamforming $\boldsymbol{y}$



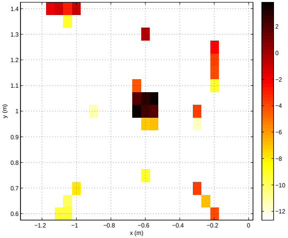
(c) DR-DAMAS.



(d) **JMAP**

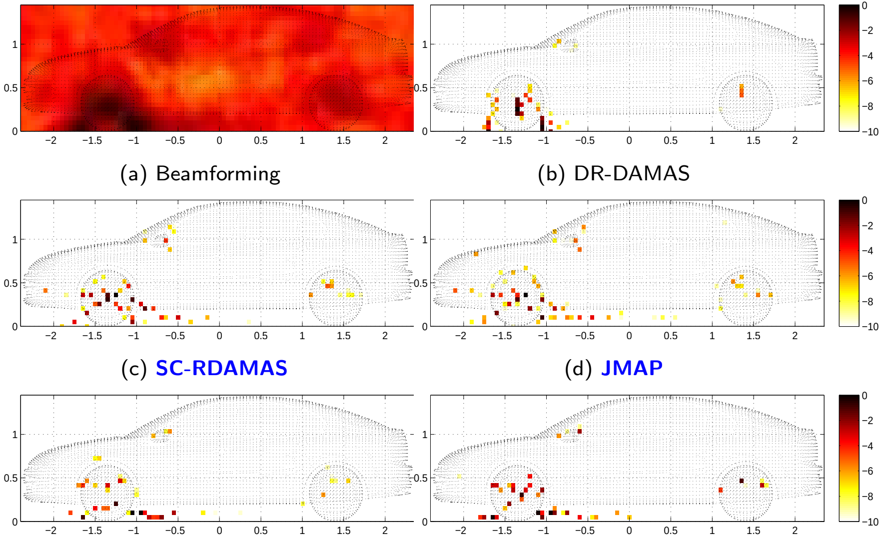


(e) **JMAP+Conv**



(f) **VBA+Conv**

Real data in wind tunnel S2A at $2500Hz$

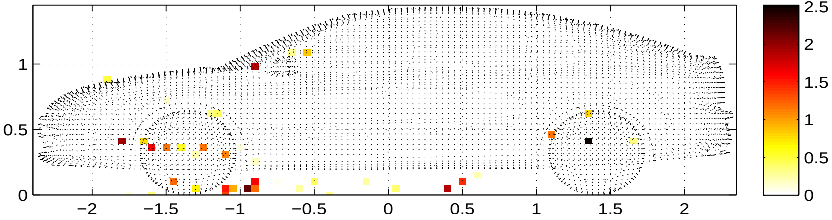


(a) Beamforming (b) DR-DAMAS

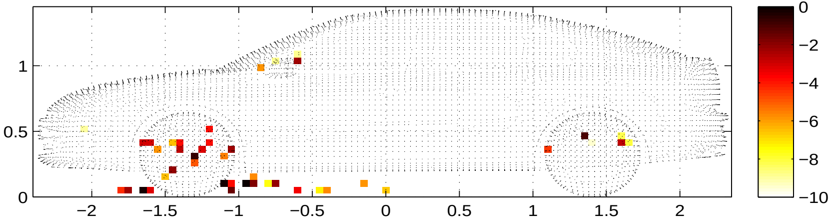
(c) **SC-RDAMAS** (d) **JMAP**

(e) **JMAP+Conv** (f) **VBA+Conv**

Covariance matrix estimation in VBA: an advantage compared with JMAP



Estimated **covariance** $\hat{\Sigma}_x$ (solution uncertainty) of estimated source powers $\widehat{x}$.



Estimated source powers $\widehat{x}$ by **VBA+Conv** approach

Contributions and Conclusions

- Improved forward models of acoustic power propagation:
  - Robust acoustic power propagation model by model uncertainty;
  - Efficient invariant convolution model by reduced PSF size, separable PSF and GPU acceleration;
- Proposed approaches:
  - Robust deconvolution approach with sparsity constraint (SC-RDAMAS)
  - Bayesian approach with sparsity enforcing prior (JMAP)
  - Non stationnarity of the model errors and sparsity enforcing with Student-t priors
  - JMAP and Variational Bayesian Approximation (VBA)
- Advantages:
  - Higher spatial resolution: **sparsity constraint/ prior**;
  - Wide dynamic range: **sparsity parameter estimation**
  - Robust to non-stationary errors: **hyper-parameter estimation** of measurement errors and model uncertainty;
  - Adaptive hyper-parameter estimations: **Bayesian** inference.

Perspectives

- In short term:
  - Real-time realization of 3D acoustic imaging by GPU: programming proposed approaches directly on GPU in order to utilize 25% and more of peak computational performance;
- In middle term:
  - More sophisticated prior models : Group sparsity prior for correlated sources; $\mathcal{G}$ or χ^2 distribution for positive source powers...
  - In middle term, forward models of full-wave propagation for correlated sources (directivity pattern);
- In long term:
  - Inversion methods based on signal models to jointly solve signal amplitude (power), phase, characteristic frequency;
  - De-reverberation in non-anechoic chamber;
  - Acoustic separation;
  - ......

List of publication

Published journals (2)

- N. CHU, A. Mohammad-Djafari and J. Picheral, Robust Bayesian super-resolution approach via sparsity enforcing priors for near-field acoustic source imaging, **Journal of Sound and Vibration**, Vol. 332, No. 18, pp 4369-4389, Feb. 2013.
- N. CHU, J. Picheral and A. Mohammad-Djafari, N. Gac, A robust super-resolution approach with sparsity constraint in acoustic imaging, **Applied Acoustics**, vol.76, pp.197-208, 2014.

To submit: (2)

- N. CHU, A. Mohammad-Djafari, N. Gac, and J. Picheral, A 2D invariant convolution model for acoustic imaging, **International Journal of Aeroacoustics**, 2013.
- N. CHU, A. Mohammad-Djafari, N. Gac, and J. Picheral, A hierarchical variational Bayesian approach approach via Student's-t priors for acoustic imaging with non-stationary noises, **Journal of the Acoustical Society of America**, 2013.

List of publications

Published in conference (5)

- N. CHU, A. Mohammad-Djafari, N. Gac, and J. Picheral, An efficient variational Bayesian inference approach via Student's-t priors for acoustic imaging in colored noises , **Journal of the Acoustical Society of America**, Vol. 133, No.5. Pt.2, POMA Vol 19, pp. 055031-40, International Conference of Acoustics (**ICA2013**), Montreal, Canada, 2013.
- N. CHU, A. Mohammad-Djafari and J. Picheral, A Bayesian sparse inference approach in near-field wideband aeroacoustic imaging, 2012 IEEE International Conference on Image Processing, Orlando (**ICIP2012**), USA, Sep. 30-Oct. 04, 2012. (EI)
- N. CHU, A. Mohammad-Djafari and J. Picheral, Bayesian sparse regularization in near-field wideband aeroacoustic imaging for wind tunnel test, 2012 IOA annual meeting and 11th Congrès Français d'Acoustique (**ACOUSTICS2012**), Nantes, France, Apr. 23-27, 2012, pp. 1391-1396.
- N. CHU, A. Mohammad-Djafari and J. Picheral, Two robust super-resolution approaches with sparsity constraint and sparse regularization for near-field wideband extended aeroacoustic source imaging, Berlin Beamforming Conference 2012 (**BeBeC2012**), Berlin, Germany, Feb. 22-23, 2012, pp. 29.
- N. CHU, J. Picheral and A.Mohammad-Djafari, A robust super-resolution approach with sparsity constraint for near-field wideband acoustic imaging, IEEE International Symposium on Signal Processing and Information Technology (**ISSPIT2011**), Bilbao, Spain, Dec. 14-17, 2011, pp. 310-315. (EI)