Comparison of microphone array denoising techniques and application to flight test measurements

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Context

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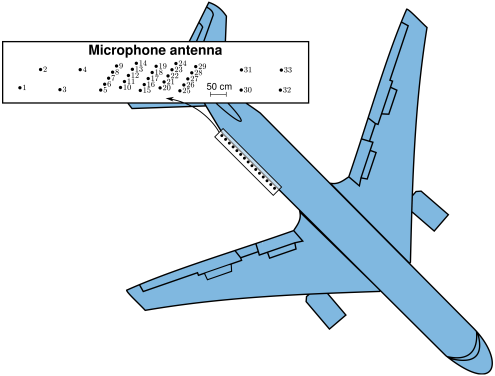
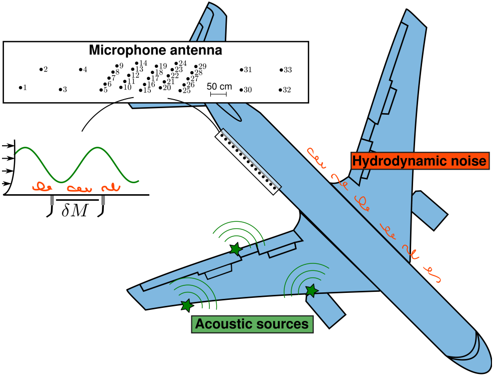


Context

- **Unwanted noise** : electronic, ambient, flow-induced, ...
- **Multi-channel acquisition** : inflight/wind tunnel tests for aircraft design
- 2 kind of pressure fluctuations:
  - from the acoustic sources (signal)
  - from the turbulent boundary layer (noise)

  } very low SNR



Context

How to separate acoustic sources from noise ?

Existing methods:

- physical removal : windscreen, mic recession, porous treatment, vibrating structure filtering,...
- background subtraction $\rightarrow$ not always available or representative
- wavenumber filtering $\rightarrow$ requires high spatial sampling
- diagonal removal $\rightarrow$ underestimation of source level
- other post-processing (inverse problem) $\rightarrow$ for long records

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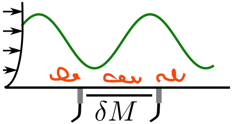
Two proposed methods

1. Solve an inverse problem: reconstruct the source signal
2. Use noise-free channels as references

Outline

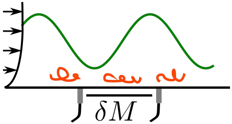
CSM properties



For $i = 1, \dots, I$ snapshots

$$\underbrace{\boldsymbol{p}_i}_{\text{measured spectra}} = \underbrace{\boldsymbol{a}_i}_{\text{acoustical part}} + \underbrace{\boldsymbol{n}_i}_{\text{unwanted noise}}$$

CSM properties

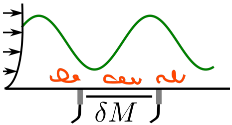


$$\boldsymbol{S}_{xy} = \sum_{i=1}^{I} \boldsymbol{x}_i \boldsymbol{y}_i^H$$

Averaged Cross-Spectral Matrix:

$$\underbrace{\boldsymbol{S}_{pp}}_{\text{measured CSM}} = \underbrace{\boldsymbol{S}_{aa}}_{\text{acoustical CSM}} + \underbrace{\boldsymbol{S}_{nn}}_{\text{unwanted noise}} + \underbrace{\boldsymbol{S}_{an} + \boldsymbol{S}_{na}}_{\text{cross-terms}}$$

CSM properties



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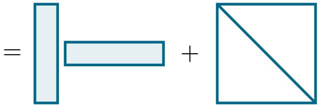

- Acoustic signal with **high** spatial correlation: **low-rank CSM**
- TBL Noise with **low** spatial correlation: **diagonal CSM**

Probabilistic Factor Analysis (PFA)

- **Statistical model**

measured spectra → $$\boldsymbol{p}_i = \boldsymbol{L} \quad \boldsymbol{c}_i + \boldsymbol{n}_i$$ ← noise (+model errors)

$\boldsymbol{L}$: mixing matrix

$\boldsymbol{c}_i$: latents factors

- Capture dominant correlation with few factors (close to PCA)
  $\hookrightarrow$ low-rank acoustic CSM
- Extract anisotropic noise

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- **Statistical model**

measured spectra

$$\boldsymbol{p}_i = \boldsymbol{L}\boldsymbol{\alpha}\boldsymbol{c}_i + \boldsymbol{n}_i$$

noise (+model errors)

mixing matrix

weights

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- Weights enforce sparsity $\rightarrow$ lower the number of factors
  $\hookrightarrow$ Data compression

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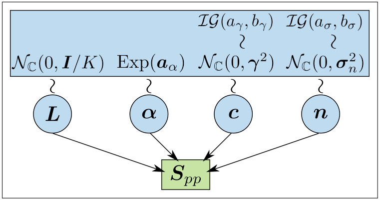
- **Bayesian approach :** See parameters as random variables

$\boldsymbol{L} \sim \mathcal{N}_{\mathbb{C}}(0, \lceil \frac{\mathbf{1}}{K} \rfloor)$	$\boldsymbol{c}_i \sim \mathcal{N}_{\mathbb{C}}(0, \lceil \boldsymbol{\gamma}^2 \rfloor)$	$\boldsymbol{n}_i \sim \mathcal{N}_{\mathbb{C}}(0, \lceil \boldsymbol{\sigma}_n^2 \rfloor)$	$\boldsymbol{\alpha} \sim \mathcal{E}(a_\alpha)$

$+$ hyperparameters : $\boldsymbol{\gamma}^2, \boldsymbol{\sigma}^2 \sim \mathcal{IG}(\boldsymbol{a}_{\gamma,\sigma}, \boldsymbol{b}_{\gamma,\sigma})$

Probabilistic Factor Analysis (PFA) – Optimization



$\longrightarrow$ **Parametric model**: $\mathcal{M}(\boldsymbol{\theta})$
with $\boldsymbol{\theta} = \{\boldsymbol{L},\ \boldsymbol{\alpha},\ \boldsymbol{c},\ \boldsymbol{n},\ \boldsymbol{a}_{\gamma,\alpha,\sigma},\ \boldsymbol{b}_{\gamma,\sigma}\}$

Optimization step:

$$\boxed{\boldsymbol{\theta} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \quad \underbrace{\mathsf{P}\left(\boldsymbol{\theta} \mid \boldsymbol{S}_{yy}\right)}_{\text{objective function}}}$$

- The input data is the averaged CSM
- The objective function is the joint posterior probability
  $\hookrightarrow$no closed-form $\rightarrow$ approximated with numerical methods

Probabilistic Factor Analysis (PFA) – Optimization

Maximizing the posterior probability distribution
$\hookrightarrow$ *Find the optimal parameter set that best fits the data*

- Numerical method: the Gibbs sampler
- MCMC algorithm
- global optimization process
- perform a biased random walk through the target distribution

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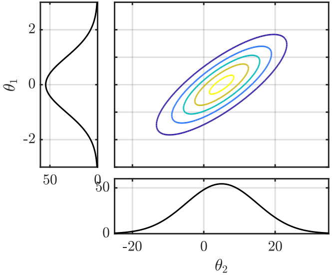

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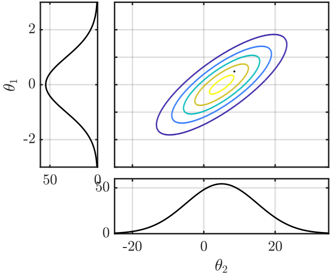

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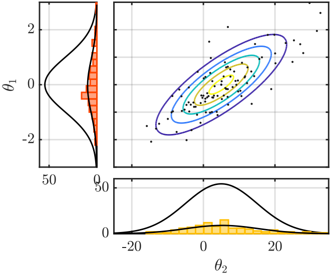

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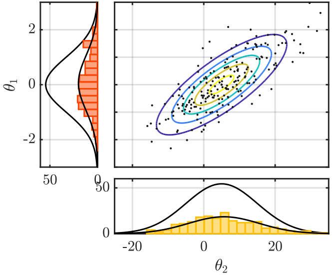

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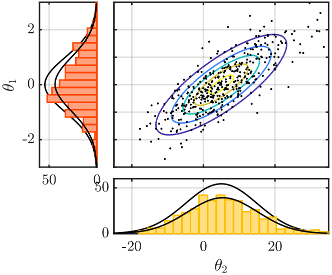

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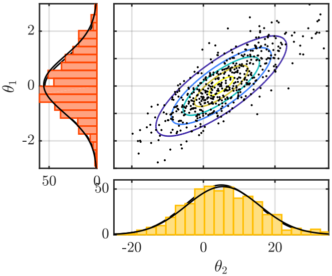

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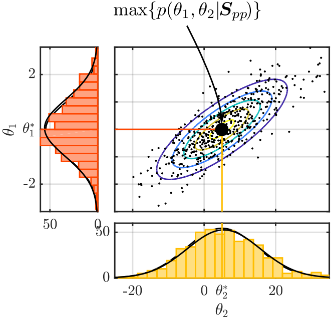

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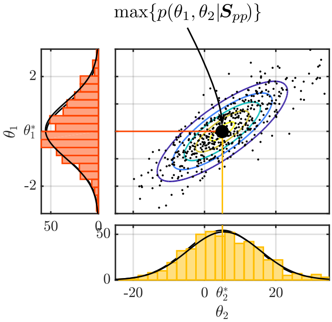

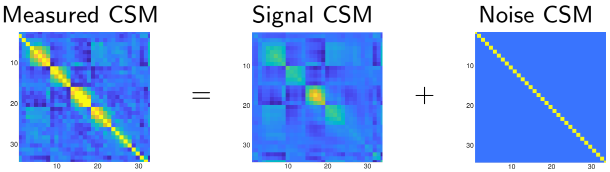

Example of inflight measurements

Probabilistic Factor Analysis (PFA)

$\oplus$

- The bayesian approach:
  - prior knowledge is part of the model
  - gives credible interval

- Probabilistic Factor Analysis :
  - preserves the CSM properties
  - reduces data dimension
  - no input parameter to set
  - adaptable model
  - can denoise several measurement datasets

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  - can denoise several measurement datasets

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- Sensitive to prior choices esp. for ill-posed problem
- Computationally expensive

Denoising with reference channel

Hypothesis : no TBL noise on the reference microphone in the cabine

$$\left.\begin{array}{ll} \boldsymbol{y} & : \text{noisy measurements} \\ \boldsymbol{r} & : \text{noise-free reference signals} \\ & \text{(e.g. inside the aircraft cabine)} \end{array}\right\} \text{synchronous acquisitions}$$

$\boldsymbol{a}$: denoised signals

$$\boxed{\boldsymbol{S}_{aa} = \boldsymbol{S}_{yr}\boldsymbol{S}_{rr}^{-1}\boldsymbol{S}_{ry}}$$

$\rightarrow$ Generalization of the coherent spectra

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+

- Simple to implement
- Low computational cost

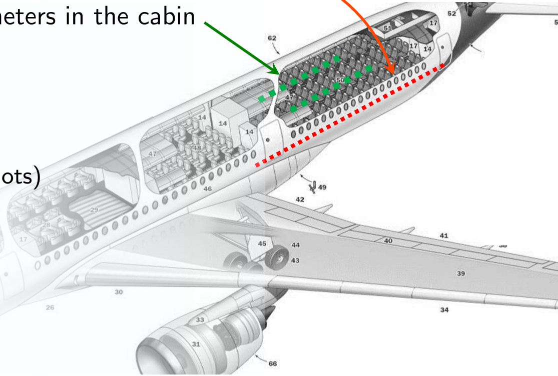
-

- Reference channels have to be noise-free (or independant from TBL)
- Require extra measurements
- The coherence threshold depends on:
  - the record length
  - the number of reference channels

Application to flight test measurements

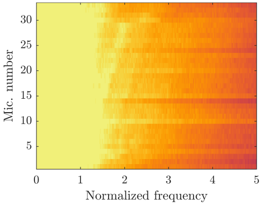
from Helffer, ICSV 2018

- Cruise flight condition: Mach 0.85
- 5 different engine speed
  + 1 background meas. (idle speed)
- 35 microphones flushmounted on the aft fuselage
- 9 microphones + 6 accelerometers in the cabin
- CSM:
  - 4 Hz resolution
  - 60 sec record length
  - Hanning window
  - overlap : 70% (500 snapshots)
- Type of noise :
  - outside: TBL
  - inside: air conditioning

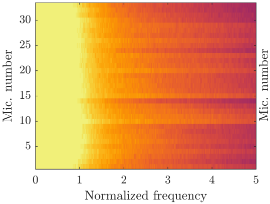


Application to flight test measurements

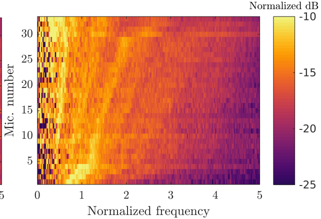
Autospectra of the outer mic. in the MF frequency range



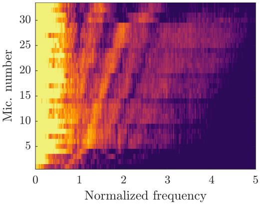
Raw (high engine speed)



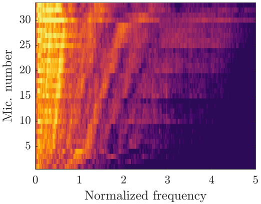
Background noise (idle)



After background subtraction



PFA denoising



Reference-based denoising

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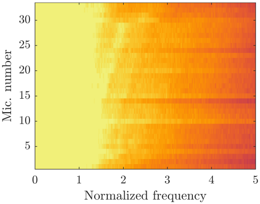

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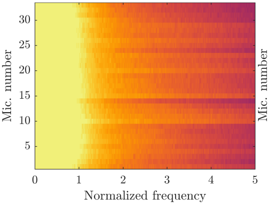

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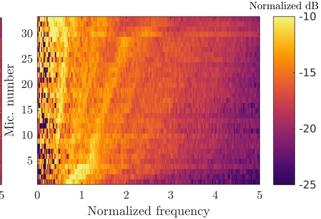
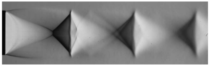
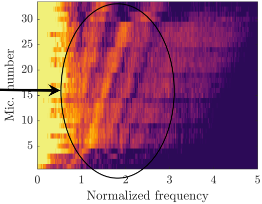


After background subtraction

- ▶ BG subtraction gives negative autospectra
- ▶ Interference patterns: shock-cell structure in the jet



From B. André, Ph.D. thesis, 2013



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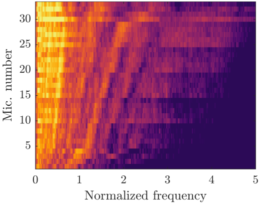

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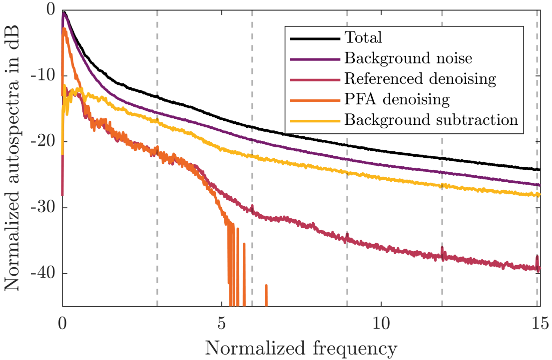
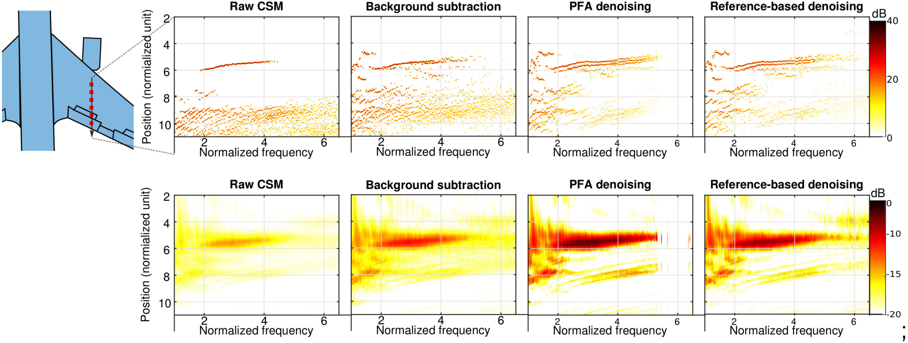


- Reduces the noise of 10-15 dB
- PFA :
  - Few denoising at very low frequency → TBL noise is correlated
  - No extracted signal at high frequency → change the statistical model
- PFA and reference-based denoising are in good agreement in the MF range

Application to flight test measurements – Imaging

Inverse method

Iterative Reweighted Least Squares, $p = 0$ + bayesian regularization



Conventional Beamforming

Application to flight test measurements – Imaging

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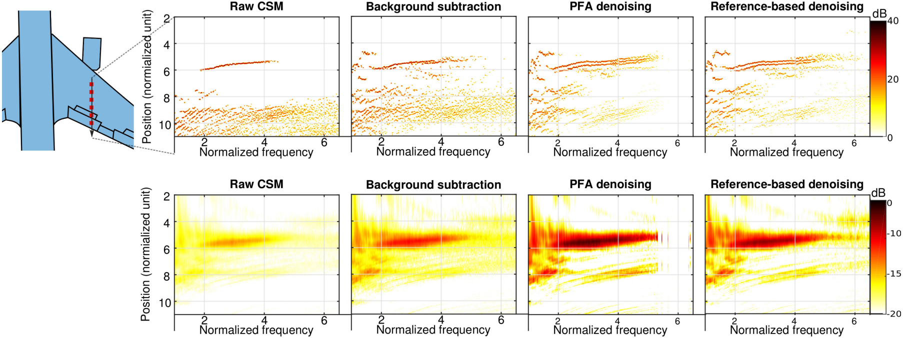

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Conventional Beamforming

- Advanced denoising increase the dynamic of the beamforming map
- 2 dominant wide-band sources $\rightarrow$ visible with advanced denoising

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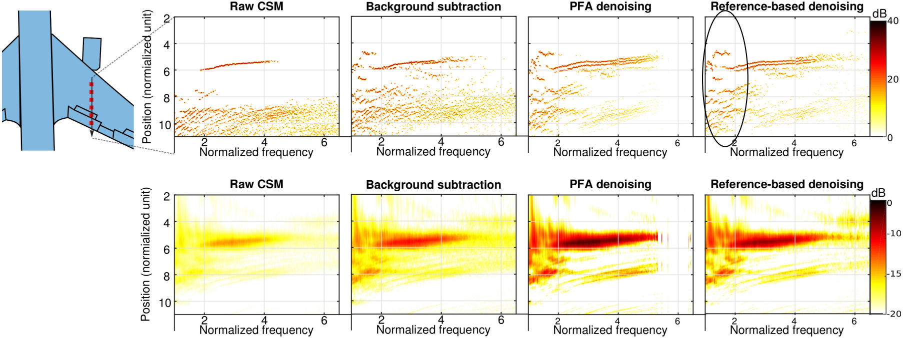

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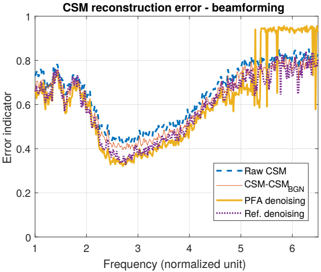
Conventional Beamforming

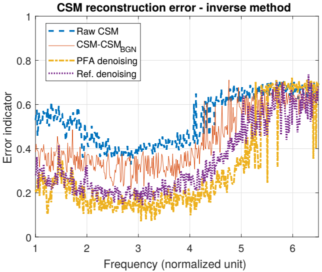
- Advanced denoising increase the dynamic of the beamforming map
- 2 dominant wide-band sources → visible with advanced denoising
- 4 correlated sources in the 1-2 frequency band (caused interference patterns)

Application to flight test measurements – Imaging

$$\text{Error} = \frac{\|\boldsymbol{S}_{yy}^{\text{denoised}} - \boldsymbol{G}\boldsymbol{S}_{qq}\boldsymbol{G}'\|_1}{\|\boldsymbol{S}_{yy}^{\text{denoised}}\|_1 + \|\boldsymbol{G}\boldsymbol{S}_{qq}\boldsymbol{G}'\|_1}$$

- $\boldsymbol{G}$ Convected Green's functions between sources and microphones
- From the beamforming map (left): based only on the maximum location





Conclusions

- Different requirements/hypothesis:

Reference denoising:

- Noise-free reference channels
- Rely on one measurement

PFA denoising:

- Uncorrelated noise on the microphones
- Extract a common noise from several measurements including background

$\hookrightarrow$ but they give similar results

- Increase of the imaging performance
  - improvement of the dynamic
  - localization of correlated sources

- Possible improvements for PFA:
  - use a more efficient/robust solver
  - change the model to have better control on sparsity level
  - account for a correlated noise model for the low-frequency range

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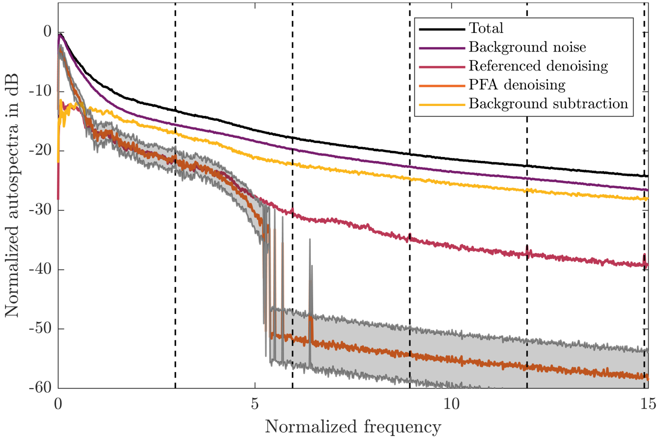
Appendix



In gray : 95% credible interval for PFA denoising