

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

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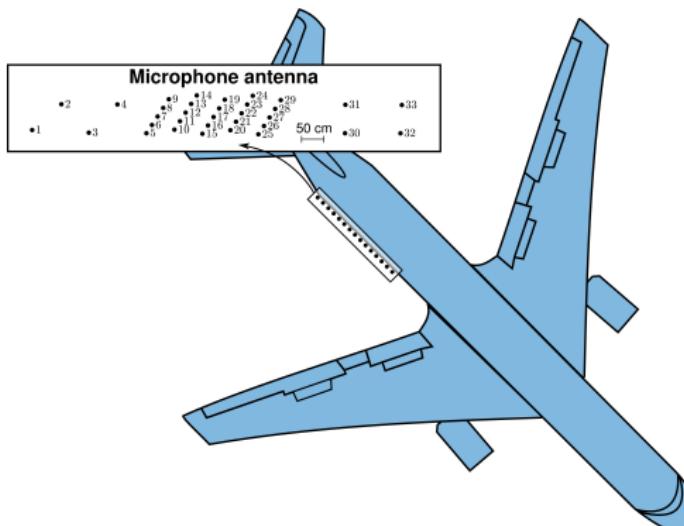
³ Airbus, Toulouse, France

AIAA/CEAS Aeroacoustics Conference – May 23, 2019



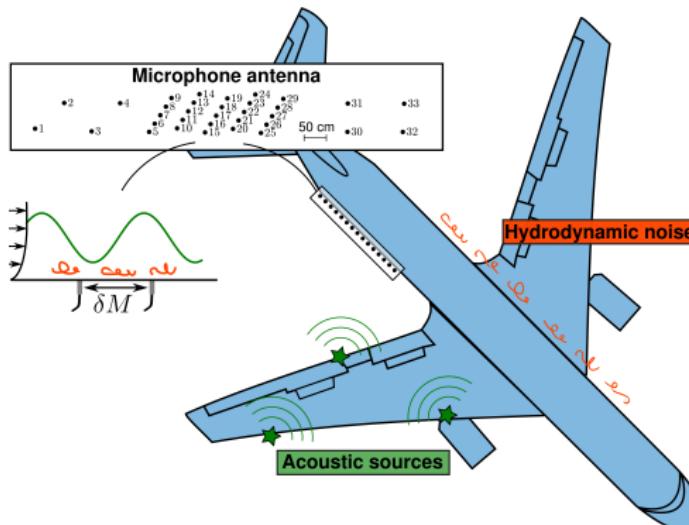
Context

- ▶ **Unwanted noise** : electronic, ambient, flow-induced, ...
- ▶ **Multi-channel acquisition** : inflight/wind tunnel tests for aircraft design



Context

- ▶ **Unwanted noise** : electronic, ambient, flow-induced, ...
 - ▶ **Multi-channel acquisition** : inflight/wind tunnel tests for aircraft design
 - ▶ 2 kinds of pressure excitation:
 - from the acoustic sources (**signal**)
 - from the turbulent boundary layer (**noise**)
- } very low SNR



Context

How to separate the acoustic sources from the noise ?

Existing methods:

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

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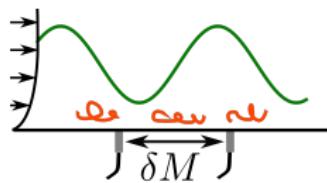
Two proposed methods

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

Outline

- 1 CSM properties**
- 2 Probabilistic Factor Analysis (PFA)**
- 3 Denoising with reference channels**
- 4 Application to flight test measurements**

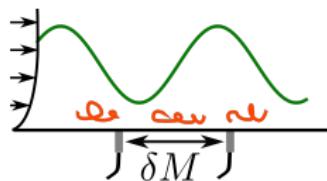
CSM properties



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

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

CSM properties

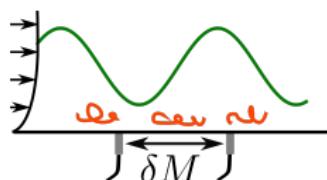


$$\mathbf{S}_{xy} = \frac{1}{I} \sum_{i=1}^I \mathbf{x}_i \mathbf{y}_i^H$$

Averaged Cross-Spectral Matrix:

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

CSM properties



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Averaged Cross-Spectral Matrix: $I \rightarrow \infty$

$$\underbrace{\mathbf{S}_{pp}}_{\text{measured CSM}} = \underbrace{\mathbf{S}_{aa}}_{\text{acoustical CSM}} + \underbrace{\mathbf{S}_{nn}}_{\substack{\text{unwanted noise} \\ \approx \text{diagonal matrix}}} + \underbrace{\mathbf{S}_{an} + \mathbf{S}_{na}}_{\substack{\text{cross-terms} \\ \rightarrow 0}}$$

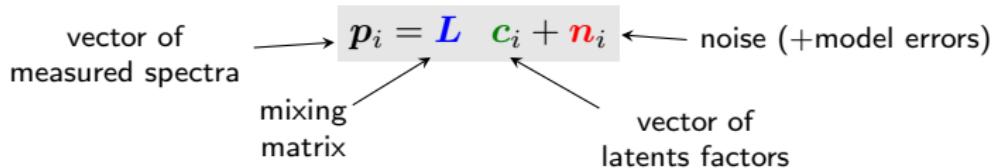


- ▶ TBL noise with short spatial correlation: **diagonal CSM**
- ▶ Acoustic signal - with high spatial correlation
 - few equivalent monopoles: **low-rank CSM**

- 1 CSM properties
- 2 Probabilistic Factor Analysis (PFA)
- 3 Denoising with reference channels
- 4 Application to flight test measurements

Probabilistic Factor Analysis (PFA)

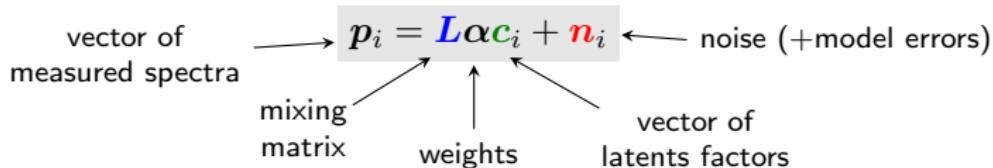
► Statistical model



- Capture dominant correlation with few factors (close to PCA)
 \hookrightarrow low-rank acoustic CSM : $S_{aa} = \mathbf{L} \mathbf{S}_{cc} \mathbf{L}^H$
- Extract anisotropic noise

Probabilistic Factor Analysis (PFA)

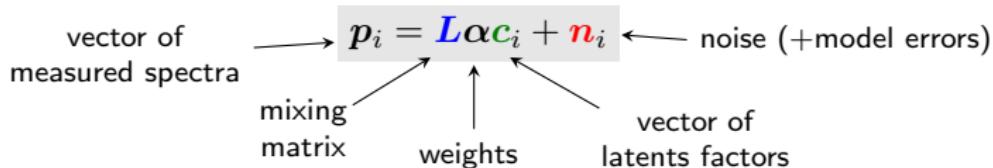
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- Weights enforce sparsity → lower the number of factors
- Strong data compression

Probabilistic Factor Analysis (PFA)

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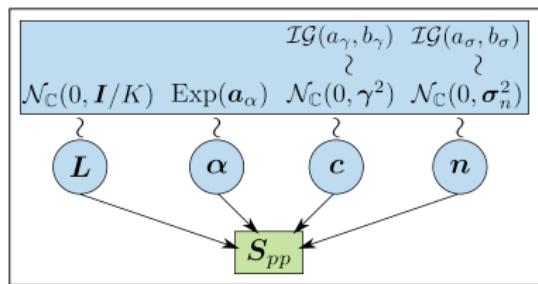
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► Bayesian approach : See parameters as random variables

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

+ hyperparameters : $\gamma^2, \sigma^2 \sim \mathcal{IG}(a_{\gamma, \sigma}, b_{\gamma, \sigma})$

Probabilistic Factor Analysis (PFA) – Optimization



Parametric model: $\mathcal{M}(\theta)$

with $\theta = \{L, \alpha, c, n, a_{\gamma, \alpha, \sigma}, b_{\gamma, \sigma}\}$

Optimization step:

$$\theta = \underset{\theta}{\operatorname{argmax}} \underbrace{P(\theta | S_{pp})}_{\text{objective function}}$$

- The objective function is the joint posterior probability
↪ no closed-form → approximated with numerical methods

Probabilistic Factor Analysis (PFA) – Optimization

Maximizing the posterior probability distribution

→ *Find the optimal parameter set that best fits the data*

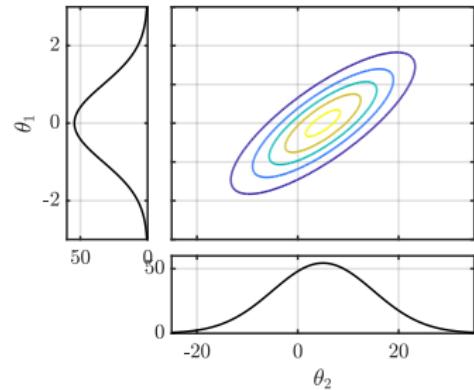
- ▶ Numerical method: the Gibbs sampler
- ▶ MCMC algorithm
- ▶ Global optimization process

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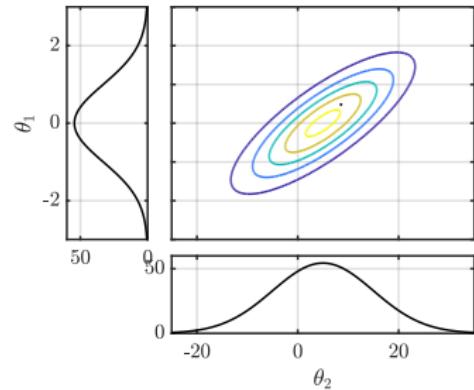


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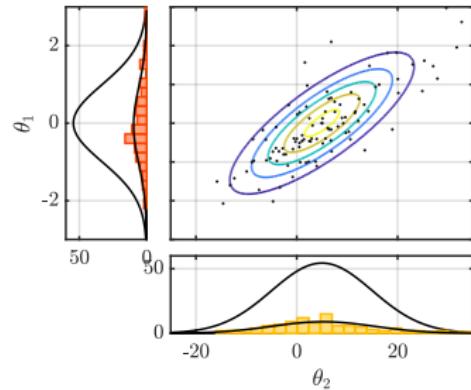


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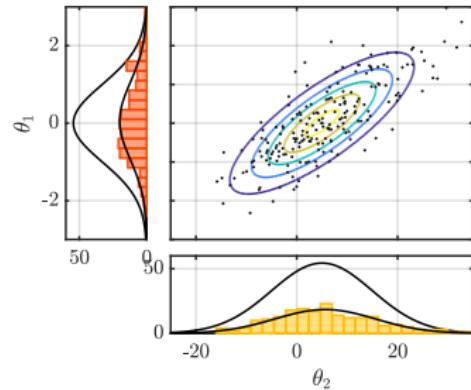


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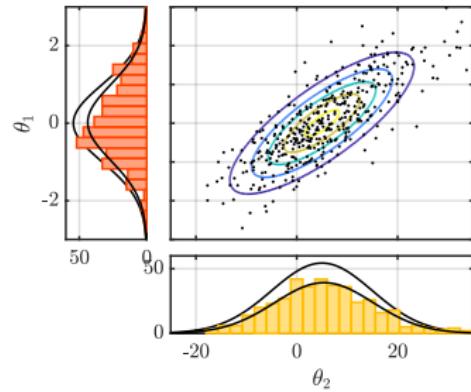


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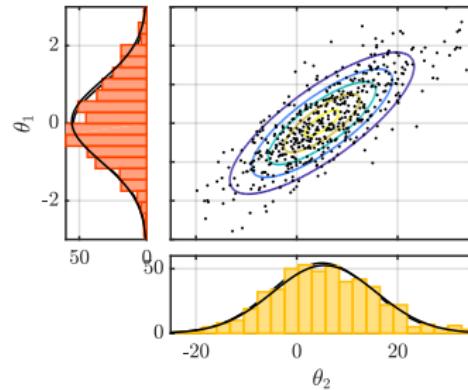


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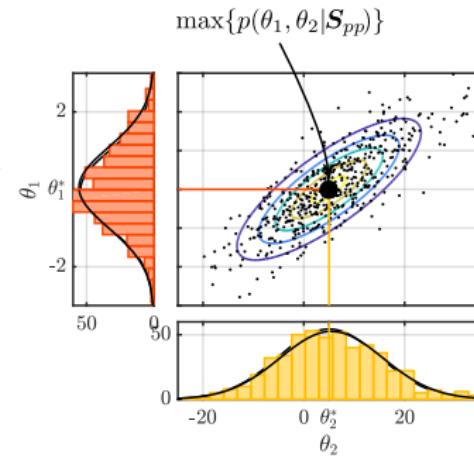


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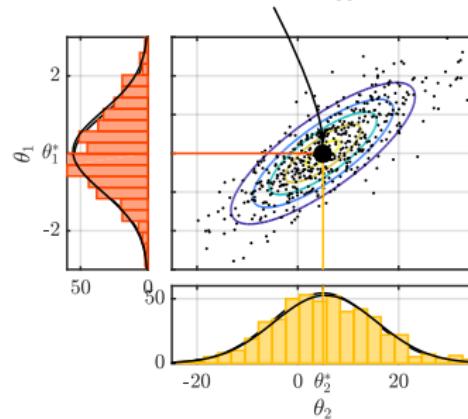


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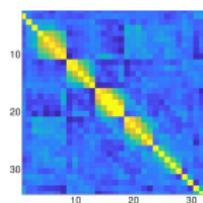
→ Find the optimal parameter set that best fits the data

$$\max\{p(\theta_1, \theta_2 | S_{pp})\}$$

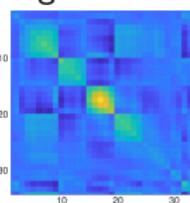


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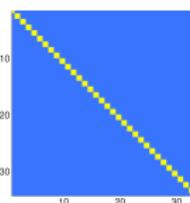
Measured CSM



Signal CSM



Noise CSM



=

+

Example of
inflight
measurements

Probabilistic Factor Analysis (PFA)



- The bayesian approach:
 - prior knowledges are 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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 - prior knowledges are 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
- Sensitive to prior choices
esp. for ill-posed problem
 - Computationally expensive

- 1 CSM properties**
- 2 Probabilistic Factor Analysis (PFA)**
- 3 Denoising with reference channels**
- 4 Application to flight test measurements**

Denoising with reference channels

Hypothesis : the TBL noise does not affect the sensors inside the cabin

p : noisy measurements
 r : noise-free reference signals
(e.g. inside the aircraft cabine)
 a : denoised signals

} synchronous acquisitions

$$\boxed{S_{aa} = S_{pr} S_{rr}^{-1} S_{rp}}$$

→ Generalization of the
coherent spectra

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- | | | |
|---|--|--------------------------|
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$$S_{aa} = S_{pr} S_{rr}^{-1} S_{rp}$$

→ Generalization of the
coherent spectra



- ▶ Simple to implement
- ▶ Low computational cost



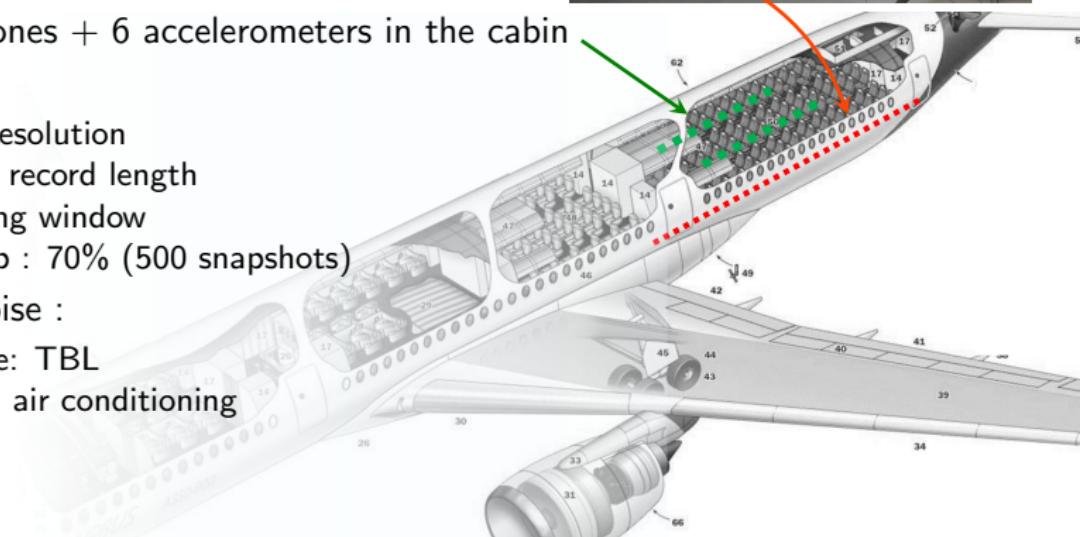
- ▶ Reference channels have to be noise-free
(or independant from TBL)
- ▶ Require extra measurements
- ▶ The coherence threshold depends on:
 - the record length
 - the number of reference channels

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Application to flight test measurements

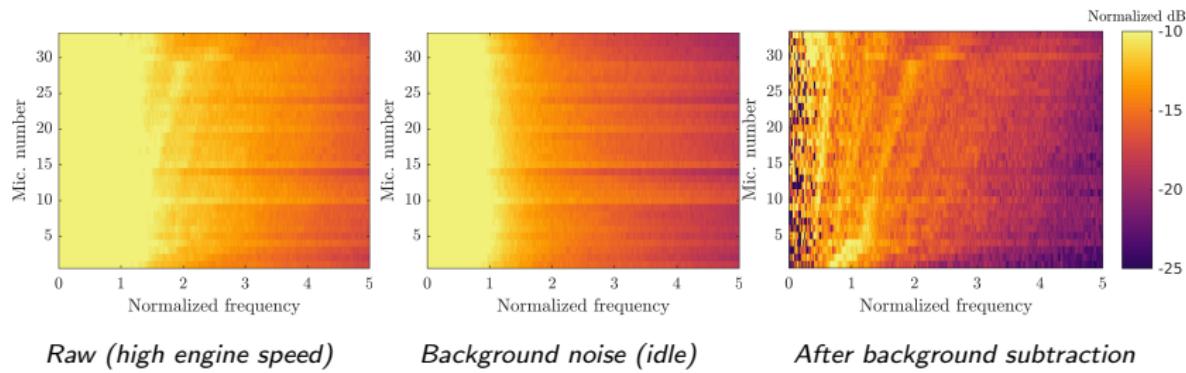
- ▶ Cruise flight condition: Mach 0.85
- ▶ 5 different engine speed
 - + 1 background meas. (idle speed)
- ▶ 35 microphones flushmounted on the aft fuselage
- ▶ 9 microphones + 6 accelerometers in the cabin
- ▶ CSM:
 - 4 Hz resolution
 - 60 sec record length
 - Hanning window
 - overlap : 70% (500 snapshots)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

from Helffer, ICSV 2018



Application to flight test measurements

Autospectra of the outer mic. in the MF frequency range



Background noise (idle)

After background subtraction

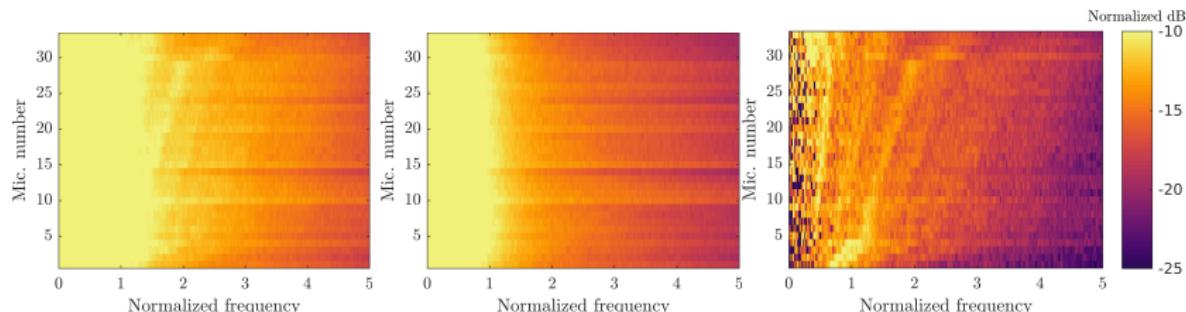
Raw (high engine speed)

PFA denoising

Reference-based denoising

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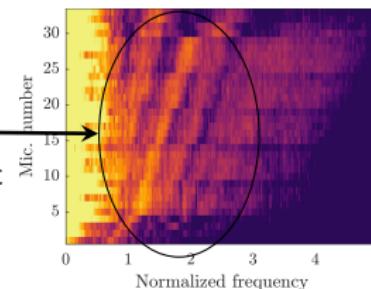
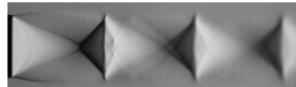


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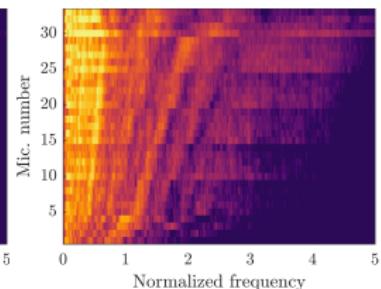
Background noise (idle)

After background subtraction

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



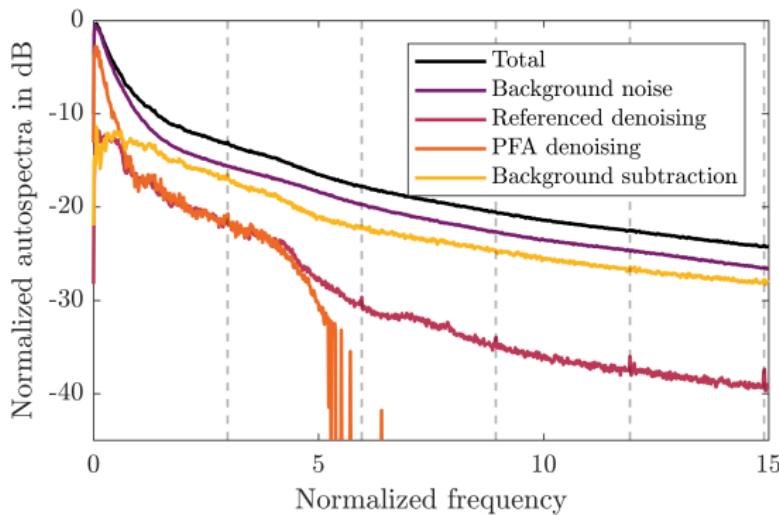
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Reference-based denoising

From B. André, Ph.D. thesis, 2013

Application to flight test measurements

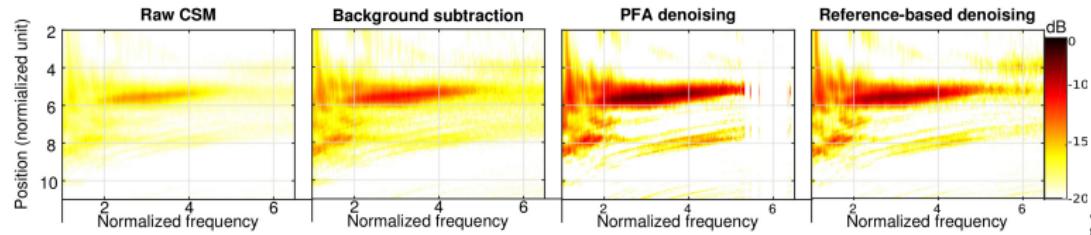
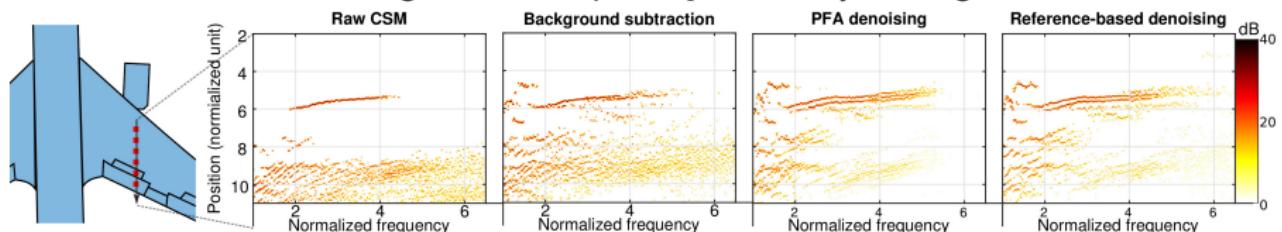


- ▶ Reduces the noise of 10-15 dB
- ▶ PFA :
 - Few denoising at very low frequency → TBL noise is correlated
 - No extracted signal at high frequency → change the statistical model
- ▶ PFA and reference-based denoising are in good agreement in the MF range

Application to flight test measurements – Imaging

Inverse method

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

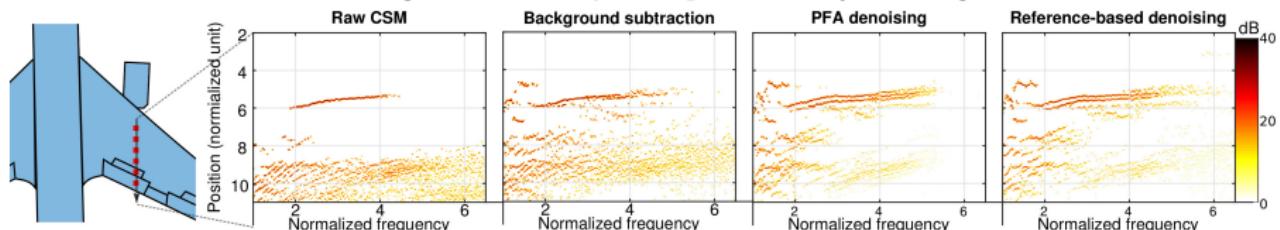


Conventional Beamforming

Application to flight test measurements – Imaging

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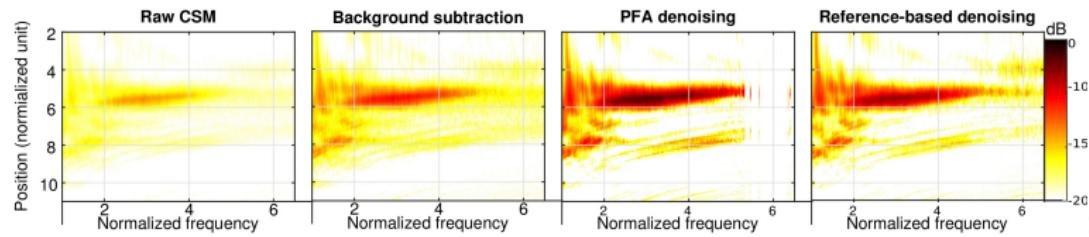
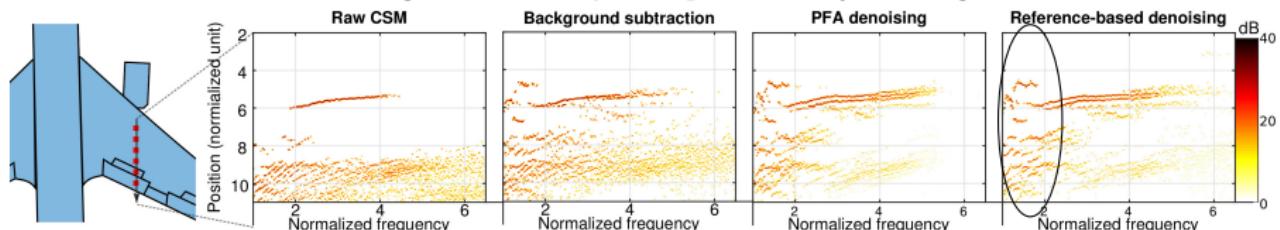
Conventional Beamforming

- ▶ Advanced denoising increase the dynamic of the beamforming map
- ▶ 2 dominant wide-band sources → visible with advanced denoising

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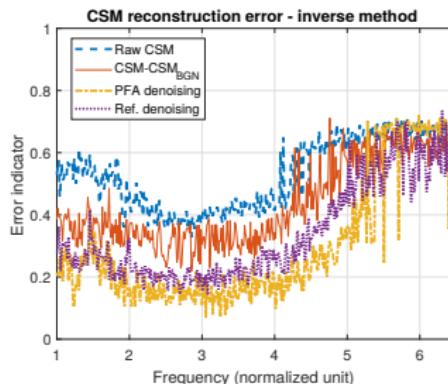
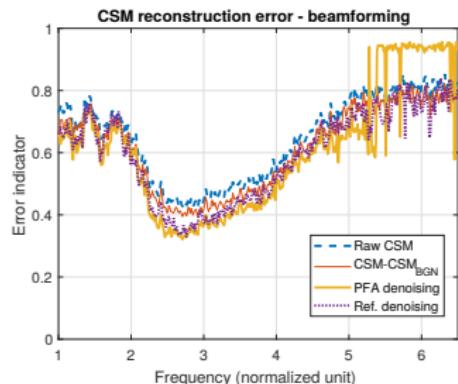
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- ▶ 4 correlated sources in the 1-2 frequency band (caused interference patterns)

Application to flight test measurements – Imaging

$$\text{Error} = \frac{\|S_{pp}^{\text{denoised}} - GS_{qq}G'\|_1}{\|S_{pp}^{\text{denoised}}\|_1 + \|GS_{qq}G'\|_1}$$

- ▶ 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

→ 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

