

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

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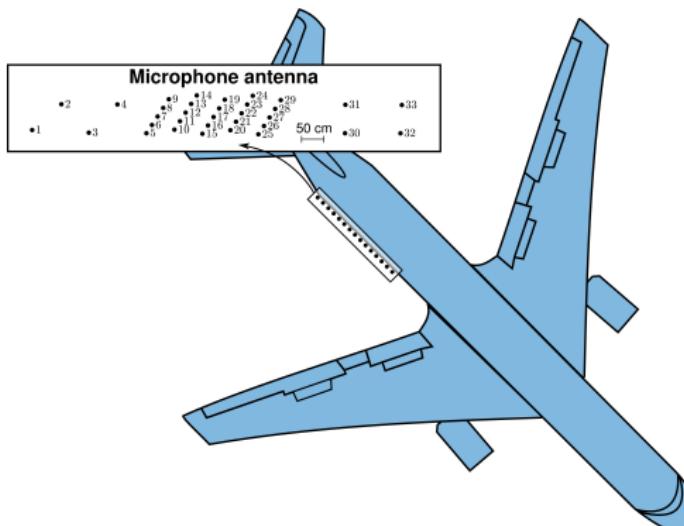
³ Airbus, Toulouse, France

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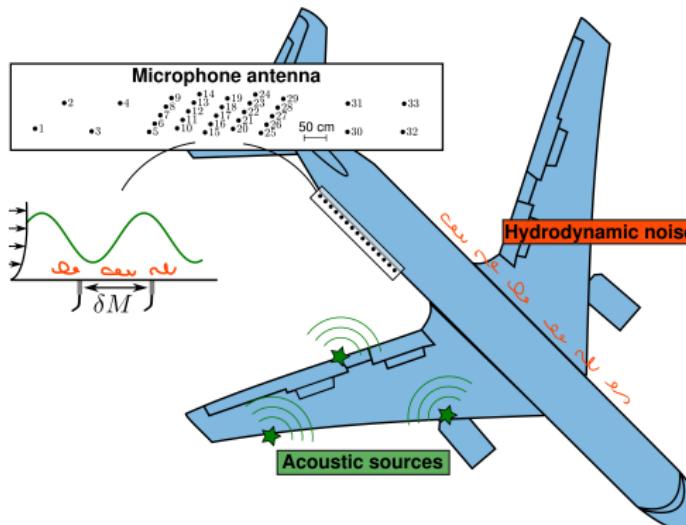
Context

- ▶ **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, . . .
- ▶ 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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We propose a new method

- ▶ Solve an inverse problem to recover the source signal

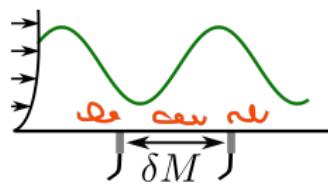
and compare it to an existing method

- ▶ 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**

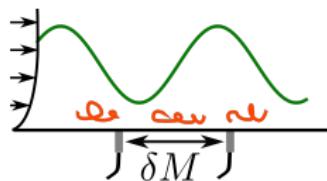
CSM properties



At one frequency and for $i = 1, \dots, I$ snapshots

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

CSM properties

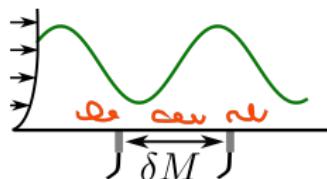


$$\mathbf{S}_{xy} = \frac{1}{I} \sum_{i=1}^I \mathbf{x}_i \mathbf{y}_i^H$$

At one frequency, for averaged Cross-Spectral Matrix:

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

CSM properties



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At one frequency, for averaged Cross-Spectral Matrix: $I \rightarrow \infty$

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



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

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- 2 Probabilistic Factor Analysis (PFA)**
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Probabilistic Factor Analysis (PFA)

► Statistical model

At one frequency and for the i^{th} snapshot:

$$\text{vector of mic. pressure} \longrightarrow \boldsymbol{p}_i = \mathbf{L} \cdot \mathbf{c}_i + \mathbf{n}_i \quad \begin{matrix} \leftarrow \text{noise (+model errors)} \\ \begin{matrix} \nearrow \text{mixing matrix} \\ \searrow \text{vector of latents factors} \end{matrix} \end{matrix}$$

- 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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mixing matrix \swarrow weights \uparrow vector of latents factors \searrow

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- Extract anisotropic noise
- Weights enforce sparsity \rightarrow lower the number of factors
- Strong data compression

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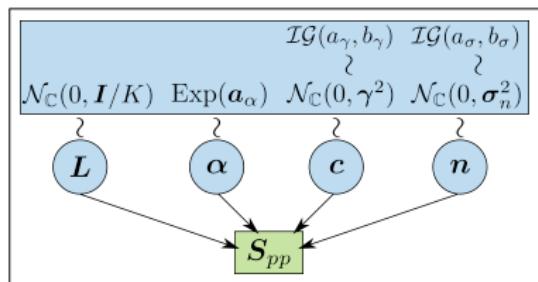
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► Bayesian approach : See parameters as random variables

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

+ 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*

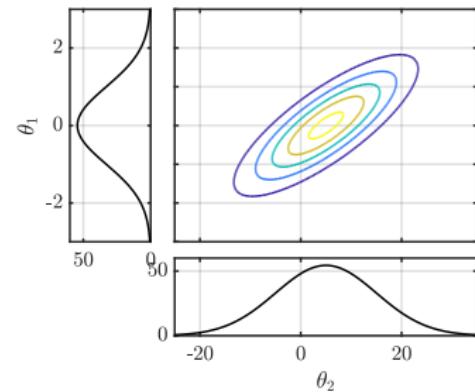
- ▶ Numerical method: the Gibbs sampler
- ▶ MCMC algorithm
- ▶ Global optimization process

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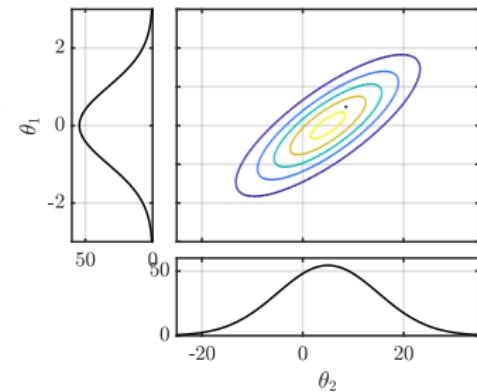


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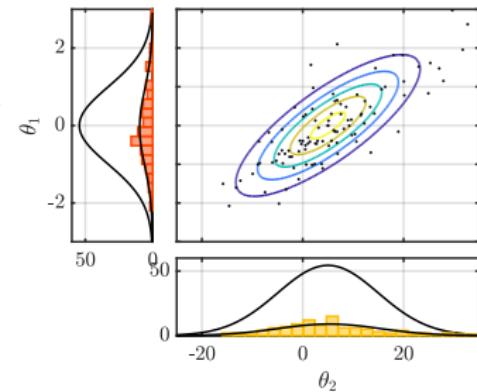


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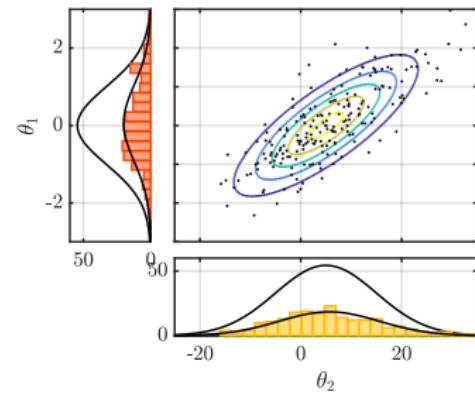


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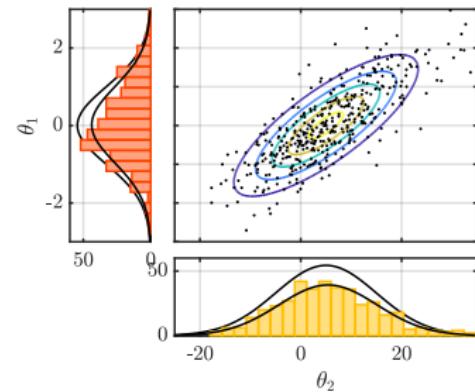


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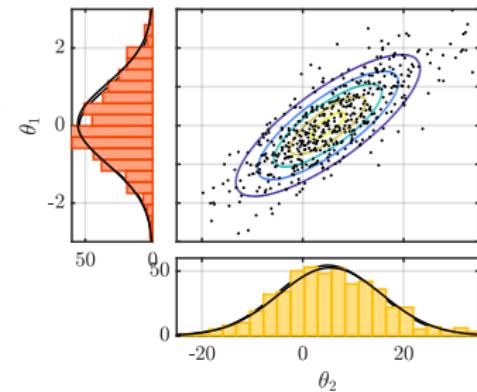


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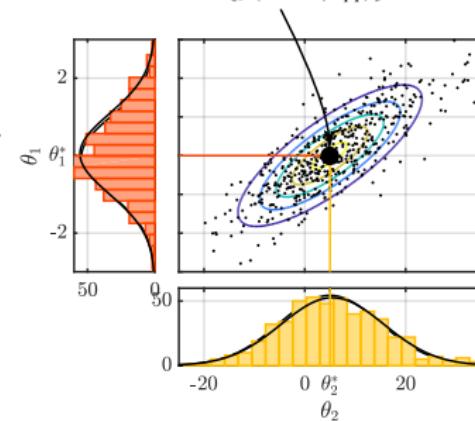
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$$\max\{p(\theta_1, \theta_2 | S_{pp})\}$$

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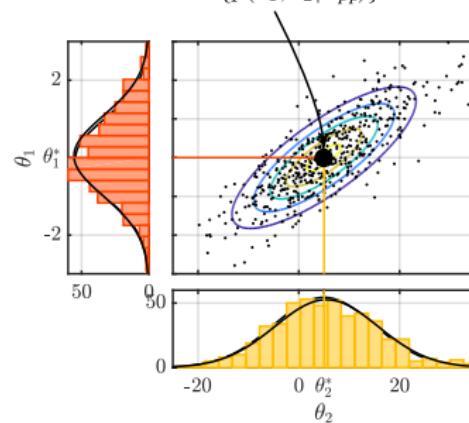
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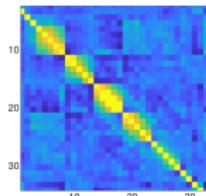
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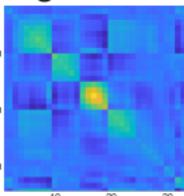


Example of inflight measurements

Measured CSM

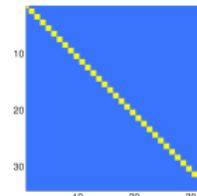


Signal CSM



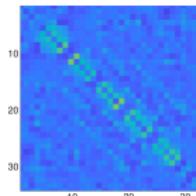
=

Noise CSM



+

Residual CSM



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
 - blind: no hypothesis on the source

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 - preserves the CSM properties
 - reduces data dimension
 - no input parameter to set
 - blind: no hypothesis on the source
- Sensitive to prior choices
esp. for ill-posed problem
 - Computationally expensive

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Denoising with reference channels

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

p : noisy measurements
 r : noise-free reference signals
 a : denoised signals

} synchronous acquisitions

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

→

Generalization of the
coherent spectrum
(Bendat and Piersol, 1980)

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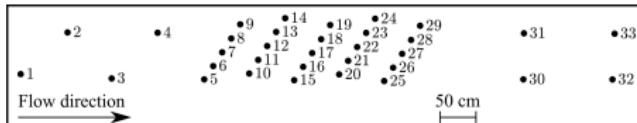


- ▶ Simple to implement
- ▶ Low computational cost
- ▶ Require extra measurements
- ▶ Reference channels have to be noise-free
(or independent from TBL)

- 1 CSM properties**
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Application to flight test measurements

- ▶ Cruise flight condition: Mach 0.85
- ▶ High engine speed + 1 background meas. (idle speed)
- ▶ 33 microphones flushmounted on the aft fuselage
- ▶ 9 microphones + 6 accelerometers in the cabin for reference only
- ▶ CSM:
 - 4 Hz resolution
 - 60 sec record length
 - Hanning window
 - overlap : 70% (500 snapshots)

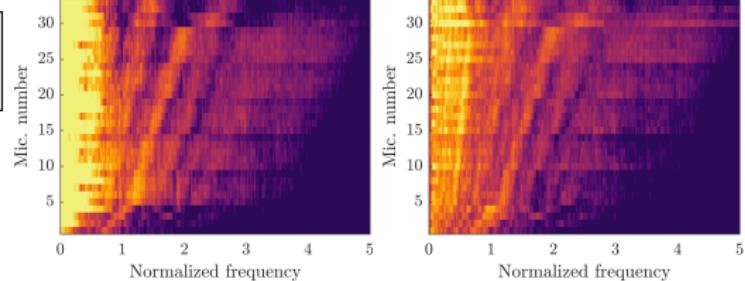
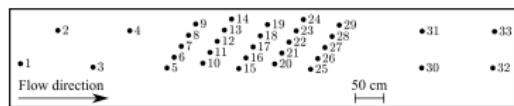
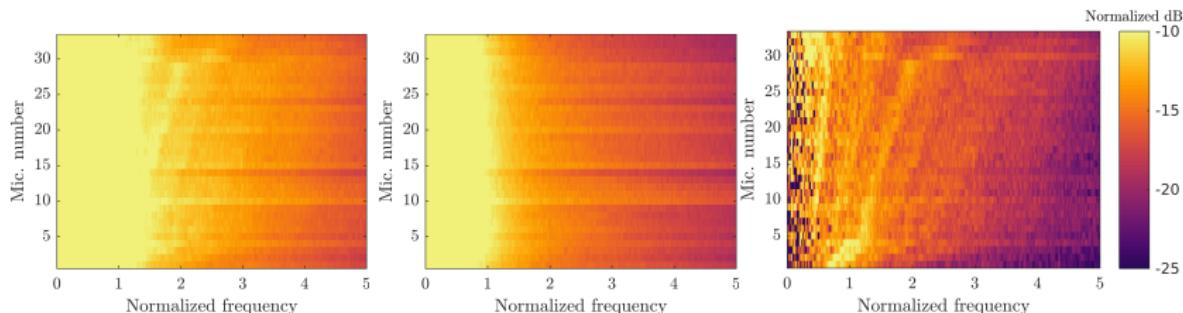


Outer microphone antenna



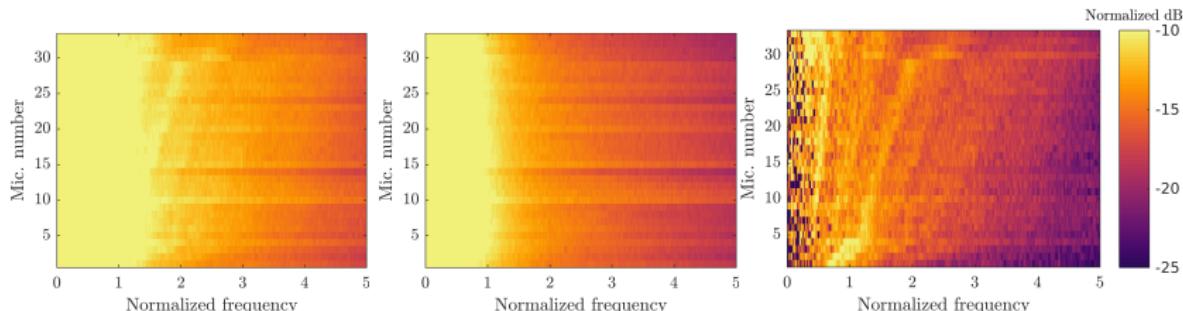
Application to flight test measurements

Autospectra of the outer mic. in the MF frequency range



Application to flight test measurements

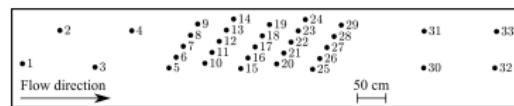
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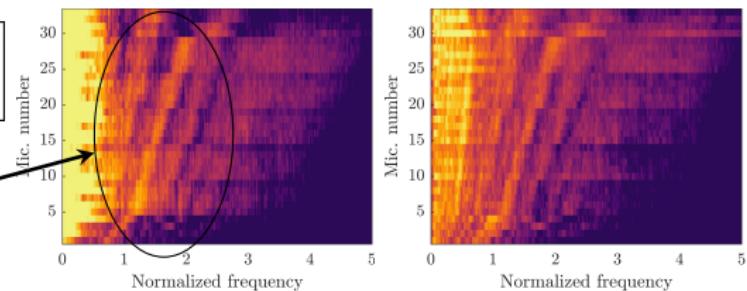
Raw (high engine speed)

Background noise (idle)

After background subtraction



► **Interference patterns:**
Regularly spaced monopoles in
the jet (BBSAN)

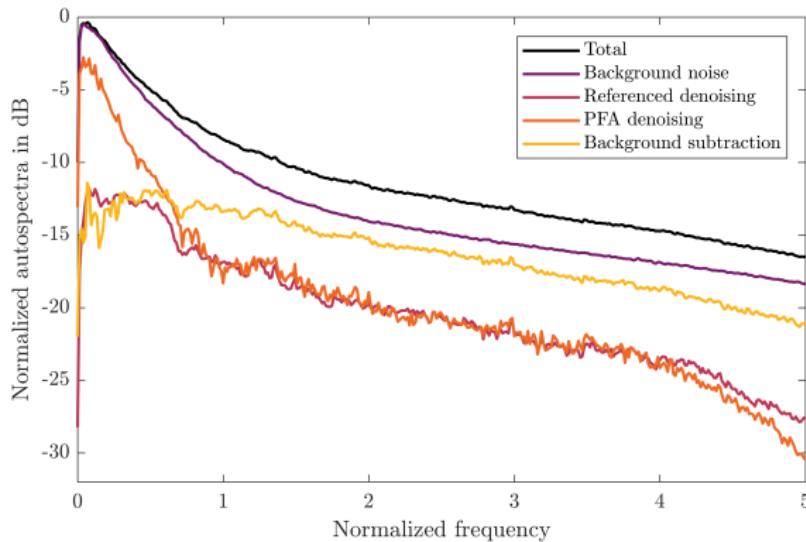


PFA denoising

Reference-based denoising

Application to flight test measurements

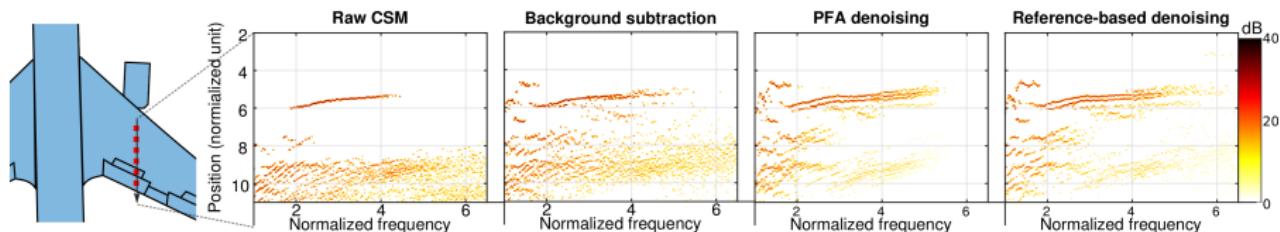
Autospectra averaged over the microphones



- ▶ Reduces the noise of 10-15 dB
- ▶ PFA : Few denoising at very low frequency → TBL noise is correlated
- ▶ PFA and reference-based denoising are in good agreement in the MF range

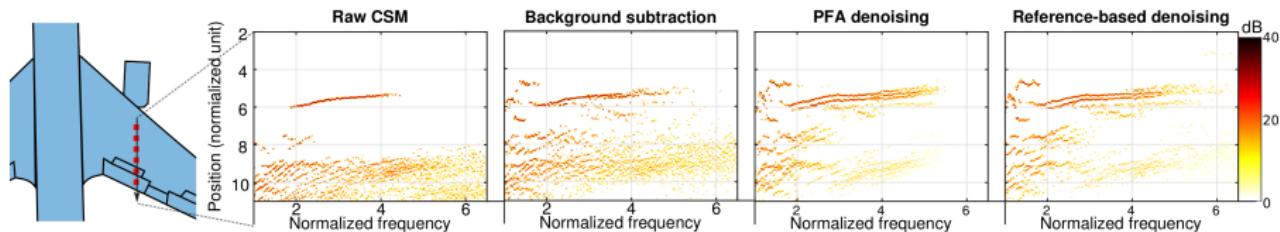
Application to flight test measurements – Imaging

Inverse method: Iterative Reweighted Least Squares, $p = 0$
and Bayesian regularization (Antoni et al., 2019)



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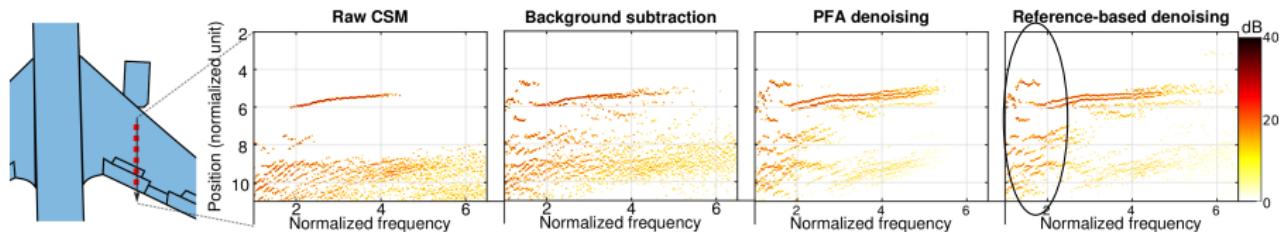
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- ▶ 2 dominant wide-band sources
↪ visible only with advanced denoising

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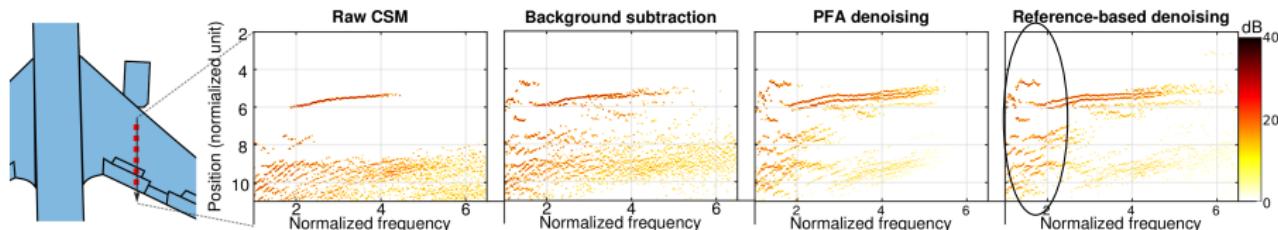
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- ▶ 4 correlated sources in the 1-2 frequency range
↪ caused interference patterns

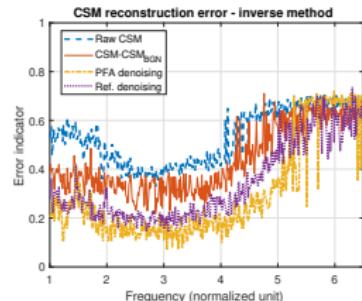
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↪ caused interference patterns
- ▶ PFA gives the lowest error

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



Conclusions

- ▶ Denoising with different requirements/hypothesis
 - but both give similar results
- ▶ Denoising increases of the imaging performance
- ▶ 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

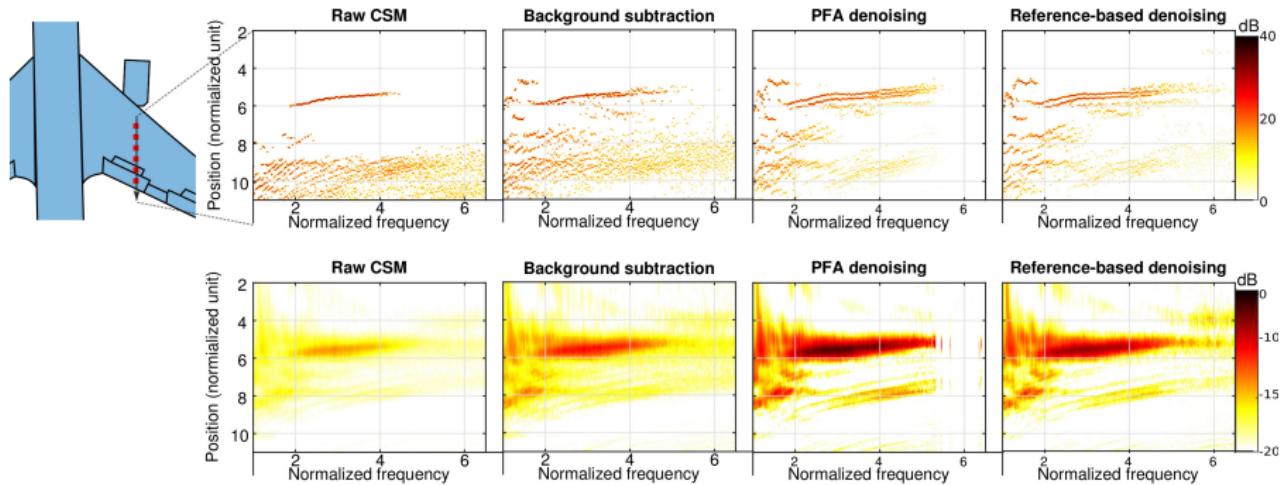
This work was performed in the framework of Clean Sky 2 Joint Undertaking, European Union (EU), Horizon 2020, CS2-RIA, ADAPT project, Grant agreement no 754881.

References

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- J. Bendat and A. Piersol. *Engineering applications of correlation and spectral analysis*. Wiley-Interscience, New York, 1980.

Appendix – Beamforming

Iterative Reweighted Least Squares, $p = 0$
and Bayesian regularization



Beamforming coherence

Appendix – Credible interval

