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

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Context

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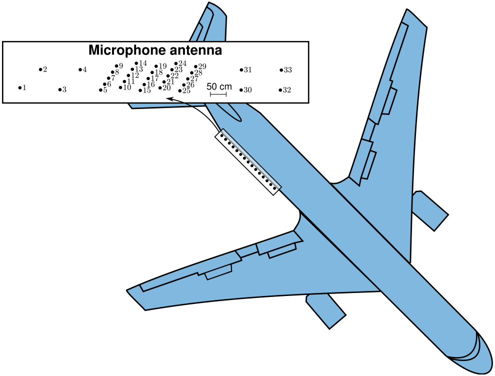
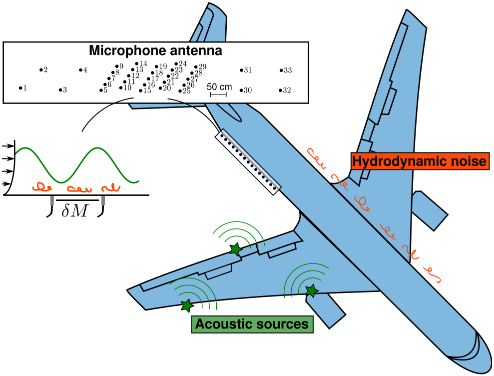


Context

- **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 signal from 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

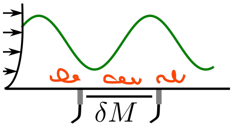
1. CSM properties

2. Probabilistic Factor Analysis (PFA)

3. Denoising with reference channel

4. Application to flight test measurements

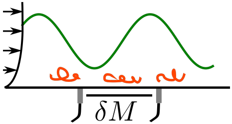
CSM properties



For $i = 1, \ldots, I$ 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:

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

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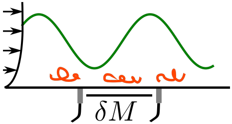

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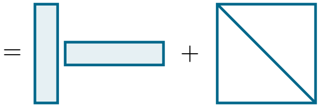

- Acoustic signal with **high** spatial correlation: **low-rank CSM**
- TBL Noise with **low** spatial correlation: **diagonal CSM**

Probabilistic Factor Analysis (PFA)

- **Statistical model**

measured spectra

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

noise (+model errors)

mixing matrix

latents factors

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

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  $\hookrightarrow$ Data compression

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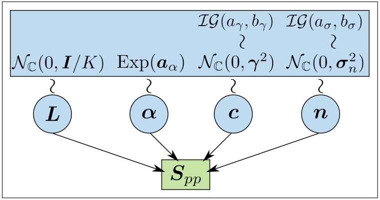
- **Bayesian approach :** See parameters as random variables

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

$+$ 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:

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

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

Probabilistic Factor Analysis (PFA) – Optimisation

Maximizing the posterior probability distribution

↪*Find the optimal parameter set that best fit 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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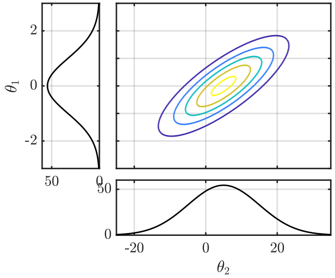

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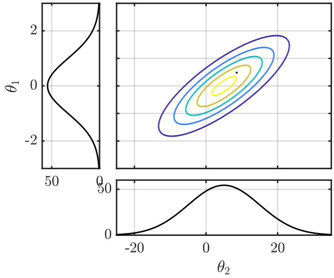

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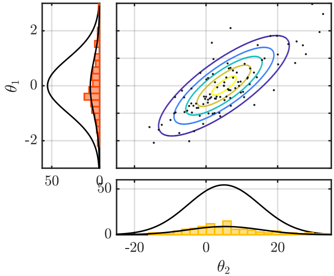

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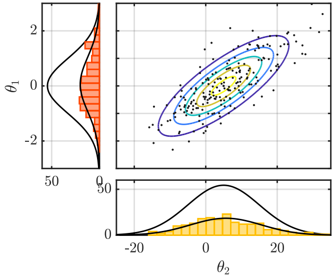

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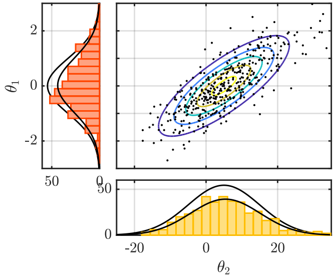

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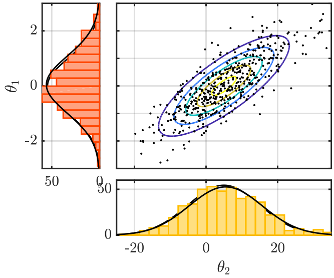

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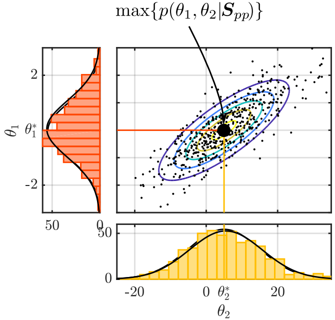

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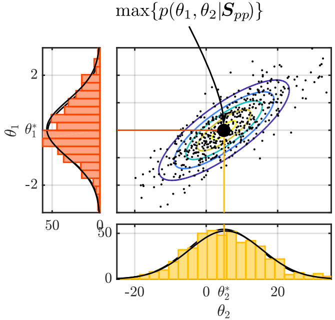

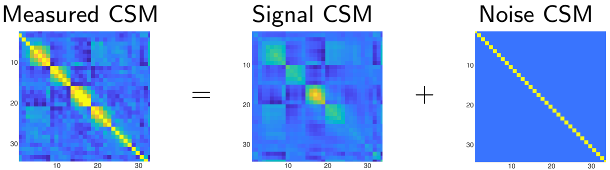

Example of inflight measurements

Probabilistic Factor Analysis (PFA)

+

- The bayesian approach:
  - prior knowledge is part of the model
  - gives credible interval
- Probabilistic Factor Analysis :
  - preserves CSM positivity
  - reduces data dimension
  - no input parameter to set
  - adaptable model
  - 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

$$\left.\begin{array}{ll} \boldsymbol{y} & : \text{noisy measurements} \\ \boldsymbol{r} & : \text{noise-free reference signals} \\ & \text{(ex : intérieur de cabine)} \end{array}\right\} \text{synchronous acquisition}$$

$\boldsymbol{a}$: 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

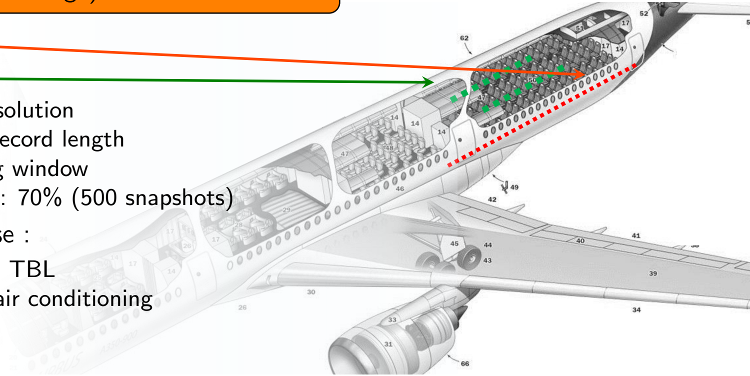
-

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

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
- 14 microphones in the cabin

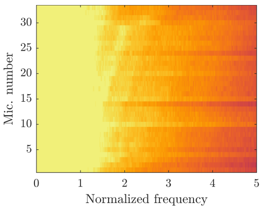
a corriger : 9 mic + 6 accel (internal side of the fuselage)



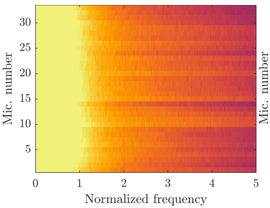
- CSM:
  - 4 Hz resolution
  - 60 sec record length
  - Hanning window
  - overlap : 70% (500 snapshots)
- Type of noise :
  - outside: TBL
  - inside: air conditioning

Application to flight test measurements

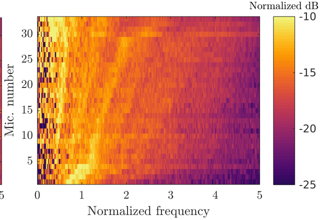
Autospectres zoomés basses-moyennes fréquences



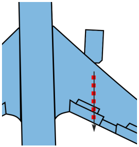
Mesure brute

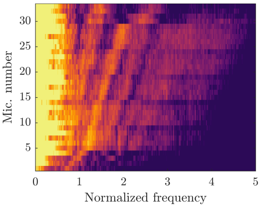


Bruit de fond

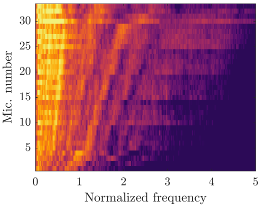


Débruitage : soustraction du bruit de fond





Débruitage : AFP



Débruitage référencé

Application to flight test measurements

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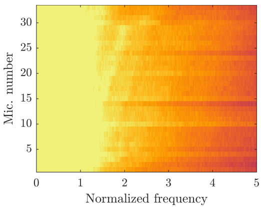

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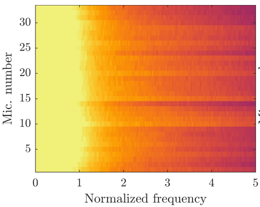

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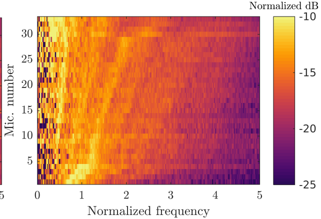

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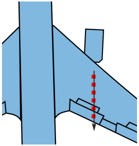
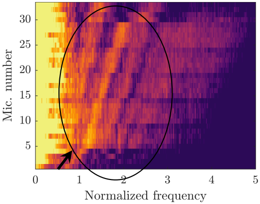
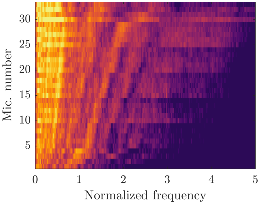


figures d'interférences : bruit de chocs large bande



Débruitage : AFP



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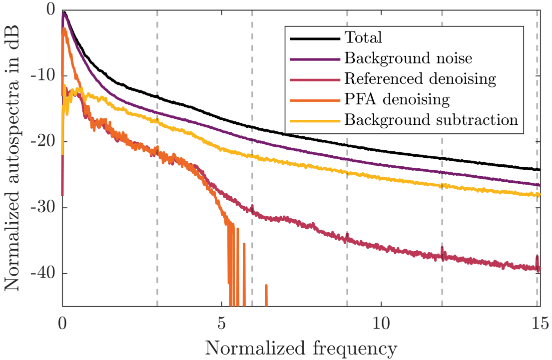
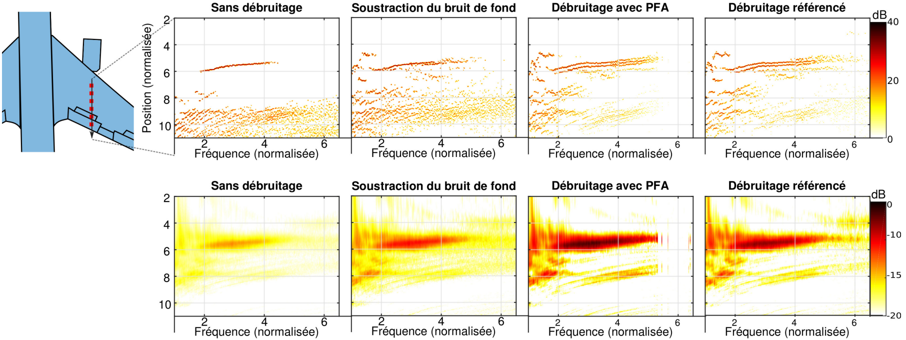


- Dynamique améliorée de 10-15 dB
- PFA :
  - Peu de bruit extrait à très basses fréquences → bruit corrélé
  - Pas de signal à moyennes fréquences → modèle/priors à adapter
- PFA et méthode référencée concordantes en BF

Application to flight test measurements – Imagerie

Méthode inverse

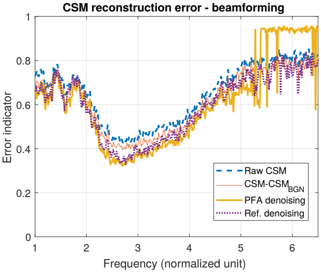
Iterative Reweighted Least Squares, $p = 0$ + régularisation baysienne

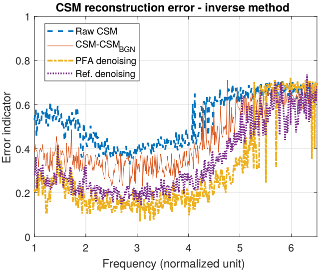


Formation de voie

Application to flight test measurements – Imagerie

$$\text{Erreur} = \frac{\|\boldsymbol{S}_{aa}^{\text{débruitage}} - \boldsymbol{S}_{aa}^{\text{repropagé}}\|_1}{\|\boldsymbol{S}_{aa}^{\text{débruitage}}\|_1 + \|\boldsymbol{S}_{aa}^{\text{repropagé}}\|_1}$$



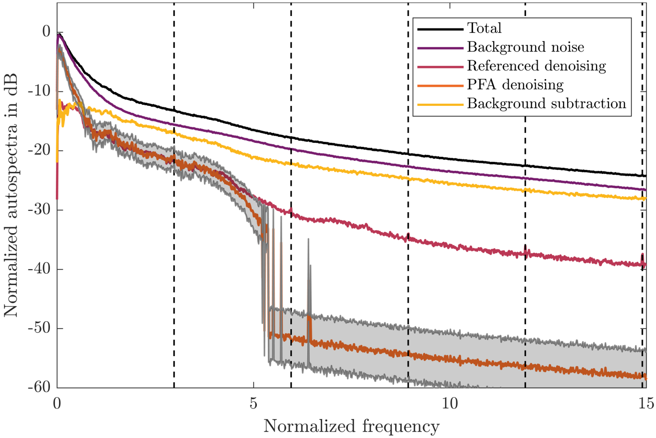


Conclusions et perspectives

- Débruitage avec différentes hypothèses, mais résultats similaires
- Amélioration des performances d'imagerie
  - dynamique
  - localisation de sources corrélées
- Corrections pour l'AFP :
  - augmenter la robustesse de l'échantillonneur
  - adapter le modèle statistique (meilleur contrôle de la parcimonie)
  - prendre en compte la corrélation du bruit en BF

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.

Appendix



In gray : 95% credible interval for PFA denoising