Joint source localization and dereverberation by sound field interpolation using sparse regularization

Niccolò Antonello[1,2], Enzo De Sena[3], Marc Moonen[1], Patrick A. Naylor[4], Toon van Waterschoot[1,2]

[1]ESAT–STADIUS, KU Leuven, BE
[2]e-Media Lab, KU Leuven, BE
[3]IoSR University of Surrey Guilford, UK
[4]Electronic Engineering, Imperial London College, UK

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Outline

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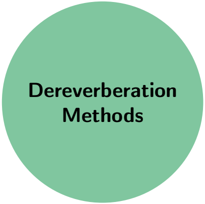
Reverberant environments reduce speech intelligibility



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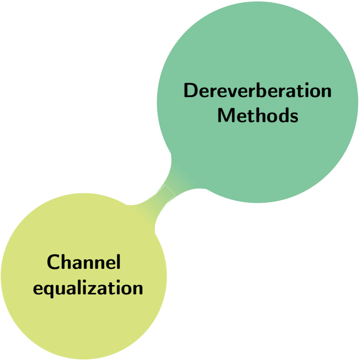

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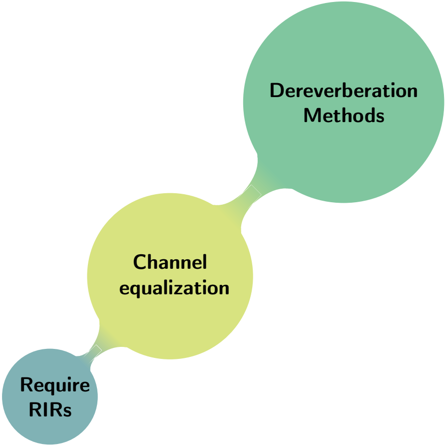

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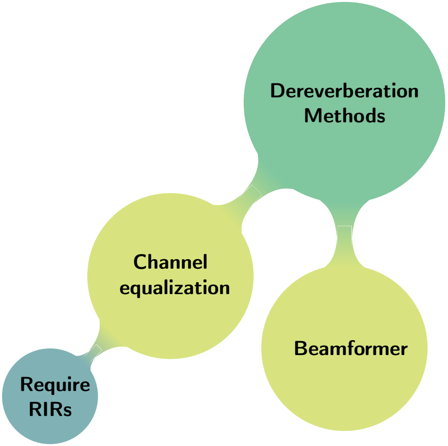

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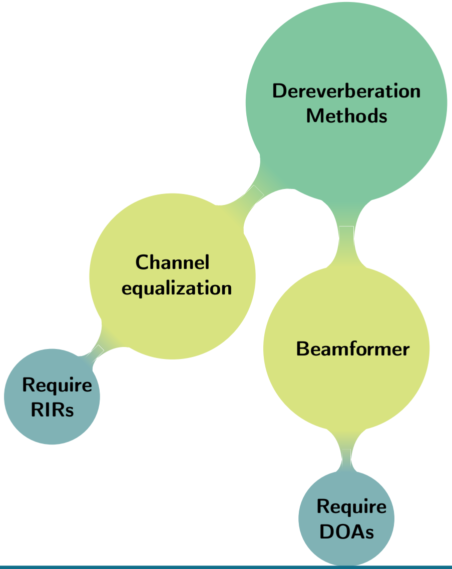

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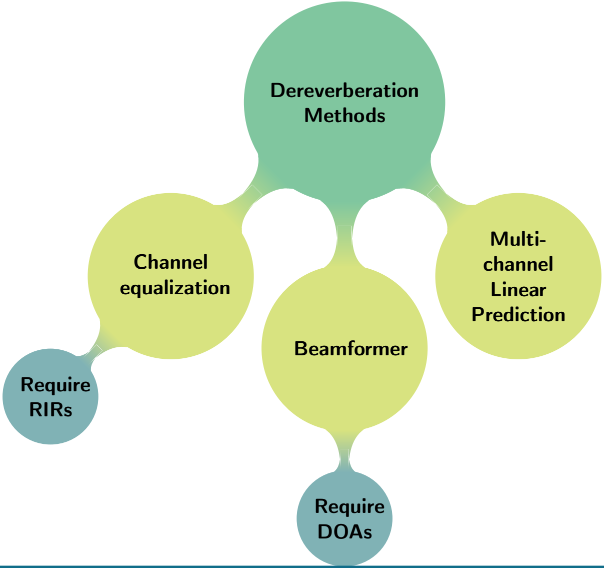

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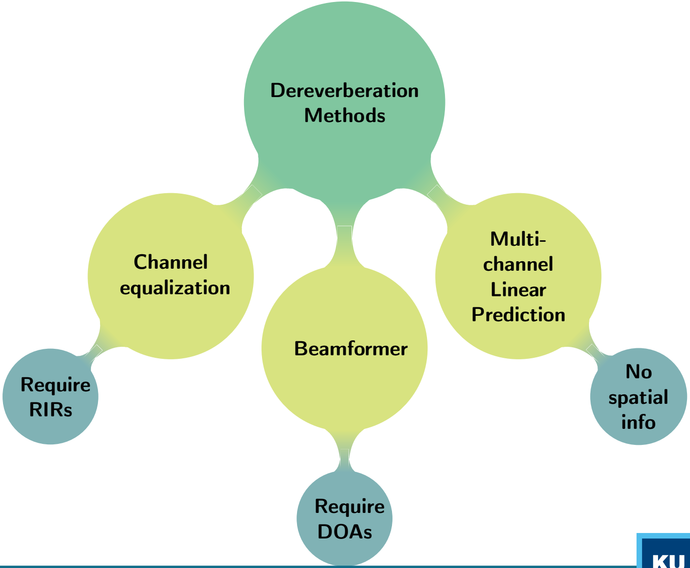

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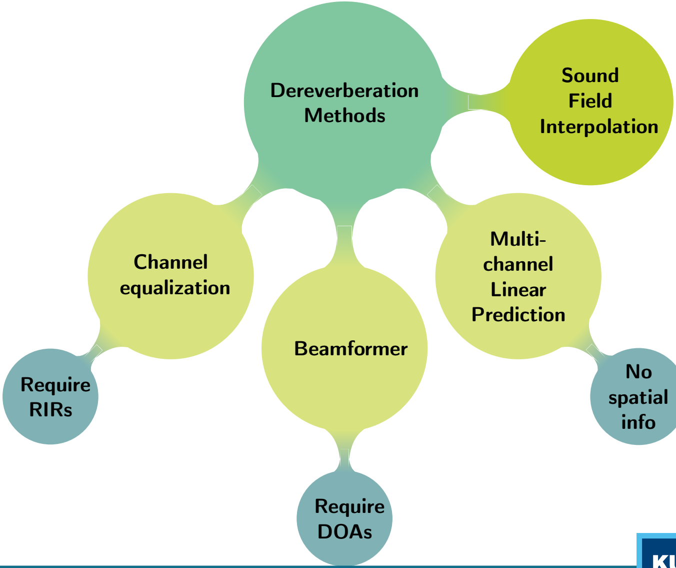

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Novel method

- Localization and dereverberation formulated jointly

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    - spatial sparsity
    - spatio-temporal sparsity
    - spatio-spectral sparsity

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  - Sparse prior
    - spatial sparsity
    - spatio-temporal sparsity
    - spatio-spectral sparsity
- Large-scale nonsmooth optimization problem:
  - accelerated variant of Proximal Gradient (PG) algorithm
  - Weighted Overlap-Add (WOLA) procedure

Outline

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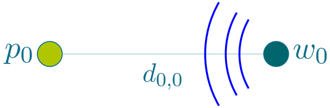
Time-domain equivalent source model (TESM)

Time-domain spherical wave definition (Green's function):

$$p(t,\mathbf{x})|_{\mathbf{x}=\mathbf{x}_m} = \frac{1}{4\pi d_{l,m}}\delta\left(t - \tfrac{d_{l,m}}{c}\right) * w(t),$$

where $w(t)$ is a *weight signal* driving the *equivalent source*.



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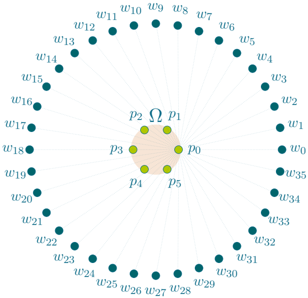
Time-domain equivalent source model (TESM)

Using many equivalent sources and discretizing over time:

$$p(\mathbf{x},t)|_{\mathbf{x}=\mathbf{x}_m} = \sum_{l=0}^{N_w-1} \frac{1}{4\pi d_{l,m}} \delta\left(t - \frac{d_{l,m}}{c}\right) * w_l(t),\ \mathbf{x}_m \in \Omega,$$

any sound pressure inside source-free volume Ω can be modeled.



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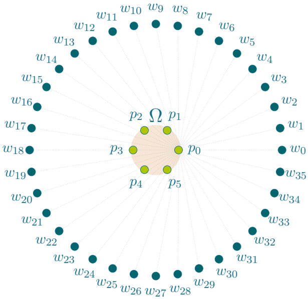
Time-domain equivalent source model (TESM)

Generalizing for many mic positions:

$$\mathbf{P} = \mathsf{D}_t \mathbf{W}$$

where $\mathsf{D}_t : \mathbb{R}^{N_t \times N_w} \to \mathbb{R}^{N_t \times N_m}$ *dictionary* of *spherical waves*.



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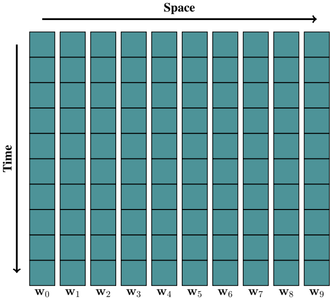

Plane wave decomposition model (PWDM)

Same using many plane waves (frequency domain):

$$\hat{p}(\mathbf{x}, f)|_{\mathbf{x}=\mathbf{x}_m} \approx \sum_{l=0}^{N_w-1} e^{-ik_f d_{l,m}} \hat{w}_l(f) \text{ for } \mathbf{x}_m \in \Omega,$$

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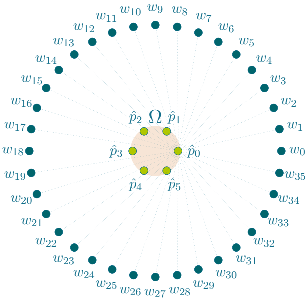

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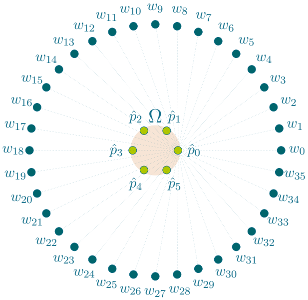

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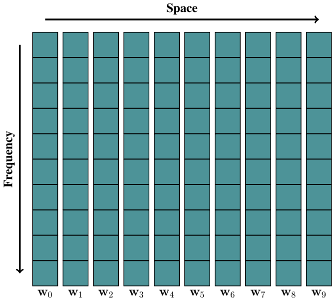

Outline

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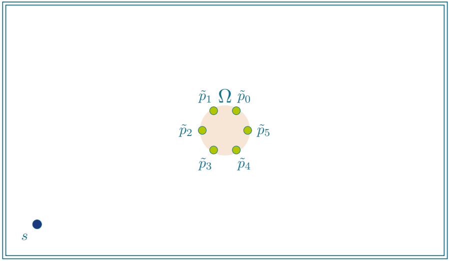
The inverse problem

Sound field created by *far field* source is recorded by an array of N_m mics.



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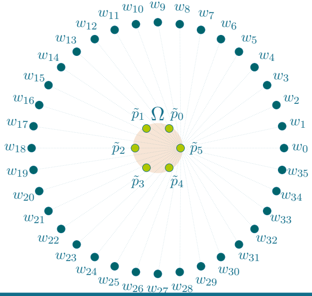
The inverse problem

Optimal weight signals $\mathbf{W}^\star$ found by solving:

$$\mathbf{W}^\star = \underset{\mathbf{W}}{\operatorname{argmin}} \quad f(\mathbf{W}) = \frac{1}{2}\|\mathrm{D}\mathbf{W} - \tilde{\mathbf{P}}\|_F^2$$

heavily *ill-posed problem* $\rightarrow$ **over-fitting**



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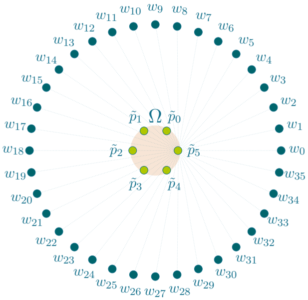
$$\mathbf{W}^\star = \underset{\mathbf{W}}{\operatorname{argmin}} \quad \frac{1}{2}\|\mathrm{D}\mathbf{W} - \tilde{\mathbf{P}}\|_F^2 + \lambda g(\mathbf{W})$$

regularize using a sparsity inducing *regularization term* g.



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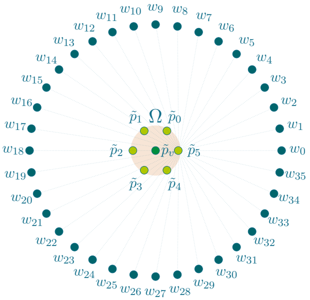
Use additional mic $\tilde{\mathbf{p}}_v$ for tuning regularization parameter λ.



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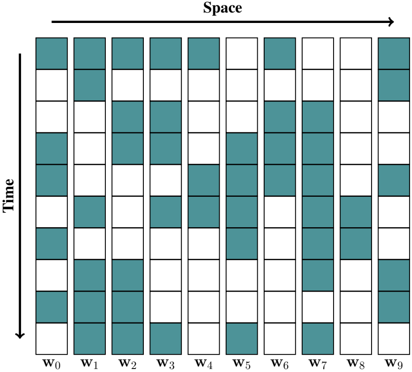
Spatio-temporal sparsity

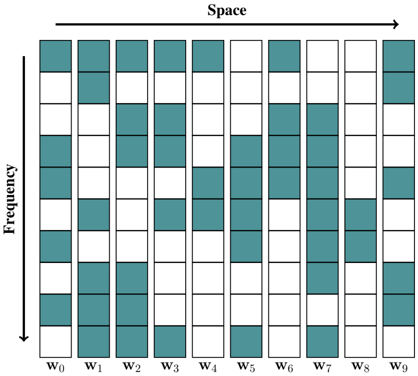
Model: TESM
Regularization: $g(\mathbf{W}) = \|\mathbf{W}\|_1$



Acoustic model and Sparsity combinations

Spatio-spectral sparsity

Model: PWDM
Regularization: $g(\mathbf{W}) = \|\mathbf{W}\|_1$



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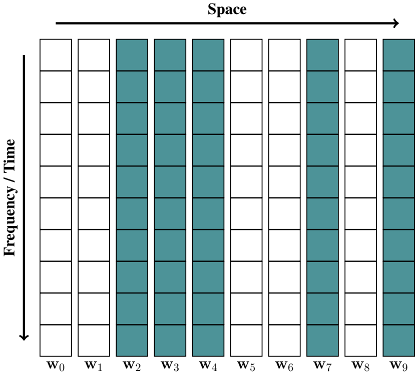
Acoustic model and Sparsity combinations

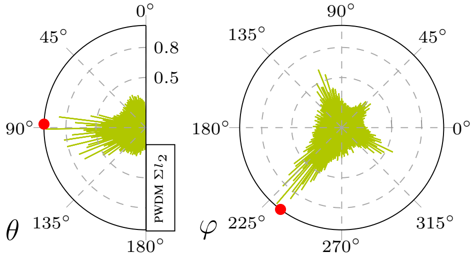
Spatial sparsity

Model: both PWDM and TESM
Regularization: $g(\mathbf{W}) = \sum_{l=0}^{N_w-1} \|\mathbf{w}_l\|_2$



Joint Dereverberation & Localization

After solving inverse problem obtain $\mathbf{W}^\star$



Plot energy of columns of $\mathbf{w}_l^\star$ as a function of azimuthal (φ) and polar (θ) angles.

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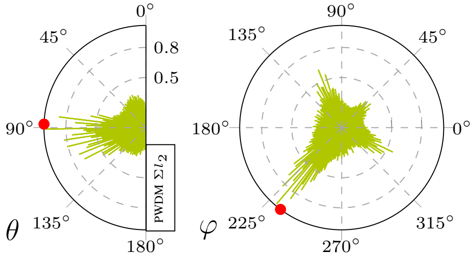

Localization

Find d-th column of $\mathbf{W}^\star$ with strongest energy.
This corresponds to equivalent source with specific DOA.

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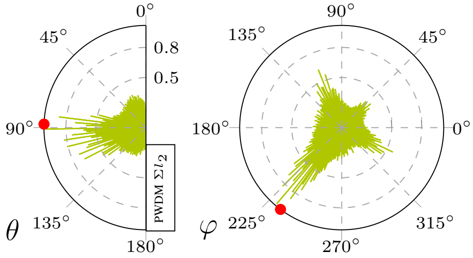

Dereverberation

Dereverberated signal readily available: $\mathbf{w}_d^{\star}$
Reverberation is spatially distributed among equivalent sources

Outline

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Optimization algorithm

Inverse problem: nonsmooth cost function

- f is smooth
- g nonsmooth

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Optimization algorithm

Proximal Gradient (PG) algorithm

- can deal with nonsmooth terms
- cheap iterations
- suitable for large scale problems
- can be accelerated using quasi Newton methods†

† N. Antonello, L. Stella, P. Patrinos and T. van Waterschoot, "Proximal gradient algorithms: applications in signal processing", arXiv:1803.01621, 2018.

`github.com/kul-forbes/StructuredOptimization.jl`

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Optimization problem may still be intractable:

- if $N_w = 500$ $N_t = 16000$ (2 s $F_s = 8$ kHz) $\rightarrow 8 \cdot 10^6$ optimization variables

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Weighted Overlap-Add procedure:

- split $\tilde{\mathbf{P}}$ into overlapping frames of $N_\tau = 512 \rightarrow 256 \cdot 10^3$ optimization variables *sub-problem*

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Outline

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Set-up

- RIRs simulated with Randomized Image Method[1]
  - $T_{60} = 1$ s
  - $[L_x, L_y, L_z] = [7.34, 8.09, 2.87]$ m
- Mic signals created with male speech signal (sensor noise SNR $= 40$dB)
- Spherical microphone array with N_m
- $N_w = 500$ equivalent sources on a Fibonacci Lattice radius 2.9 m

[1] E. De Sena, N. Antonello, M. Moonen, and T. van Waterschoot, "On the Modeling of Rectangular Geometries in Room Acoustic Simulations", IEEE Transactions of Audio, Speech Language Processing, vol. 21, no. 4, 2015.

github.com/nantonel/RIM.jl

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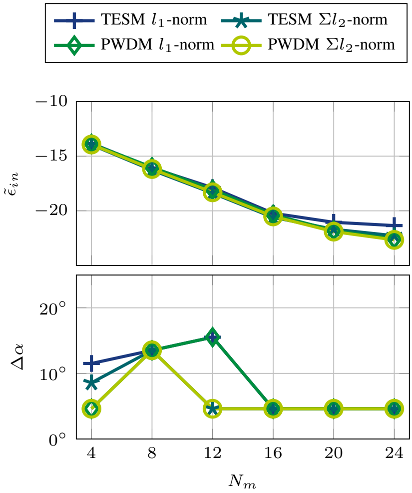
Interpolation error & DOA estimate



- Average interpolation error $\bar{\epsilon}_{in}$
  - Similar performances
  - Spatio-temporal sparsity slightly worse
- DOA estimate
  - good performance even with few mics
  - minimum angular distance of $4.5°$ due to finite number of directions

$\rightarrow$ more mics, better results

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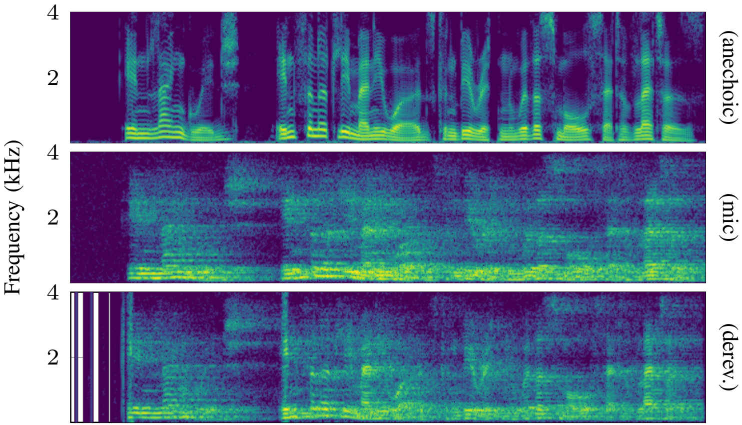
Dereverberation - Spatio-temporal sparsity $N_m = 16$



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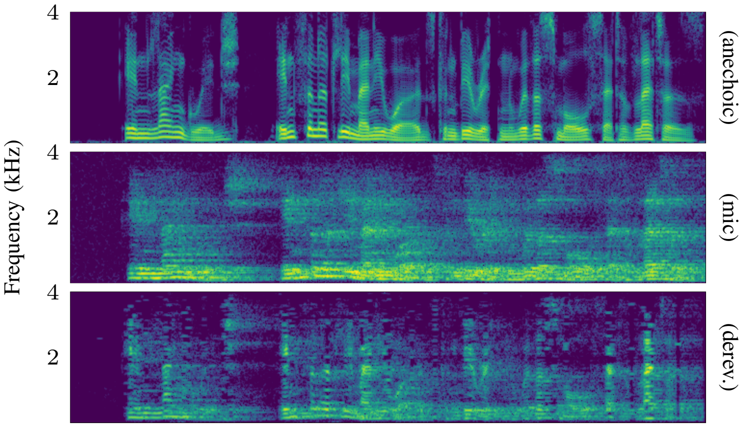
Dereverberation - Spatio-spectral sparsity $N_m = 16$



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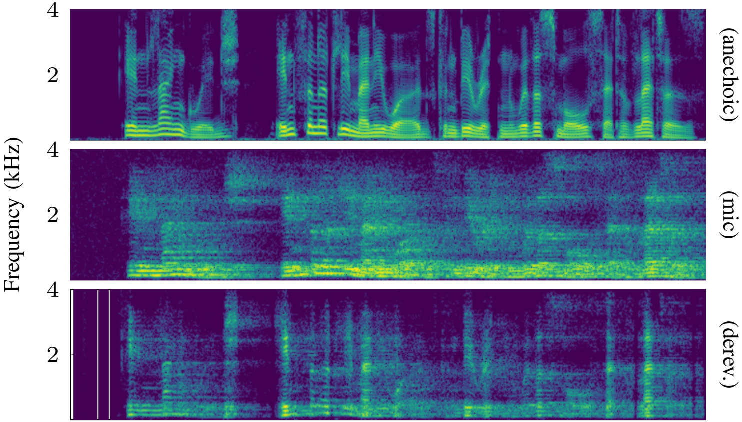
Dereverberation - Spatial sparsity sparsity $N_m = 16$



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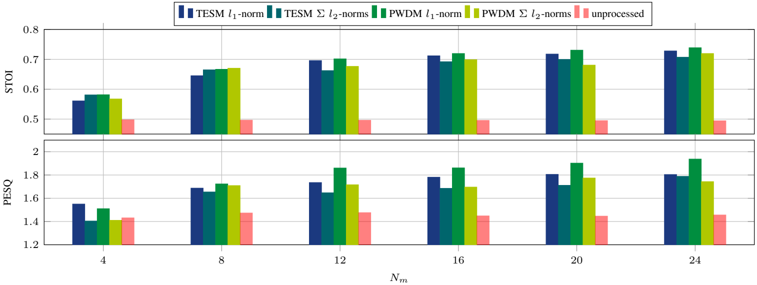
Objective measures



- Speech intelligibility (STOI) & Speech Quality (PESQ) scores
- In line with interpolation error and DOA estimates
- Better performance with spatio-spectral sparsity
- Informal listening test: worse results are with spatio-temporal sparsity
- Sound samples

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Conclusions

- Novel method for joint source localization and dereverberation
  - Inverse problem rely on acoustic model and sparse prior
    - Spatio-temporal sparsity (TESM + l_1-norm)
    - Spatio-spectral sparsity (PWDM + l_1-norm)
    - Spatial sparsity (Σl_2-norm)
  - Solve with accelerated PG algorithm & WOLA procedure
- Simulation results
  - good DOA estimates with few mics
  - Better dereverberation as more mics are used