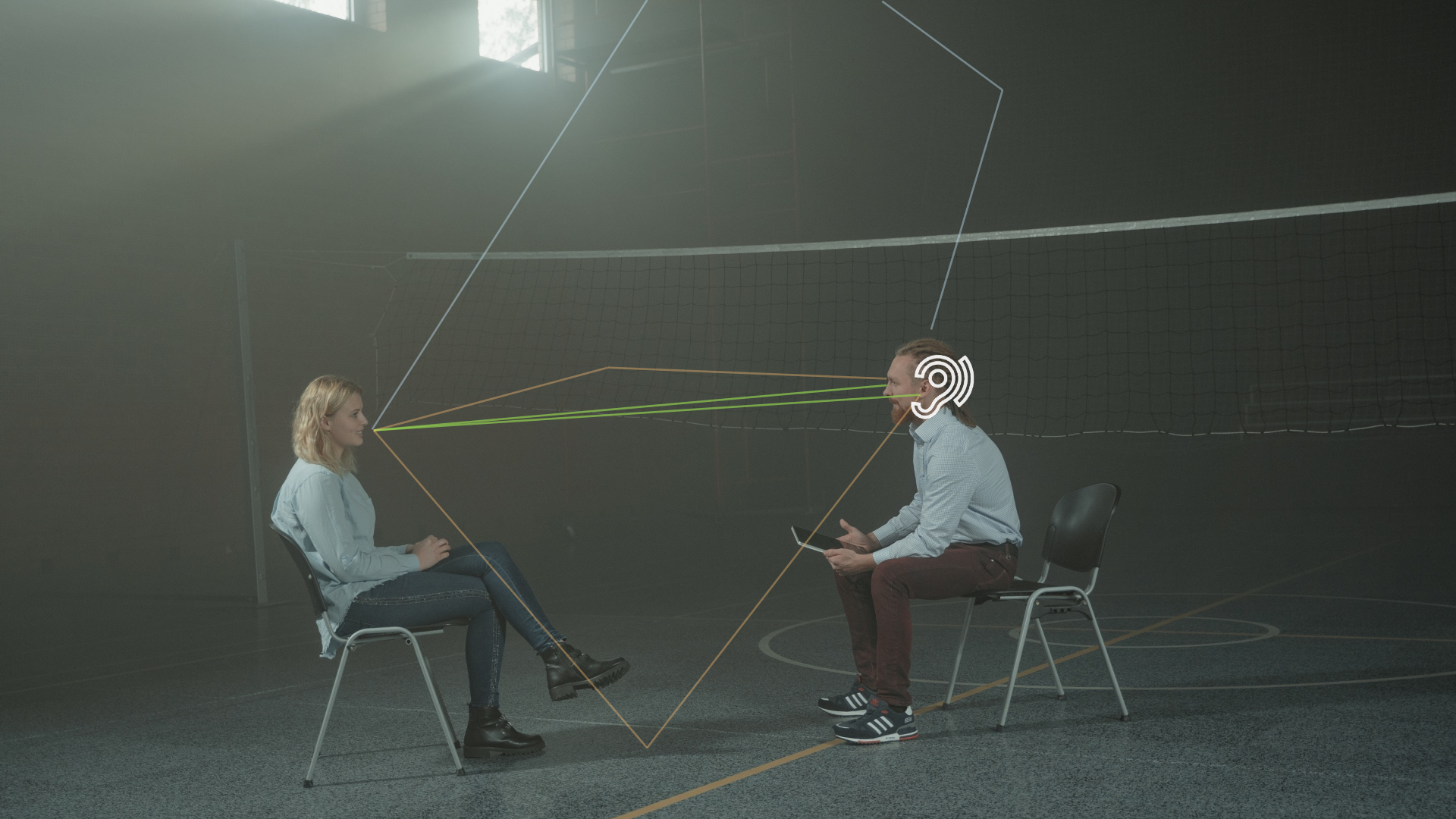


Who am I?





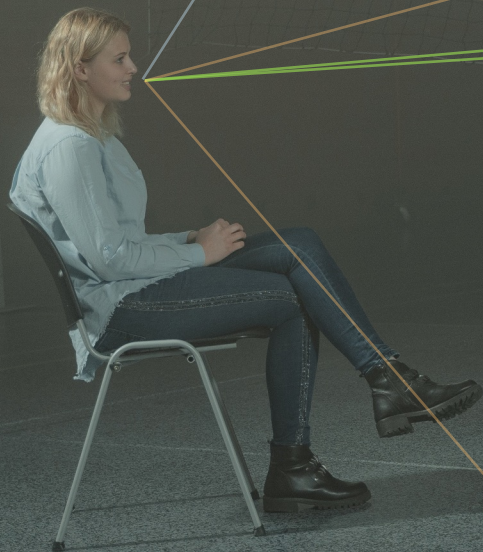




Estimate channel
(room transfer function)



Adjust acoustic scene to
hearing impaired user



Estimate channel
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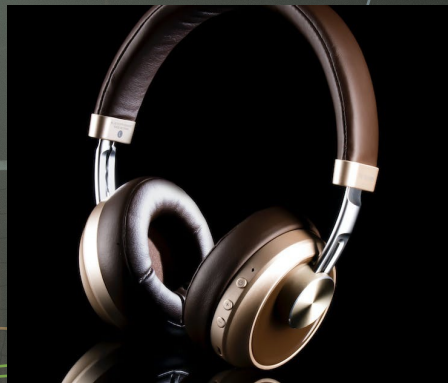


Adjust acoustic scene to
hearing impaired user

Why is it so hard?

- Signals change fast (non-stationarity)
- Spatial cues preservation
- Must be real-time
- Battery





Cramér-Rao bound for acoustic transfer function estimation

Giovanni Bologni (G.Bologni@tudelft.nl), Richard Hendriks, Richard Heusdens
18 December, 2023

On the menu today

Intro

Cramér-Rao bound for acoustic transfer function estimation

1. Parameter estimation & Cramér-Rao bound (CRB)
2. Case study – ATF estimation

My research & open questions

Acoustic transfer function estimation with **inter-frequency correlation**

Parameter estimation

A quantity θ needs to be estimated

Given a (random) model, what is best achievable accuracy on estimating unknown quantity?

Parameter estimation

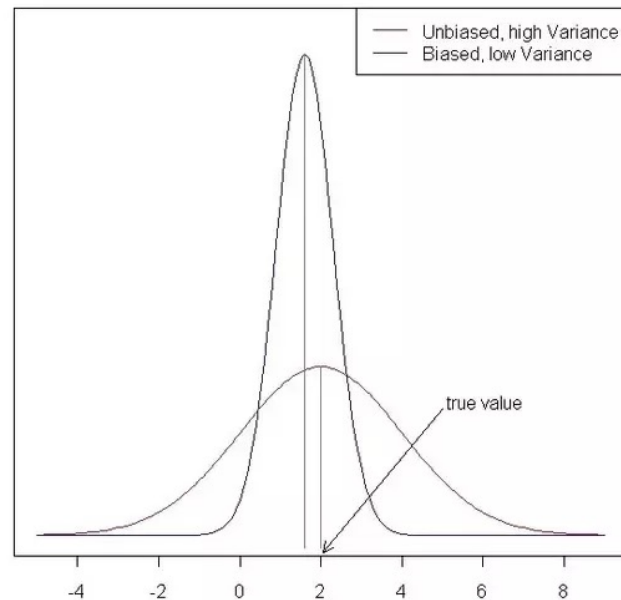
A quantity θ needs to be estimated

Given a (random) model, what is best achievable accuracy on estimating unknown quantity?

Best accuracy = minimum MSE = minimum variance (unbiased estimator)

$$\text{MSE}(\theta, \hat{\theta}) = \text{var}(\hat{\theta}) + \text{bias}^2(\hat{\theta}, \theta).$$

Sampling Distributions of Estimated Parameters



Cramér-Rao bound

Under regularity assumptions on probability distribution $p(x; \theta)$,

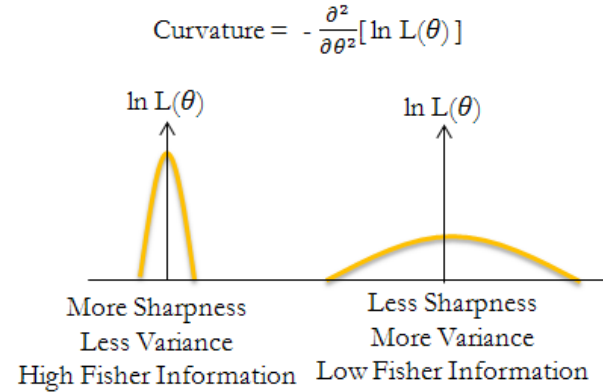
$$\text{var}(\hat{\theta}) \geq I^{-1}(\theta) = \frac{1}{-\mathbf{E}\left[\frac{\partial^2 \ln p(x; \theta)}{\partial \theta^2}\right]}.$$

Cramér-Rao bound

Under regularity assumptions on probability distribution $p(x; \theta)$,

$$\text{var}(\hat{\theta}) \geq I^{-1}(\theta) = \frac{1}{-\mathbf{E}\left[\frac{\partial^2 \ln p(x; \theta)}{\partial \theta^2}\right]}.$$

If PDF $p(x; \theta)$ is influenced by parameter more, estimation will be more accurate



Deterministic function of parameter

Suppose we want to estimate a function $g(\theta)$ of the parameter

Example *measure parameter in noise, but instantaneous power desired:*

$$g(\theta) = \theta^2$$

In this case,

$$\text{var}(\hat{\theta}) \geq \frac{\left(\frac{\partial g}{\partial \theta}\right)^2}{-\mathbf{E}\left[\frac{\partial^2 \ln p(x; \theta)}{\partial \theta^2}\right]}.$$

Cramér-Rao bound – multiple parameters

$$\text{var}(\hat{\theta}) \geq I^{-1}(\theta) = \frac{1}{-\mathbf{E}\left[\frac{\partial^2 \ln p(x; \theta)}{\partial \theta^2}\right]}.$$

Cramér-Rao bound – multiple parameters

The Fisher information matrix (FIM) is the negative expected Hessian of the log-likelihood function:

$$\mathbf{I}_\theta = -\mathbf{E}\left[\nabla_\theta \nabla_\theta^H \ln p(\mathbf{x})\right] = -\mathbf{E}\left[\nabla_\theta^2 \ln p(\mathbf{x})\right], \quad (1)$$

where the expectation is taken with respect to $p(\mathbf{x})$ and

$$[\nabla_\theta f]_i = \partial f / \partial \theta_i, \quad [\nabla_\theta^2 f]_{ij} = \partial^2 f / \partial \theta_i \partial \theta_j^*.$$

$$\text{var}(\hat{\theta}) \succeq I^{-1}(\theta) = \frac{1}{-\mathbf{E}\left[\frac{\partial^2 \ln p(x; \theta)}{\partial \theta^2}\right]}.$$

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The covariance matrix $\mathbf{R}_{\hat{\theta}}$ of any unbiased estimator $\hat{\theta}$ of θ satisfies $\mathbf{R}_{\hat{\theta}} \succeq \mathbf{I}_\theta^{-1}$.

$\mathbf{A} \succeq \mathbf{B}$ means $\mathbf{A} - \mathbf{B}$ is positive semidefinite with \mathbf{A} and \mathbf{B} Hermitian: $\mathbf{A} = \mathbf{A}^H$, $\mathbf{B} = \mathbf{B}^H$.

CRB – complex parameters

CRB described until now holds for real parameters.
How to extend to complex parameters z ?

Two equivalent approaches:

- ▶ Consider real $Re(z)$ and imaginary part $Im(z)$ separately (cumbersome)
- ▶ Consider complex number z and its conjugate z^* (also cumbersome 😊 but generally easier)

On the menu today

Intro

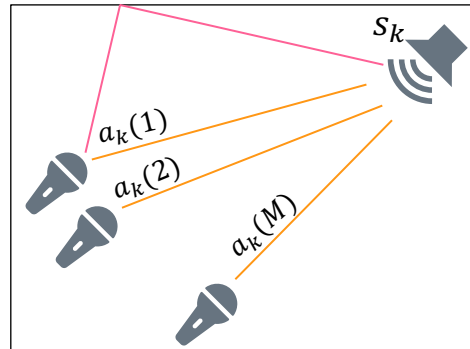
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Case study – channel estimation

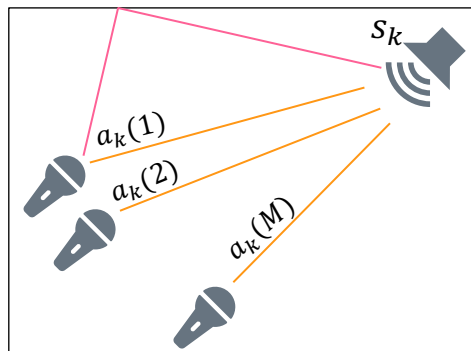


Signal model – frequency domain

Let a point source emit sound. The sound is measured by an array of M sensors. The received signal in the short-time Fourier transform (STFT) domain is

$$\mathbf{x}_k(l) = s_k(l) \mathbf{a}_k + \mathbf{v}_k(l) \in \mathbb{C}^M, \quad l = 1, \dots, L, \quad k = 1, \dots, K$$

Our goal: recover transfer function \mathbf{a}_k from noisy recording \mathbf{x}_k



Deriving CRB for channel estimation

$$\text{var}(\hat{\theta}) \geq I^{-1}(\theta) = \frac{1}{-\mathbf{E}\left[\frac{\partial^2 \ln p(x; \theta)}{\partial \theta^2}\right]}.$$

$$\mathbf{R}_{\hat{\theta}} \succeq \mathbf{I}_{\theta}^{-1} = (-\mathbf{E}[\nabla_{\theta}^2 \ln p(\mathbf{x})])^{-1}.$$

Likelihood function

Collect IID measurements in data matrix \mathbf{X}

Assume noise \mathbf{v} is **complex circular Gaussian** process

Unknown parameters $\theta = [\mathbf{a}^T \mathbf{a}^H]^T \in \mathbb{C}^{2M}$

Conditional likelihood is

$$p(\mathbf{X}; \theta, s(l)) = \frac{1}{|\pi \mathbf{R}|^L} \exp \left(- \sum_{l=1}^L (\mathbf{x}(l) - s(l)\mathbf{a})^H \mathbf{R}^{-1} (\mathbf{x}(l) - s(l)\mathbf{a}) \right),$$

Log-likelihood and its derivatives

Define log-likelihood

$$L(\theta) = \ln p(\mathbf{X}; \theta) = -L \ln |\pi \mathbf{R}| - \sum_{l=1}^L (\mathbf{x}(l) - s(l)\mathbf{a})^H \mathbf{R}^{-1} (\mathbf{x}(l) - s(l)\mathbf{a})$$

We then have

$$\nabla_{\mathbf{a}^*} L(\theta) = \mathbf{R}^{-1} \sum_{l=1}^L (s(l)^* \mathbf{x}(l) - |s(l)|^2 \mathbf{a})$$

$$\nabla_{\mathbf{a}} L(\theta) = (\nabla_{\mathbf{a}^*} L(\theta))^*$$

$$-\mathbf{E}[\nabla_{\mathbf{a}^*} \nabla_{\mathbf{a}^*}^H L(\theta)] = -\mathbf{E}[\nabla_{\mathbf{a}^*} \nabla_{\mathbf{a}}^T L(\theta)] = \mathbf{E}\left[\mathbf{R}^{-1} \sum_{l=1}^L |s(l)|^2\right] = E_s L \mathbf{R}^{-1}$$

$$-\mathbf{E}[\nabla_{\mathbf{a}^*} \nabla_{\mathbf{a}}^H L(\theta)] = \mathbf{0}$$

$$E_s = \mathbf{E}[|s(l)|^2]$$

$$\mathbf{I}_\theta = -\mathbf{E}[\nabla_\theta \nabla_\theta^H \ln p(\mathbf{x})] = -\mathbf{E}[\nabla_\theta^2 \ln p(\mathbf{x})], \quad (1)$$

where the expectation is taken with respect to $p(\mathbf{x})$ and

$$[\nabla_\theta f]_i = \partial f / \partial \theta_i, \quad [\nabla_\theta^2 f]_{ij} = \partial^2 f / \partial \theta_i \partial \theta_j.$$

Fisher information matrix

With this, the Fisher information matrix is

$$\mathbf{I}_\theta = \begin{bmatrix} E_s L \mathbf{R}^{-*} & \mathbf{0} \\ \mathbf{0} & E_s L \mathbf{R}^{-1} \end{bmatrix}. \quad (1)$$

The block-diagonal matrix can be easily be inverted, leading to

$$\mathbf{I}_\theta^{-1} = \begin{bmatrix} \frac{1}{E_s L} \mathbf{R}^* & \mathbf{0} \\ \mathbf{0} & \frac{1}{E_s L} \mathbf{R} \end{bmatrix} \quad (2)$$

Variance is finally bounded as:

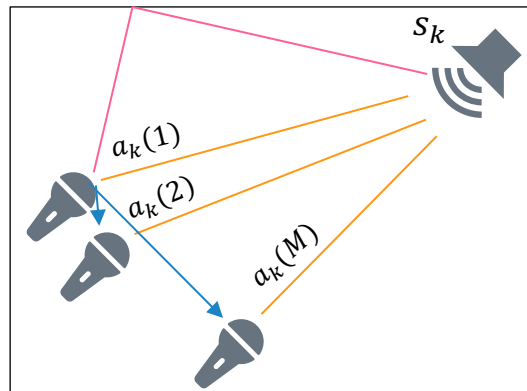
$$\text{var}(\hat{a}_i) \geq \frac{[R]_{ii}}{E_s L}, \quad i = 1, \dots, M. \quad (3)$$

Deterministic function of parameter

ATFs are often estimated in relation to a reference microphone r , as in $g(\theta) = g(\mathbf{a}, \mathbf{a}^*) = \mathbf{a}/a_r$. In this case,

$$\mathbf{R}_{g(\theta)} - (\nabla_{\theta} \mathbf{g}) \mathbf{I}_{\theta}^{-1} (\nabla_{\theta}^H \mathbf{g}) \geq 0, \quad (1)$$

where $\mathbf{R}_{g(\theta)}$ is the covariance matrix of $g(\theta)$.



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where $\mathbf{R}_{g(\theta)}$ is the covariance matrix of $g(\theta)$. Choosing $r = 1$, Jacobian is

$$\nabla_{\theta} \mathbf{g} = [\nabla_{\mathbf{a}} \mathbf{g} \quad \nabla_{\mathbf{a}^*} \mathbf{g}] \quad (2)$$

$$= \left[\begin{array}{cccc|c} 0 & 0 & 0 & \dots & 0 \\ -\theta_2/|\theta_1|^2 & 1/\theta_1 & 0 & \dots & 0 \\ -\theta_3/|\theta_1|^2 & 0 & 1/\theta_1 & \dots & 0 \\ \vdots & & & \ddots & \vdots \\ -\theta_M/|\theta_1|^2 & 0 & \dots & 0 & 1/\theta_1 \end{array} \right] \mathbf{0}_{M \times M}, \quad (3)$$

where $[\nabla_{\theta} \mathbf{f}]_{ij} = \partial f_i / \partial \theta_j$.

Experiments

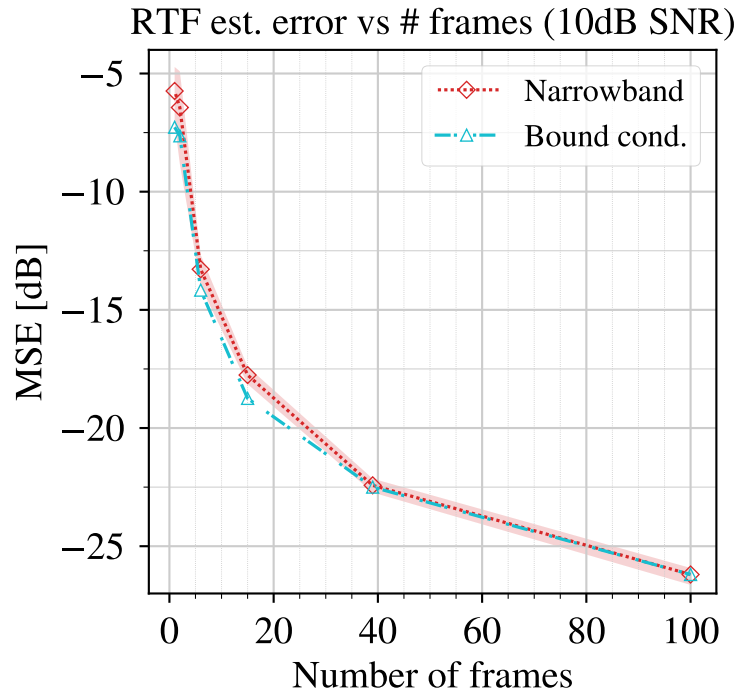
Settings

- ▷ 3 microphones,
random ATF,
covariance matrices estimated from N snapshots,
results averaged over 1000 experiments

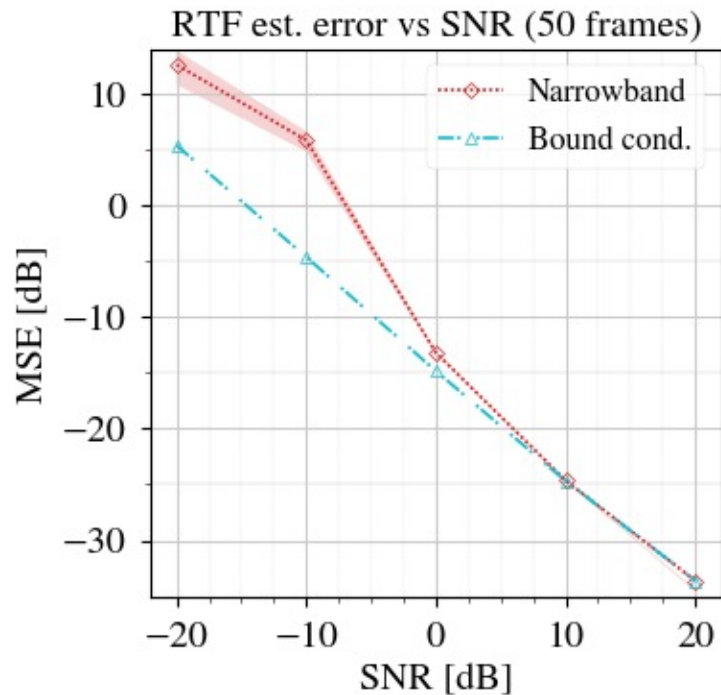
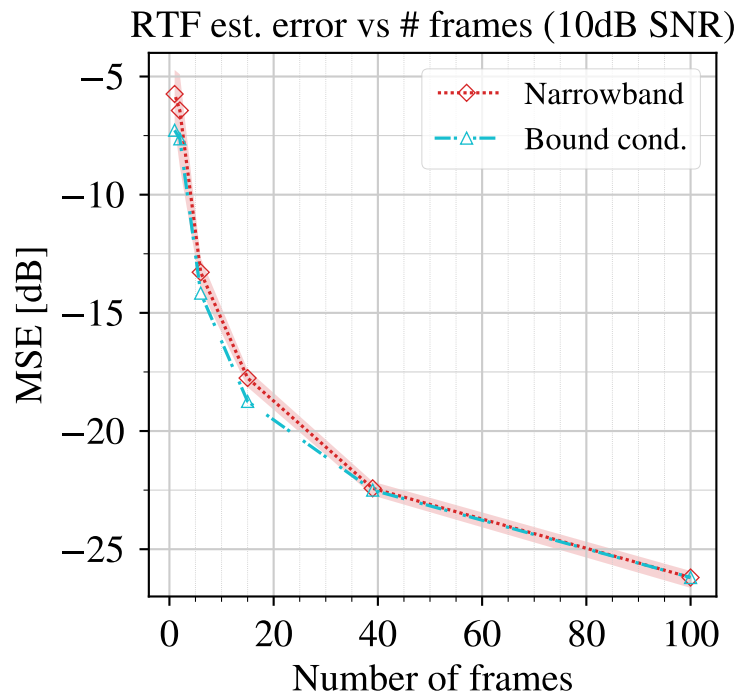
Performance metric

- ▷ Mean-squared error (in dB) between actual and estimated RTFs

Experiments



Experiments



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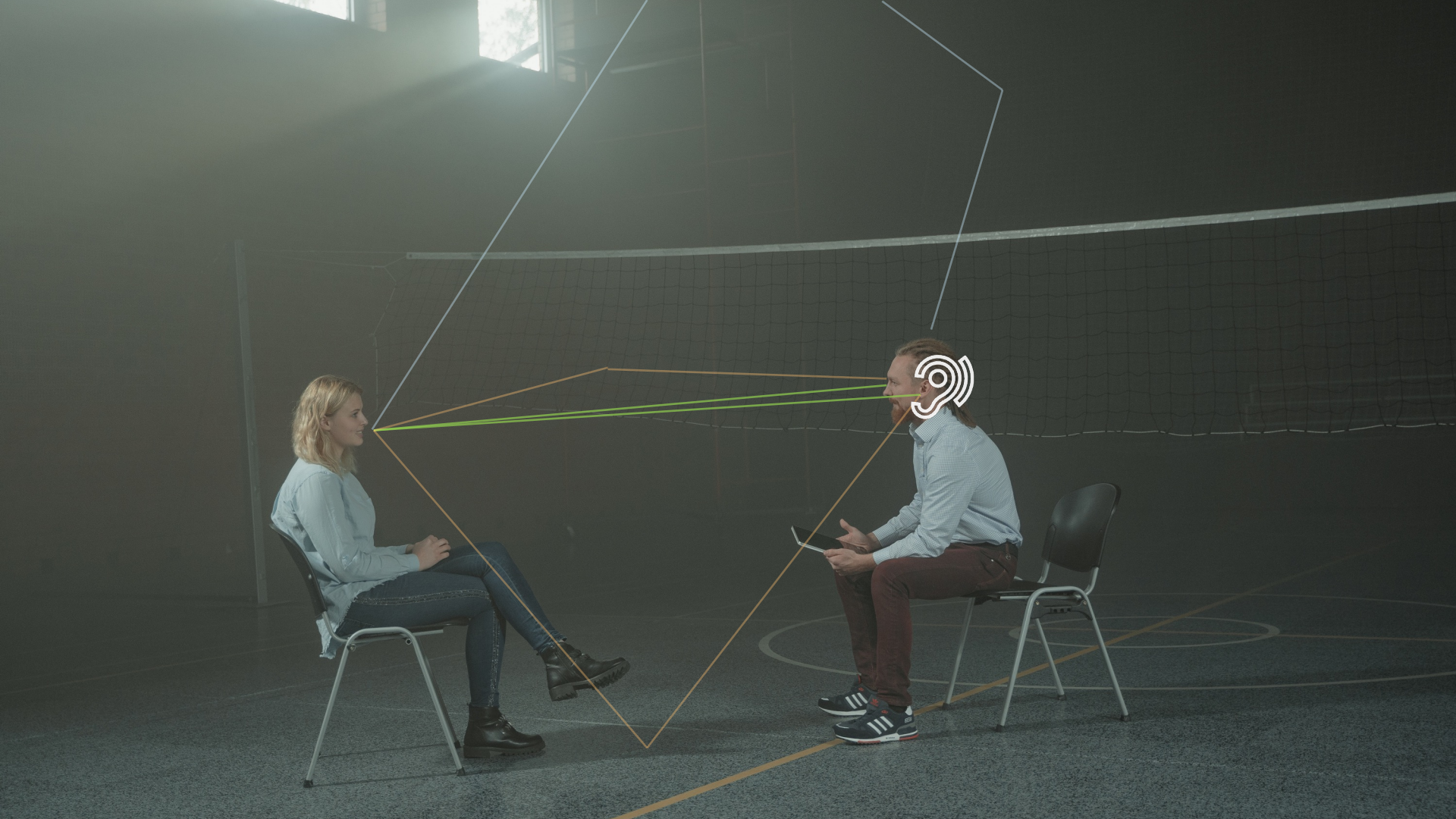
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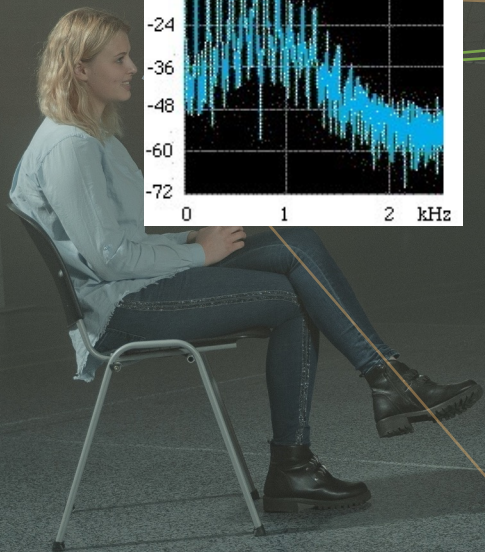
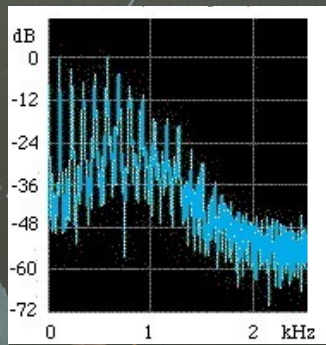
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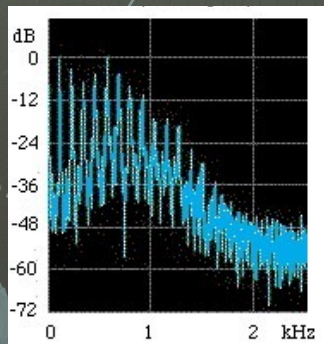
My research & open questions

Acoustic transfer function estimation with **inter-frequency correlation**

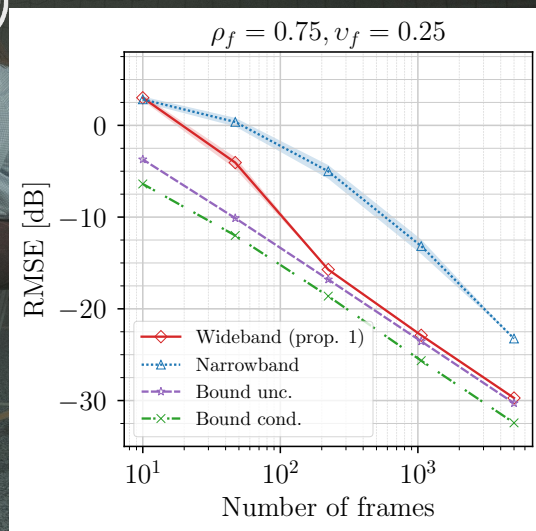
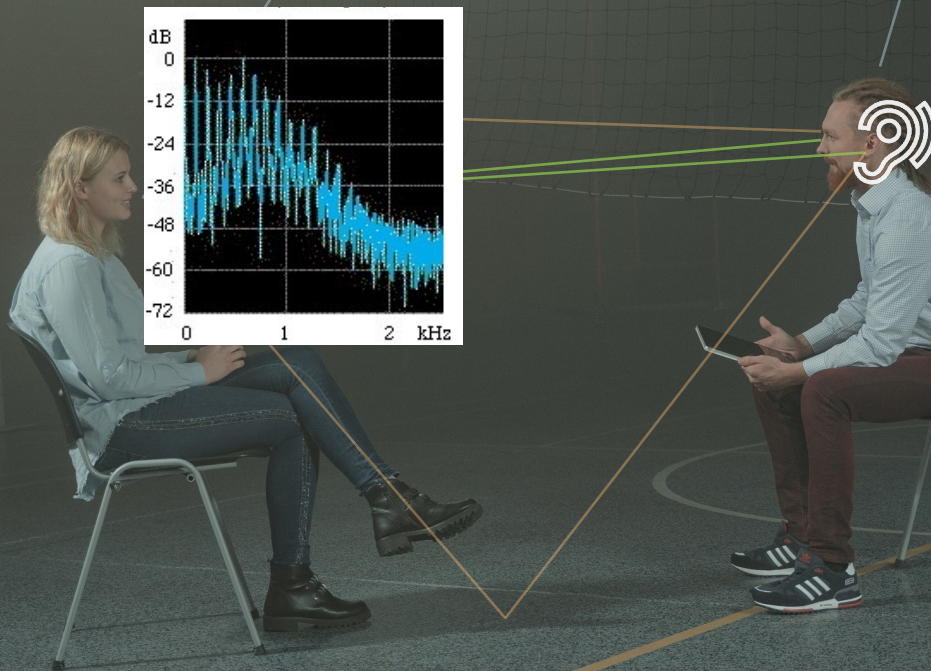




Can acoustic parameter estimation be improved by exploiting “hidden” correlations across frequencies?



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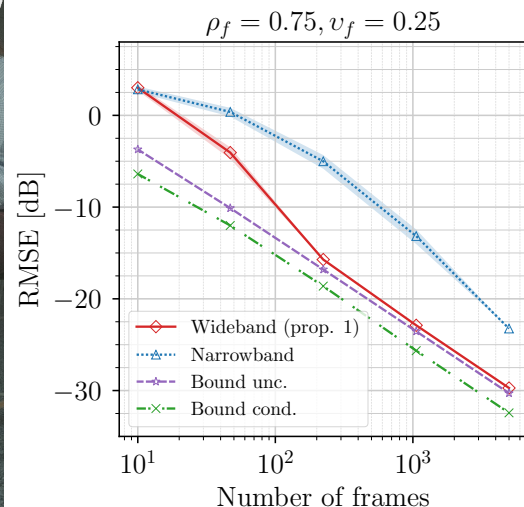
Open questions - these projects

- How to find optimal RTF estimation algorithm?
 - Maximum likelihood [1], tensor methods
- *Wideband* beamforming?
 - *Wideband* MVDR with cue preservation
 - ATF informed DNN [2]
- How to estimate spectral correlation covariance?
 - Cyclostationary model [3]

[1] Y. Laufer and S. Gannot, "Scoring-Based ML Estimation and CRBs for Reverberation, Speech, and Noise PSDs in a Spatially Homogeneous Noise Field," TALSP 2020.

[2] A. Briegleb, M. M. Halimeh, and W. Kellermann, "Exploiting Spatial Information with the Informed Complex-Valued Spatial Autoencoder for Target Speaker Extraction," ICASSP 2023

[3] J. Antoni, "Cyclostationarity by examples," Mechanical Systems and Signal Processing 2009



Recap

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