# ECHO-AWARE signal processing for audio scene analysis

Diego DI CARLO
November 25, 2020

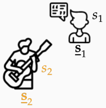
PhD Director: Nancy BERTIN
PhD Supervisor: Antoine DELEFORGE
Jury members: Laurent GIRIN (reviewer)
Simon DOCLO (reviewer)
Fabio ANTONACCI
Renaud SEGUIER
Collaborators: Clément ELVIRA,
Robin SCHEIBLER, Ivan DOKMANIĆ,
Sharon GANNOT, Pinchas TANDEITNIK

Université de Rennes 1, IRISA/INRIA, Panama research group

# Overview

## Echo-aware signal processing for audio scene analysis

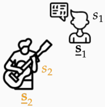
# Introduction

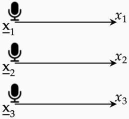



Sound

- produced by sources

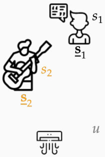
# Scenario

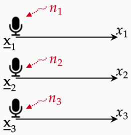



Sound

- produced by sources
- recorded by microphones

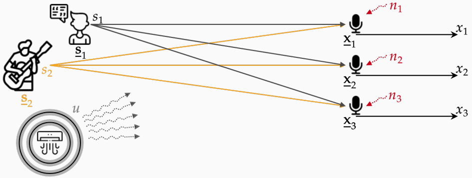



## Sound

- produced by sources
- recorded by microphones
- corrupted by noise

# Scenario




Sound

- produced by sources
- recorded by microphones
- corrupted by noise
- propagates in the space

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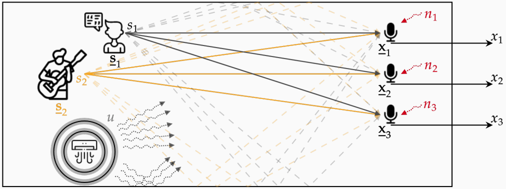
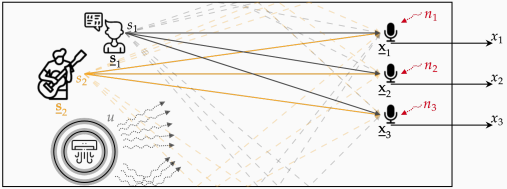



Sound

- produced by sources
- recorded by microphones
- corrupted by noise
- propagates in the room
  ↪ reverberation




Sound

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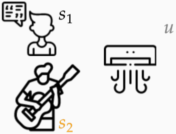
  ↪ reverberation

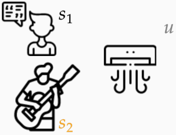
Attention: artificial sound vs **(natural) microphone recordings**

Semantic information



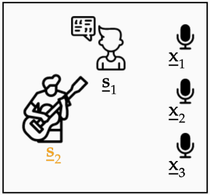

on nature and content

Semantic information




on nature and content

Spatial information




on position and geometry

# Echo-aware signal processing for audio scene analysis

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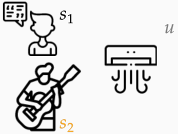


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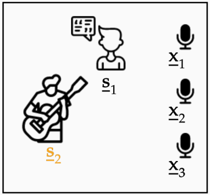
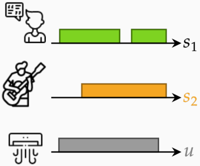


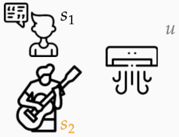

on position and geometry

Temporal information




on events activity

Semantic information

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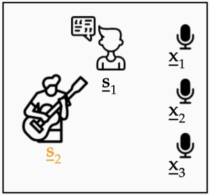


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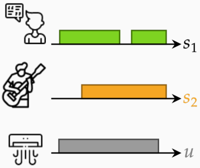
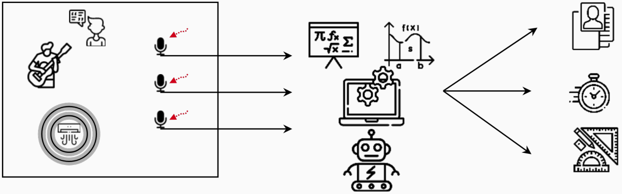


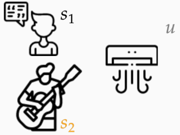

on events activity

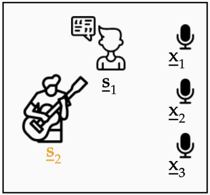
**Audio Scene Analysis**

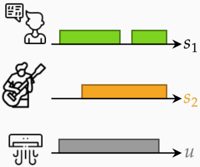
Extraction and organization of all the information in the sound



| Semantic information | Spatial information | Temporal information |
|---|---|---|




| on nature and content | on position and geometry | on events activity |
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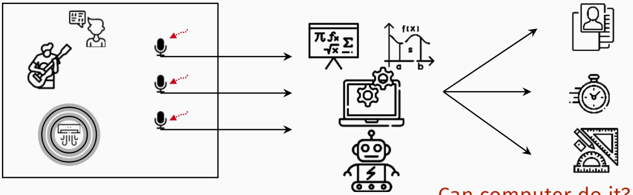
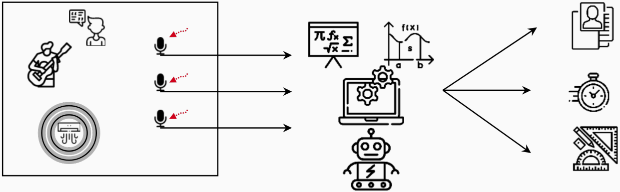
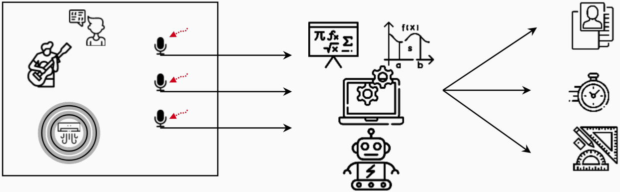


Can computer do it?



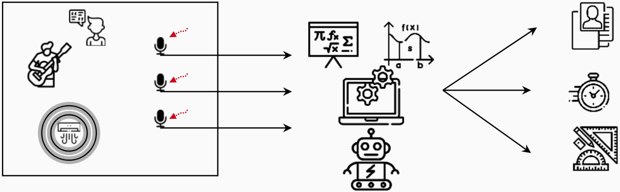
f(x)
s
a
b

# Echo-aware signal processing for audio scene analysis




**Signal Processing**

Mathematical models, frameworks and tools to tackle and solve such problems

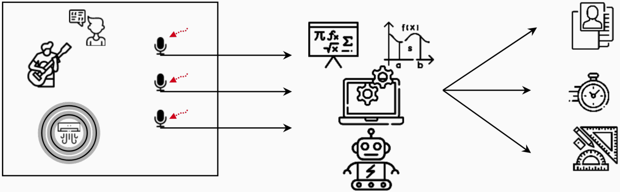



## Signal Processing

Mathematical models, frameworks and tools to tackle and solve such problems

Some (inverse) problems

- Speaker Identification
- Sound Source Separation (SSS)
- Speech Enhancement (SE)
- Automatic Speech Recognition (ASR)
- Sound Source Localization (SSL)
- Room Geometry Estimation (RooGE)
- Voice Activity Detection
- Diarization
- $\mathrm{RT}_{60}$ estimation
- Acoustic Channel Estimation
- Wall Absorption Estimation
- *and many many other*

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Mathematical models, frameworks and tools to tackle and solve such problems

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- Speaker Identification } Who?
- Sound Source Separation (SSS)
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- Automatic Speech Recognition (ASR) } What?
- Sound Source Localization (SSL)
- Room Geometry Estimation (RooGE) } Where?

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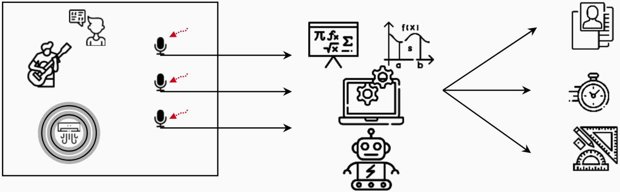
- *and many many other*

# Echo-aware signal processing for audio scene analysis



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Who?

What?

Where?

- Voice Activity Detection
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- $\mathrm{RT}_{60}$ estimation
- Acoustic Channel Estimation
- Wall Absorption Estimation
- *and many many other*

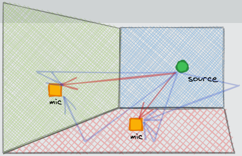
When?

How?

HOW $\xrightarrow{\text{helps}}$ WHERE $\xrightarrow{\text{helps}}$ WHEN $\xrightarrow{\text{helps}}$ WHAT $\xrightarrow{\text{helps}}$ HOW $\xrightarrow{\text{helps}}$ ...

## Acoustic Echoes

- Elements of the sound propagation
- Standing out for time and strength
- Repetition of a sound but later
- Both outdoor and indoor




Audio signal processing methods

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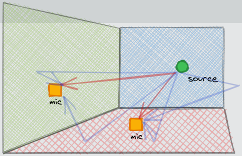


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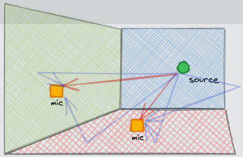
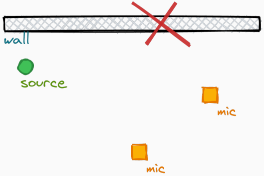



Audio signal processing methods

- ignore it



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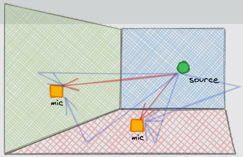
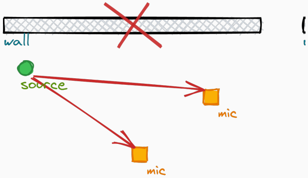



### Audio signal processing methods

- ignore it
- assume it free-field



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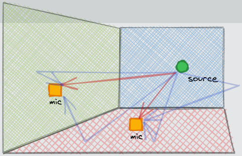


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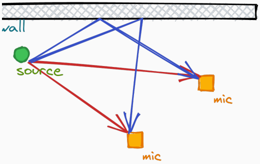
- ignore it
- assume it free-field
- model it entirely



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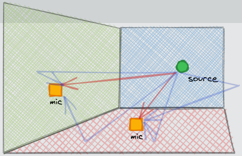
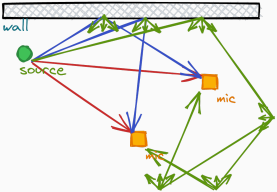



Audio signal processing methods

- ignore it
- assume it free-field
- model it entirely
- model as few reflection



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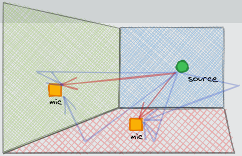


Audio signal processing methods

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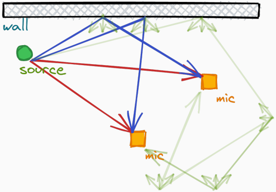
- model it as early and late parts



# Echo-aware signal processing for audio scene analysis

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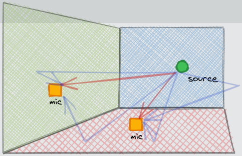


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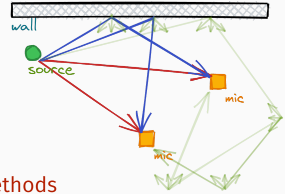
Echo-aware methods



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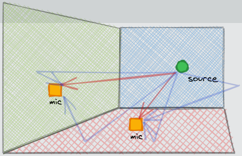


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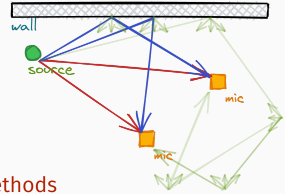
Echo-aware methods




### Modelling the sound field

- as free field $\Longrightarrow$ reverberation is noise
- entirely $\Longrightarrow$ it is very challenging

# Goals and contributions

Audio Scene Analysis

↓

context and problems

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Audio Scene Analysis
↓
context and problems

Signal Processing
↓
models and frameworks

# Goals and contributions

| Audio Scene Analysis | Signal Processing | Acoustic Echoes |
| --- | --- | --- |
| ↓ | ↓ | ↓ |
| context and problems | models and frameworks | better processing |

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| Audio Scene Analysis | Signal Processing | Acoustic Echoes |
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**Goals**

1. How to **estimate** acoustic echoes?
2. How to **extend methods** for echo-aware audio scene analysis

# Goals and contributions

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1. How to **estimate** acoustic echoes?
2. How to **extend methods** for echo-aware audio scene analysis

1. Estimation

2. Application

# Goals and contributions

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### 1. Estimation

- Knowledge-based echo estimation
  ↪ `Blaster`
- Learning-based echo estimation
  ↪ `Lantern`

### 2. Application

# Goals and contributions

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- Echo-aware Source Separation
  ↪ `Separake`
- Echo-aware Source Localization
  ↪ `Mirage`
- Echo-aware Speech Enhancement
- Echo-aware Room Geometry Estimation

# Goals and contributions

Audio Scene Analysis
↓
context and problems

Signal Processing
↓
models and frameworks

Acoustic Echoes
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### 3. Data:

Echo-aware database → `dEchorate`

# Modeling

# Acoustic Impulse Response

Sound interacts with environment

- it is reflected (specularly and diffusely)
- \+ it is diffracted
- \+ it is absorbers and transmitted
- \+ other physical interaction

# Acoustic Impulse Response

Sound interacts with environment

$$\left.\begin{array}{ll} & \text{it is reflected (specularly and diffusely)} \\ + & \text{it is diffracted} \\ + & \text{it is absorbers and transmitted} \\ + & \text{other physical interaction} \end{array}\right\} = \text{all sound propagation}$$

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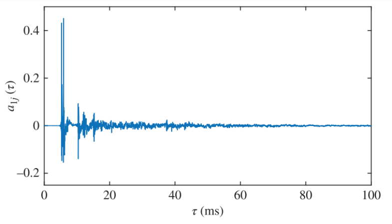
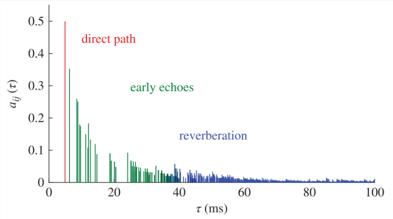
**Sound propagation** process = **source** $\rightarrow$ **filter** $\rightarrow$ **receiver** process

$$x(t) = (a * s)(t)$$ $\leftarrow$ continuous time domain!

The filter $a(t)$ is linear and is called **Acoustic Impulse Response**, (AIR)



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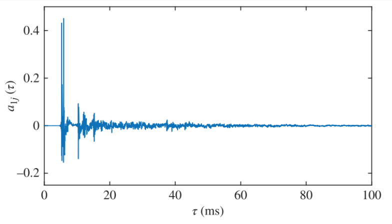
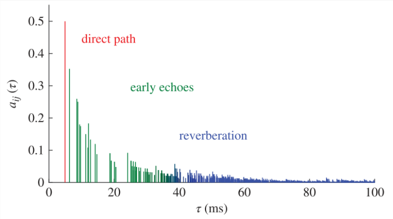
Indoor **Sound propagation** process = **source** $\rightarrow$ **filter** $\rightarrow$ **receiver** process

$$x(t) = (h * s)(t)$$

$\leftarrow$ continuous time domain!

The filter $h(t)$ is linear and is called Room **Impulse Response**, (RIR)



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$\leftarrow$ continuous time domain!

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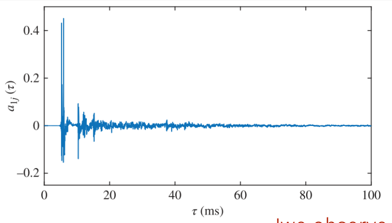
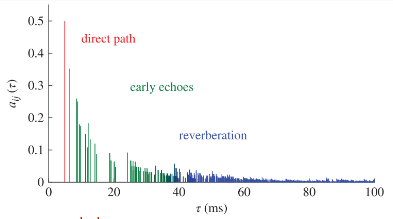



$\overset{?}{\approx}$




!we observe filters, not delays

# Echoes and Room Impulse Response

RIRs can be modeled with the Image Methods

- specular reflection only
- for cuboid room, **it describes** the sound prop.
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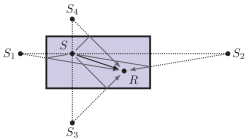


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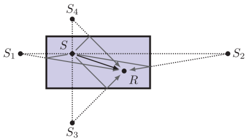


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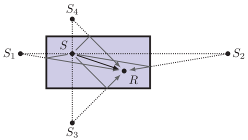


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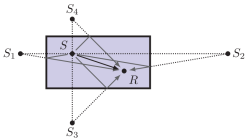


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- Room shape and size
- Mic and Source position
- other objects (eg. reflectors)

the **acoustic properties** of

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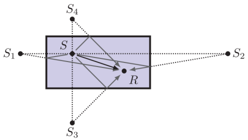


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**Echoes**

strong and distinct specular reflection

# Acoustic Echo Estimation

## The acoustic echoes retrieval (AER) problem

Estimating early (strong) acoustic reflections:

- their time of arrivals $\rightarrow$ TOAs Estimation
- their amplitude

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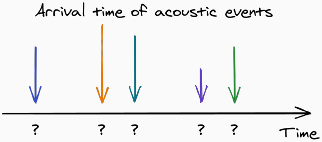

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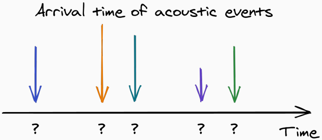
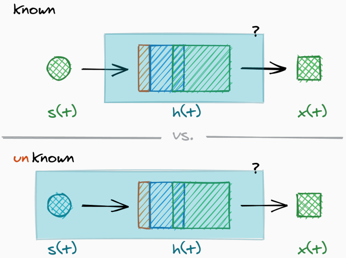



Approaches

Source signal is



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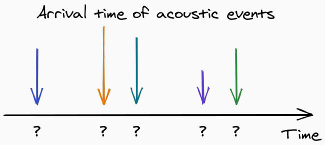


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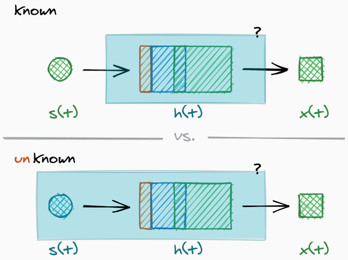


### Active approaches

- **easier** problem
- **intrusive** or specific setup
- Time of Arrival accessible
- single mic

Application Sonar, Calibration, Measurements

### Passive approaches

- more difficult problem — blind inverse problem
- passive hearing
- Time Difference of Arrivals only
- only multi-microphones

Application smart speakers, robot

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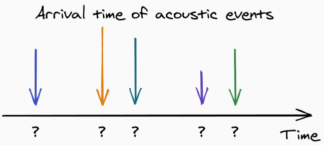


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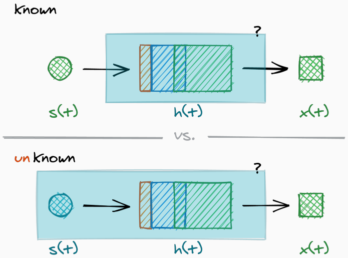


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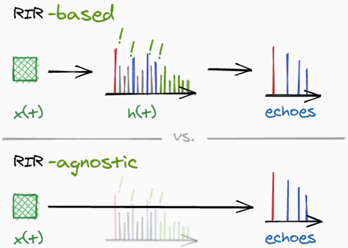

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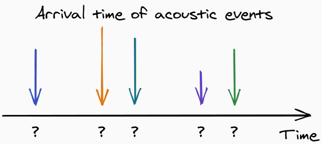


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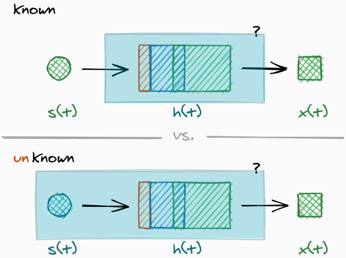


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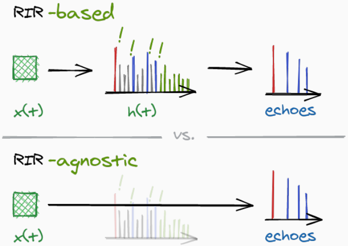


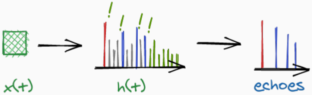

**Scenario:** signal source, only TOAs and passive system

Passive Acoustic Echo Estimation:

# Passive Acoustic Echo Estimation

## Passive Acoustic Echo Estimation:

RIR-based approaches

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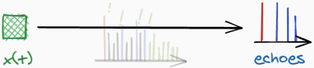
RIR-agnostic approaches




1. Estimation in the space $\left\{\tau_i^{(r)}, \alpha_i^{(r)}\right\}_{i,r}$

   (+ direction of arrivals can be used instead)

## Passive Acoustic Echo Estimation:

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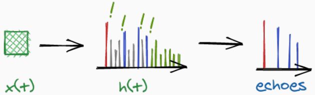


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- SIMO BCE is well studied
- Good in some scenario

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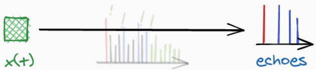


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- No need for full RIRs
- Sub-sampling accuracy
- Low complexity
- Sparsity and Non-negativity are respected

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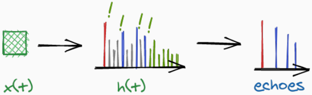


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- Full RIR is estimated
- Peak picking
- on-grid estimation

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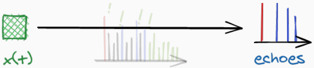


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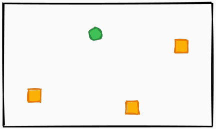
Cons

- echo sorting
- exploratory

## AER as discrete SIMO BCE

Key ingredient – *Cross relation identity*

$$x_i = h_i * s$$



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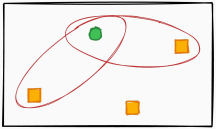

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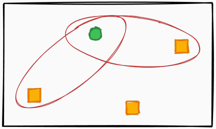

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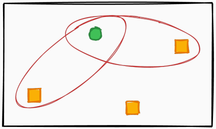

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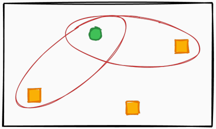

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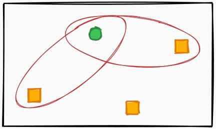

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3. Find echoes $\rightarrow$ **find sparse vectors $\mathbf{h}_1, \mathbf{h}_2$** of length $L$
4. Modeled as **Lasso**-like problem

$$\widehat{\mathbf{h}}_1, \widehat{\mathbf{h}}_2 \in \underset{\mathbf{h}_1, \mathbf{h}_2 \in \mathbf{R}^n}{\arg\min} \|\mathbf{x}_1 * \mathbf{h}_2 - \mathbf{x}_2 * \mathbf{h}_1\|_2^2 + \lambda \mathcal{P}(\mathbf{h}_1, \mathbf{h}_2) \quad \text{s.t.} \quad \mathcal{C}(\mathbf{h}_1, \mathbf{h}_2)$$

$\mathcal{P}(\mathbf{h_1}, \mathbf{h_2}) \longrightarrow$ sparse promoting regularizer

$\mathcal{C}(\mathbf{h_1}, \mathbf{h_2}) \longrightarrow$ non-negativity / anchor constraints

✓ [Tong et al., 1994] ✓ [Lin et al., 2007, Lin et al., 2008] ✓ [Aissa-El-Bey and Abed-Meraim, 2008] ✓ [Kowalczyk et al., 2013] ✓ [Crocco and Del Bue, 2015, Crocco and Del Bue, 2016]

$\mathbf{x_i} * \mathbf{h}_j$ computed as $\mathcal{T}(\mathbf{x}_i)\mathbf{h_j} \in \mathcal{O}(L^2)$

# AER as SIMO BCE: Limitations & bottleneck

1. Estimation is on-grid

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- *Body guard* effect [Duval and Peyré, 2017]
  - $\rightarrow$ low recall $\implies$ low accuracy
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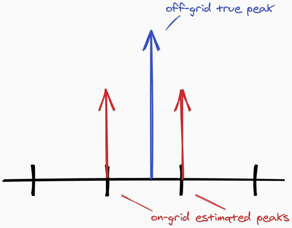

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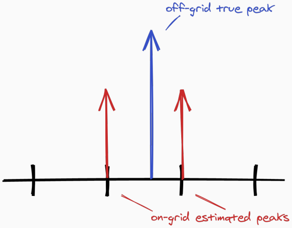


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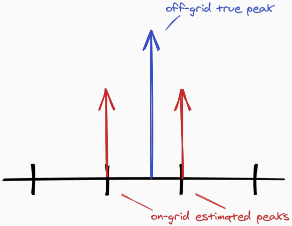


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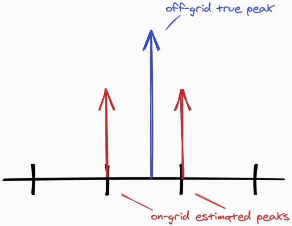


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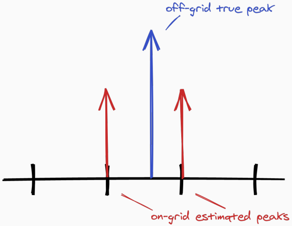


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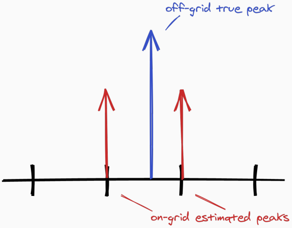


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    - Computational complexity: at best $\mathcal{O}(F_s^2)$ per iteration
    - the higher the sampling frequency, the more ill-conditioned

      $\longrightarrow$ slow convergence

How to solve this?

# AER: Challenges and Contribution

State Of The Art

1. discrete (sparse) SIMO BCE
   based on time-domain XREL
2. Peak-picking

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# AER: Challenges and Contribution

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$\implies$ however

- Estimation in the RIR space memory issue
- Echoes are “off-grid” accuracy issues and mismatch
- Peak picking and labeling tuned and NP-hard

$\implies$ we propose

`Blaster`[Di Carlo et al., 2020]

1. Knowledge-based approach
2. BCE + Continuous Dictionary based on XREL
3. Iterative-like approach
4. Inputs:
   - stereo mic recordings
   - # echoes
5. Output: $\tau_i^{(r)}, \alpha_i^{(r)}{}_{i,r}$

`Lantern`[Di Carlo et al., 2019]

1. Learning-based regression
2. Deep Learning used for SSL
3. Inputs: stereo audio feature
4. Output in the TDOA space ($\neq$ Echo space)

# Blaster- Knowledge-based Off-grid AER

Observation 1: the cross relation remains true in the frequency domain

$$\mathcal{F}x_1 \cdot \mathcal{F}h_2({}^{n}/{}_{F_s}) = \mathcal{F}x_2 \cdot \mathcal{F}h_1({}^{n}/{}_{F_s}) \qquad n = 0 \dots N-1$$

Observation 2: $\mathcal{F}\delta_{\text{echo}}$ is known in closed-form

Observation 3: $\mathcal{F}\mathrm{x_i}$ can be (well) approximated by DFT

$$\mathbf{X}_i = \mathsf{DFT}(\mathbf{x}_i) \simeq \mathcal{F}\mathbf{x}_i(nF_s) \qquad n = 0 \dots N-1$$

**Idea: Recover echoes by matching a finite number of frequencies**

$$\underset{h_1,h_2 \in \substack{\text{measure}\\ \text{space}}}{\arg\min} \ \tfrac{1}{2}\|\mathbf{X}_1 \cdot \mathcal{F}h_2(f) - \mathbf{X}_2 \cdot \mathcal{F}h_1(f)\|_2^2 + \lambda\|h_1 + h_2\|_{\text{TV}} \quad \text{s.t.} \begin{cases} h_1(\{0\}) = 1 \\ h_l \geq 0 \end{cases}$$

Looks like a **Lasso** problem, but $\mathcal{F}h_2(f)$ is a continuous function.
Instance of a **BLasso** problem[Bredies and Carioni, 2020]
Solved with Sliding Frank-Wolfe algorithm [Denoyelle et al., 2019]

✓no Toeplitz matrix

✓ Solutions is a train of Dirac

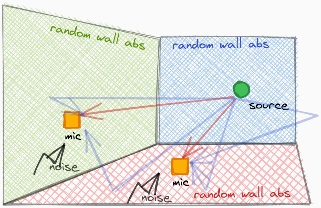
✓ anchor prevents trivial solution

In the manuscript:

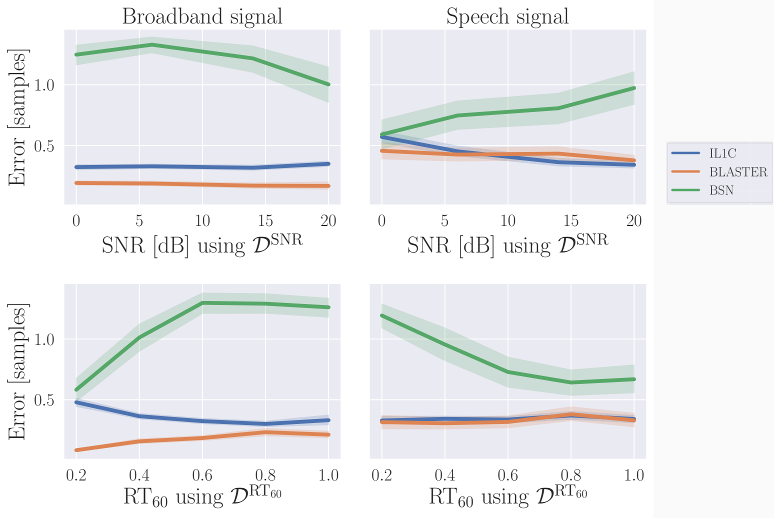
## Methods

- BSN [Lin et al., 2007]
- IL1C: iteratively-weighted $\ell_1$ constraint SIMO BCE [Crocco and Del Bue, 2015]
- Blaster: Proposed off-grid approach

Baseline method are xvalidated on other dataset



# Error per Dataset/Signal while recovering 7 echoes




✓Lower RMSE

✓ Robustness to SNR and $\mathrm{RT}_{60}$

✗ Source signal dependent

# Performance per # of echoes

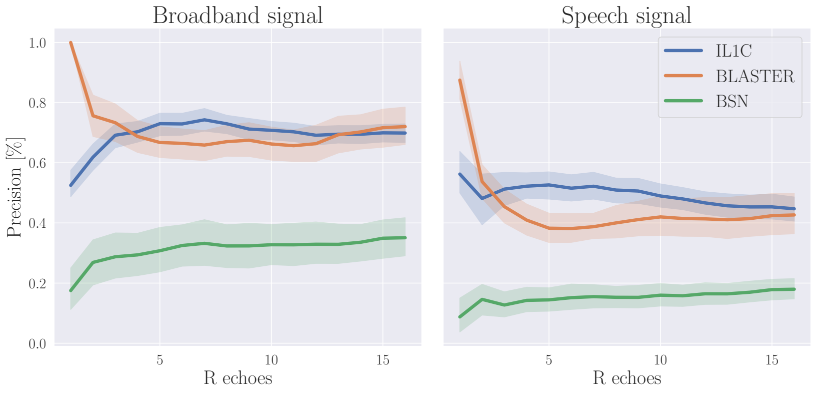



**Figure 1:** $\text{RT}_{60} = 400$ ms and SNR = 20 dB.

✗ Sensitive to # echoes

✗ Sensitive source signal

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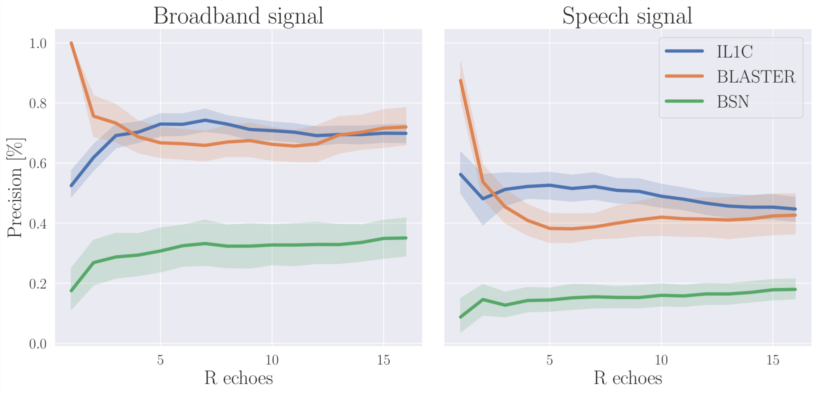


**Figure 1:** $\mathrm{RT}_{60} = 400$ ms and SNR = 20 dB.

✗ Sensitive to # echoes

✗ Sensitive source signal

✓ Good for 2 echoes [Scheibler et al., 2018, Di Carlo et al., 2019]

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Later echoes are not considered, they may help

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# Lantern- Data-driven off-grid AER

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Acoustic simulators based on ISM + annotation for free

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Echoes are strongly related to the source position

Idea: Use Deep Learning for AER

- Extend previous work on source localization for Echo Estimation
- Estimate the first echo TOA
  ↪ simple case, but with important application in SSL

# Lantern- Data & Models

**Input:** features

**Output:** target

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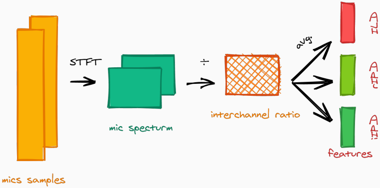


$\longrightarrow$

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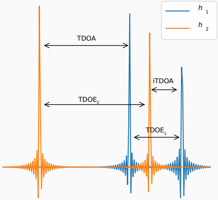


Relative Transfer Function

$$\mathtt{ReTF}[f] = \frac{H_2[f]}{H_1[f]} \approx \underset{t}{\mathtt{avg.}} \left( \frac{X_2[f,t]}{X_1[f,t]} \right)$$

This is the instantaneous ReTF

TDOAs inter and intra reflection

$$\mathcal{V} = \{\mathtt{TDOA}, \mathtt{iTDOA}, \mathtt{TDOE}_1\}$$

First strongest echo $\Leftrightarrow$ close surface

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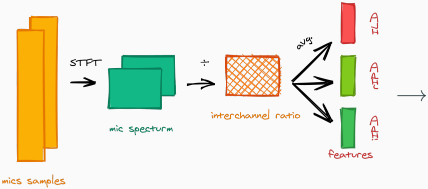


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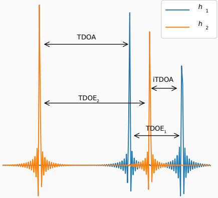


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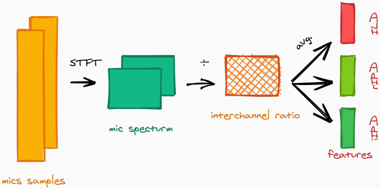


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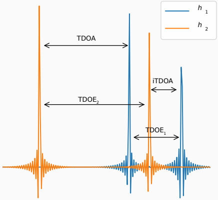


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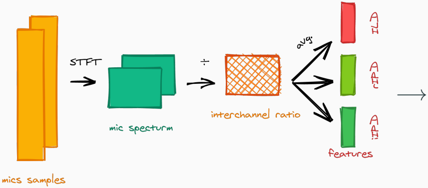


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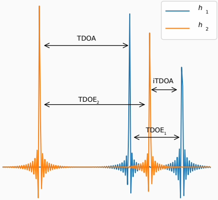


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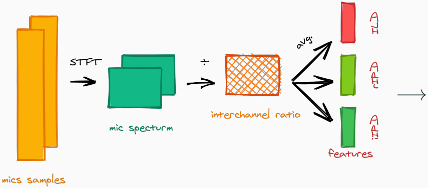


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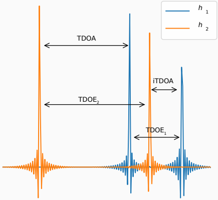


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  } Generative models ← for data fusion / similar to **MDN** [Bishop, 1994]
- Virtually Supervised Learning (= data from acoustic simulator)

Baseline: GCCPHAT (only TDOA),
$\texttt{MLP}_{\mathcal{V}}$ [Di Carlo et al., 2019]

Proposed: $\texttt{CNN}_{\mathcal{V}}$, $\texttt{CNN}_{\mathcal{V}_{\mathcal{N}}}$, $\texttt{CNN}_{\mathcal{V}_{\mathcal{T}}}$

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- random RT60, random SNR
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- instantaneous RTF

Test: similar to train

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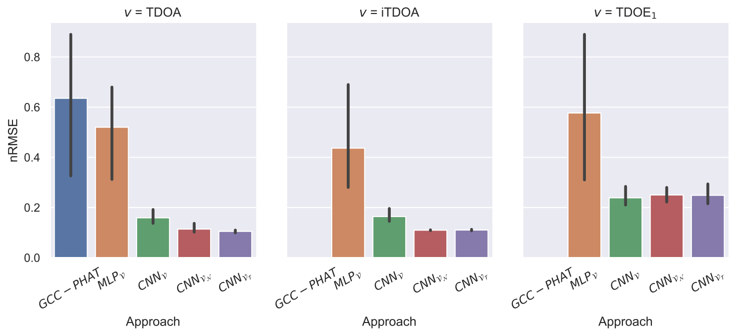


✓ CNNs outperform GCC-PHAT, MLP

✓ CNNs less variance

✗ Gaussian ∼ Student-T

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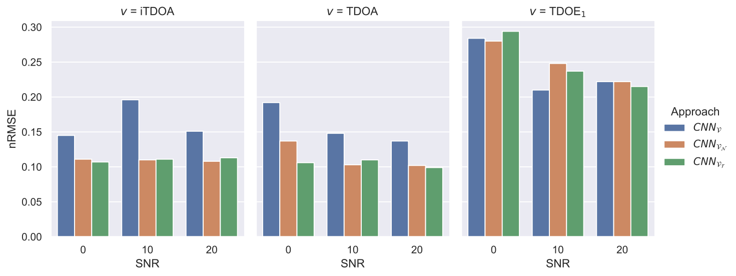


✓ Generative better than Normal

✗ Gaussian ∼ Student-T

✗ Bigger error on TDOE

# Echo-aware Application

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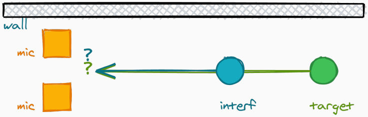
Echoes = same content, different time/direction



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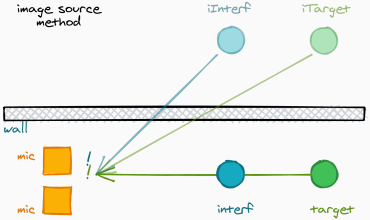

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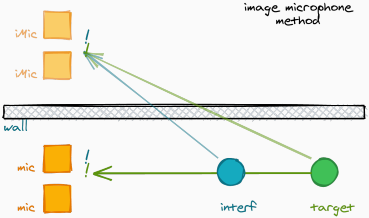

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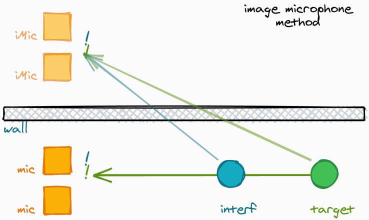


Recent literature on echo-aware processing:

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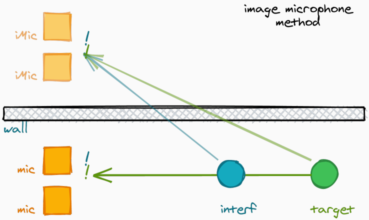


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**What?**
Echoes = repetitions

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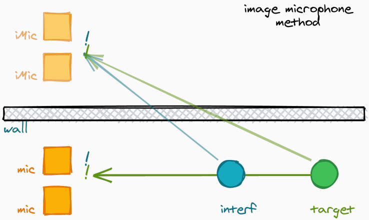


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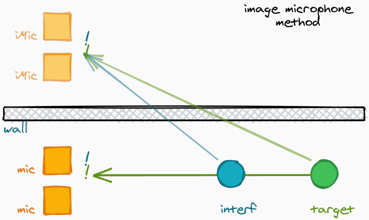


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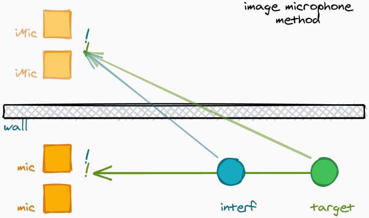


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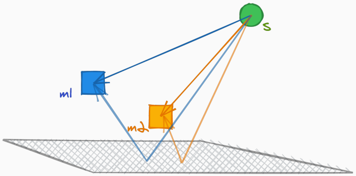
# Mirage- Sound Source Locatization with Echoes

The Picnic Scenario:

- One source
- Two microphones
  - → passive scenario
  - → generalizable to more pairs



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  - → $\alpha_{\text{picnic}}$ const. $\forall f$
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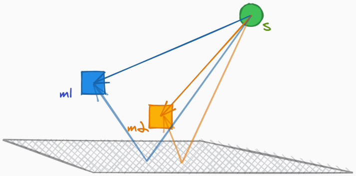

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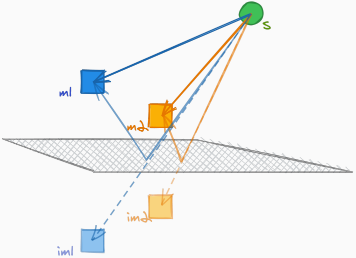
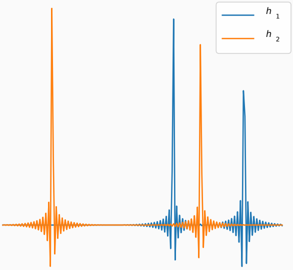



Each pair is augmented with echoes

Mirage Array

How to access the *image* microphones?



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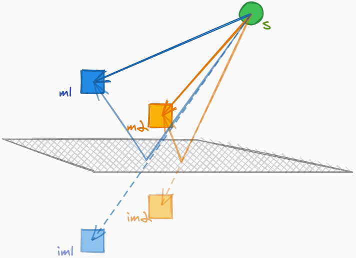


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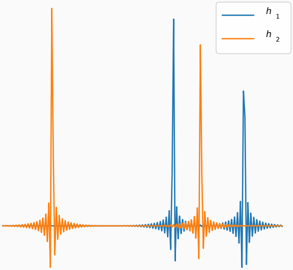

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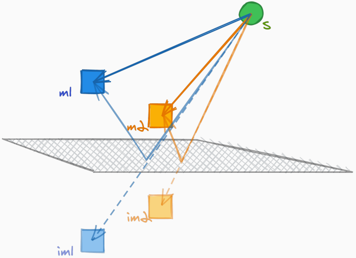


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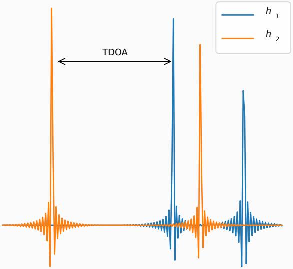

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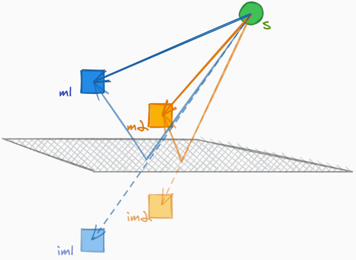


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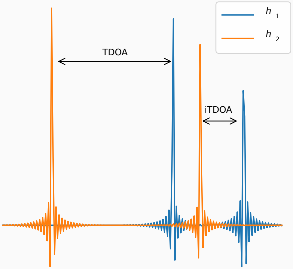

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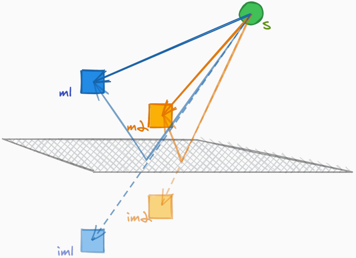


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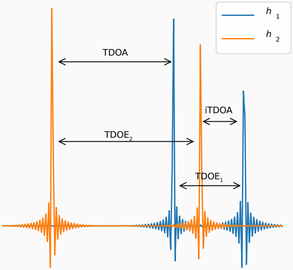

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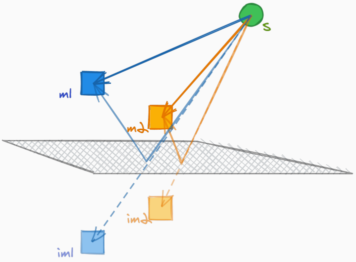


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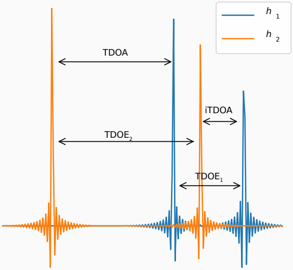
**idea:** use SSL algorithm on it

**recall:** echoes are known



## SSL with 2 microphones

- 1D SSL: only angle of arrival (AOA)
- e.g. GCC-PHAT for TDOA estimation [Knapp and Carter, 1976]
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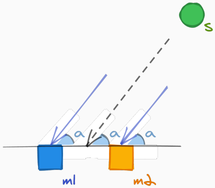

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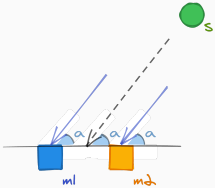


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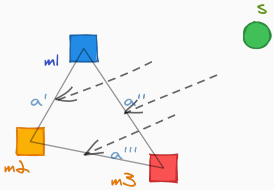

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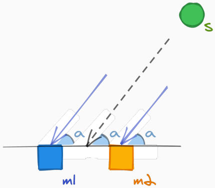


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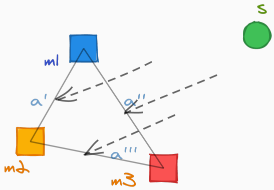


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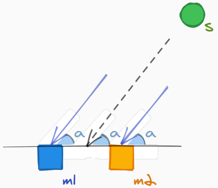


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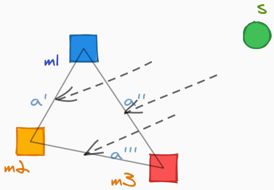


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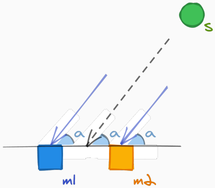


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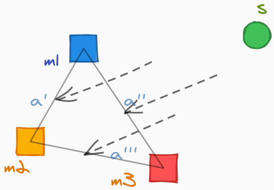


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**issue:** just punctual estimation cannot be "fused"
**solution:** use Lantern in generative mode (mic pos assumed known)

# Mirage- Results

**Data:** virtually generated closeddataset as for Lantern
**Metric:** angular mean error and accuracy (thr=10, 20)

## AOA estimation

- ✓ Similar when wn
- ✗ Huge drop when noise
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| AOA | Input | ACCURACY $\theta < 10$ | $\theta < 20$ |
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| MIRAGE | wn | 4.10 (77) | 5.97 (97) |
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(both Az. and El.)

| DoA | | ACCURACY $< 10$ | | ACCURACY $< 20$ | |
|---|---|---|---|---|---|
| | Input | $\theta$ | $\phi$ | $\theta$ | $\phi$ |
| MIRAGE | wn | 4.5 (59) | 3.9 (71) | 6.8 (79) | 5.9 (88) |
| MIRAGE | wn+n | 4.4 (18) | 5.5 (26) | 9.4 (35) | 11.1 (66) |
| MIRAGE | sp | 4.6 (45) | 4.8 (59) | 8.1 (71) | 7.2 (83) |
| MIRAGE | sp+n | 5.2 (17) | 5.9 (12) | 10.7 (38) | 12.3 (43) |

✓ Solved “impossible” localization

✗ Performance depending on echo estimation

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2. necessary for validation/learning
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For SE: strong echoes✓, but not annotated✗, specific array✗
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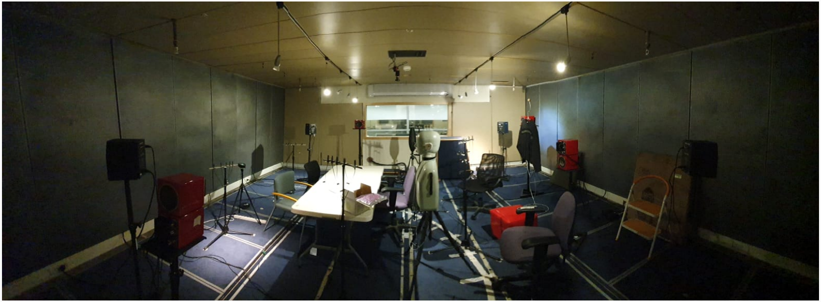
A good echo-aware dataset should allow **SE**, **RooGE** and **AER**
HOW?
signal annotation $\Longleftrightarrow$ geometric annotation

dEchorate: echo-aware dataset



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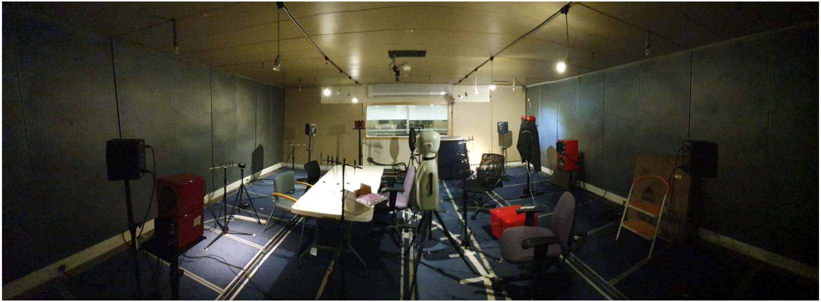

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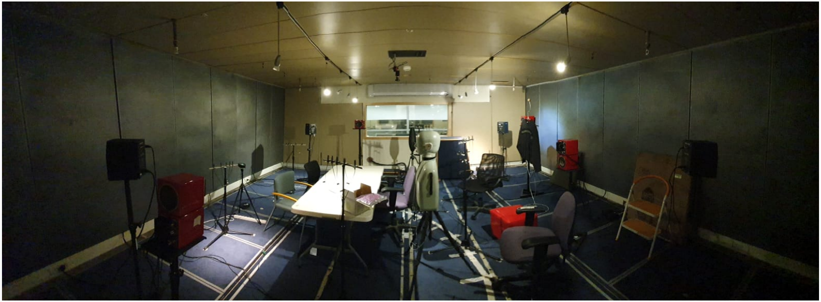

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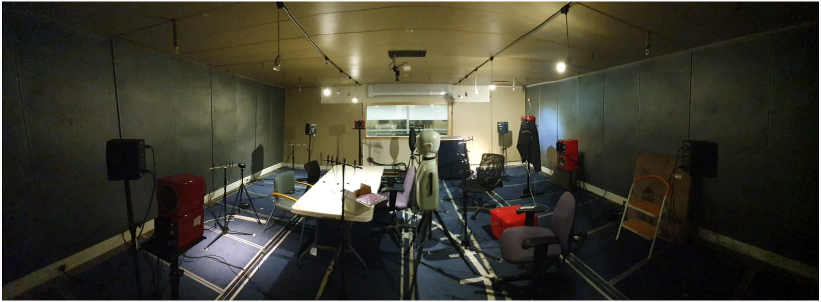

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Key features:

- revolving panels (different $\mathrm{RT}_{60}$ and echo prominency)
- 6 nULA with 5 mics and 4 sound sources
- geometry annotated & echo annotated
- measured RIRs $\leftarrow$ (matching) $\rightarrow$ simulated RIRs

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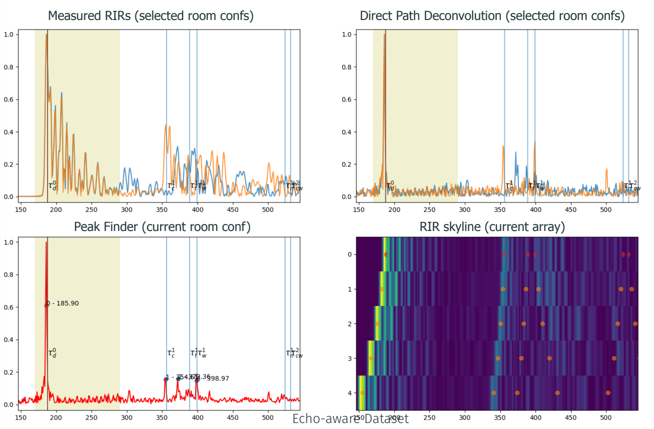

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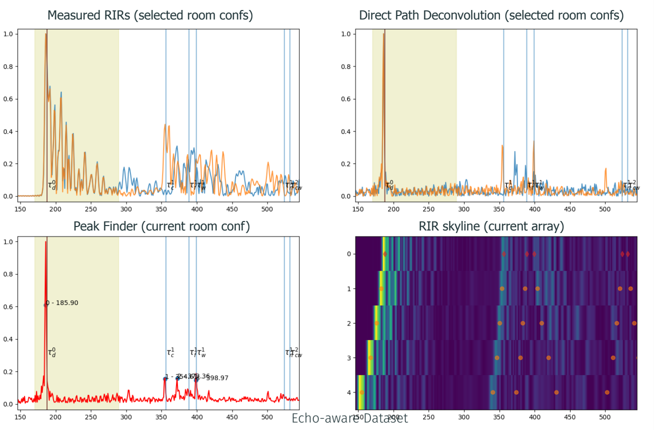

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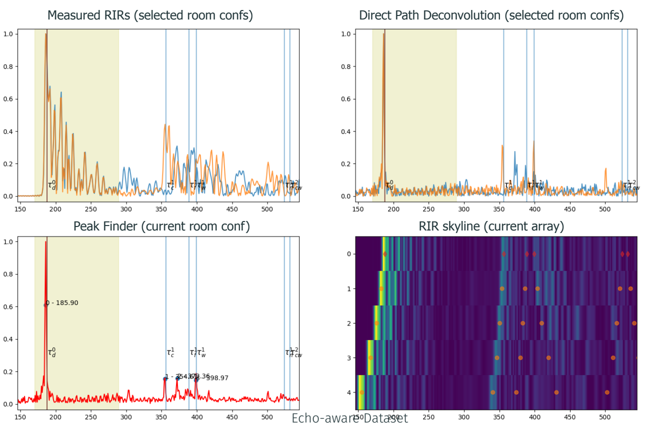
5. **iterate including ceiling** (perfectly flat)



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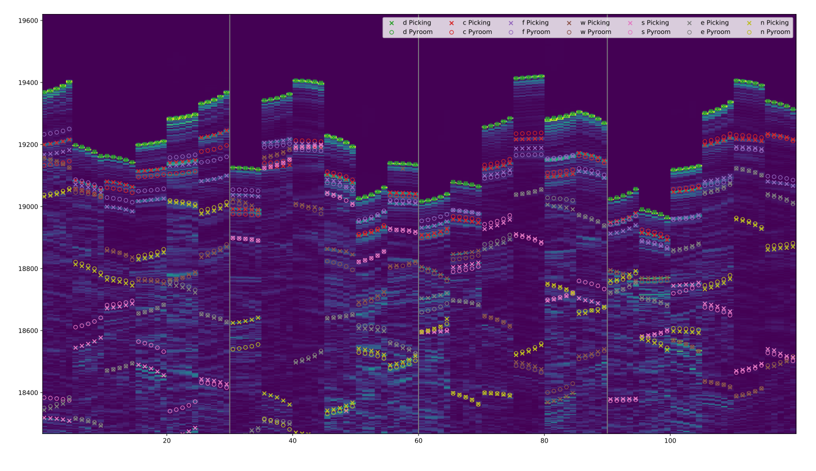


RIR Skyline showing

- absolute value of stacked RIRs as a figure
- × manual echo annotation
- ∘ *matching* echo annotation for `ISM simulator`

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Estimate shape, volume or reflector position from signal (or form TOAs).

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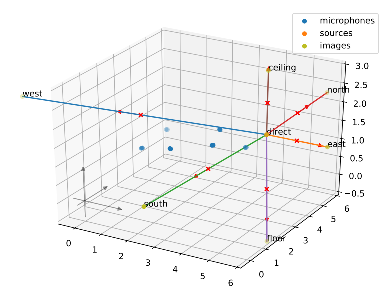

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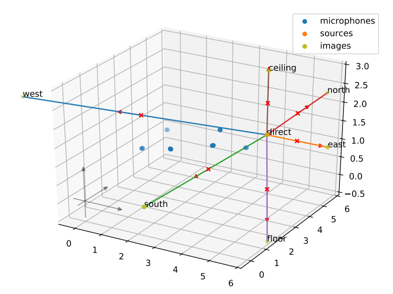


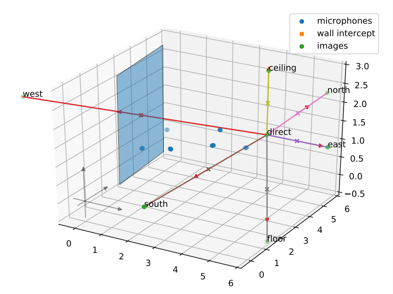

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| source id | 1 | | 2 | | 3 | | 4 | |
|---|---|---|---|---|---|---|---|---|
| wall | DE | AE | DE | AE | DE | AE | DE | AE |
| west | 0.74 | 8.99 | 4.59 | 8.32 | 5.89 | 5.75 | **0.05** | **2.40** |
| east | **0.81** | **0.08** | 0.9 | 0.50 | *69.51* | *55.70°* | 0.31 | 0.21 |
| south | 3.94 | *16.08°* | **0.18** | 1.77 | *14.37* | *18.55°* | 0.82 | **1.65** |
| north | 1.34 | 0.76 | 1.40 | 8.94 | **0.63** | **0.17** | 2.08 | 1.38 |
| floor | **5.19** | **1.76** | 7.27 | 2.66 | 7.11 | 2.02 | 5.22 | 1.90 |
| ceiling | 1.16 | 0.28 | 0.67 | 0.76 | **0.24** | 1.16 | 0.48 | **0.26** |

Distance Error (DE) [cm] and Angular Error (AE), **best**, *outliers*

# Echo-aware Speech Enhancement with dEchorate

**Speech Enhancement (SE)**

Improve the quality of a target sound source w.r.t.:

| interfering sources | + | noise | + | reverberation |
|---|---|---|---|---|
| ↓ | | ↓ | | ↓ |
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SE via **linear spatial filtering**

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$$\widehat{\mathbf{w}} = \arg\min_{\mathbf{w}} \mathbb{E}\left\{\left\|\mathbf{w}^{\mathsf{H}}\mathbf{x}\right\|_2^2\right\} \quad \text{s.t.} \quad \mathbf{w}^{\mathsf{H}}\mathbf{h} = 1$$

Reducing output energy + distortionless ⇔ reduce any noise

Closed-form solution, but it requires:

| | Noise covariance matrix | Steering Vectors |
|---|---|---|
| DS | - | Direct Path (AOA) |
| $\mathtt{MVDR}_{\mathtt{DP}}$ | Noise | Direct Path (AOA) |
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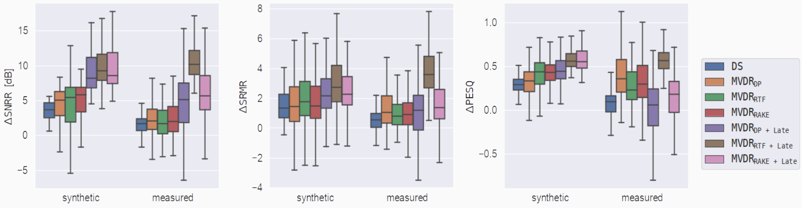

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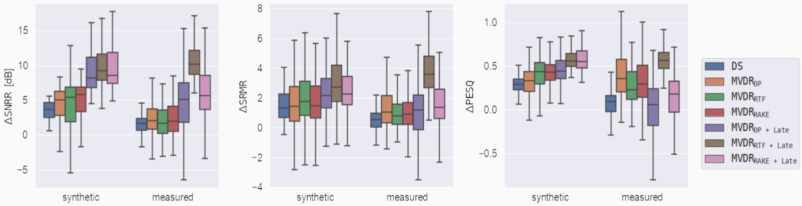

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| $\mathrm{MVDR}_{\mathrm{DP+Late}}$ | Noise + Late Diffusion | Direct Path (AOA) |
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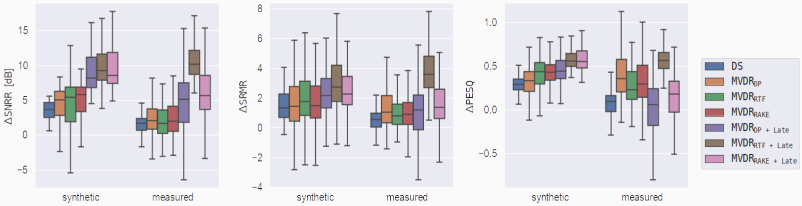
Comparison on dEchorate data




- *In theory* echo-aware ws. echo-agnostic?
  → Better than Direct Path, but ReTF and Rake are comparable

# Echo-aware Speech Enhancement

Closed-form solution, but it requires:

| | Noise covariance matrix | Steering Vectors |
|---|---|---|
| DS | - | Direct Path (AOA) |
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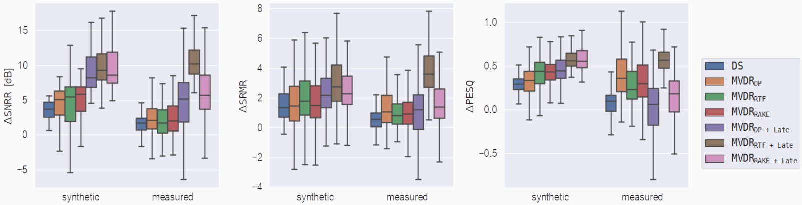


- *In theory* echo-aware ws. echo-agnostic?
  $\rightarrow$ Better than Direct Path, but ReTF and Rake are comparable
- Spatial filtering on Synthetic data vs. Measured data?
  $\rightarrow$ Rake suffer from mismatch, but better than DP

# Conclusion

# Summary of contributions

1. How to estimate echoes?

2. How to use echoes?

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`Blaster`: knowledge-based

- ✓ non-neg.ty and sparsity
- ✓ low RMSE by super-resolution
- ✗ dep. on source and # echoes
- ✗ vanilla solver

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- ✗ only 2 echoes, how more?
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### 3. Where to find echoes?

**dEchorate**: dataset
- ✓ dataset for AER, SE and RooGE
- ✓ geom labels $\leftrightarrow$ echo labels
- ✗ few inconsistency
- ✗ shoebox, linear array and directional

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`dEchorate`: Validation
- ✓ on RooGE
- ✓ on echo-aware SE
- ✗ echo-SE similar to ReTF-SE
- ✗ echo-SE suffer for mismatch

# Echo-aware perspective

Directions for future work:

# Echo-aware perspective

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- on **estimation**

  **Blaster** extended to multichannel [Tukuljac, 2020] and ReTF [Doclo and Moonen, 2002]

  use high-level priors ($RT_{60}$, DRR, Diffusion) [Badeau, 2019]

  **Lantern** extended physic-based learning

  more than 2 echoes: network or learning

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  - Lantern extended physic-based learning
  - more than 2 echoes: network or learning
- on **application**
  - validation on real data (eg. smart home speaker)
  - use dEchorate data for validation
  - other Audio Scene Analysis problem
  - other field of echoes (Seismology, Underwater acoustic, Volcano tomography)
- on dEchorate
  - Synthetic to Real RIRs
  - popularization and divulgation of these data
  - write how to and how not echo-aware dataset

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- Echo estimation $\Longleftrightarrow$ Audio Analysis

# List of publications and artifacts

## Publications

- Estimation
  - `Lantern` [Di Carlo et al., 2019]
  - `dEchorate` [Di Carlo et al., 2020]
- Application
  - `Mirage` [Di Carlo et al., 2019]
  - `Separake` [Scheibler et al., 2018]
- Data
  - `dEchorate` (Unpublished)
- Other
  - Signal Processing CUP 2019 [Deleforge et al., 2019]
  - LOCATA Challenge 2019 [Lebarbenchon et al., 2018]
  - Collaboration with Honda [Di Carlo and Deleforge, ]

## Code

`dEchorate`: GUI and code for `dEchorate` (and RooGE)

`Risotto`: library for Relative Transfer Function

`Brioche`: library for echo-aware Spatial filtering

`pyMBSSLocate`: MBSSLocate in Python

`Separake`: Multichannel NMF in Python

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