Echo-aware signal processing for audio scene analysis

Diego Di Carlo

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

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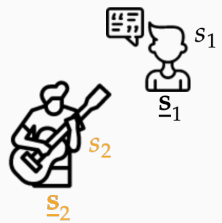
Introduction

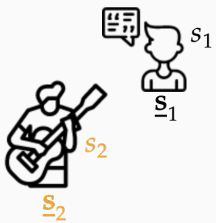
Scenario

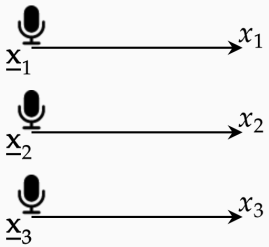


Sound

- produced by sources

Scenario

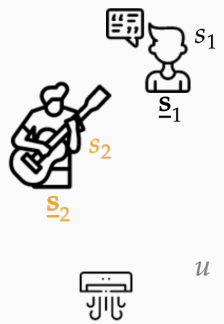


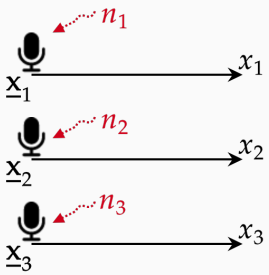


Sound

- produced by sources
- recorded by microphones

Scenario

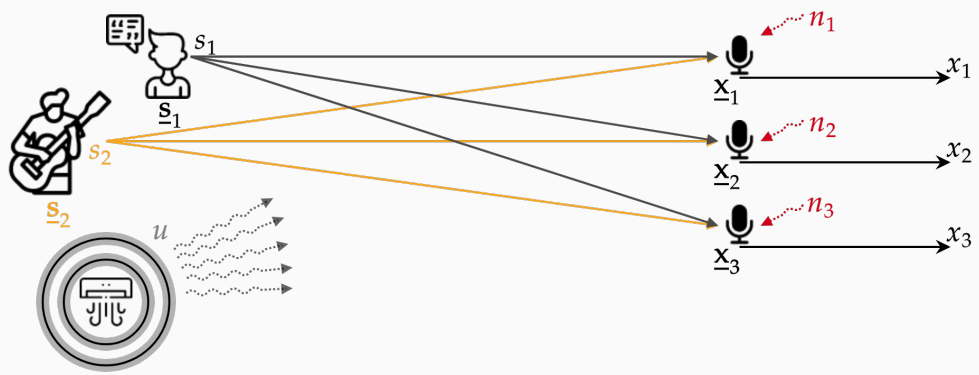




Sound

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

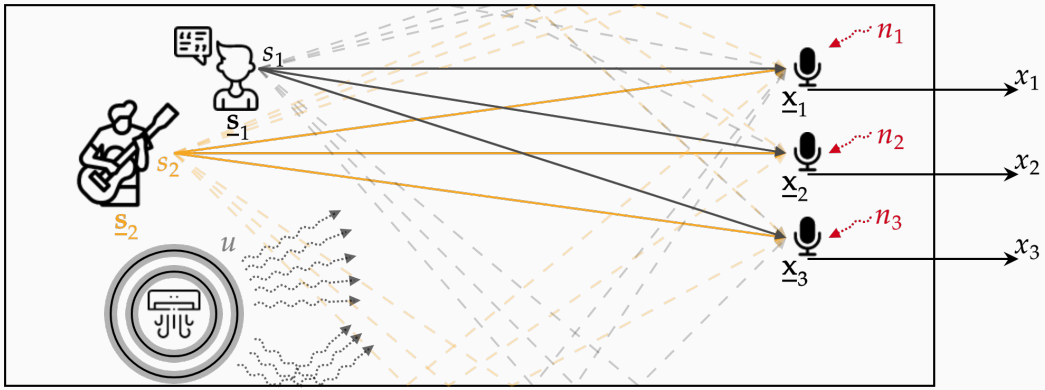
Scenario



Sound

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

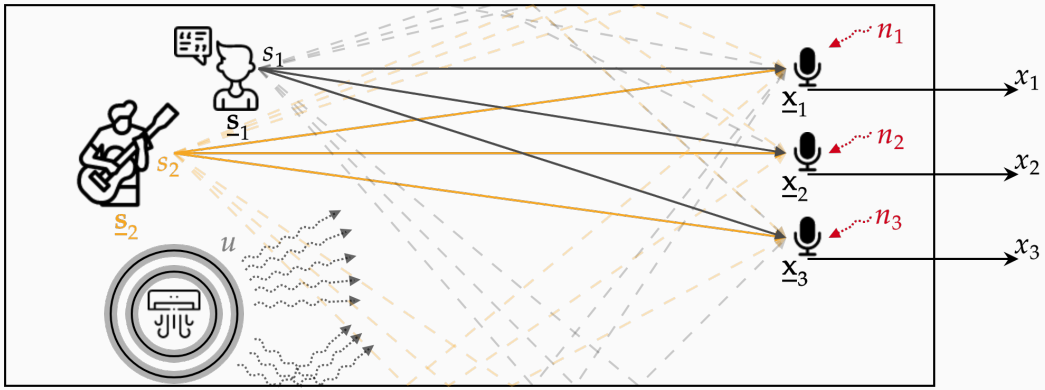
Scenario



Sound

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

Scenario

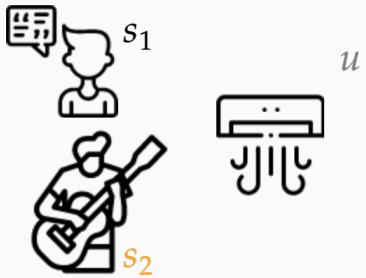


Sound

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

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

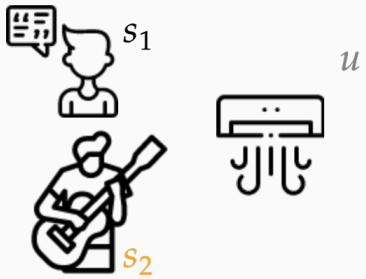
Semantic information



on nature and content

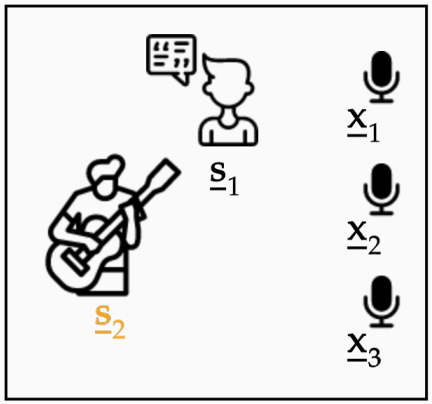
Echo-aware signal processing for audio scene analysis

Semantic information



on nature and content

Spatial information



on position and geometry

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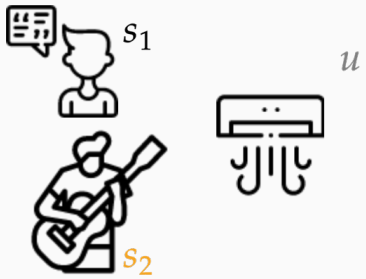

on nature and content

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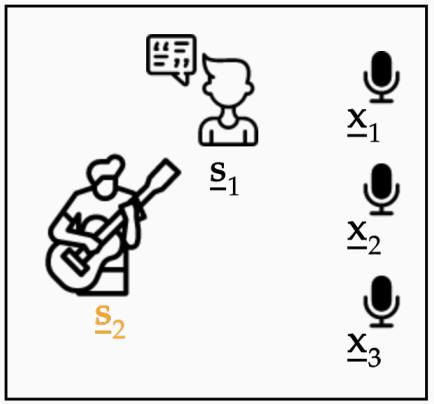
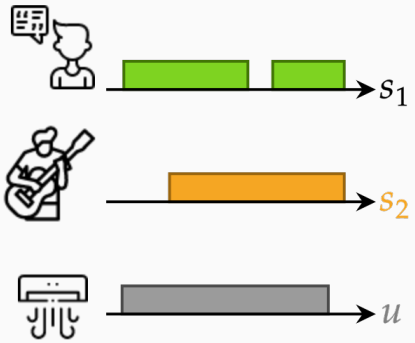


on position and geometry

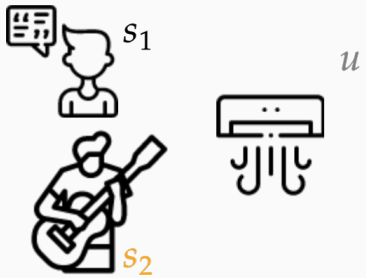
Temporal information



on events activity

Echo-aware signal processing for audio scene analysis

Semantic information



on nature and content

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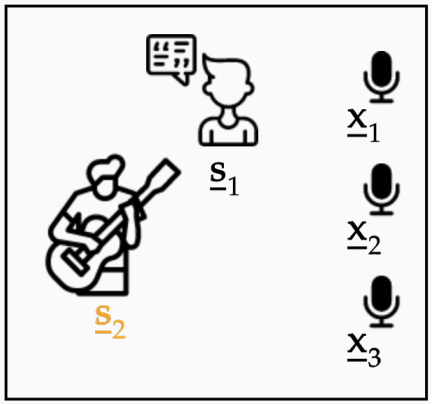

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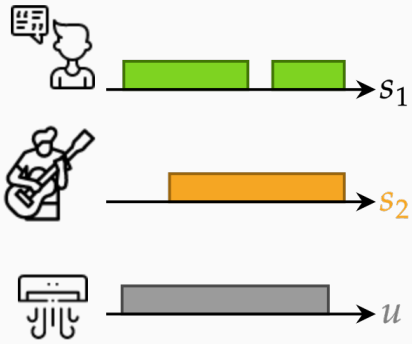
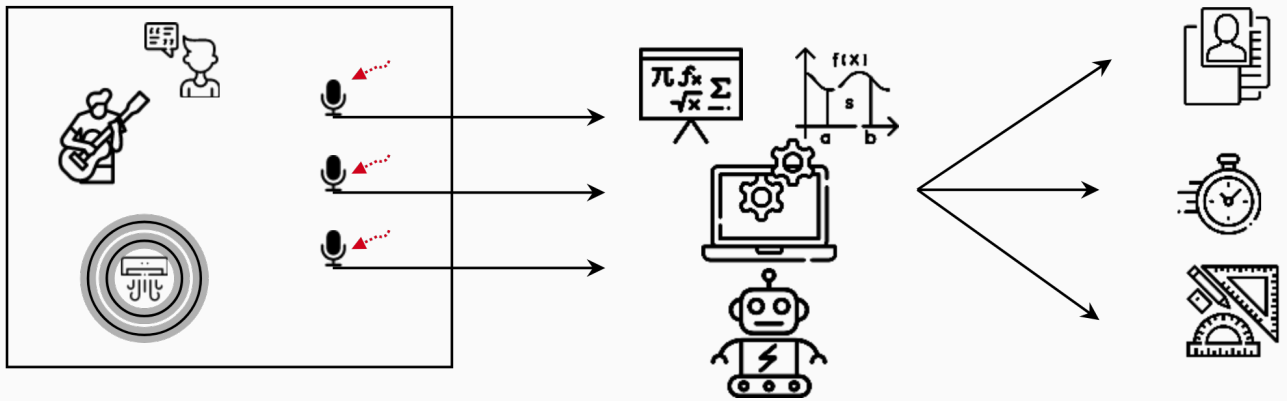


on events activity

Audio Scene Analysis

Extraction and organization of all the information in the sound



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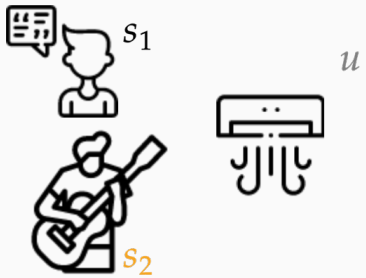

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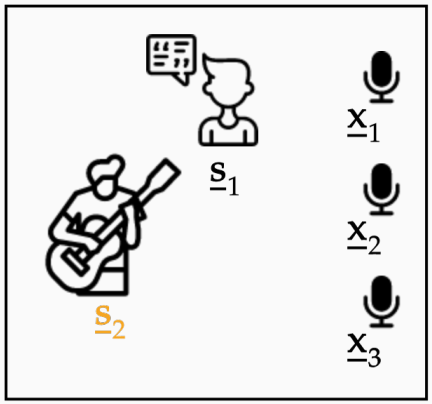
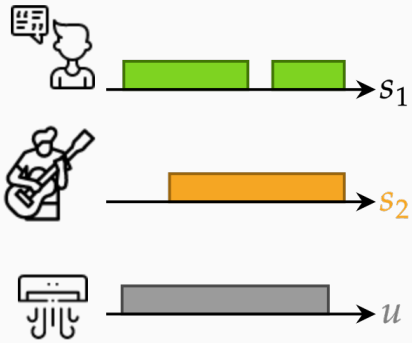


on position and geometry

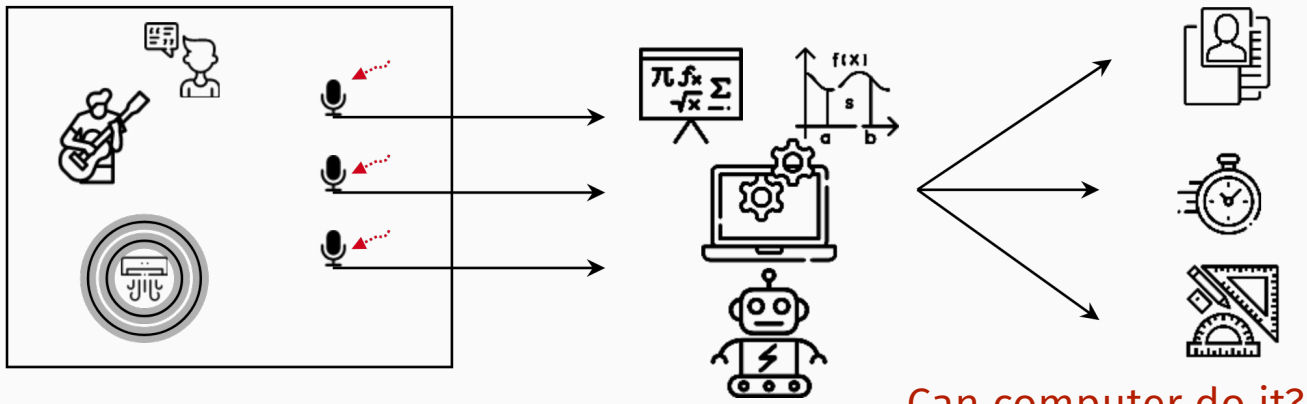
Temporal information



on events activity

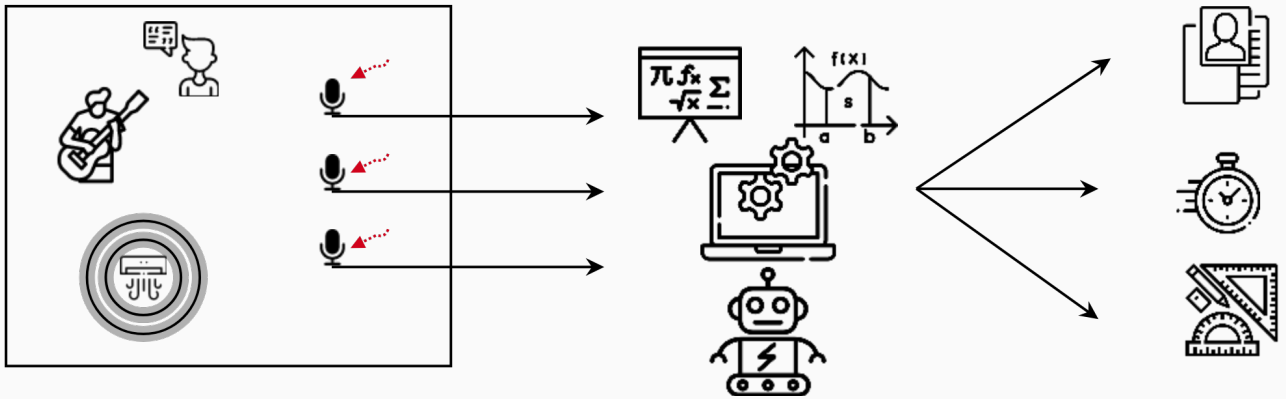
Audio Scene Analysis

Extraction and organization of all the information in the sound



Can computer do it?

Echo-aware signal processing for audio scene analysis



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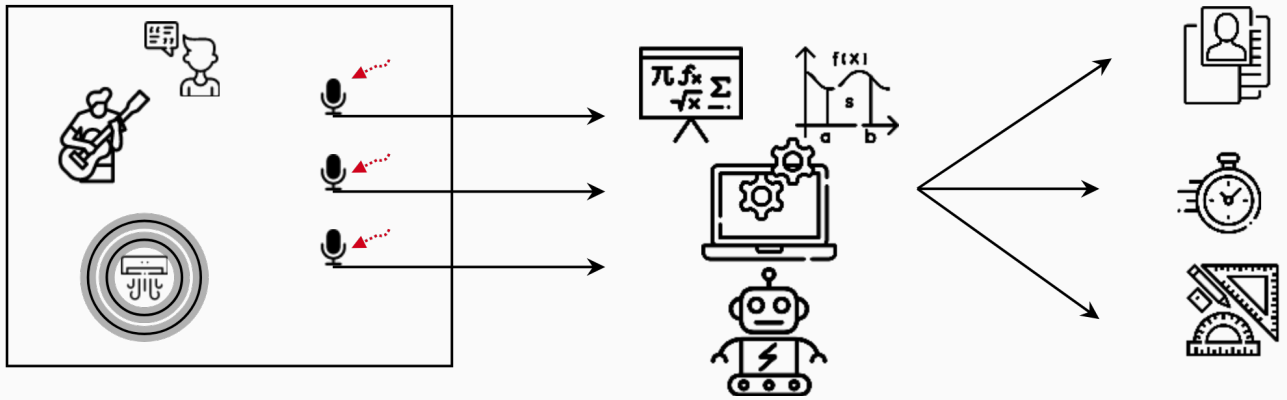
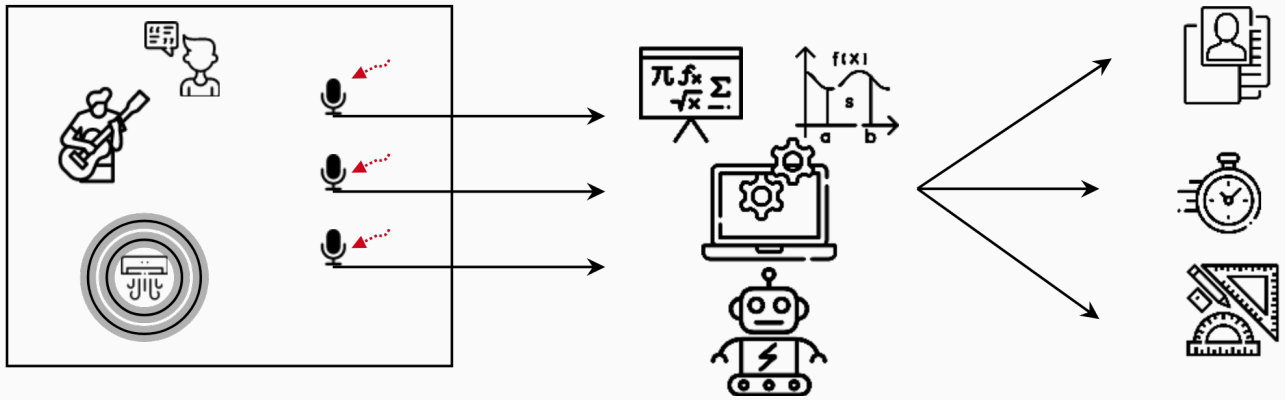


Signal Processing

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



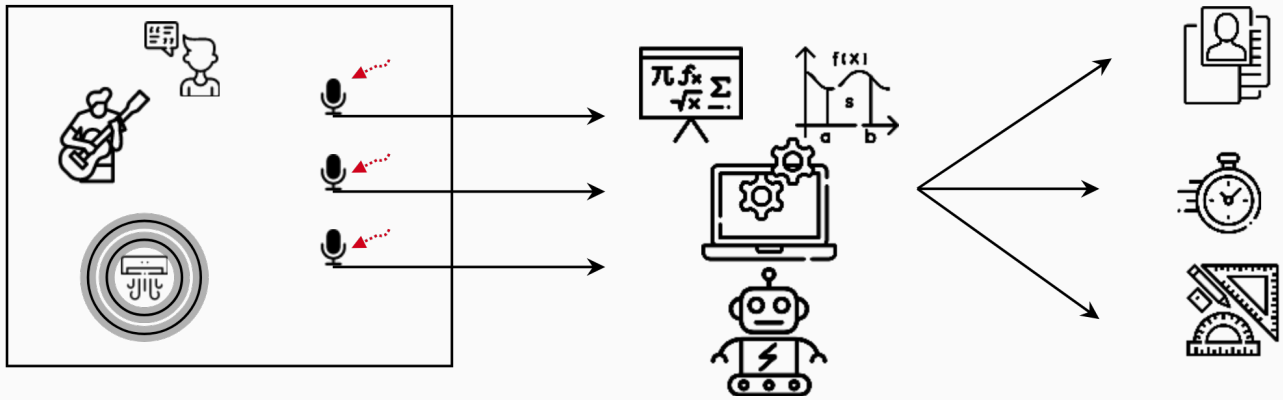
Signal Processing

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
- RT_{60} estimation
- Acoustic Channel Estimation
- Wall Absorption Estimation
- *and many many other*

Echo-aware signal processing for audio scene analysis

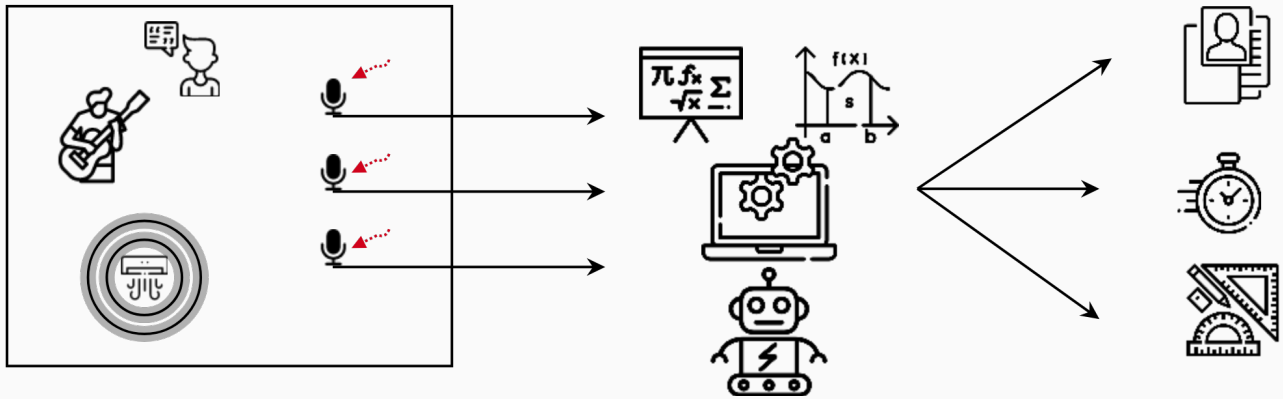


Signal Processing

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

Some (inverse) problems

- Speaker Identification — Who?
- Sound Source Separation (SSS) — What?
- Speech Enhancement (SE) — What?
- Automatic Speech Recognition (ASR) — What?
- Sound Source Localization (SSL) — Where?
- Room Geometry Estimation (RooGE) — Where?
- Voice Activity Detection — When?
- Diarization — When?
- RT_{60} estimation — How?
- Acoustic Channel Estimation — How?
- Wall Absorption Estimation — How?
- *and many many other*



Signal Processing

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

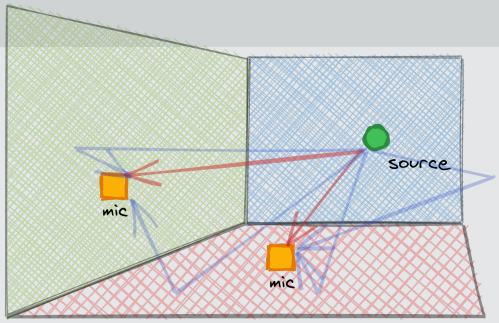
Some (inverse) problems

• Speaker Identification	Who?	• Voice Activity Detection	When?
• Sound Source Separation (SSS)		• Diarization	
• Speech Enhancement (SE)	What?	• RT_{60} estimation	How?
• Automatic Speech Recognition (ASR)		• Acoustic Channel Estimation	
• Sound Source Localization (SSL)	Where?	• Wall Absorption Estimation	
• Room Geometry Estimation (RooGE)		• *and many many other*	

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

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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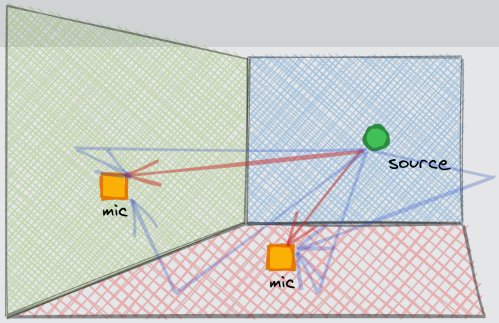

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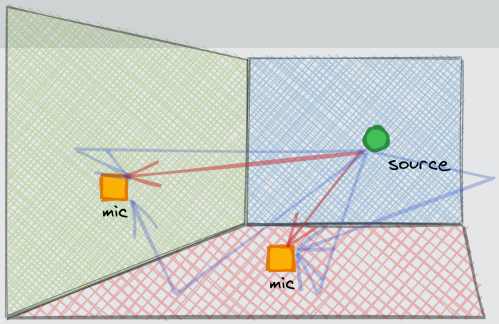
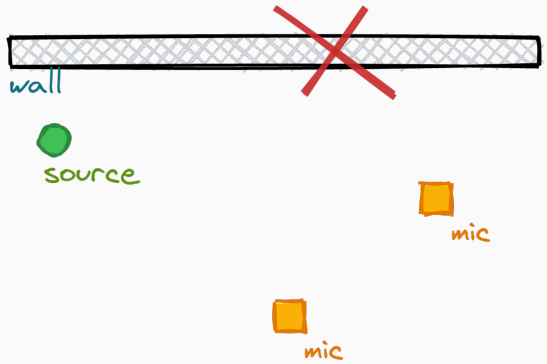


Audio signal processing methods

- ignore it



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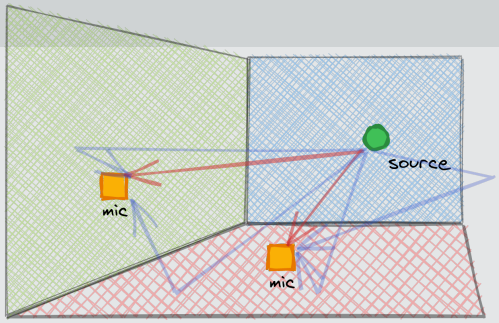
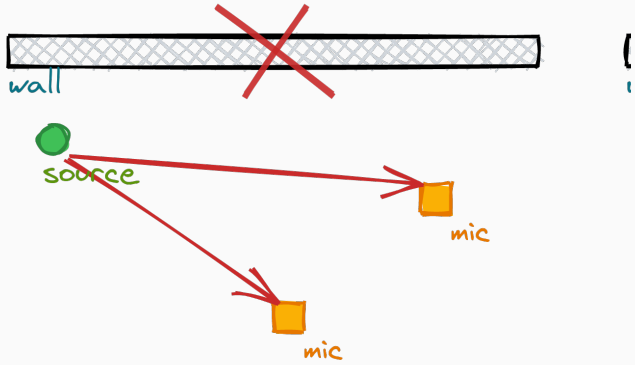


Audio signal processing methods

- ignore it
- assume it free-field



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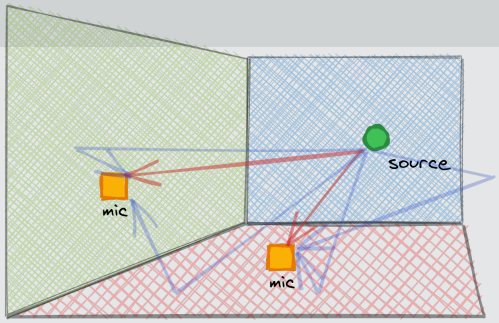
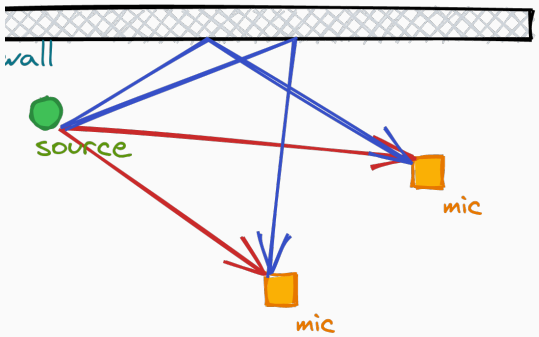


Audio signal processing methods

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



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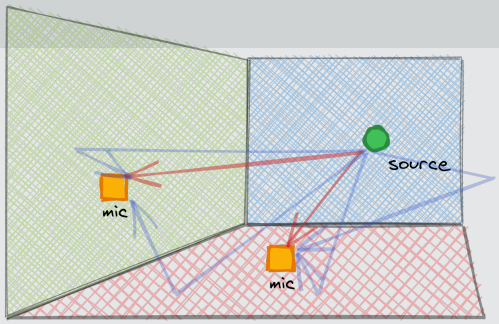
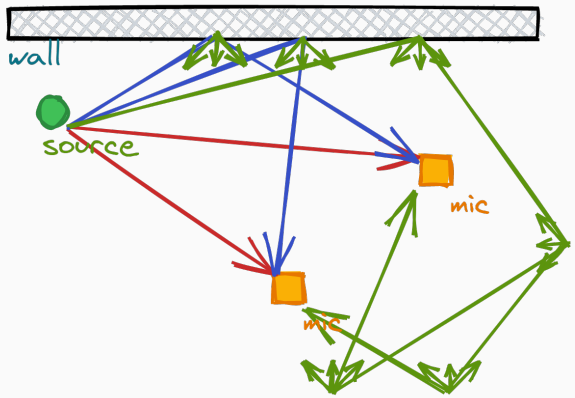


Audio signal processing methods

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



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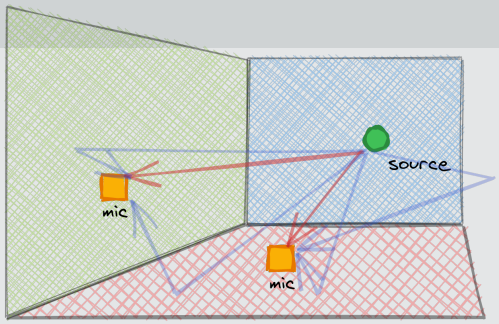
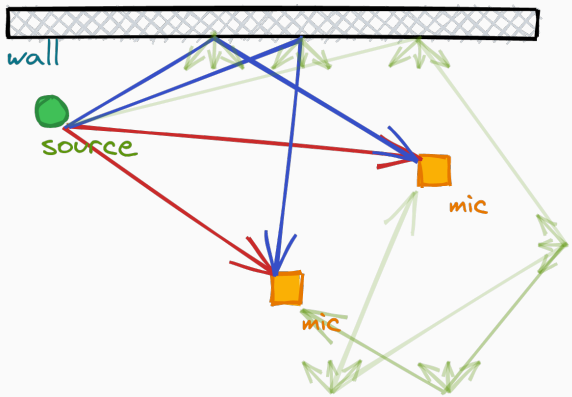


Audio signal processing methods

- ignore it
- assume it free-field
- model it entirely
- model as few reflection
- model it as early and late parts



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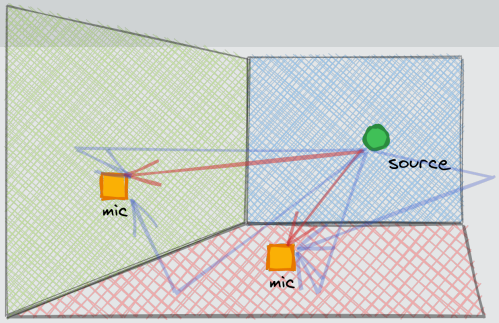

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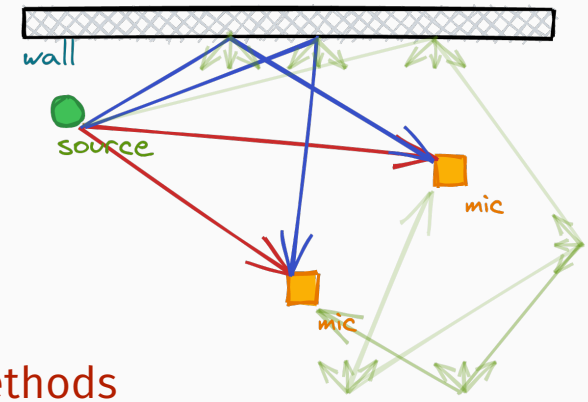

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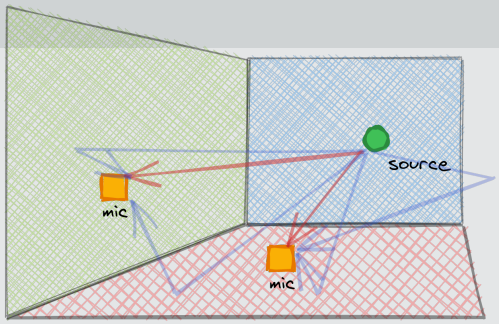

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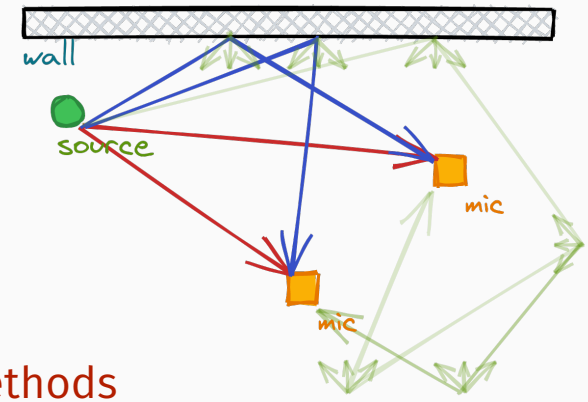

Modelling the sound field

- as free field $\Longrightarrow$ **simple**, but **incoherent** processing (lost of energy)
- entirely $\Longrightarrow$ **coherent** processing, but very **challenging**

Goals and contributions

Audio Scene Analysis

↓

context and problems

Goals and contributions

Audio Scene Analysis

↓

context and problems

Signal Processing

↓

models and frameworks

Goals and contributions

Audio Scene Analysis	Signal Processing	Acoustic Echoes
↓	↓	↓
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1. How to **estimate** acoustic echoes?
2. How to **extend methods** for echo-aware audio scene analysis

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2. How to **extend methods** for echo-aware audio scene analysis

1. Estimation

2. Application

Goals and contributions

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- Literature review on echo estimation
- Knowledge-based echo estimation
  ↪ `Blaster`
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- Echo-aware Source Separation
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- Echo-aware Source Localization
  ↪ `Mirage`
- Echo-aware Speech Enhancement
- Echo-aware Room Geometry Estimation

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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

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

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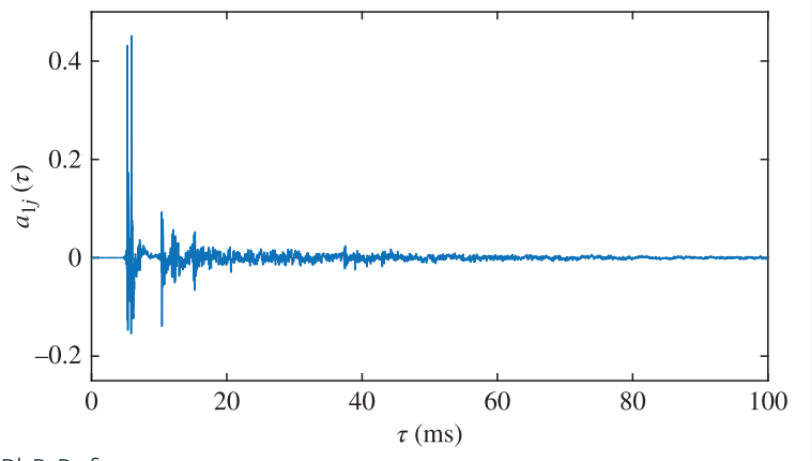
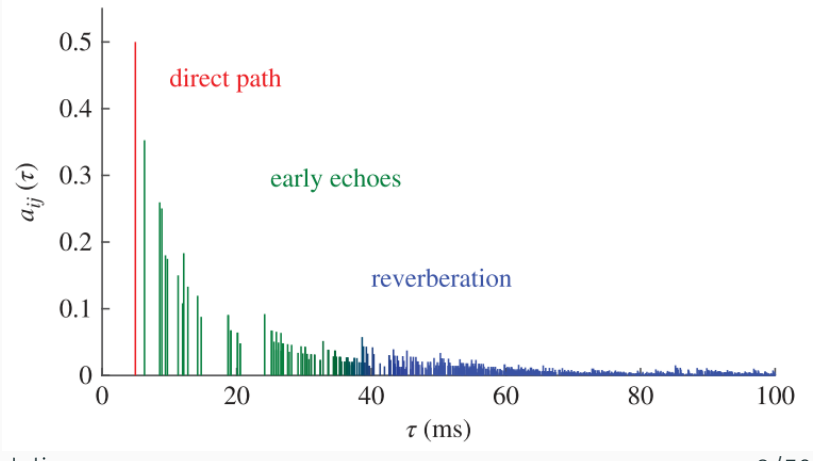
Sound propagation process = **source** $\rightarrow$ **filter** $\rightarrow$ **receiver** process

$$x_i(t) = (a_{ij} * s_j)(t) \qquad \leftarrow \text{continuous time domain!}$$

The filter $a_{ij}(t)$ is linear and is called **Acoustic Impulse Response**, (AIR)





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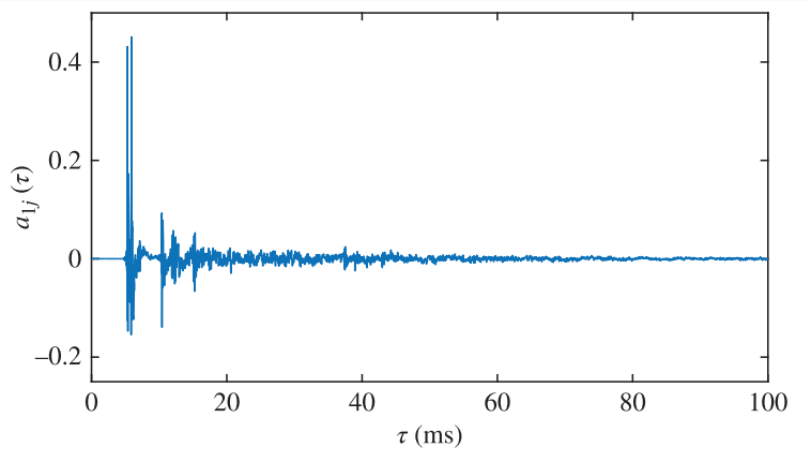
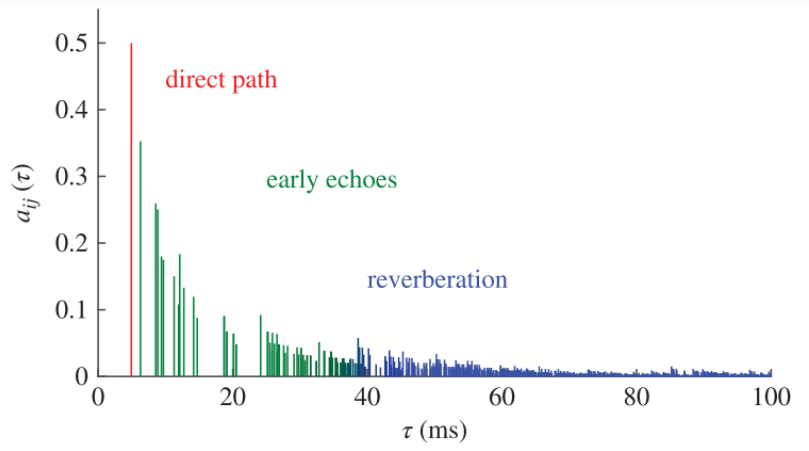
Indoor Sound propagation process = source → filter → receiver process

$$x_i(t) = (h_{ij} * s_j)(t)$$ ← continuous time domain!

The filter $h_{ij}(t)$ is linear and is called Room Impulse Response, (RIR)





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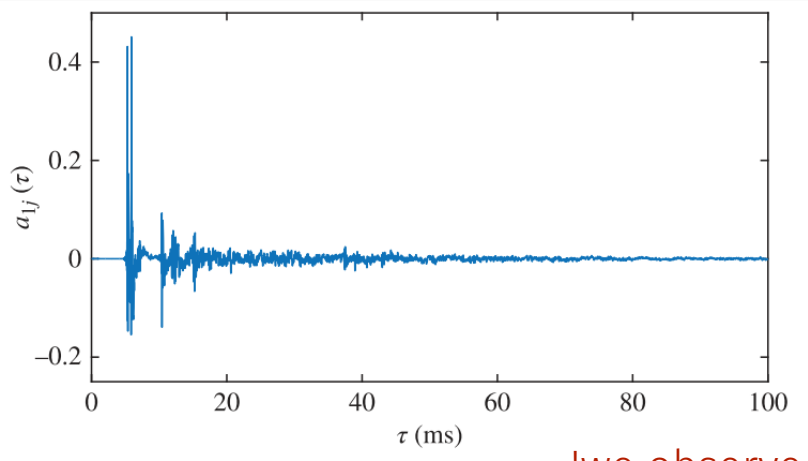
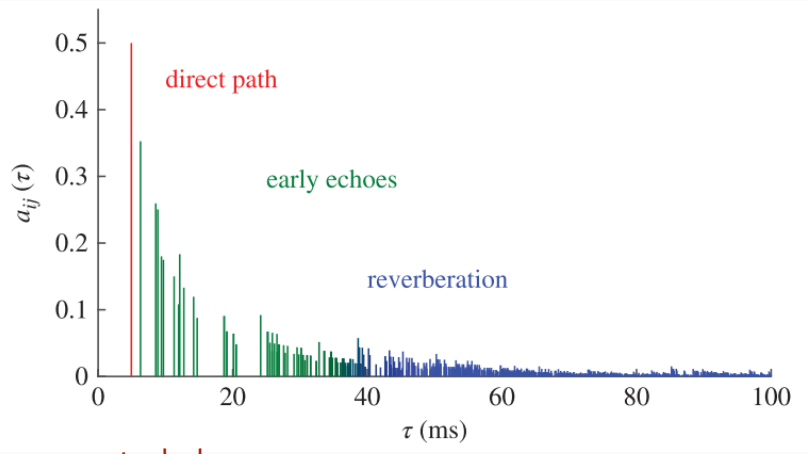


$\approx^{?}$

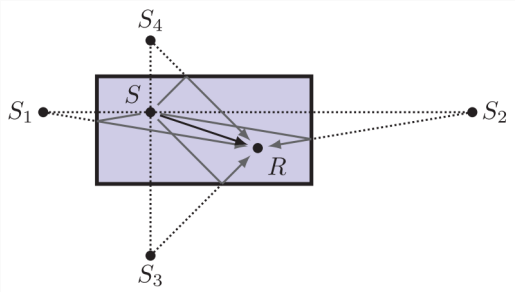


!we observe filters, not delays

Echoes and Room Impulse Response

RIRs can be modeled with the Image Methods

- **specular reflection** only
- for cuboid room, **it is** the sound prop.
- in general, **well models the early part** of RIRs.
- unique for each source and mic source



"playing billiard in a concert hall"

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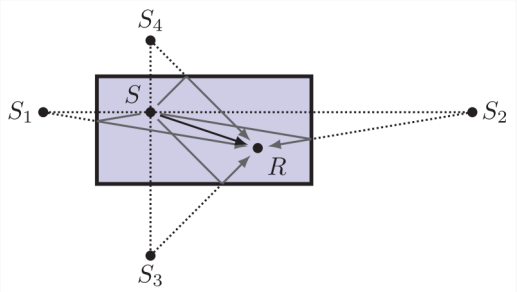

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$$h_i^e(t) = \sum_{r=0}^{R} \alpha_i^{(r)} \delta(t - \tau_i^{(r)})$$

sum of Dirac's delta

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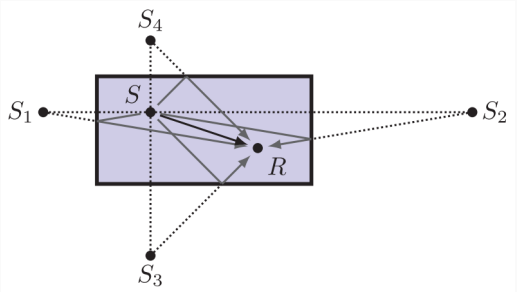

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$$h_i^e(t) = \sum_{r=0}^{R} \alpha_i^{(r)} \delta(t - \tau_i^{(r)}) \qquad \xrightarrow{\text{more realistic}} \qquad H_i^e(f) = \sum_{r=0}^{R} \alpha_i^{(r)}(f) \mathrm{e}^{-\mathrm{i}2\pi f \tau_i^{(r)}}$$

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sum of filters

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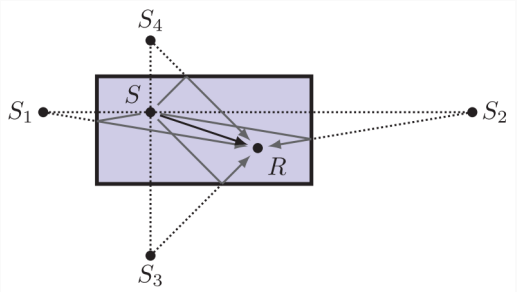

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sum of filters

RIRs accounts for

the **geometry** of the room

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

the **acoustic properties** of

- surface materials
- objects materials

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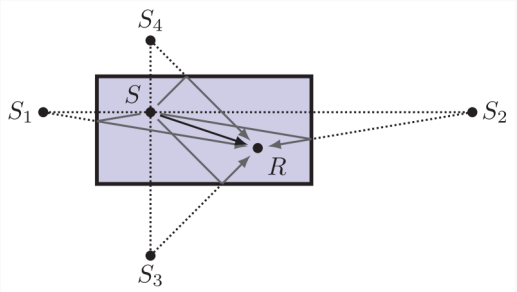

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Echoes

strong and distinct specular reflection

Acoustic Echo Estimation

Acoustic Echo Retrieval

The acoustic echoes retrieval (AER) problem

Estimating early (strong) acoustic reflections:

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

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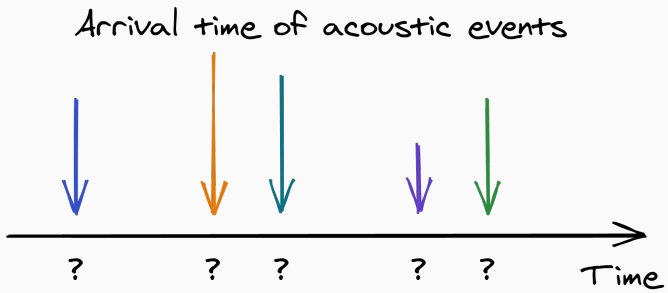

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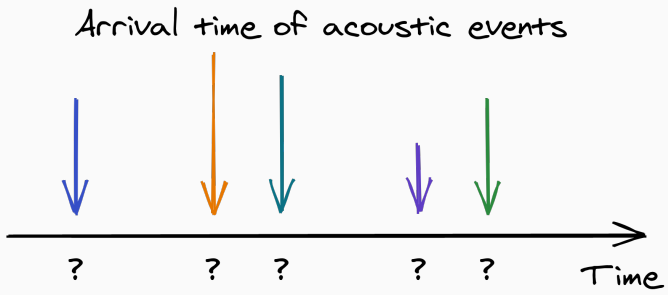
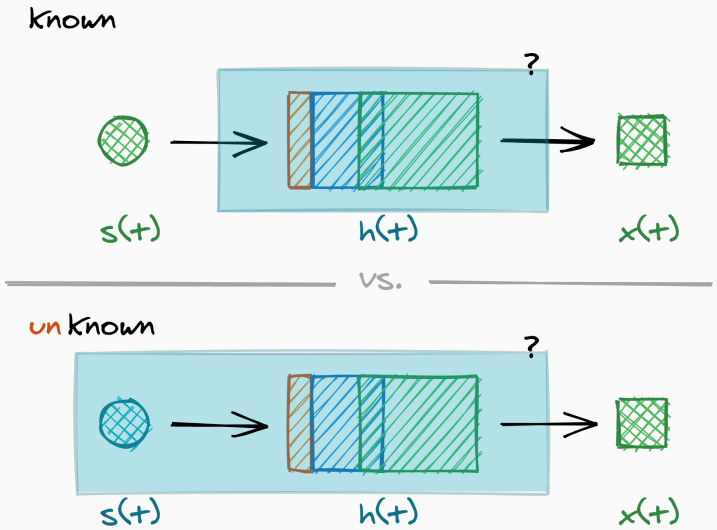


Approaches

Source signal is



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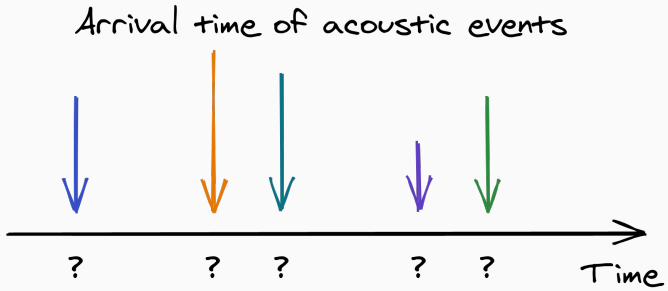

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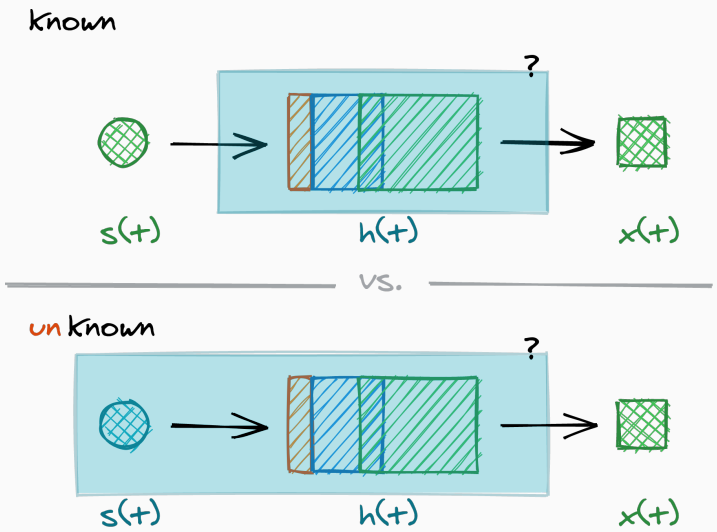

Active approaches

- **easier** problem
- **intrusive** or specific setup
- Time of Arrival (**TOA**s) accessible
  $\Longrightarrow$ **single** mic

Application sonar, calibration, measurements

Passive approaches

- **blind inverse** problem (harder)
- **passive** listening
- Time Difference of Arrivals (**TDOA**s) only
  multi-mic

Application a-posteriori processing, smart speakers, ...

The acoustic echoes retrieval (AER) problem

Estimating early (strong) acoustic reflections:

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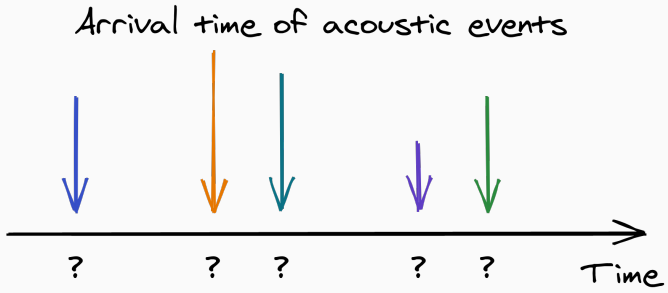

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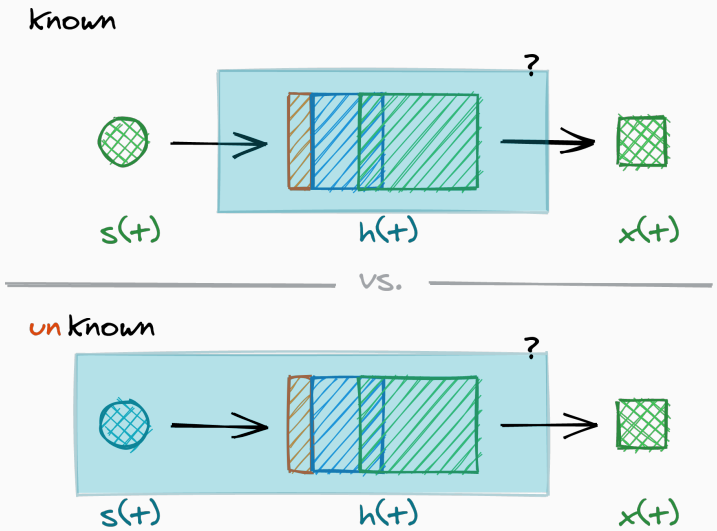
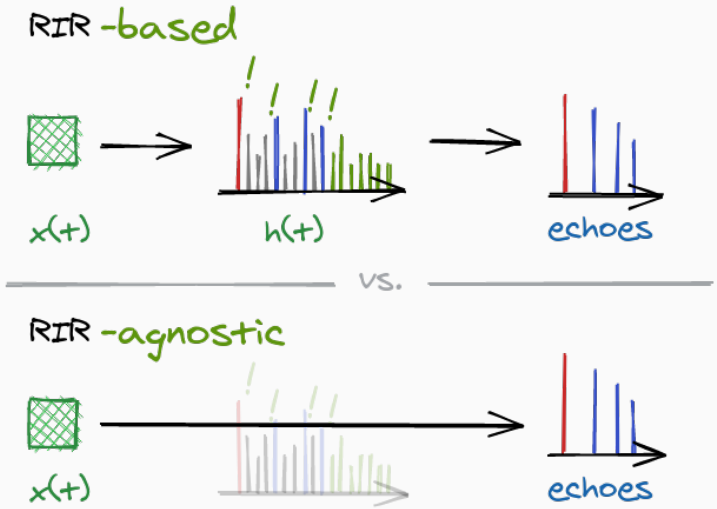


Estimation is



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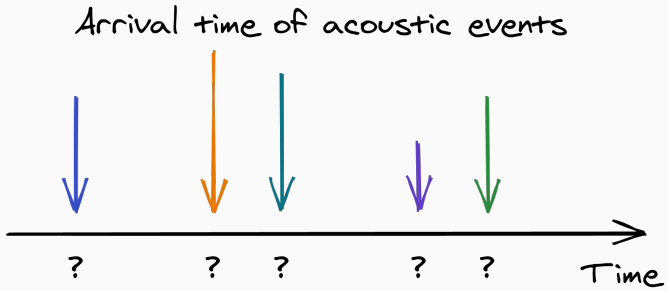

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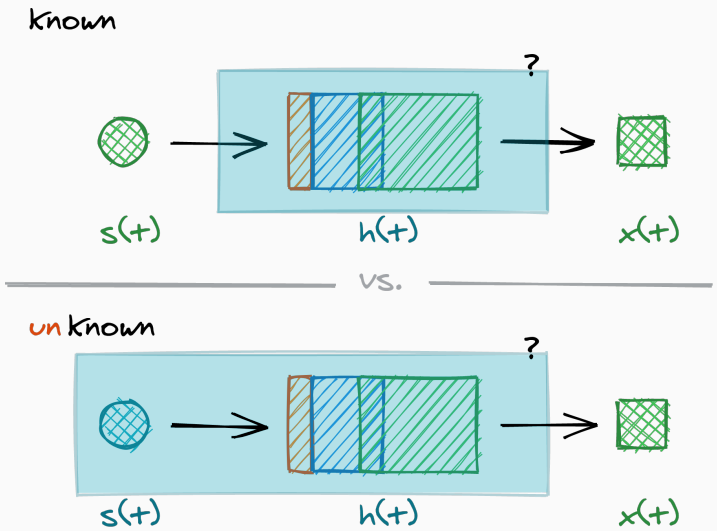

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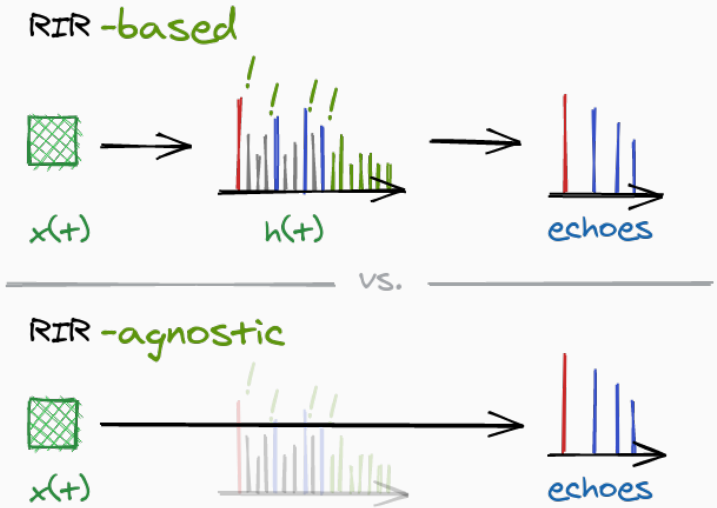
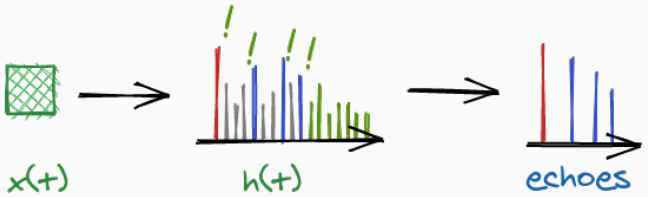


Our case: signal source, only TOAs and passive system (I mics)

Passive Acoustic Echo Estimation

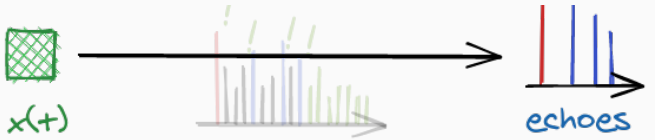
Passive Acoustic Echo Estimation:

Passive Acoustic Echo Estimation:
RIR-based approaches



1. SIMO BCE problem $\Longrightarrow$ RIRs
2. Peak picking $\Longrightarrow$ Echoes

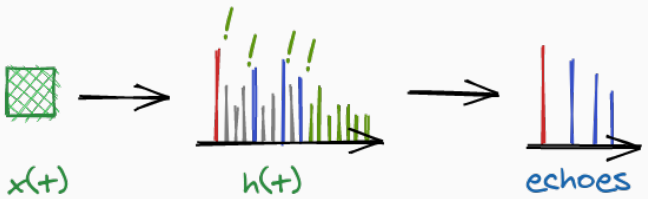
RIR-agnostic approaches



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:
RIR-based approaches



1. SIMO BCE problem $\Longrightarrow$ RIRs
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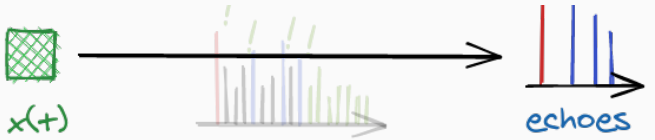
Pros

- SIMO BCE is well studied (eg. LASSO) (many frameworks and solver)
- Good in some scenario

RIR-agnostic approaches

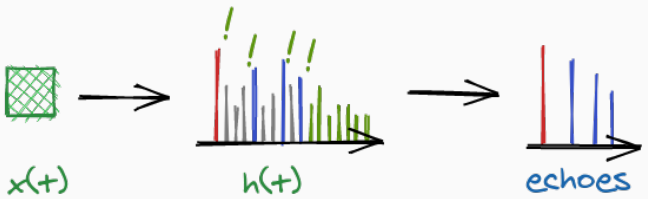


1. Estimation in the space $\left\{\tau_i^{(r)}, \alpha_i^{(r)}\right\}_{i,r}$ (+ direction of arrivals can be used instead)

Pros

- No full RIRs, no peak picking
- Sub-sampling accuracy
- Low complexity
- Sparsity and Non-negativity are respected

Passive Acoustic Echo Estimation: RIR-based approaches



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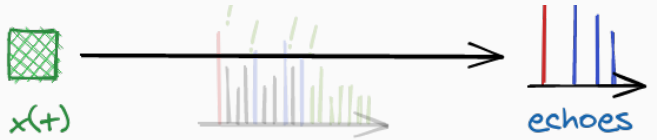
Cons

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

RIR-agnostic approaches



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Pros

- No full RIRs, no peak picking
- Sub-sampling accuracy
- Low complexity
- Sparsity and Non-negativity are respected

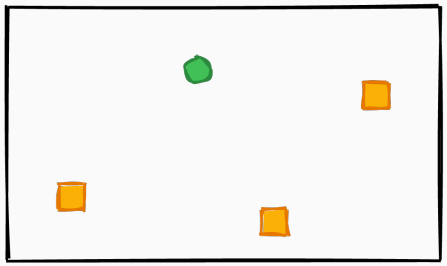
Cons

- no direct re-use of LASSO studies
- exploratory (no solver)
- easy ill-conditioned
- only few works [Tukuljac et al., 2018, Condat and Hirabayashi, 2015]

AER as discrete SIMO BCE

Key ingredient – *Cross relation identity*

$$x_i = h_i * s$$



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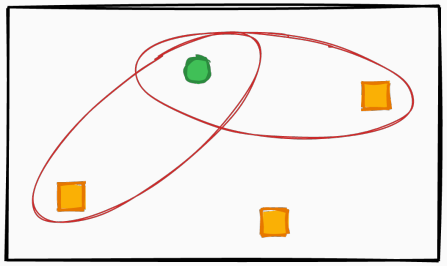
$$h_2 * x_1 = h_2 * h_1 * s = h_1 * h_2 * s = h_1 * x_2$$



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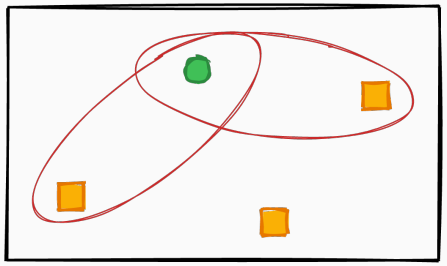

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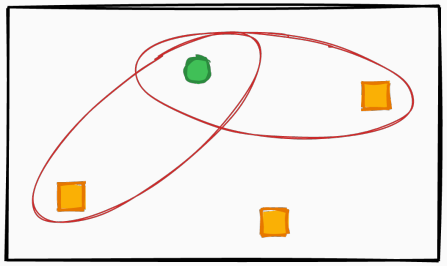

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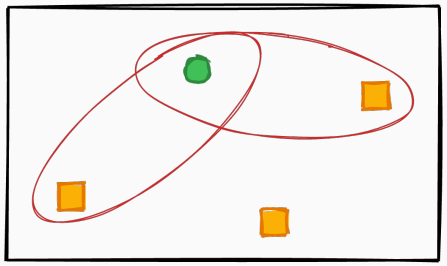

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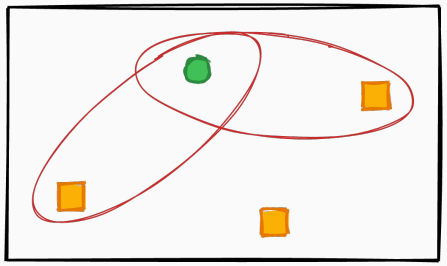

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4. Modeled as **Lasso**-like problem

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

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

- Sparsity and non-negativity not true “on grid”
- *Body guard* effect [Duval and Peyré, 2017]
  - → low recall $\implies$ low accuracy
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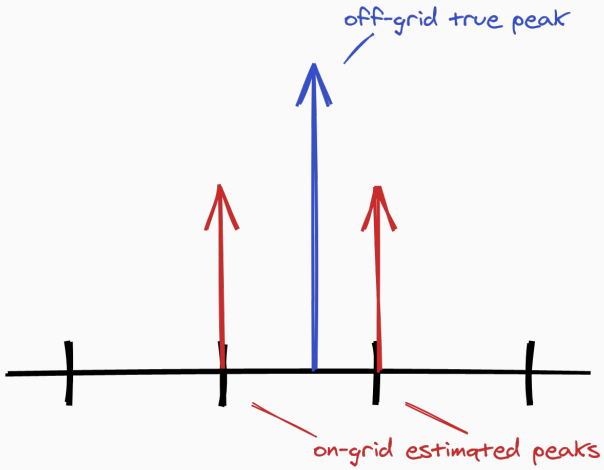

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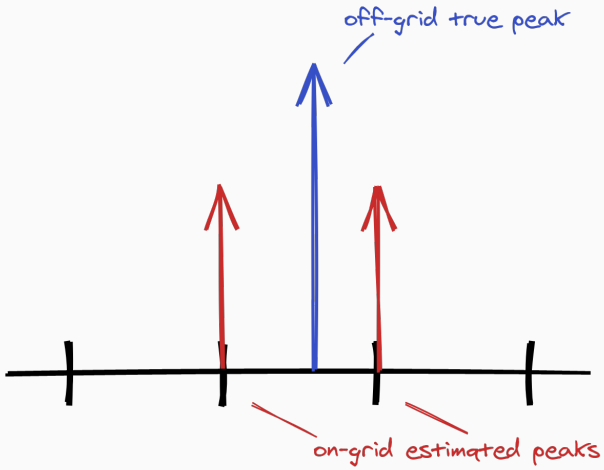

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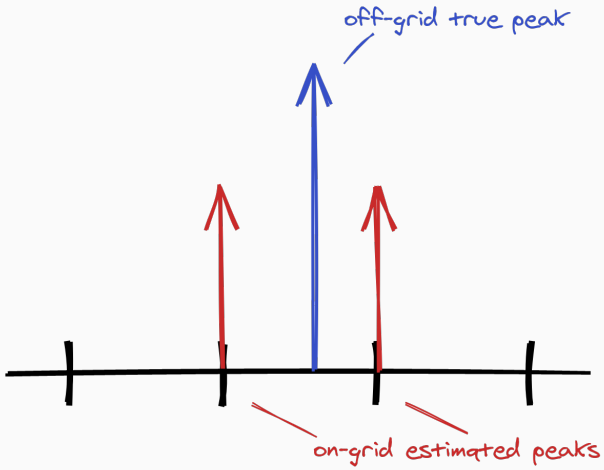

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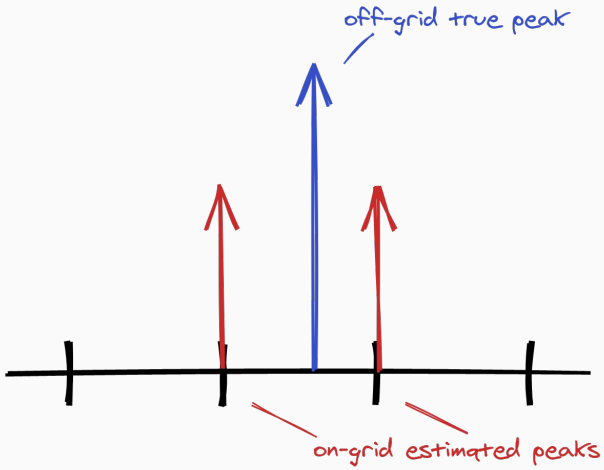

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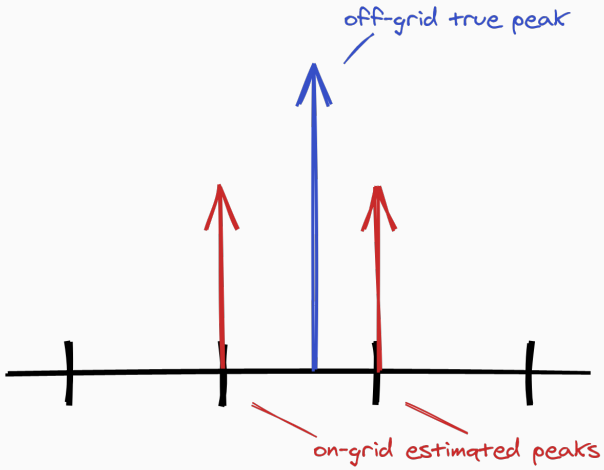

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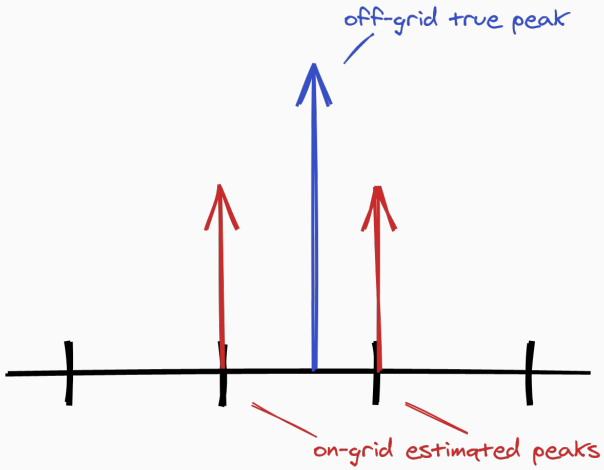

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   - Computational complexity: at best $\mathcal{O}(F_s^2)$ per iteration
   - the higher the sampling frequency, the more ill-conditioned
     $\longrightarrow$ slow convergence

How to solve this?

AER: Challenges and Contribution

$\Longrightarrow$ 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)

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

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

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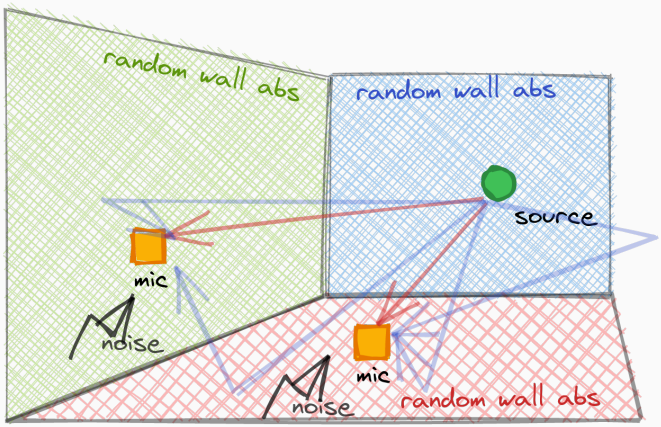
$\sim$ **Lasso** problem, but $\mathcal{F}h_2(f)$ is a continuous function.
Instance of a **BLasso** problem [Bredies and Carioni, 2020]
Solved with Sliding Frank-Wolfe algorithm [Denoyelle et al., 2019]

✓no Toeplitz matrix ✓ Solutions is a train of Dirac ✓ anchor prevents trivial solution

Methods

- BSN — SIMO BCE[Lin et al., 2007]
- IL1C: iteratively-weighted ℓ_1 constraint SIMO BCE [Crocco and Del Bue, 2015]
- Blaster: Proposed off-grid approach

Baseline method are xvalidated on other dataset



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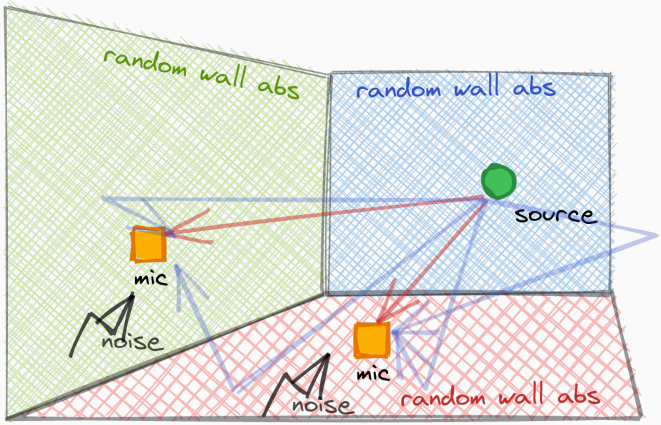

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- $\mathcal{D}^{\text{SNR}}$: $SNR \in [0, 20]$ dB, $\text{RT}_{60} = 400$ ms
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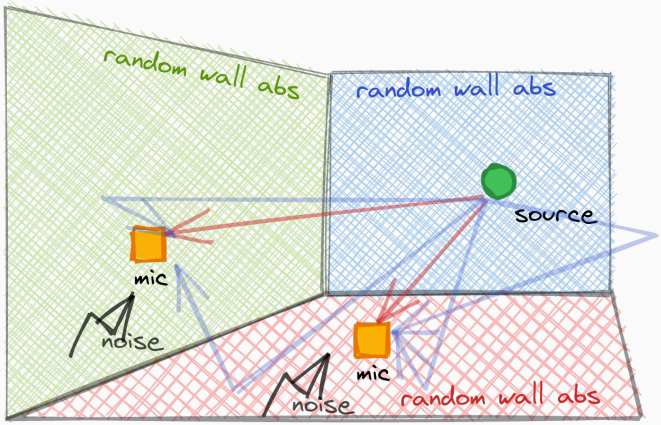

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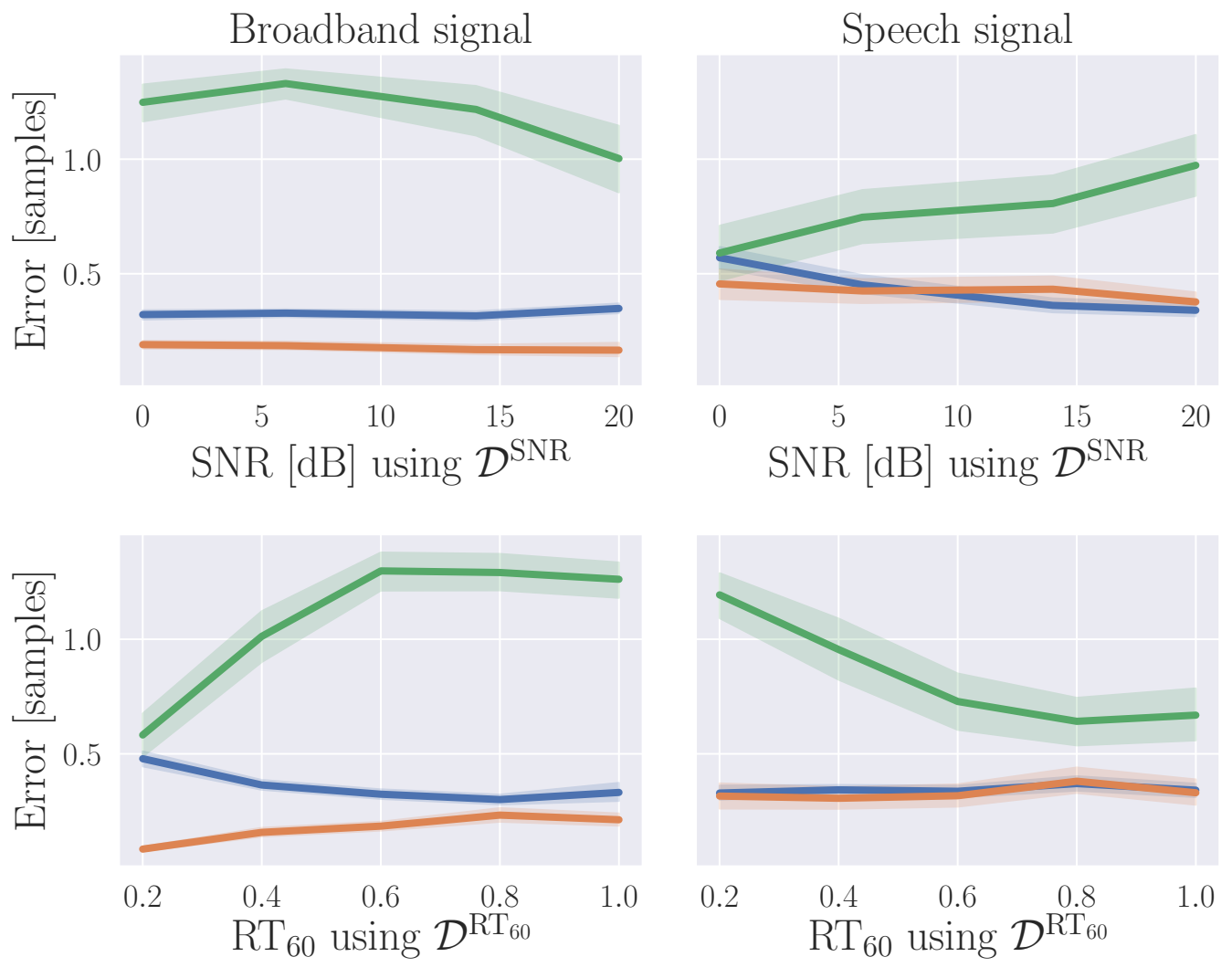
Metrics

- Precision (how many estimated echoes are correct)
- RMSE (error on the correct guess)

Error per Dataset/Signal while recovering 7 echoes



✓Lower RMSE

✓ Robustness to SNR and RT_{60}

✗ Source signal dependent

Performance per # of echoes

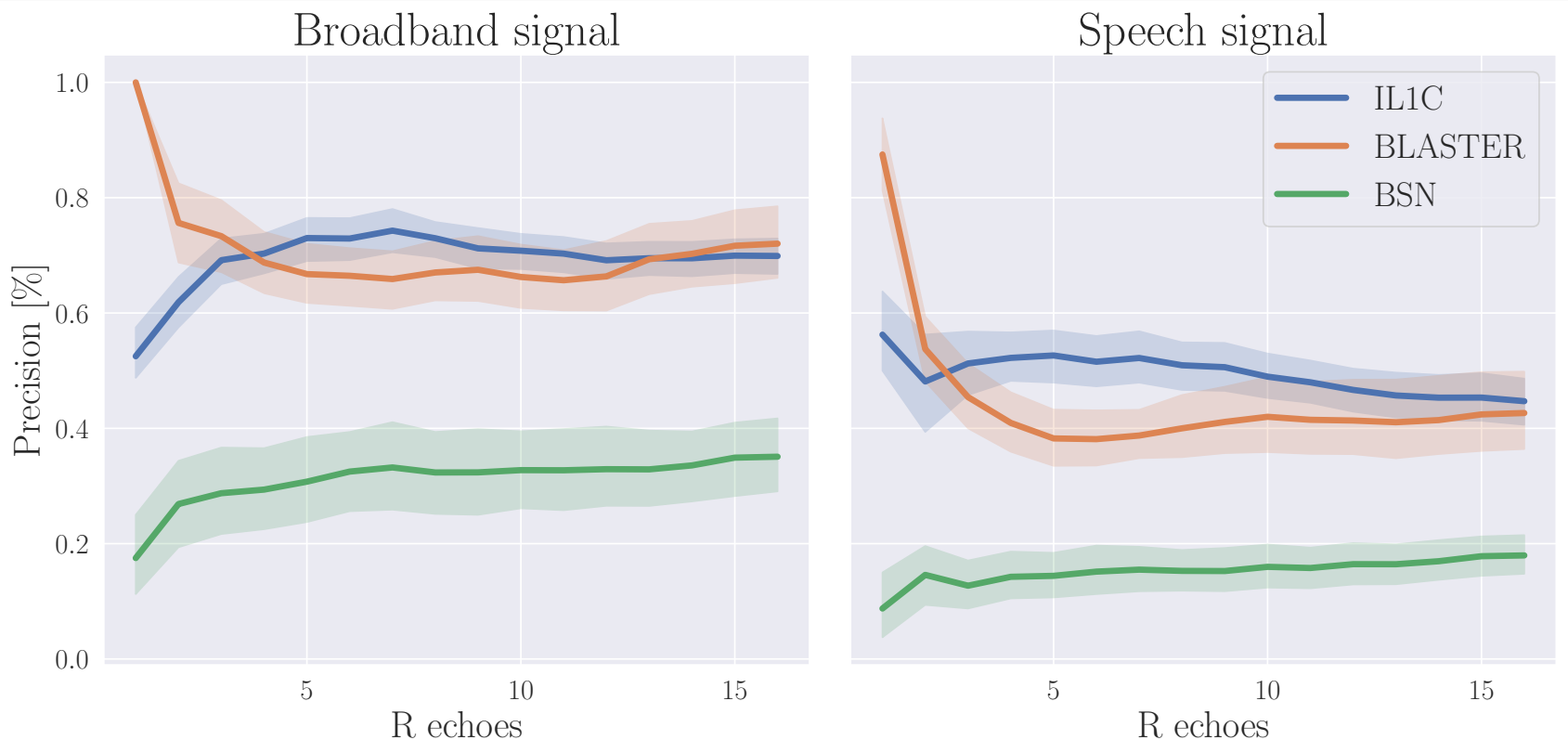


Figure 1: $\mathrm{RT}_{60} = 400$ ms and SNR = 20 dB.

✗ Sensitive to # echoes

✗ Sensitive source signal

✓ Good for 2 echoes

Performance per # of echoes

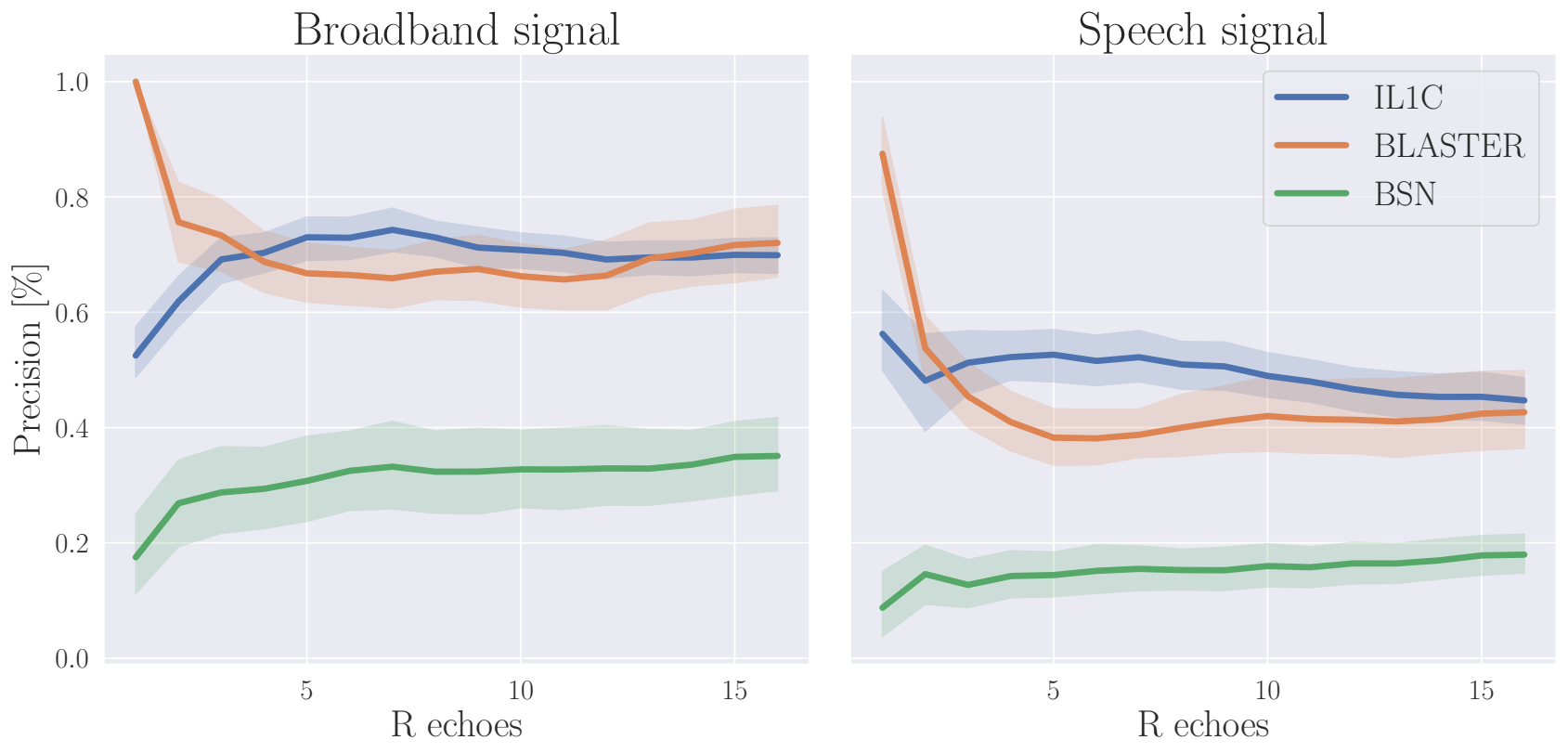


Figure 1: $RT_{60} = 400$ ms and SNR = 20 dB.

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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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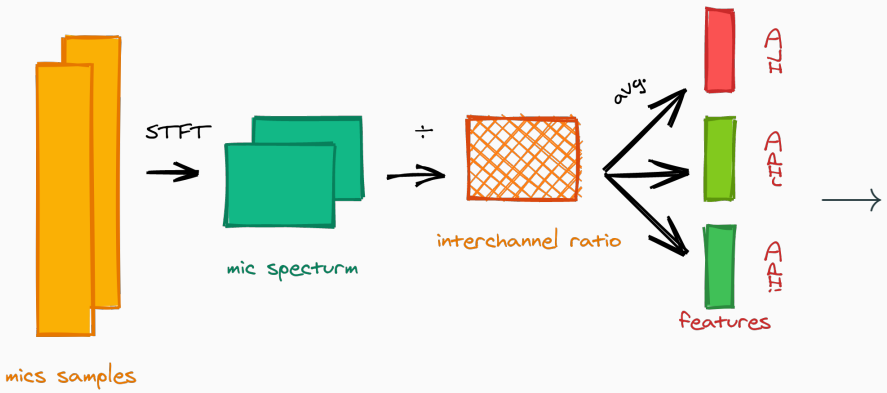

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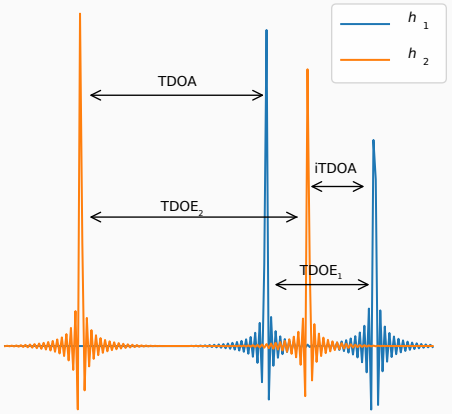

Relative Transfer Function

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

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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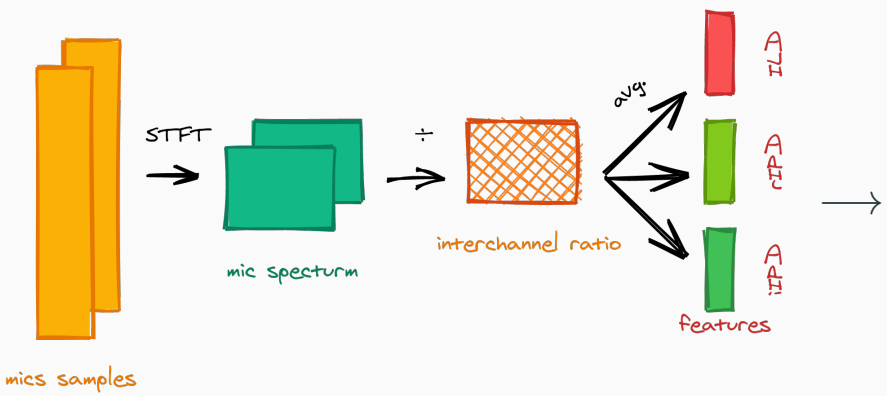

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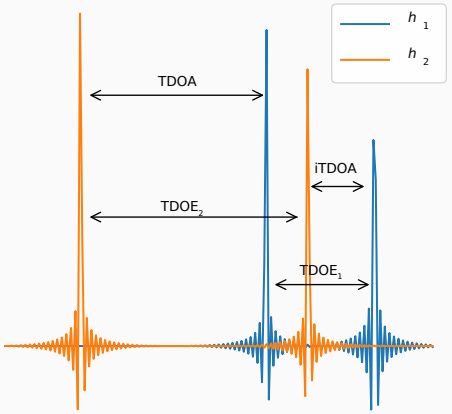

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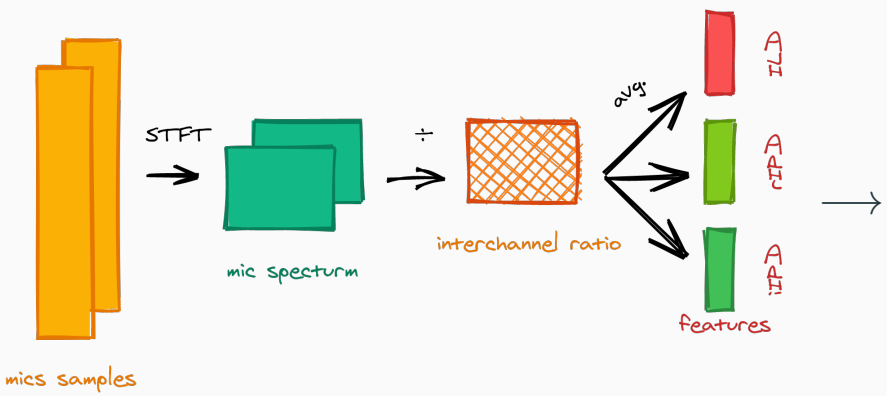

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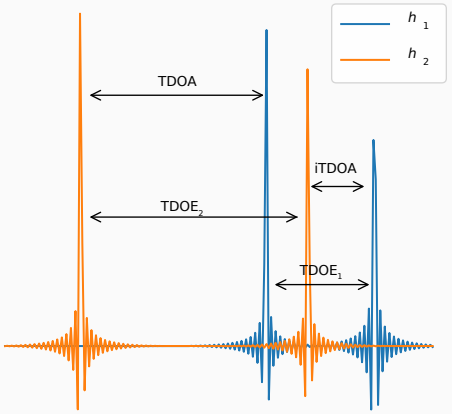

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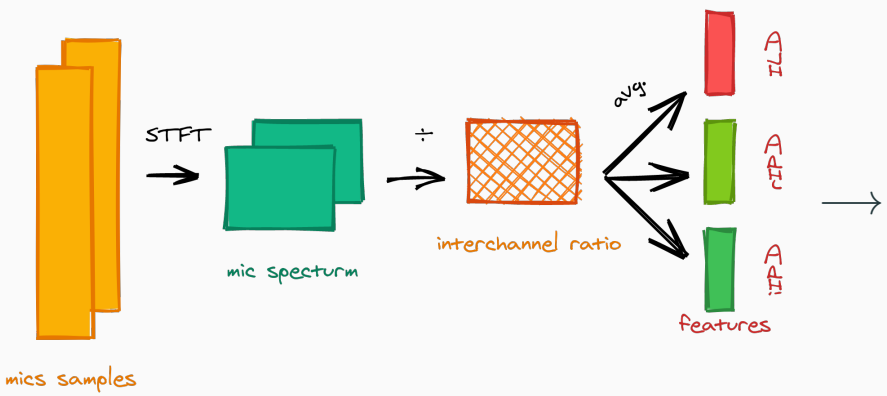

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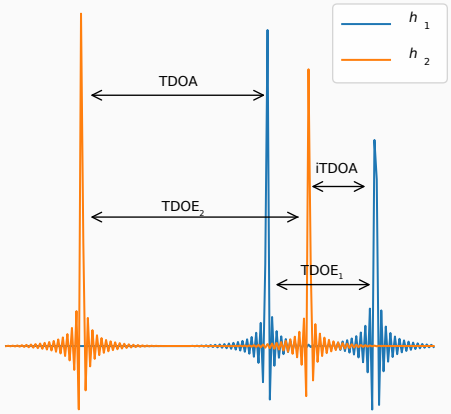

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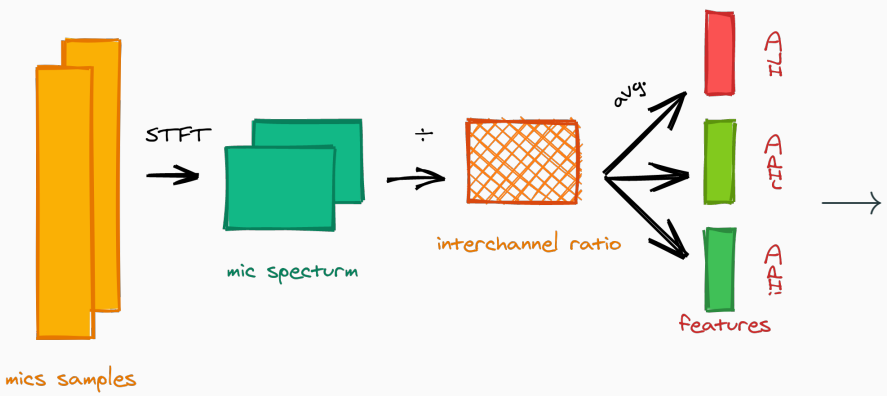
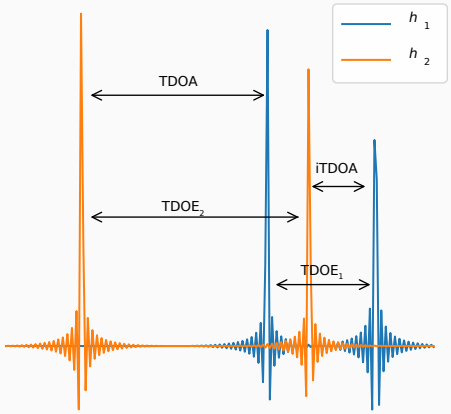
- Virtually Supervised Learning (= data from acoustic simulator)

Input: features



Output: target



Relative Transfer Function

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

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

Model

- Architecture: **CNN** [Chakrabarty and Habets, 2017, Nguyen et al., 2018]
- Loss Function:
  1. RMSE (Multi-label regression) on $\mathcal{V}$
  2. Gaussian log-likelihood $\rightarrow \{\mu, \sigma^2\}$
  3. Student log-likelihood $\rightarrow \{\mu, \lambda, \nu\}$

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

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

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

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Train:

- random RT60, random SNR
- broadband source (wn)
- instantaneous RTF

Test: similar to train

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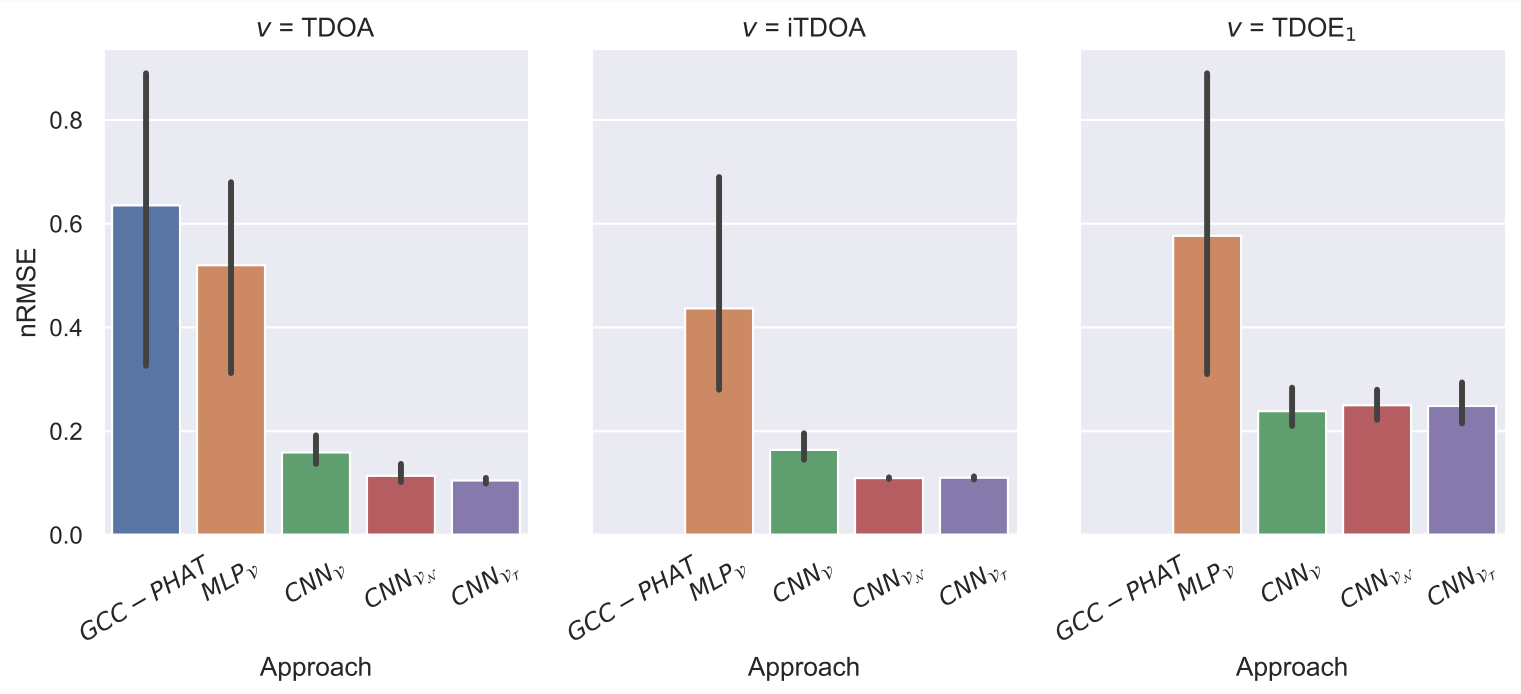

✓ CNNs outperform GCC-PHAT, MLP

✓ CNNs less variance

✗ Gaussian ∼ Student-T

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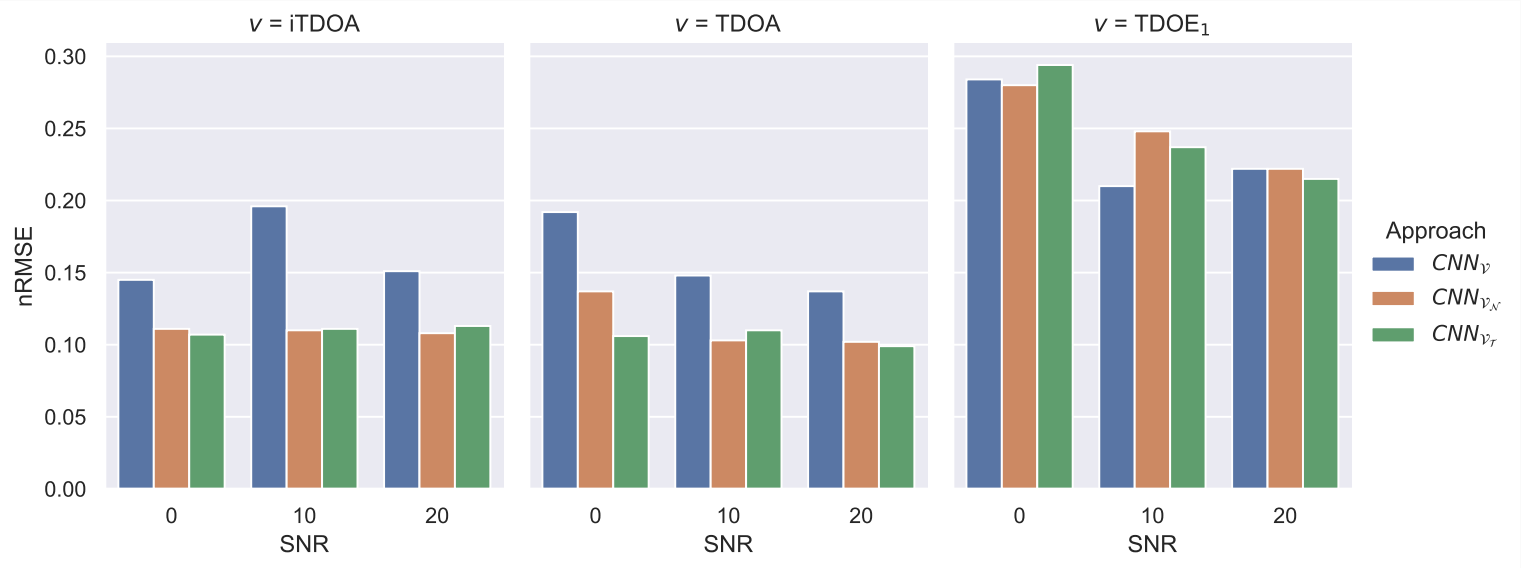


✓ Generative better than Normal

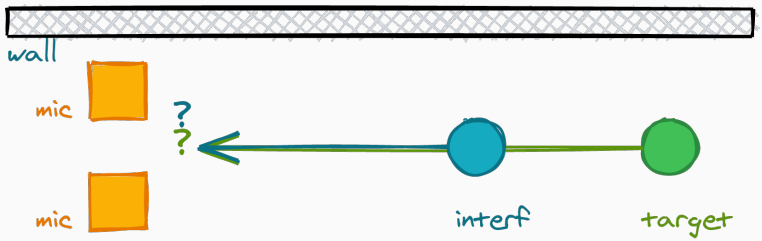
✗ Gaussian ∼ Student-T

✗ Bigger error on TDOE

Echo-aware Application

Echo-aware Application

Echoes = same content, different time/direction



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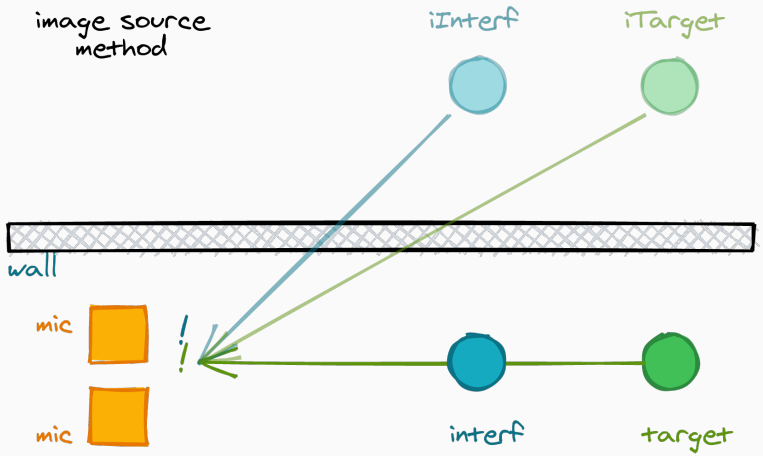

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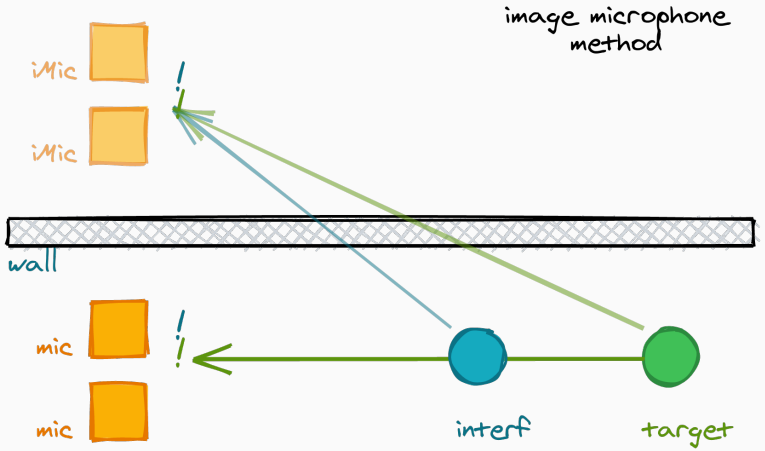

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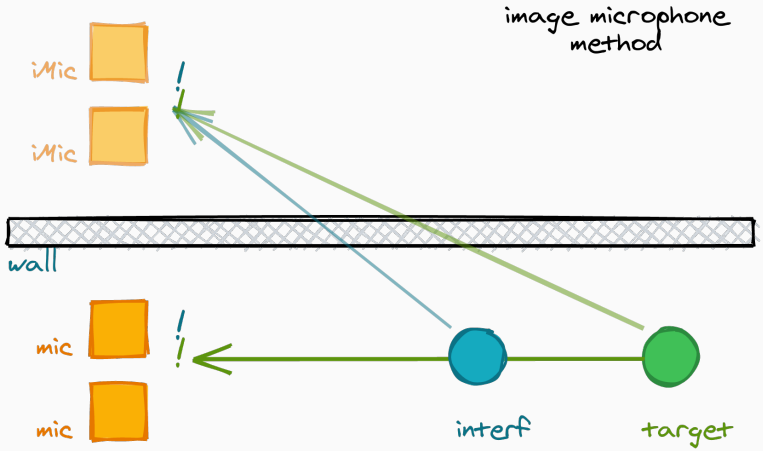

Recent literature on echo-aware processing:

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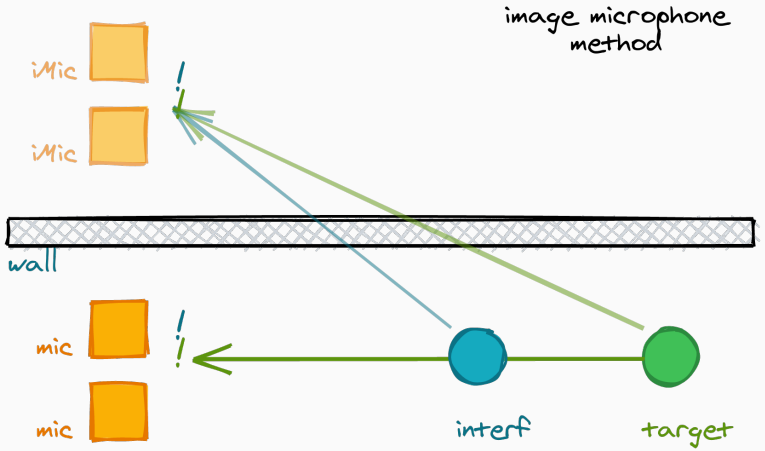

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Echoes = repetitions

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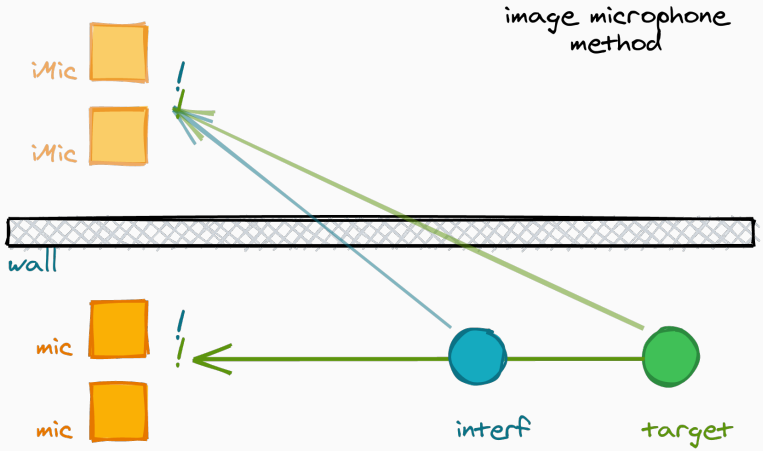

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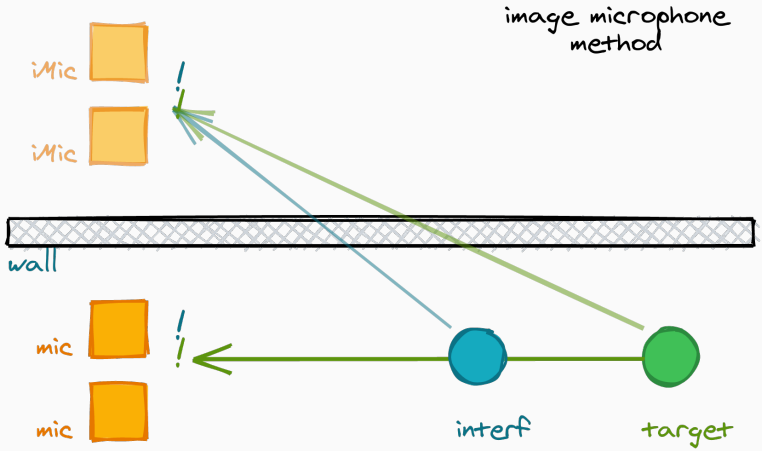

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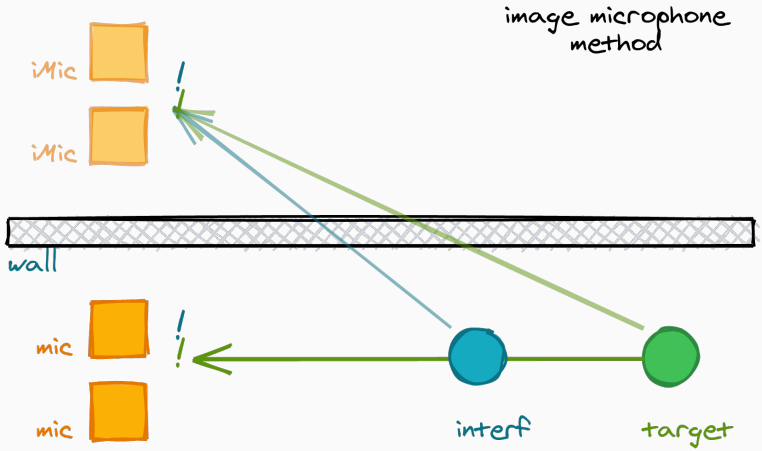

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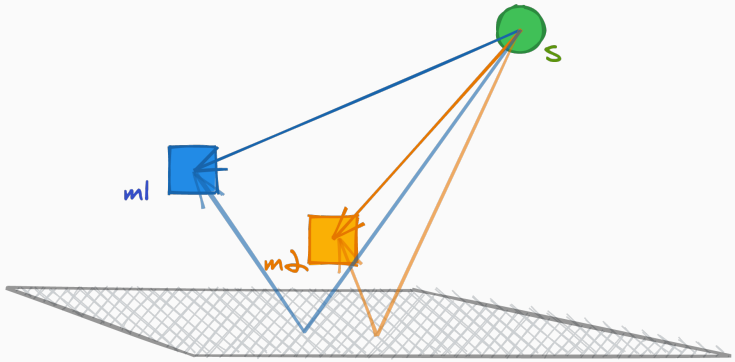
The Picnic Scenario:

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



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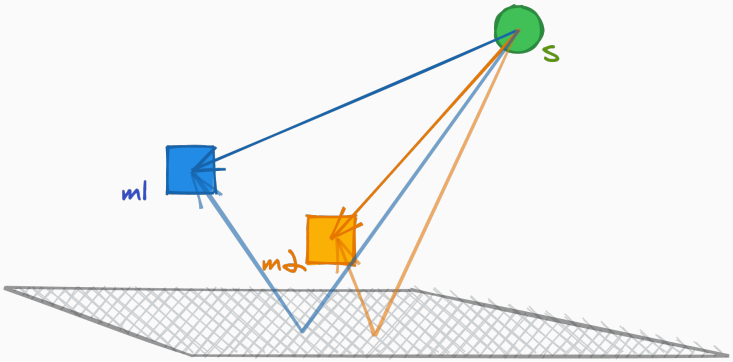

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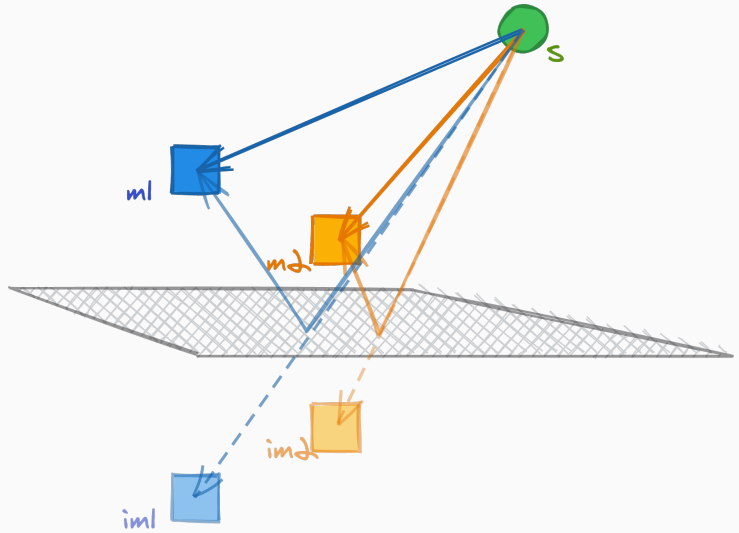
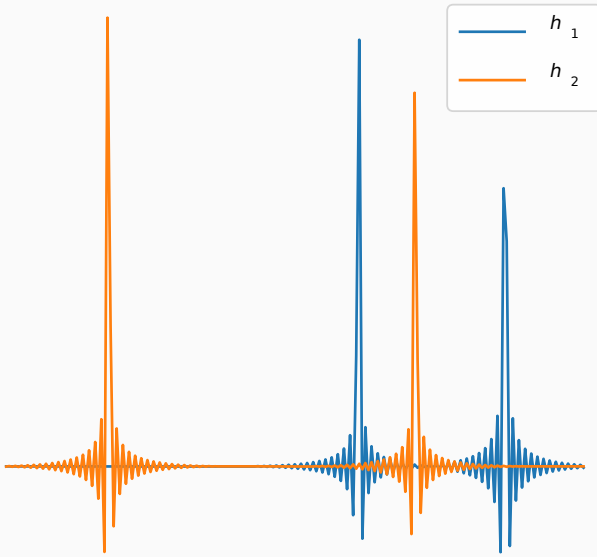


Each pair is augmented with echoes

Mirage Array

How to access the *image* microphones?



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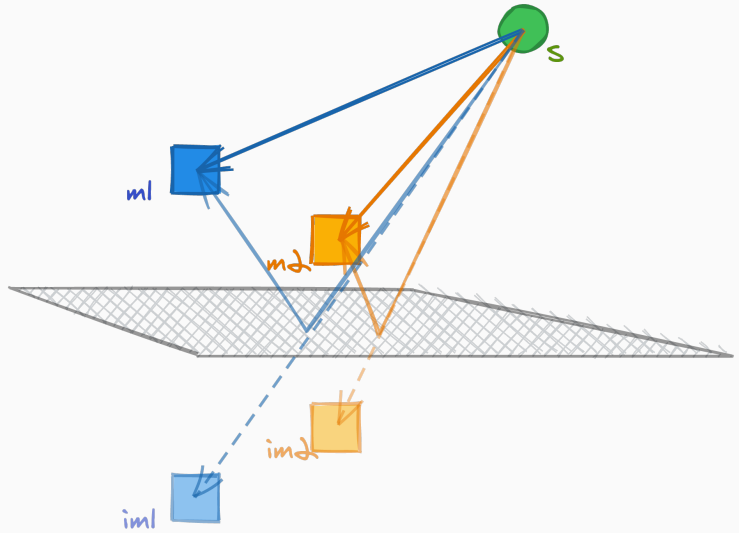

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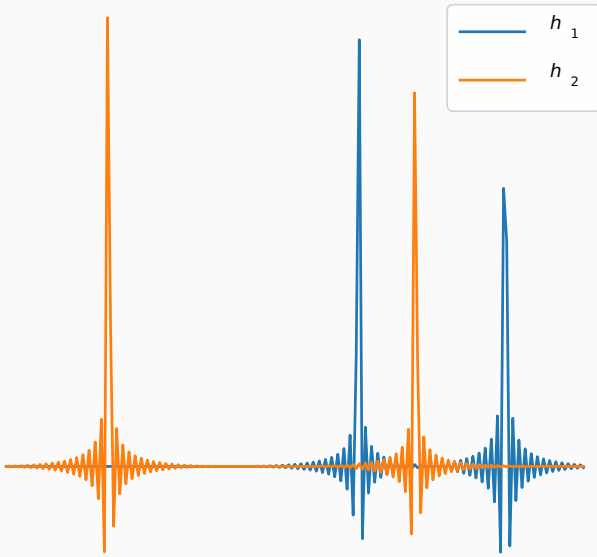

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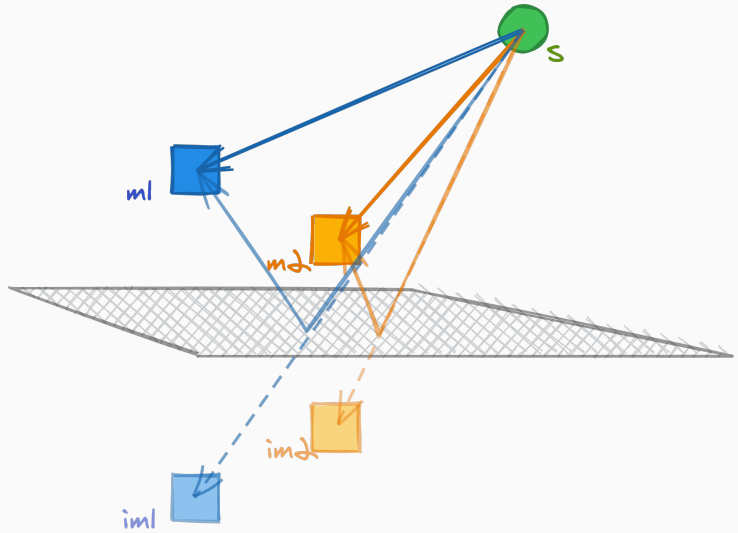

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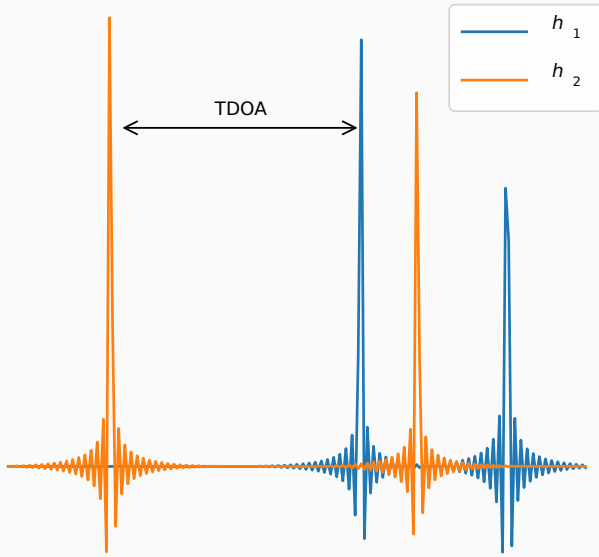

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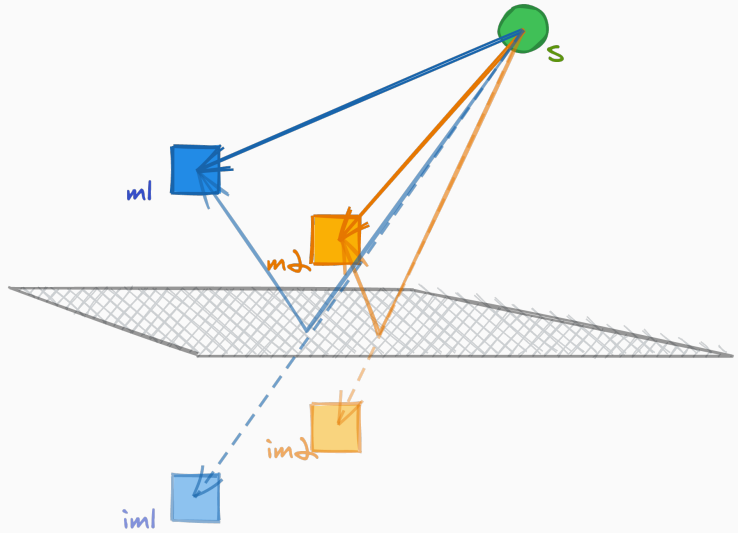

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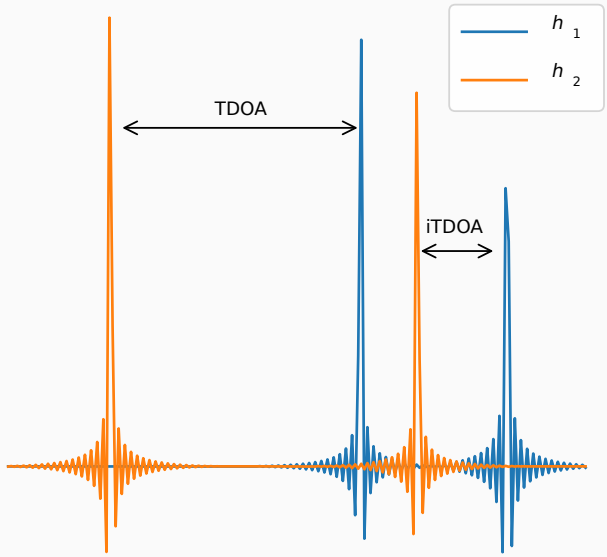

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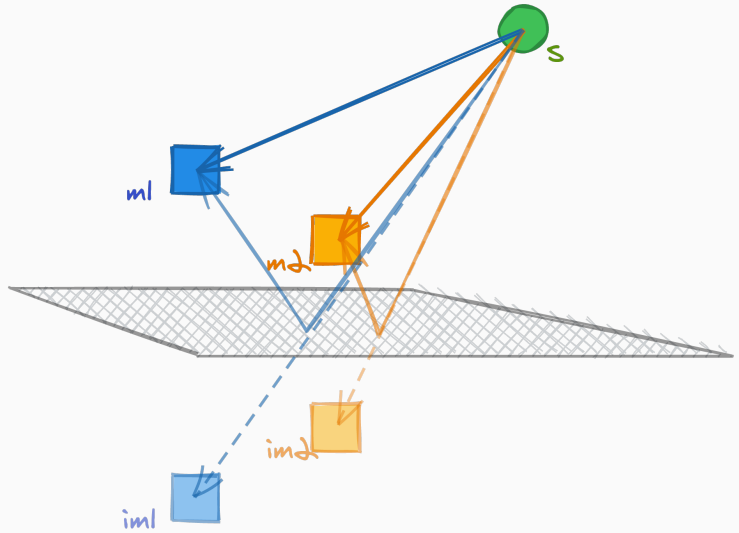

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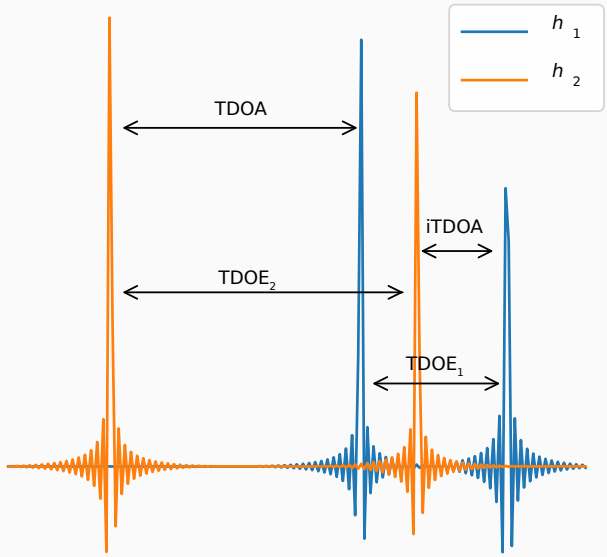

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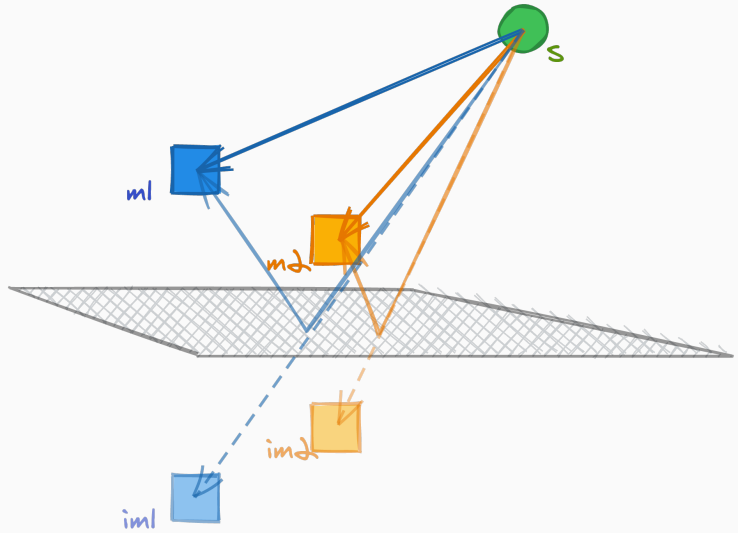

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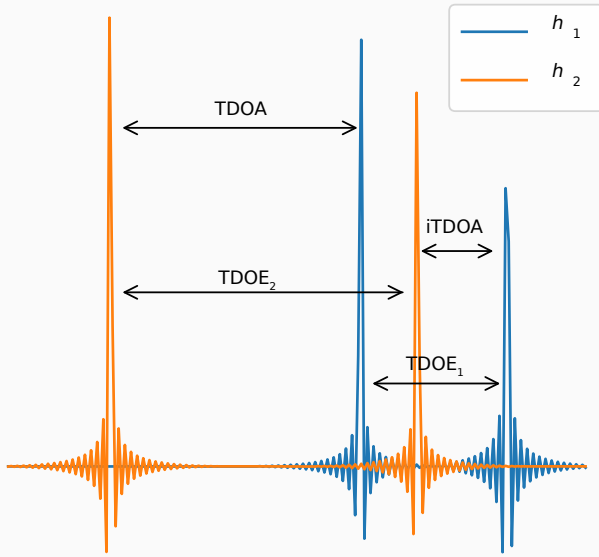
How to access the *image* microphones?

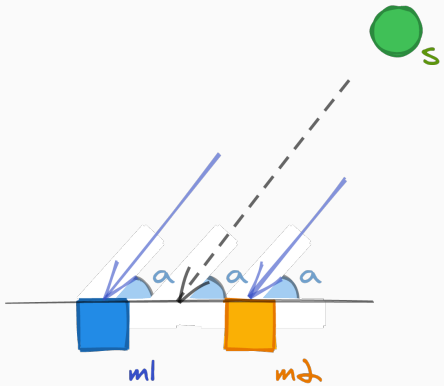
idea: use SSL algorithm on it

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]
  (known limitation, but good in practice)



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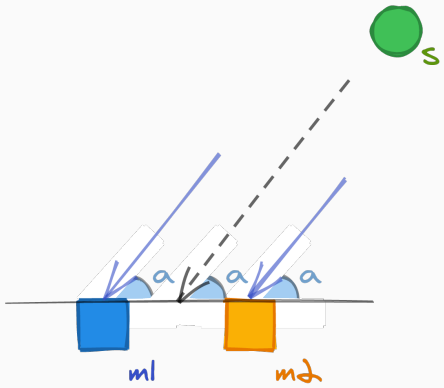
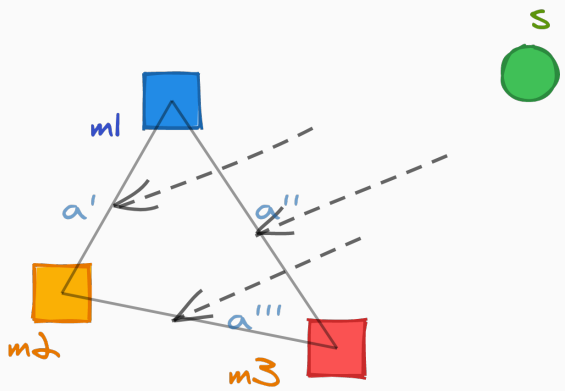


SSL with more microphones

- 2D SSL: azimuth and elevation

1. For each pair p:
   $\text{AOA}_p \leftarrow$ TDOA-based 2-mic-SSL
2. "Fuse" together all the observation
   (Angular spectra, Probability distributions)

- e.g. SRP-PHAT [DiBiase et al., 2001]



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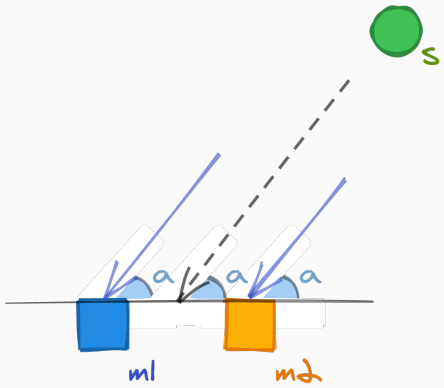

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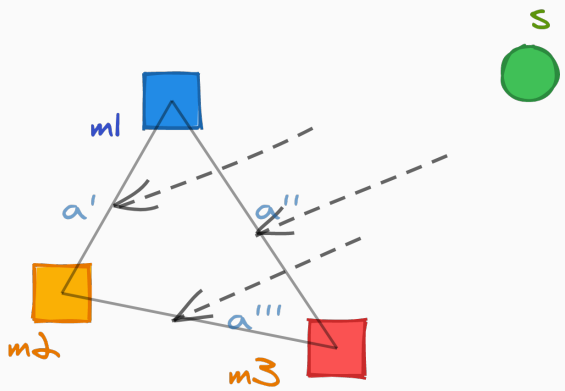

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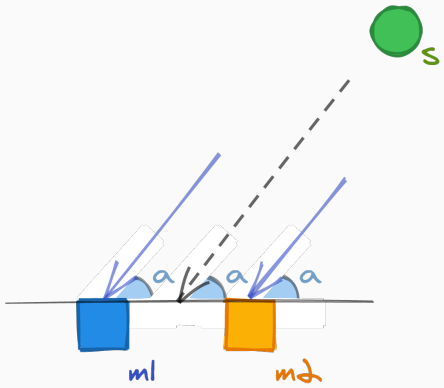

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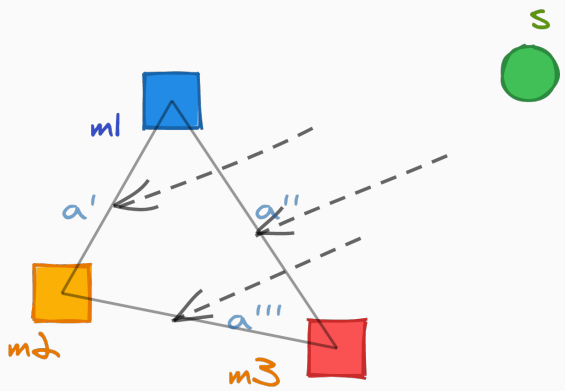

Baseline: GCC-PHAT on true microphones

Proposed Approach: using Lantern (DNN-based TDOA estimation)

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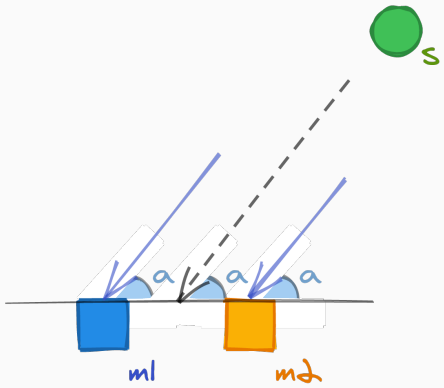
- e.g. GCC-PHAT for TDOA estimation [Knapp and Carter, 1976]
  (known limitation, but good in practice)

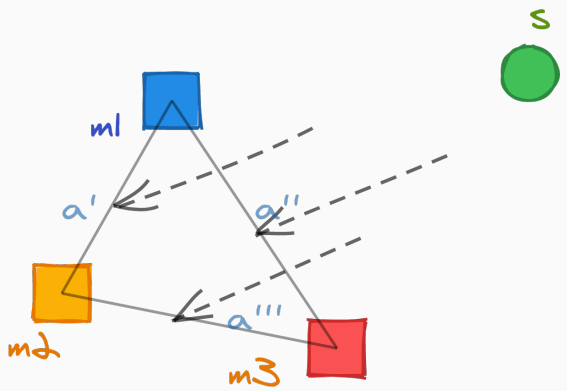


SSL with more microphones

- 2D SSL: azimuth and elevation

1. For each pair p:
   $\text{AOA}_p \leftarrow$ TDOA-based 2-mic-SSL
2. "Fuse" together all the observation
   (Angular spectra, Probability distributions)

- e.g. SRP-PHAT [DiBiase et al., 2001]



Baseline: GCC-PHAT on true microphones

Proposed Approach: using Lantern (DNN-based TDOA estimation)

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
- ✗ Huge drop when speech and noise

AOA	Input	ACCURACY $\theta < 10$	ACCURACY $\theta < 20$
MIRAGE	wn	4.10 (77)	5.97 (97)
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2D SSL estimation
(both Az. and El.)

DoA	Input	ACCURACY < 10 θ	ACCURACY < 10 ϕ	ACCURACY < 20 θ	ACCURACY < 20 ϕ
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

Echo-aware Dataset

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Data in audio signal processing

1. typically RIRs
2. necessary for validation/learning
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Echo-aware real data in audio signal processing

For SE: strong echoes✓, but not annotated✗, specific array✗
[Szöke et al., 2019, Bertin et al., 2019, Remaggi et al., 2016]

For RooGE: good geom annotation✓, but a few acoustic scenarios✗
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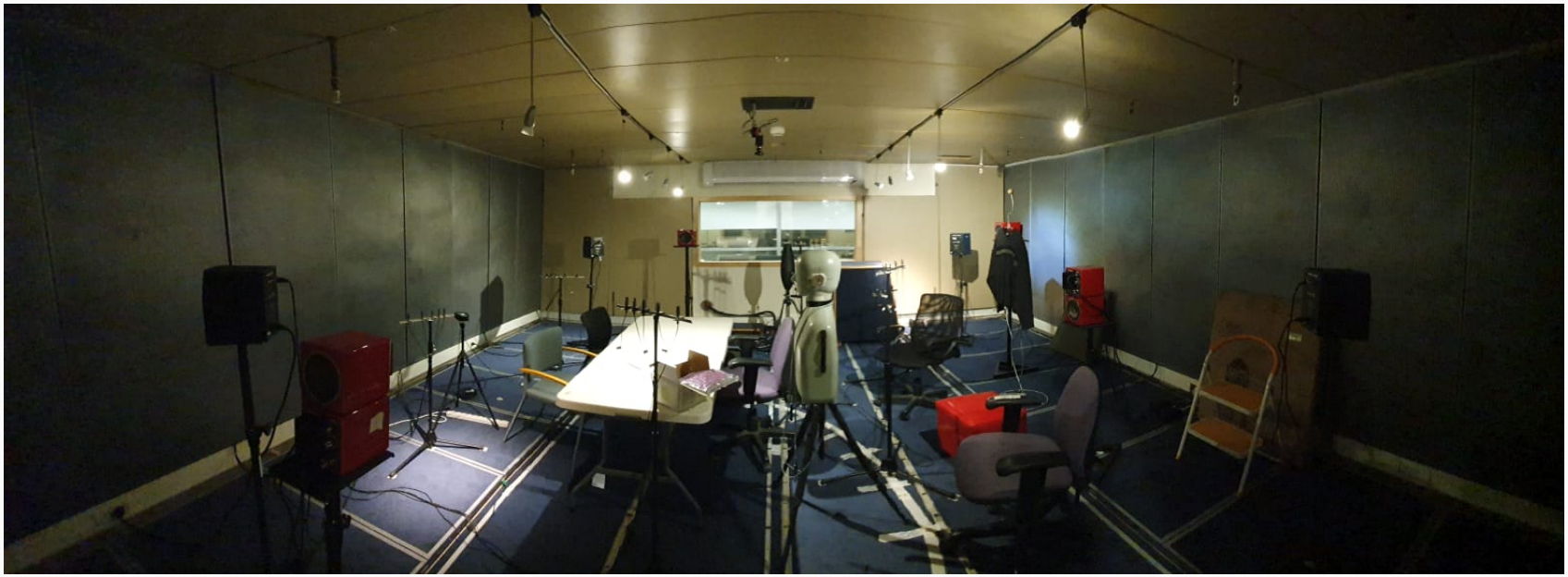
A good echo-aware dataset should allow SE, RooGE and AER
HOW?
signal annotation $\Longleftrightarrow$ geometric annotation

dEchorate: echo-aware dataset



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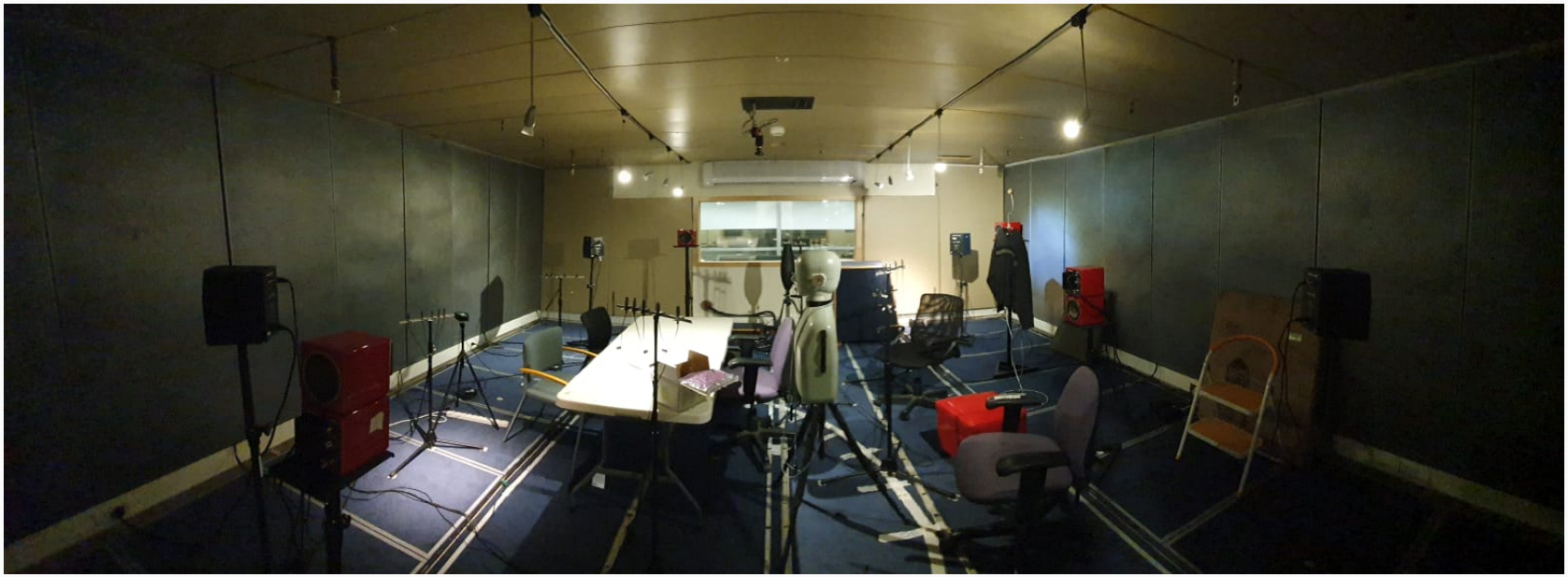

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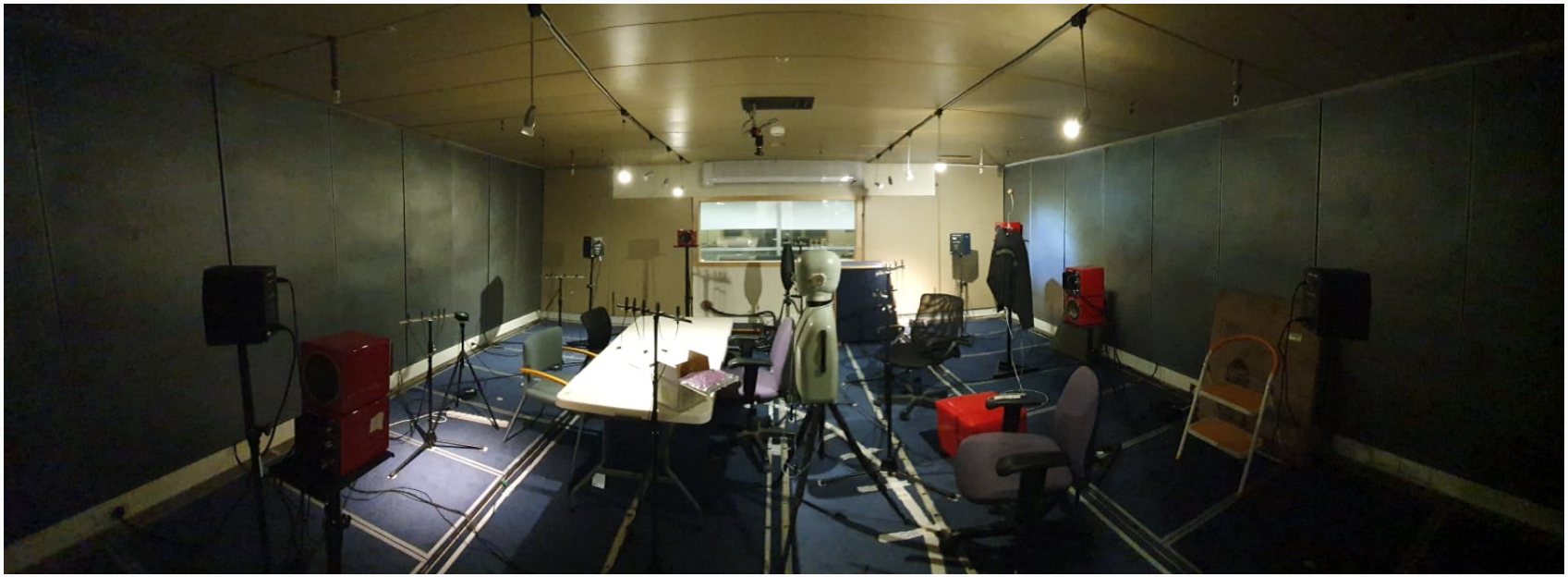

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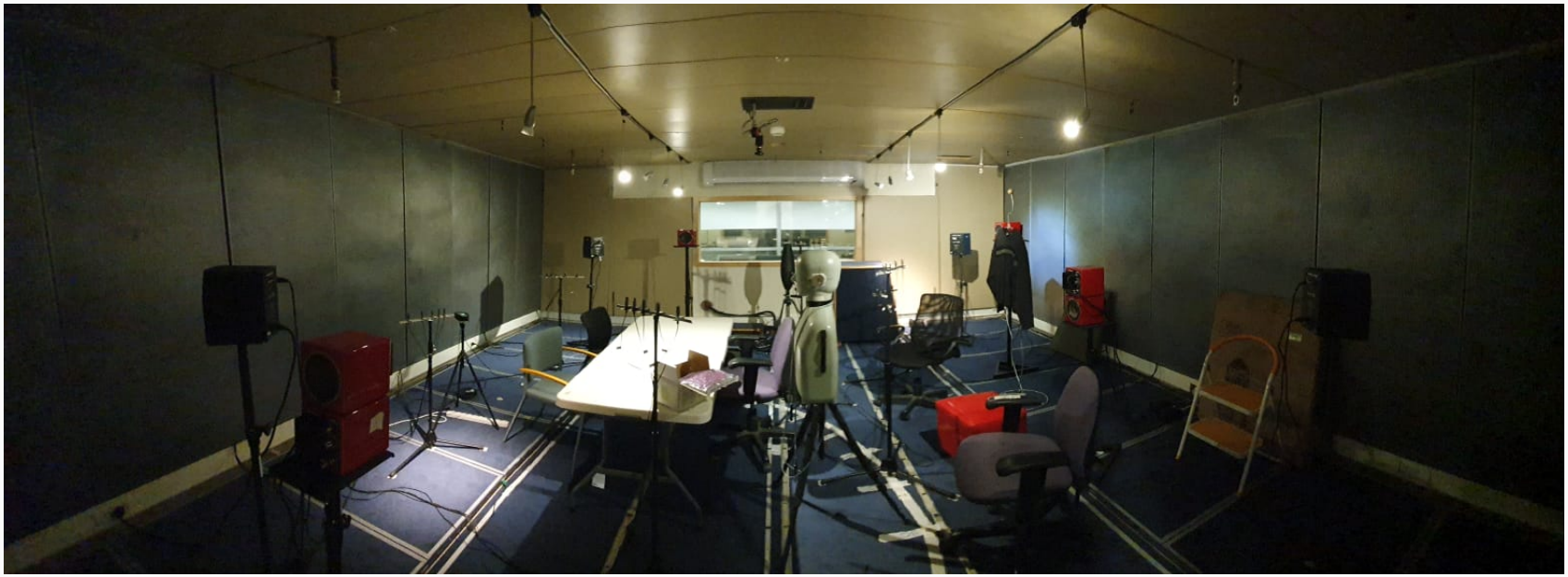

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Key features:

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

dEchorate: annotation

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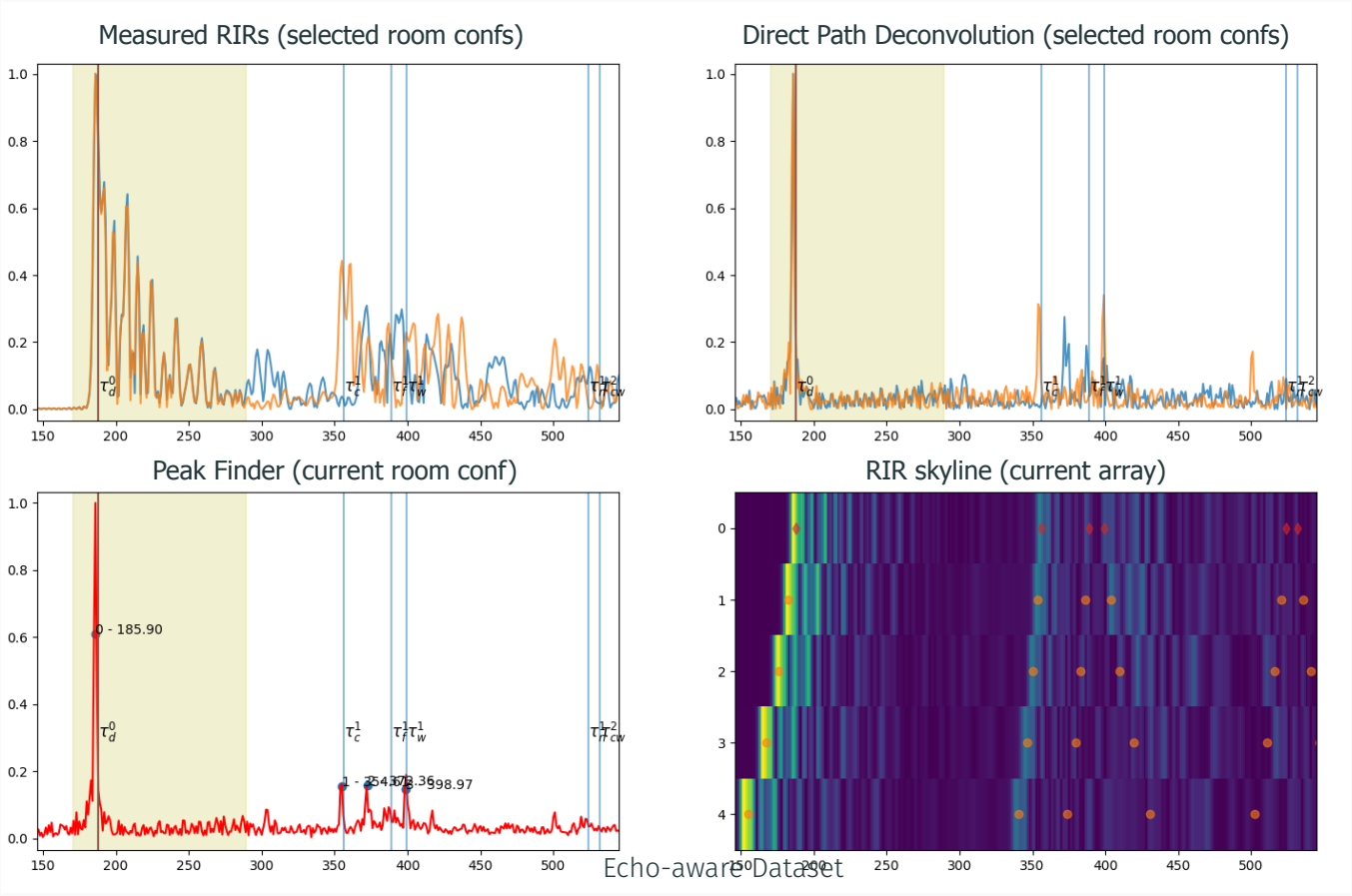

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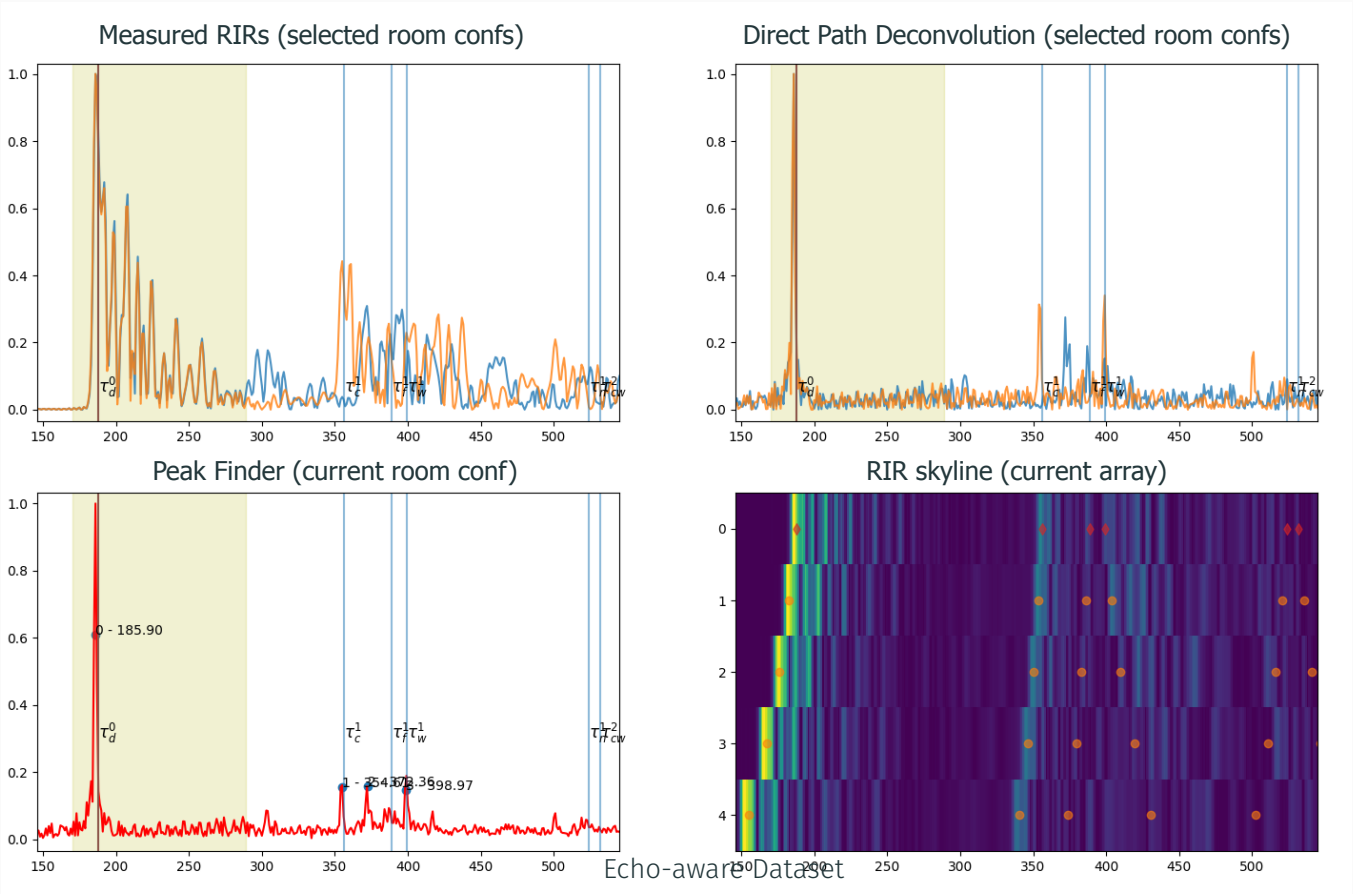

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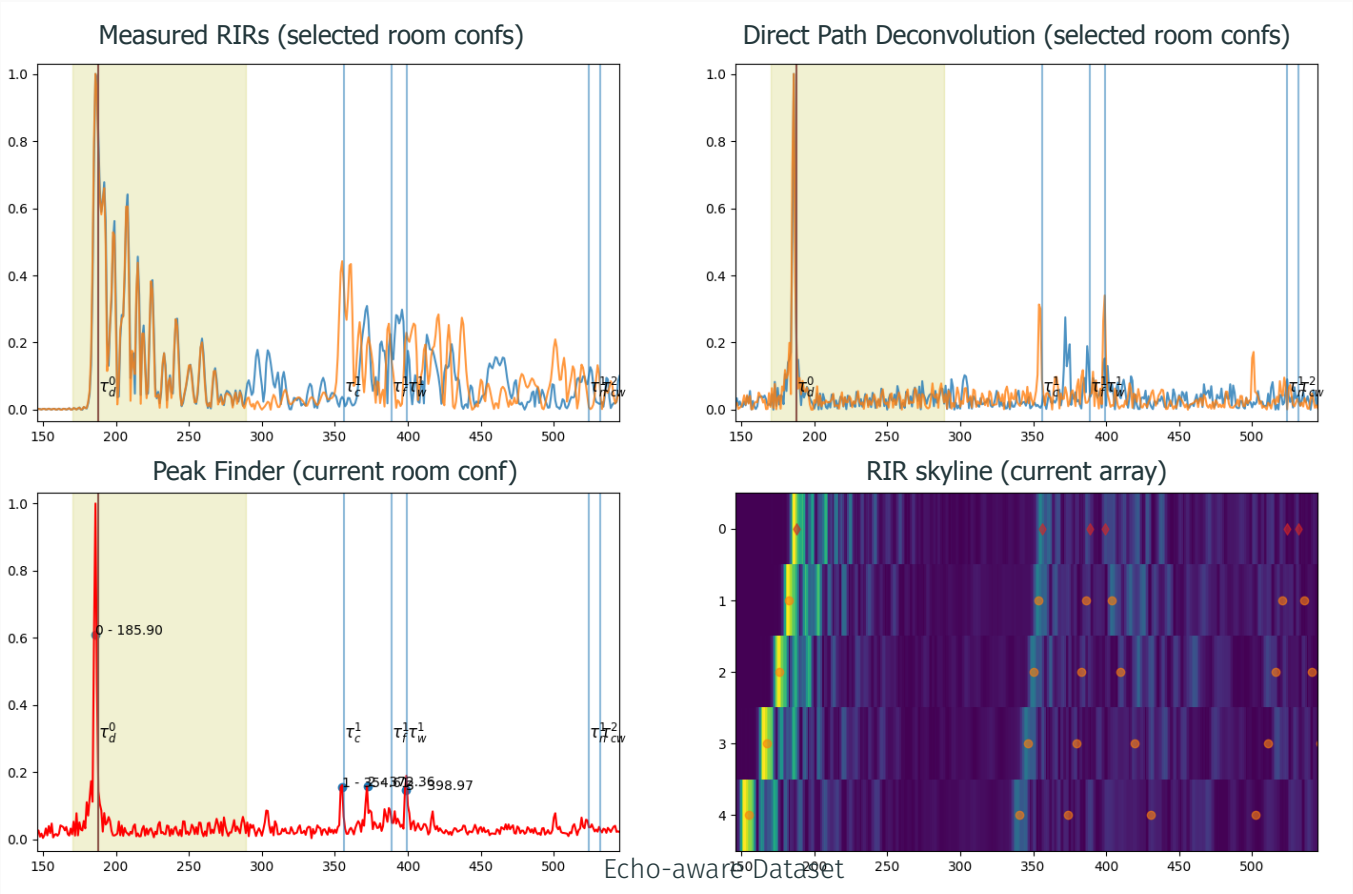
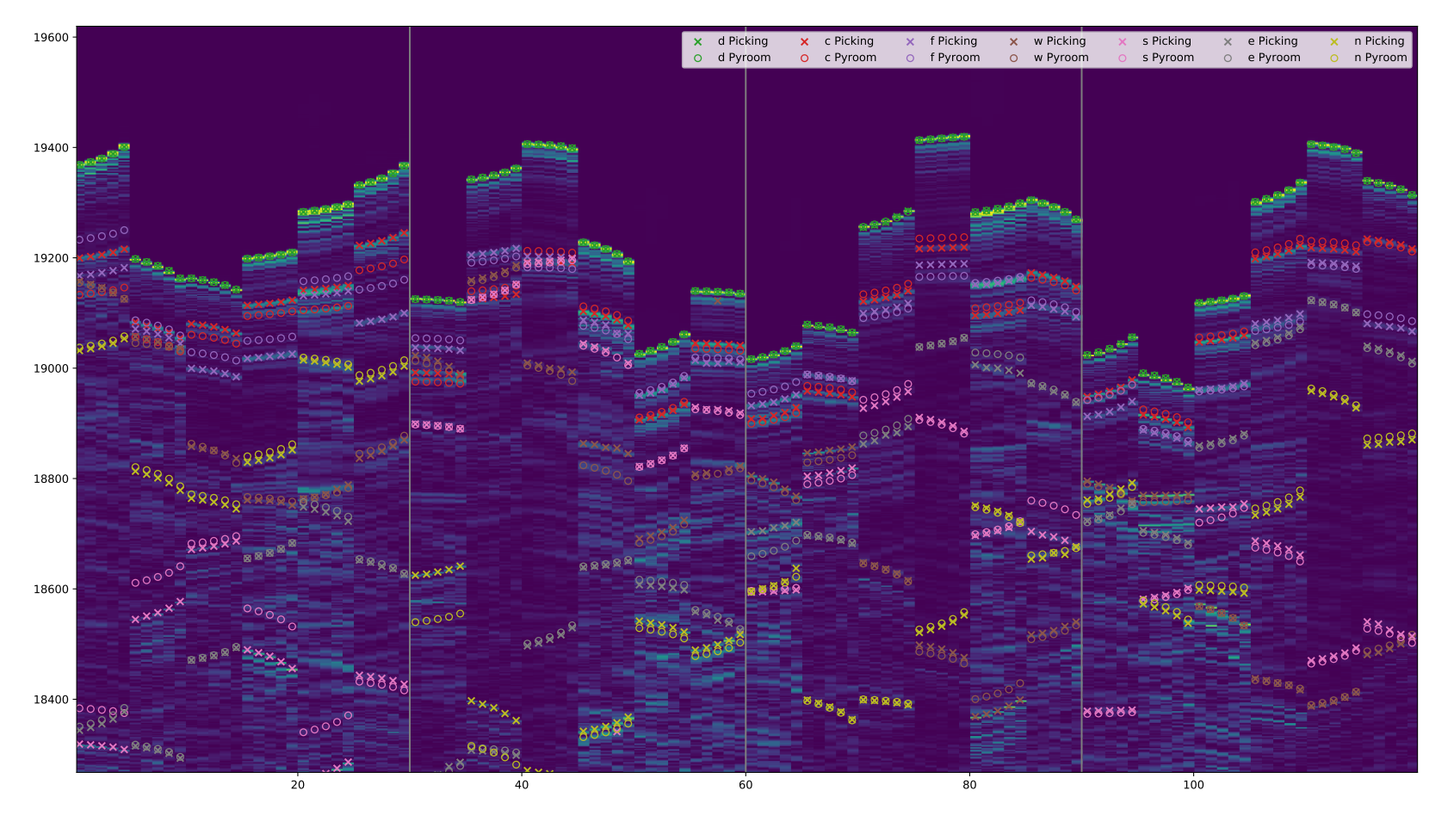
5. **iterate including ceiling** (perfectly flat)





RIR Skyline showing

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

Room Geometry Estimation (RooGE)

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

Room Geometry Estimation (RooGE) with dEchorate

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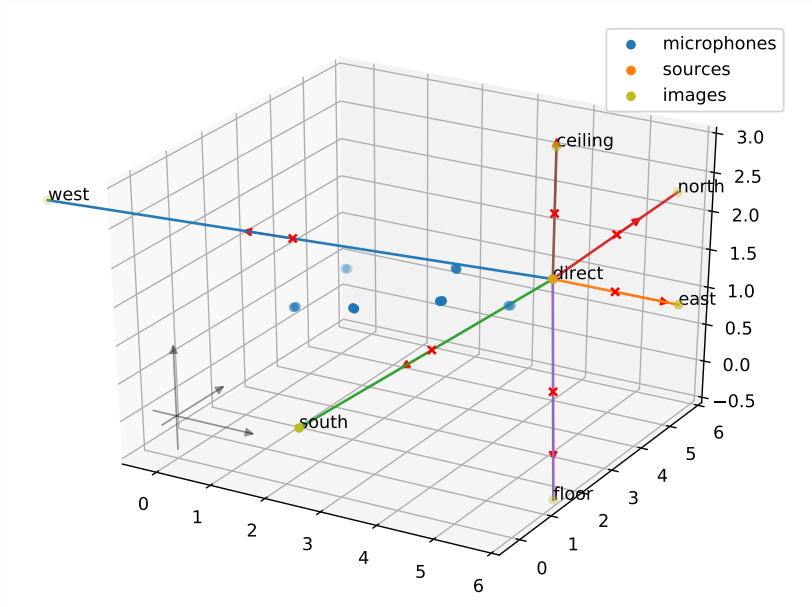

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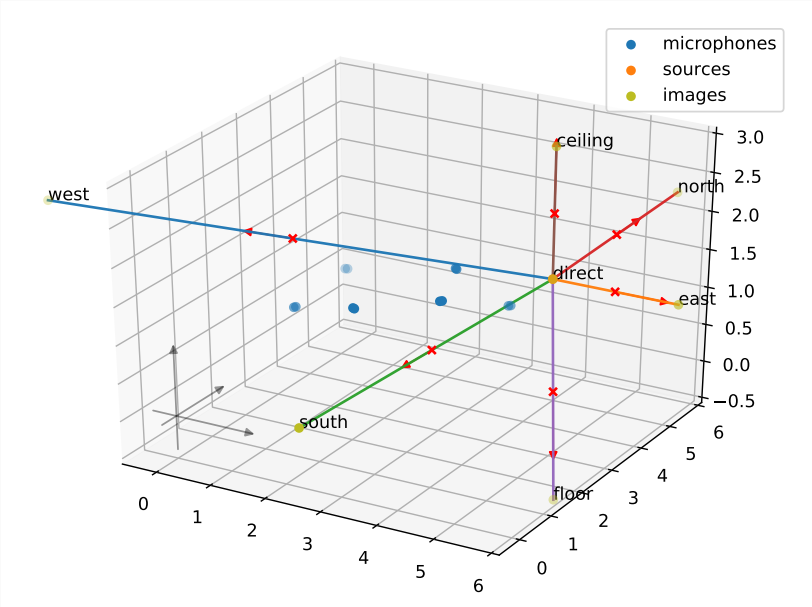

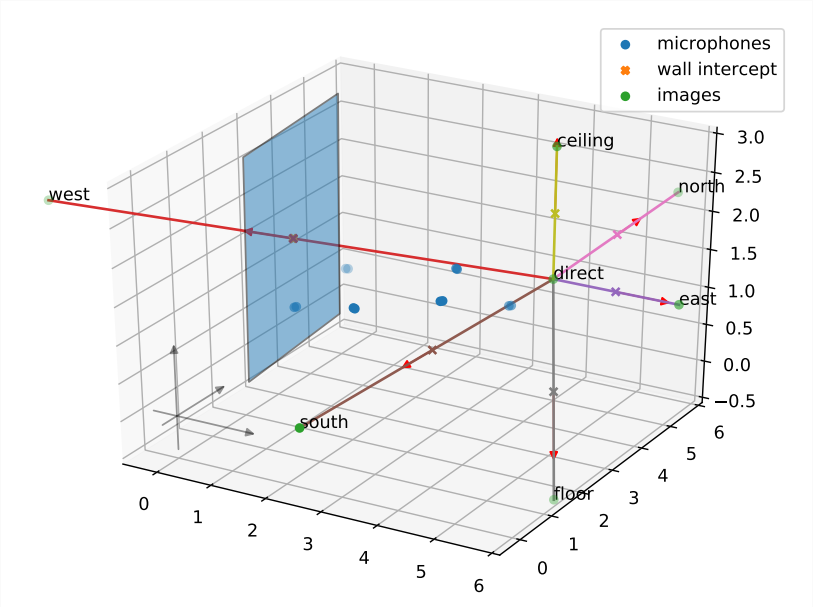

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source id	1		2		3		4	
wall	DE	AE	DE	AE	DE	AE	DE	AE
west	0.74	8.99	4.59	8.32	5.89	5.75	**0.05**	**2.40**
east	**0.81**	**0.08**	0.9	0.50	*69.51*	*55.70°*	0.31	0.21
south	3.94	*16.08°*	**0.18**	1.77	*14.37*	*18.55°*	0.82	**1.65**
north	1.34	0.76	1.40	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*

Speech Enhancement (SE)

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

interfering sources ↓ source separation	+	noise ↓ denoising	+	reverberation ↓ dereverberation room equalization

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SE via **linear spatial filtering**

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- Partial *steering vectors* from **geometry** (if anechoic $\implies$ DS based on AOA)
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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 $\Leftrightarrow$ reduce any noise

Echo-aware Speech Enhancement

Closed-form solution, but it requires:

	Noise covariance matrix	Steering Vectors
DS	-	Direct Path (AOA)
MVDR_{DP}	Noise	Direct Path (AOA)
$\text{MVDR}_{\text{ReTF}}$	Noise	Relative Transfer Function
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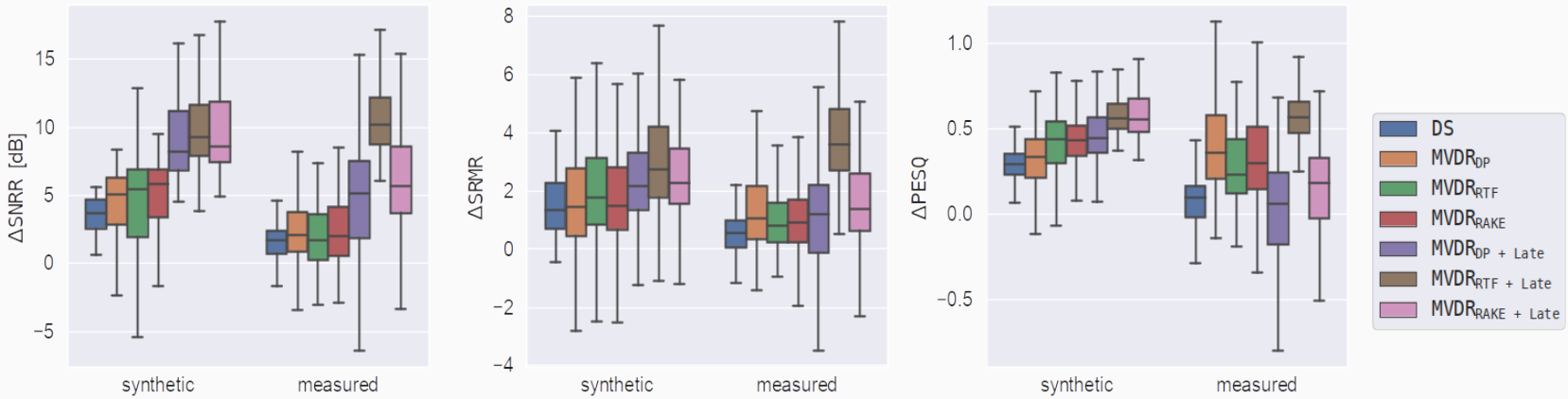

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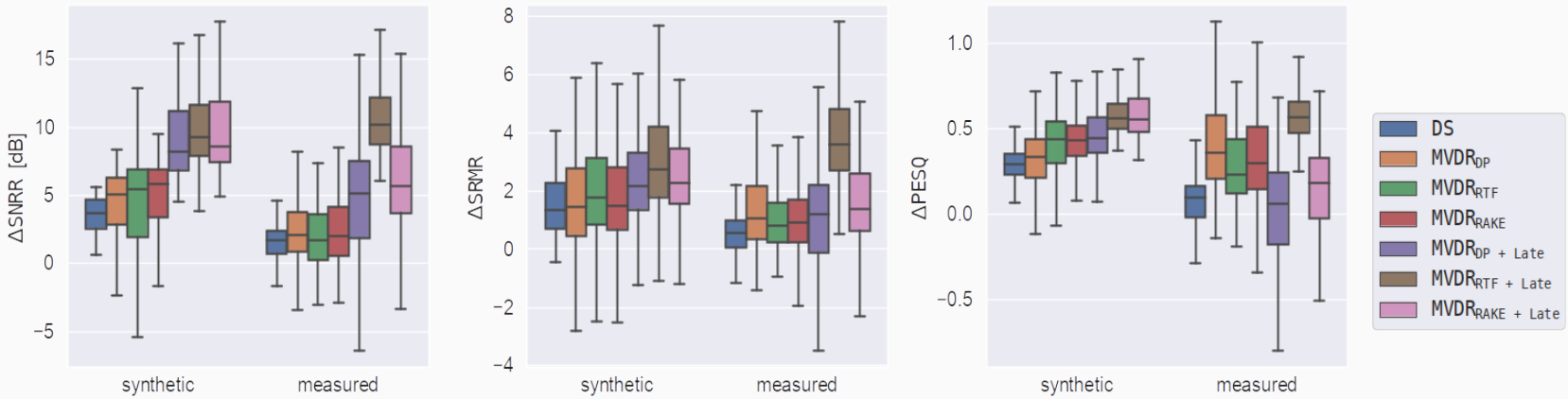

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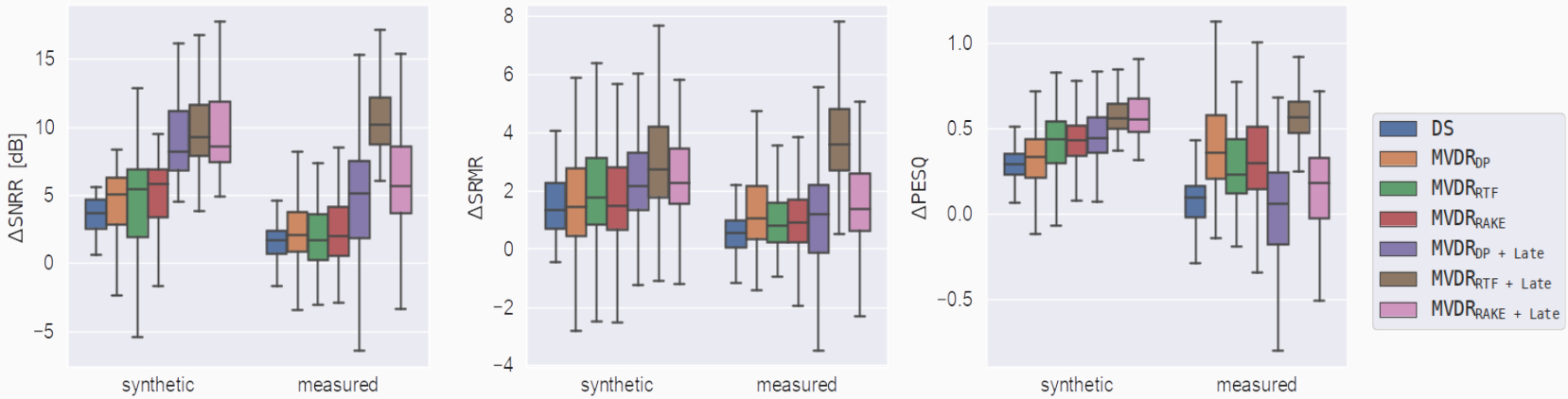

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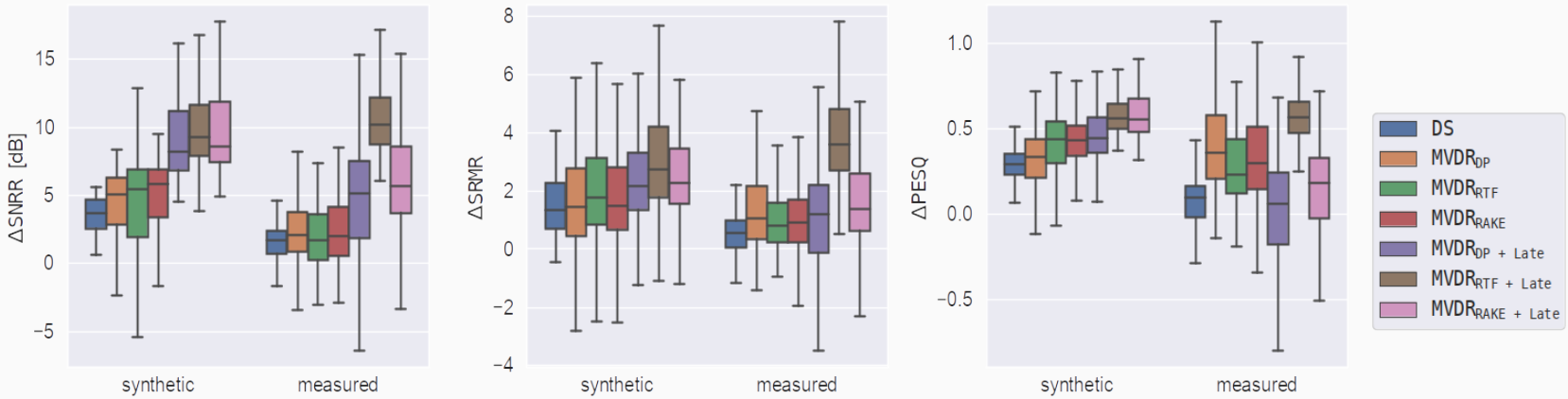

- *In theory* echo-aware ws. echo-agnostic?
  → Better than Direct Path, but ReTF and Rake are comparable
- Spatial filtering on Synthetic data vs. Measured data?
  → Rake suffer from mismatch, but better than DP

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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Lantern: Learning-based

- ✓ promising results
- ✗ only 2 echoes, how more?
- ✗ dep. on source

2. How to use echoes?

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- ✗ only 2 echoes, how more?
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both:

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- ✓ dataset for AER, SE and RooGE
- ✓ geom labels ↔ echo labels
- ✗ few inconsistency
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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

Directions for future work:

- on **estimation**

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

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

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  - validation on real data (eg. smart home speaker)
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  - other field of echoes (Seismology, Underwater acoustic, Volcano tomography)
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  - 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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