Echo-aware signal processing for audio scene analysis

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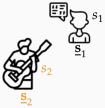
Université de Rennes 1, IRISA/INRIA, Panama research group

Introduction

Echo-aware signal processing for audio scene analysis



Sound

- produced by sources

Echo-aware signal processing for audio scene analysis

Sound

- produced by sources
- recorded by (array of) microphones

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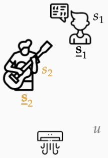

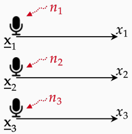

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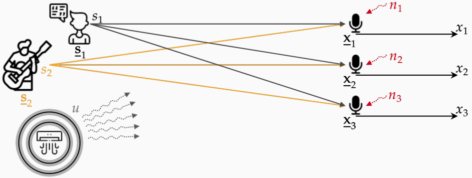

Sound

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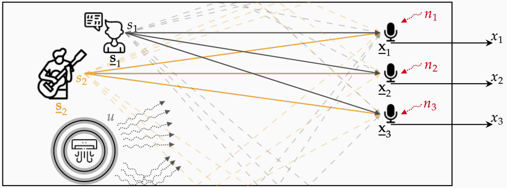
- corrupted by noise
- propagates in the space

Echo-aware signal processing for audio scene analysis

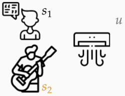


Sound

- produced by sources
- recorded by (array of) microphones
- corrupted by noise
- propagates in the space
- interacts with the room
  ↪ reverberation

Echo-aware signal processing for audio scene analysis

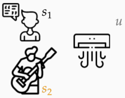
Semantic information



on nature and content

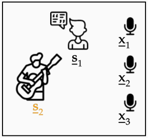
Echo-aware signal processing for audio scene analysis

Semantic information



on nature and content

Spatial information



on position and geometry

Echo-aware signal processing for audio scene analysis

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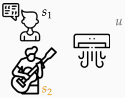

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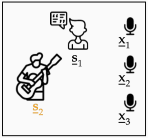
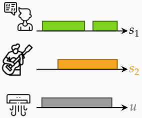


on position and geometry

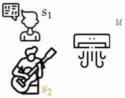
Temporal information

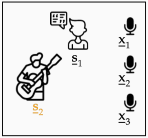


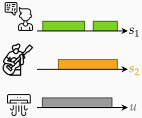
on events activity

Echo-aware signal processing for audio scene analysis

Semantic information | Spatial information | Temporal information



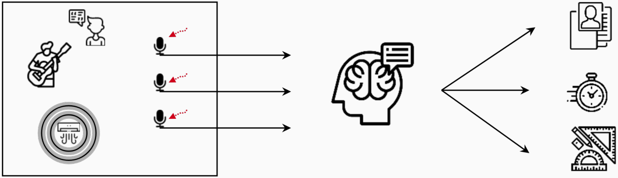




on nature and content | on position and geometry | on events activity

Audio Scene Analysis

Extraction and organization of all the information in the sound



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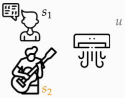

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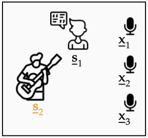

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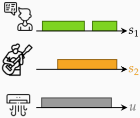

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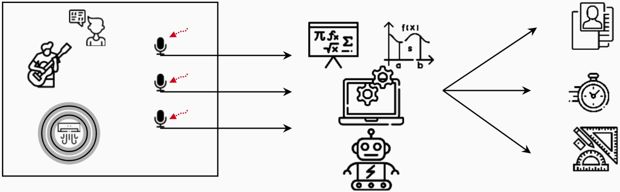
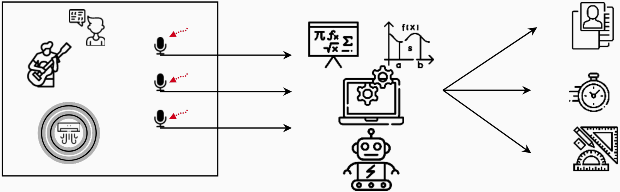


Can computer do it?

Echo-aware signal processing for audio scene analysis



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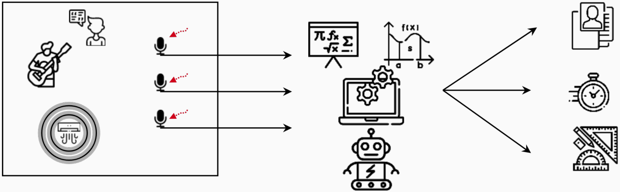
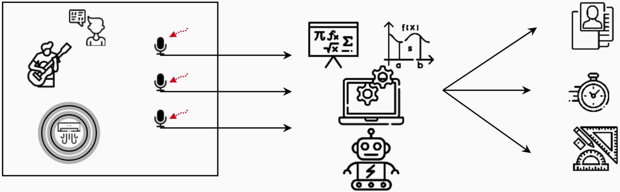


Signal Processing

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

Echo-aware signal processing for audio scene analysis



Signal Processing

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

- Sound Source Separation
- Speech Enhancement

What?

- Sound Source Localization
- Room Geometry Estimation

Where?

- Voice Activity Detection

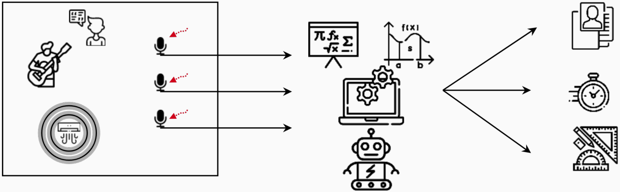
When?

- Reverberation level estimation
- Acoustic Channel Estimation

How?

- ...

Echo-aware signal processing for audio scene analysis



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} How?

- ...

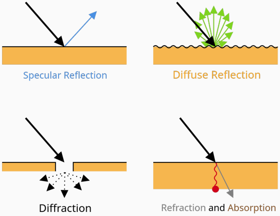
$$\text{HOW} \xrightarrow{\text{helps}} \text{WHERE} \xrightarrow{\text{helps}} \text{WHEN} \xrightarrow{\text{helps}} \text{WHAT} \xrightarrow{\text{helps}} \text{HOW} \xrightarrow{\text{helps}} \dots$$

Echo-aware signal processing for audio scene analysis

Sound interacts with indoor environment:

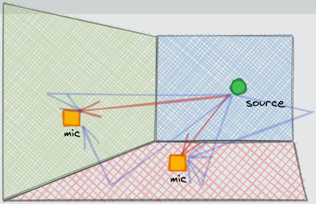
it is reflected
specularly and diffusely
+ it is absorbed,
+ it is transmitted,
+ it is diffracted, ect.

= reverberation



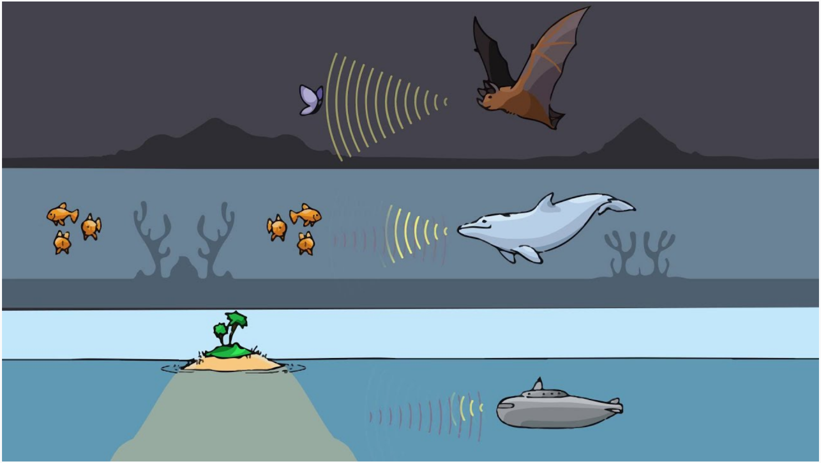
Acoustic Echoes: distict specular reflection

- Specular reflection standing out for time and strength
- Repetition of a sound but after
  - same content
  - delay ⇔ distance



Echo-aware signal processing for audio scene analysis

Everyday examples: bats, dolphins and sonars



(© Skin Bones)

Echo-aware signal processing for audio scene analysis

In audio signal processing, sound propagation is typically

- ignored $\implies$ simple processing but reverberation = noise
- fully modeled and estimated $\implies$ very challenging

Echo-aware methods

- explicitly account for some acoustic reflection to boost the performances
- attractive alternative between ignoring reverberation and model it entirely

Turing Enemies into Friends:
Using reflections to improve sound source localization.

[Ribeiro et al., 2010]

Outline and contributions

Thesis title

Audio Scene Analysis	Signal Processing	Echo-aware
↓	↓	↓
context and problems	models and frameworks	better processing

Thesis content:

1. How to estimate them?
   - Learning-based method
   - Analytical method

2. How to use them?
   - Source Localization
   - Source Separation
   - Speech Enhancement
   - Room Geometry Estimation

3. Where to find them?
   - `dEchorate`
     Echo-aware database for both estimation and application

Outline and contributions

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1. How to estimate them?
   - Learning-based method **1a**
   - Analytical method **2a**
2. How to use them?
   - Source Localization **2a**
   - Source Separation(not today)
   - Speech Enhancement **3b**
   - Room Geometry Estimation(not today)
3. Where to find them?
   - `dEchorate` **3a**
     Echo-aware database for both estimation and application

Problem Statement

Signal model

For one source and I microphones:

mic. signal

source signal

$$\tilde{x}_i(t) = (\tilde{h}_i * \tilde{s})(t) + \tilde{n}(t) \quad i \in I$$

noise term

⚠ continuous-time convolution

Room Impulse Response (RIR)

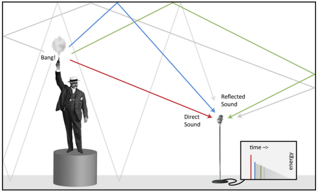
- linear filtering effect of the sound propagation (reverberation)
- acoustic response of a room to a (prefect) impulsive sound
- depends on spatial properties (room geometry, mic/src position)
- $\tilde{h}_i \neq \tilde{h}_j$

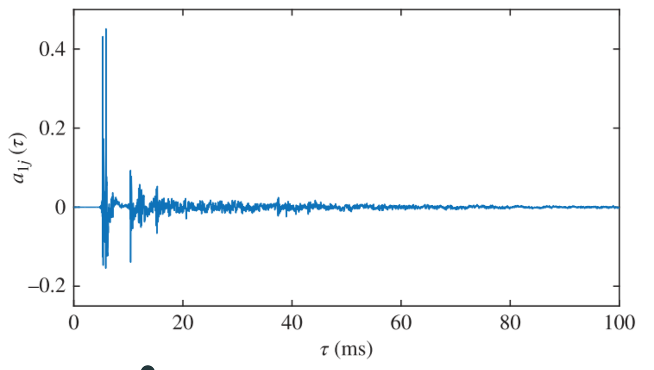
Signal model

$$\tilde{x}_i(t) = (\tilde{h}_i * \tilde{s})(t) + \tilde{n}(t)$$

$$\tilde{h}_i(t) = \tilde{h}_i^{\mathsf{d}}(t) + \tilde{h}_i^{\mathsf{e}}(t) + \tilde{h}_i^{\mathsf{lrev}}(t)$$

- $\tilde{h}_i^{\mathsf{d}}(t)$ = direct path
- $\tilde{h}_i^{\mathsf{e}}(t)$ = early reflection
- $\tilde{h}_i^{\mathsf{lrev}}(t)$ = late reverberation





Problem Statement

Echoes can be modeled as sum of Dirac's delta function:

models later echoes, reverberation and other.

$$\tilde{h}_i(t) = \tilde{h}_i^{\mathsf{d}}(t) + \tilde{h}_i^{\mathsf{e}}(t) + \varepsilon_i(t) \approx \sum_{r=0}^{R} \alpha_i^{(r)} \delta(t - \tau_i^{(r)}) + \varepsilon_i(t)$$

Goals: Acoustic Echo Retrieval (AER)

Estimated $\left\{\tau_i^{(r)}, \alpha_i^{(r)}{}_i\right\}_{i,r}$ for the microphone signal $\{x_i\}_i$

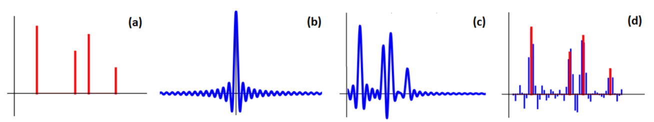
Problem Statement

Goals: Acoustic Echo Retrieval (AER)

Estimated $\left\{\tau_i^{(r)}, \alpha_i^{(r)}{}_i\right\}_{i,r}$ for the microphone signal $\{x_i\}_i$

Challenges:

- RIRs depend on the scene geometry (room, source and mic position)
- Big under-modelling error (late reverberation and noise)
- $\alpha_i^{(r)}$ are distorted:
  - due to air attenuation, wall absorption:
  - $\alpha_i^{(r)} \to \alpha_i^{(r)}(t) \implies$ echo model is sum of filters
  - due to sampling process [Tukuljac et al., 2018]



(Courtesy of Helena Tukuljac [Tukuljac et al., 2018])

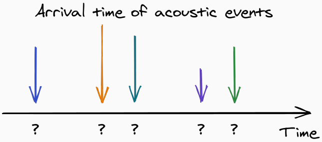
⚠ sampling breaks sparsity and non-negativity

Acoustic Echo Estimation

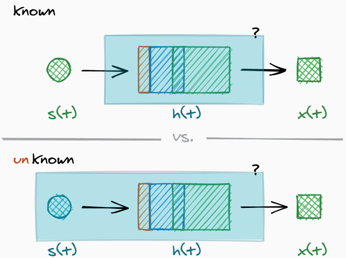
Acoustic Echo Retrieval

Estimating early (strong) reflections for microphones recordings, i.e.,

$$\{\tilde{x}_i\}_i \longrightarrow \{\tau_i^{(r)}, \alpha_i^{(r)}\}_{i,r}$$



Scenarios: the source signal is



Our case: signal source and passive system of (I microphones)

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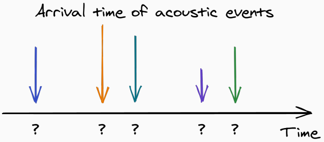

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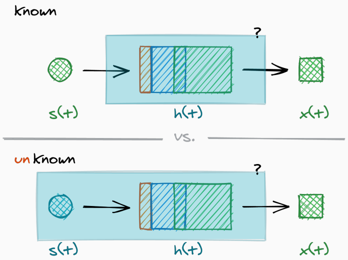

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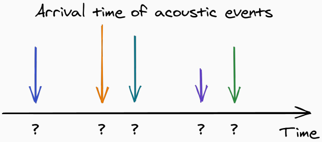

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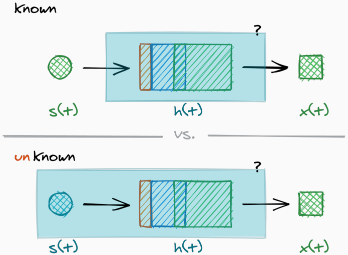

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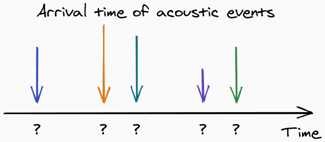

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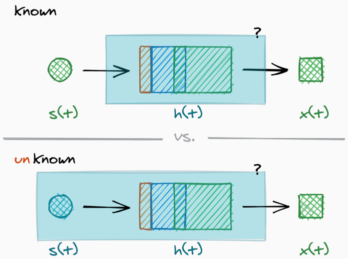

Active

- **non-blind** problem
- **intrusive** or specific setups
  (**Application:** sonar, calibration, measurements, etc.)

Passive

- **blind inverse** problem (harder)
- **passive** and more common setups
  (**Applications:** recording on smart speakers, laptop, etc.)

Our case: signal source and passive system of (I microphones)

Acoustic Echo Retrieval

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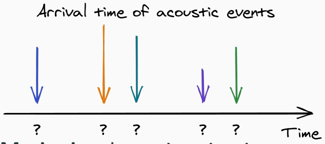

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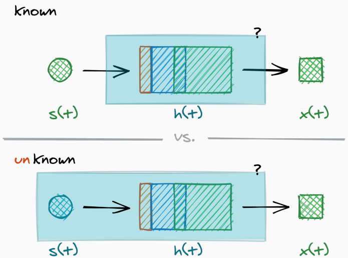
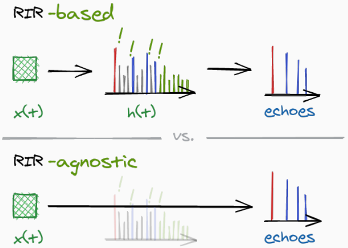


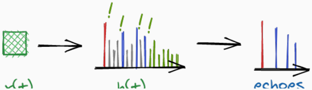
Methods: the estimation is



Our case: signal source and passive system of (I microphones)

Passive Acoustic Echo Retrieval

RIR-based approaches



1. Discrete optimization $\implies$ RIRs
2. Peak picking $\implies$ Echoes

✓ BCE is well and known studied

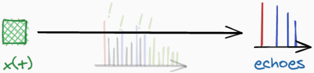
✓ reasonably good for some application
[Crocco and Del Bue, 2016]

✗ Full RIRs need to be estimated

✗ Peak picking has hyperparameters

✗ Issues due to *discrete* estimation

RIR-agnostic approaches



1. Direct off-grid estimation of $\left\{\tau_i^{(r)}, \alpha_i^{(r)}\right\}$
e.g., with maximum-likelihood

✓ No full RIRs & no peak picking
→ lower complexity
→ less hyperparameters

✓ Sparsity, Non-negativity are respected

✗ exploratory
(no standard solver, few works on audio)

Proposed appoach RIR-agnostic & off-grid:

1. Learning-based approach
2. analytical approach

Proposed approach: learning-based & off-grid

Idea: (Deep) Learning-based AER

1. Use virtually supervised deep learning models
2. Estimate first echo (simple but important)
   ([See Section Application])
3. Only 2 microphones

Motivations:

- This *direct* mapping is difficult, the *inverse* "is not"
  → acoustic simulators: mic/src/room geometry $\longrightarrow$ $\left\{\tau_i^{(r)}, \alpha_i^{(r)}\right\}$, $\tilde{h}_i$, $\tilde{x}_i$
- Acoustic simulator are "simple", versatile and fast
  → many data
- This approach is successful in *Sound Source Localization*
  → position is related to echoes
  [Kataria et al., 2017, Nguyen et al., 2018, Perotin et al., 2019] ⚠ Not only DNN

Proposed approach: models

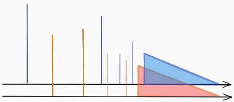
Inputs: Interchannel level and phase difference features[1] from

$$R[f] = \underset{t}{\text{avg.}} \frac{X_2[f,t]}{X_1[f,t]} \approx \underset{t}{\text{avg.}} \frac{H_2[f]S[f,t]}{H_1[f]S[f,t]}$$

$\approx$ the relative transfer function

$\rightarrow$ remove source dependency

Output: Inter and intra arrival delays



4 TOA
↓
3 Time Difference of Arrivals (**TDOAs**)[1]

HP: first $\Leftrightarrow$ strongest echo

[1] $\mathtt{ILD} = \log|R|$, $\mathtt{IPD} = \arg R/|R|$

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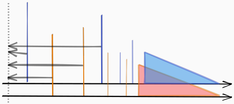

4 TOA

$\downarrow$

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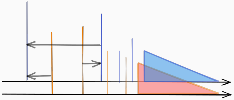
$$R[f] = \underset{t}{\texttt{avg.}} \frac{X_2[f,t]}{X_1[f,t]} \approx \underset{t}{\texttt{avg.}} \frac{H_2[f]S[f,t]}{H_1[f]S[f,t]}$$

$\approx$ the relative transfer function

$\rightarrow$ remove source dependency

Output: Inter and intra arrival delays



4 TOA

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3 Time Difference of Arrivals (**TDOAs**)[1]

HP: first $\Leftrightarrow$ strongest echo

[1] $\texttt{ILD} = \log|R|$, $\texttt{IPD} = \arg R/|R|$

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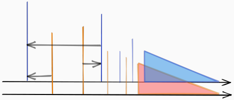

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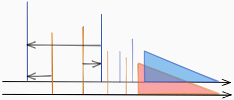

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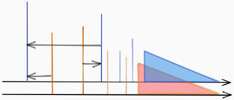

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  } Good for data fusion. Similar to **MDN** [Bishop, 1994]
- Data:
  - Virtually-supervised learning (= data from acoustic simulator)
  - white-noise as source signal + AWGN of 0, 10, 20 dB
  - 2 microphone in close-surface scenario

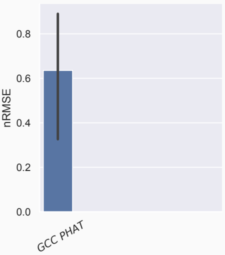
[1] $\text{ILD} = \log|R|$, $\text{IPD} = \arg R/|R|$

Experimental results

Proposed Method: MLP, CNN, $\mathtt{CNN}_{\mathcal{N}}$, $\mathtt{CNN}_{\mathcal{T}}$

Baseline: GCC PHAT [Knapp and Carter, 1976]

Metrics: normalized RMSE (0 = best fit, 1 = random fit)



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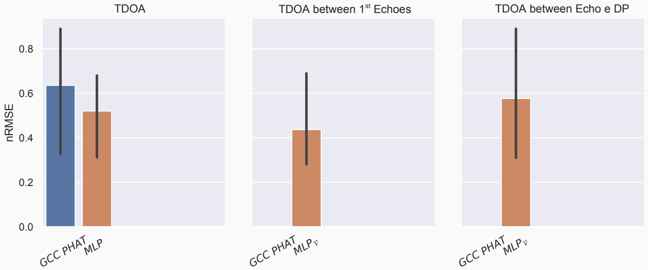

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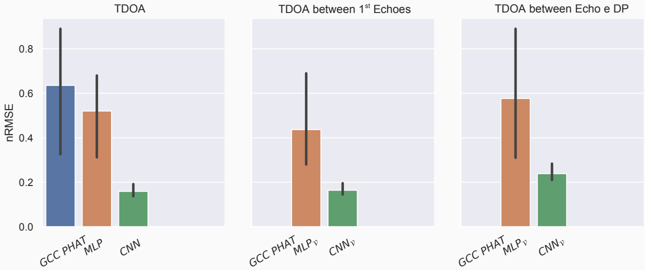

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✓ `MLP` outperforms `GCC PHAT` on TDOA estimation

✓ `CNN` outperforms `MLP` (lower error and smaller variance)

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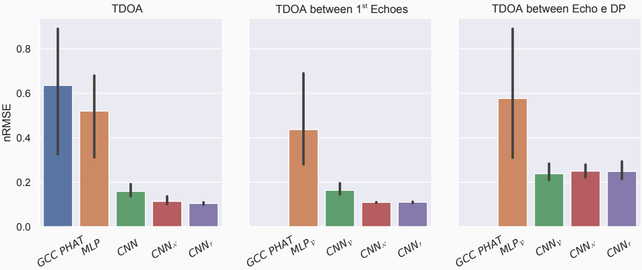

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- ✓ $\text{CNN}_{\mathcal{N}}$ and $\text{CNN}_{\mathcal{T}}$ outperform CNN (lower error and smaller variance)
- ✗ TDOA between DP and 1$^{\text{st}}$ echo more difficult

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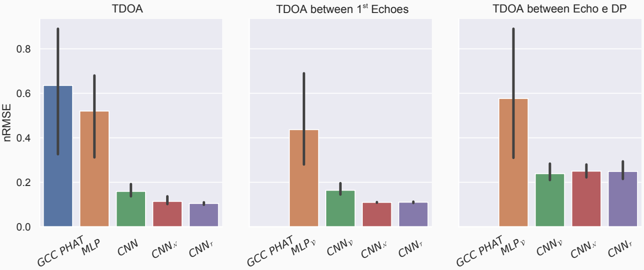

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- ✓ $\text{CNN}_{\mathcal{N}}$ and $\text{CNN}_{\mathcal{T}}$ outperform CNN (lower error and smaller variance)
- ✗ TDOA between DP and 1$^{\text{st}}$ echo more difficult
- ✗ In general, only the first echo on white noise

(Discrete) RIR-based methods: the State of the Art

Key ingredient – *Cross relation identity*

$$\begin{cases} \tilde{x}_1 &= \tilde{h}_1 * \tilde{s} \\ \tilde{x}_2 &= \tilde{h}_2 * \tilde{s} \end{cases}$$

$$\tilde{h}_2 * \tilde{x}_1 = \tilde{h}_2 * \tilde{h}_1 * \tilde{s} = \tilde{h}_1 * \tilde{h}_2 * \tilde{s} = \tilde{h}_1 * \tilde{x}_2$$

Ideas:

1. Sampled version of $\tilde{x}_1, \tilde{x}_2$ are available: x_1, x_2
2. Echo TOAs $\propto$ sampling frequency
3. Find echoes $\rightarrow$ **find sparse non-negative vectors** h_1, h_2 of length L
4. Modeled as **Lasso**-like problem

$= \texttt{Toeplitz}(x_i) h_j \in \mathcal{O}(L^2)$

$$\hat{h}_1, \hat{h}_2 \in \underset{h_1, h_2 \in \mathbf{R}^n}{\arg\min} \; \|x_1 * h_2 - x_2 * h_1\|_2^2 + \lambda \mathcal{P}(h_1, h_2) \quad \text{s.t.} \quad \mathcal{C}(h_1, h_2)$$

$\mathcal{P}(h_1, h_2) \longrightarrow$ sparse promoting regularizer $\qquad \mathcal{C}(h_1, h_2) \longrightarrow$ constraints e.g. nonnegativity, anchor

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

Proposed approach: analytical & off-grid

C. Elvira.

Observation 1: the cross-relation remains true in the continuous 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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$$\mathbf{X}_i = \mathtt{DFT}(x_i) \simeq \mathscr{F}\tilde{x}_i(nF_s) \qquad n = 0 \dots N-1$$

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Idea: Recover echoes by matching a finite number of frequencies

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

$\sim$ **Lasso**, but $\mathcal{F}h_2(f)$ is a continuous function $\rightarrow$ **BLasso** [Bredies and Carioni, 2020]

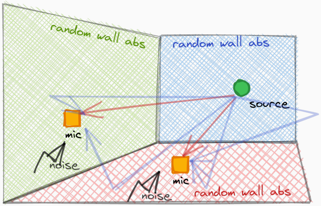
✓No huge matrix ✓ Solutions is a train of Dirac ✓ anchor prevents trivial solution

Experimental results

✓Promising results on noiseless data with RIRs macthing the echo-model

Syntetic Dataset at 16 kHz

- 2 microphones, 1 sound source
- Shoebox with random geometry
- 2 signals: broadband and speech
- $\mathcal{D}^{\text{SNR}}$: $SNR \in [0, 20]$ dB, $\text{RT}_{60} = 400$ ms
- $\mathcal{D}^{\text{RT60}}$: $\text{RT}_{60} = [100, 1000]$ ms, $SNR = 20$ dB



Baseline: discrete RIR-based methods based on LASSO

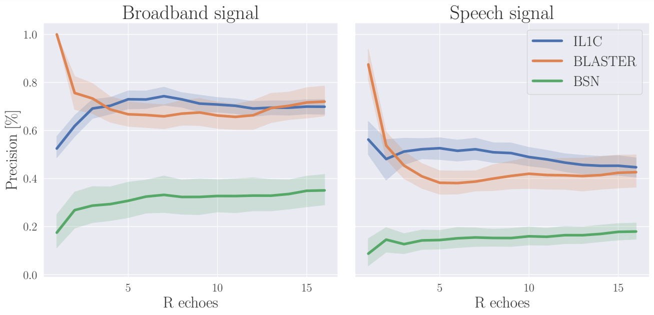
- BSN: Blind, Sparse and Non-negative [Lin et al., 2007]
- IL1C: iteratively-weighted ℓ_1 constraint [Crocco and Del Bue, 2015]
  ↪ State of the Art

hyperparameters and peak-picking tuned via cross-validation

Proposed method: off-grid rir-agnostic based on BLasso
Blind and Sparse Technique for Echo Retrieval (`Blaster`)

Performance per # of echoes

Metric: Precision = how many estimated echoes are correct (within 2 samples)



($RT_{60} = 400$ ms and SNR = 20 dB.)

✗ Sensitive to # echoes

✗ Sensitive source signal

✓ Good for 2 echoes

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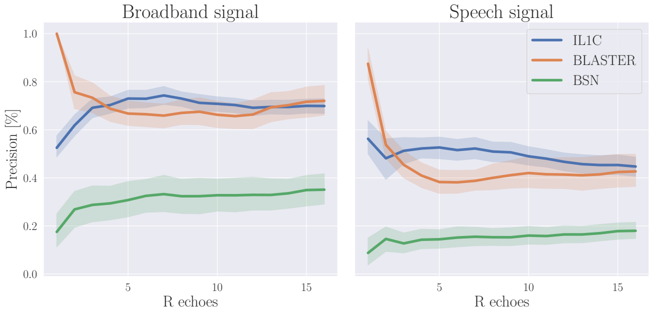


($RT_{60} = 400$ ms and SNR = 20 dB.)

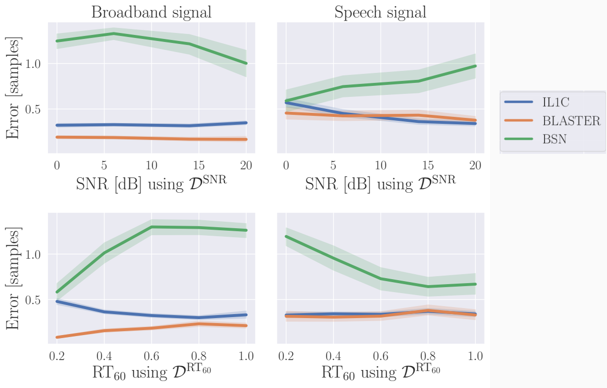
✗ Sensitive to # echoes

✗ Sensitive source signal

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

Error per Dataset/Signal while recovering 7 echoes

Metric: RMSE on the mather echoes = error on the correct guess



(Fs = 16 kHz)

✓Lower RMSE

✓ Robustness to SNR and RT_{60}

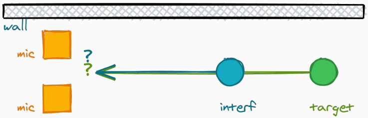
✗ Source signal dependent

Echo-aware Application

Echo-aware Application

Echoes = same content, different time/direction

Image Source Model
⇔
Image Microphone Mode



Some literature on echo-aware processing:

What?
Echoes = repetitions

- Sound Source Separation
  [Leglaive et al., 2016]
- Speech Enhancement
  [Flanagan et al., 1993,
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Where?
Echoes ← image

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- Room Geometry Estimation

How?
Echoes ∈ sound propagation

- Blind Channel Estimation
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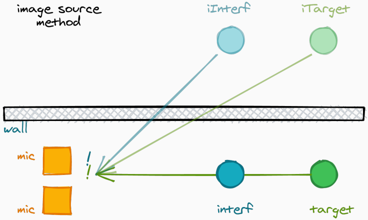

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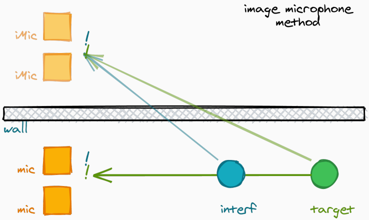

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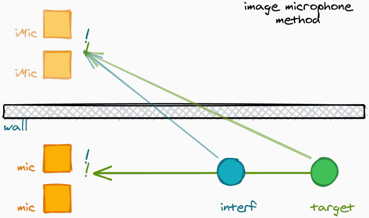

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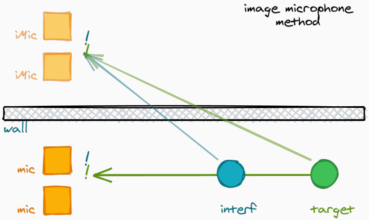

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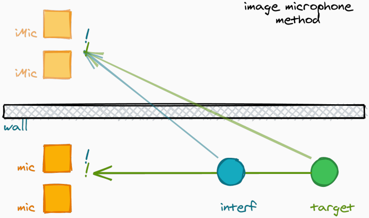

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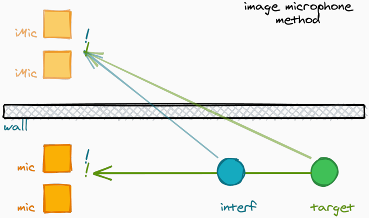

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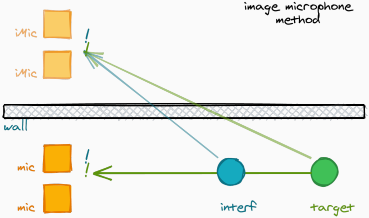

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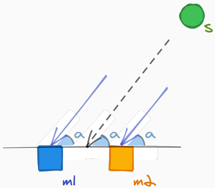
Sound Source Localization (SSL)

(common knowledge)

We do not consider here distance estimation.

SSL with 2 microphones

- Only angle of arrival (AOA)
- can be approximated from TDOA using e.g. GCC PHAT[1]
  (known limitation, but good in practice)



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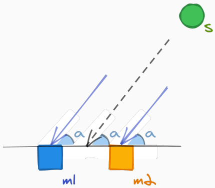
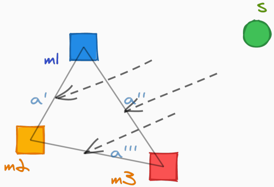


SSL with more microphones

- Only Directon of Arrival (DoA): azimuth (↔) and elevation (↕)

1. AOA for each pair can be “fuse” together (e.g. angular spectra in SRP-PHAT[2])
   (known limitation, but good in practice)



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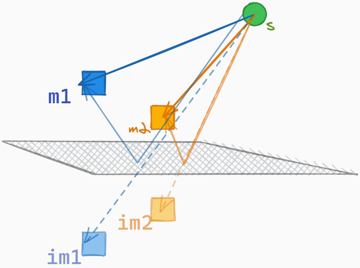
[2] [DiBiase et al., 2001]

[1] [Knapp and Carter, 1976]

Sound Source Localization with Echoes

The Picnic Scenario:

- One source
- Two microphones
  - → passive scenario
  - → generalizable to any array geometry



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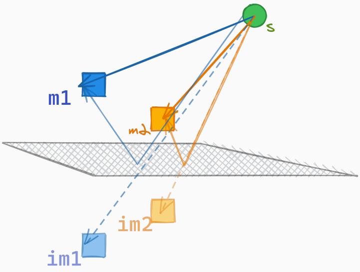

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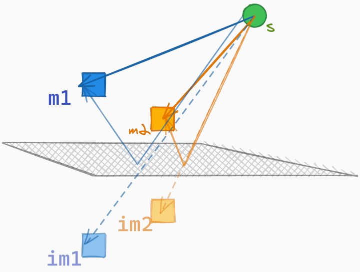
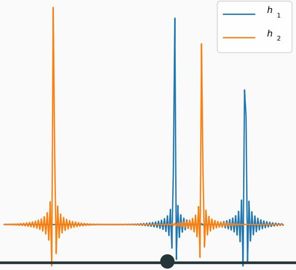


Each pair is augmented with echoes

Mirage Array

(Microphone Array Augmetation with Echoes)

How to access the *image* microphones?



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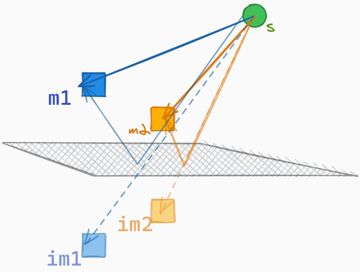

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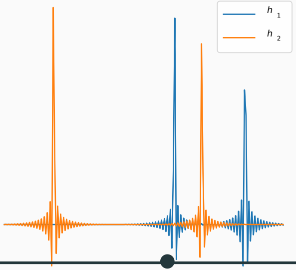

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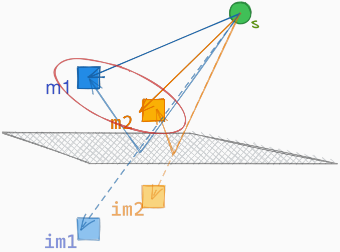

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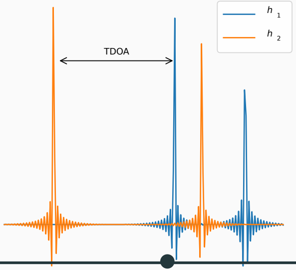

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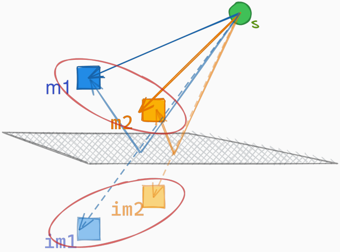

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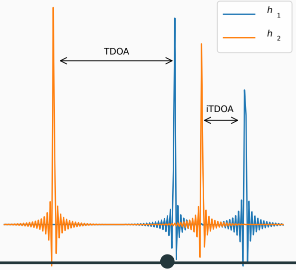

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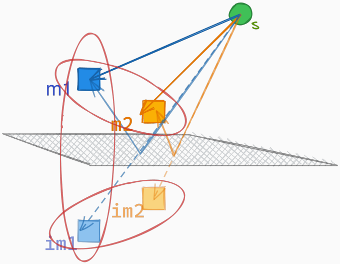

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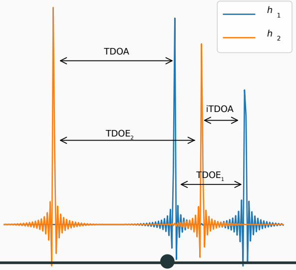
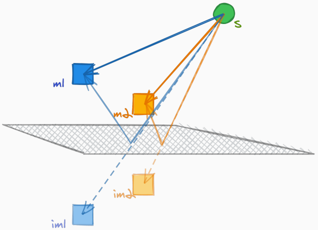


Sound Source Localization with Echoes

Idea: DoA estimate on the MIRAGE array.
Recall: these TDOAs are the same of the DNN-based method



Proposed Approach:

1. use proposed `MLP` model for TDOAs estimation
2. fuse together the estimation ...
   - of the `Mirage` array (similar to SRP-PHAT[1])
   - knowing the position of the microphones;
   - use the error on a validation set as measure of uncertainty.

Baseline: `GCC PHAT`on true microphones[2]

2 [DiBiase et al., 2001]
1 [Knapp and Carter, 1976]

Experimental results

Proposed: MLP with Mirage

Baseline: GCC PHAT[1]

Data: 200 synthetic stereophonic recordings for close-surface scenario
Metric: accuracy in % (<10°, <20°) (also error in the manuscript)

AOA	Input	ACCURACY $\alpha < 10°$	$\alpha < 20°$
Mirage	wn	77	97
GCC PHAT	wn	**81**	**97**

Observation

✓ comparable to baseline when white noise source in noiseless case

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✗ not generalize to noisy and speech data

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DoA	Input	< 10° θ	< 10° ϕ	< 20° θ	< 20° ϕ
Mirage	wn	**59**	**71**	**79**	**88**
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Mirage	sp+n	17	12	38	43

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- ✓ Solved “impossible” localization

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Observation

- ✓ comparable to baseline when white noise source in noiseless case
- ✗ not generalize to noisy and speech data
- ✓ Solved "impossible" localization
- ⚠ Performance depending on echo estimation methods

27

Echo-aware Dataset

Echo-aware datasets

⚠ Everything so far was a simulation

Echo-aware database requires:

- annotation of the echoes;
- annotation of the geometry;
- should cover a vast number of echo-aware applications;
- expertise in signal processing, acoustics and
- proper recording devices.

dEchorate

Characteristics of dEchorate

- different room configurations and RT60 (→ flipping wall panels)
- 6 array × 5 mics × 4 sources × 11 wall conf. = **1320 annotated RIRs** at 48 kHz
- geometry annotation ⇔ echo annotation in the RIRs
- real RIRs ⇔ synthetic RIRs
- application to Acoustic Echo Retrieval, Room Geometry Estimation, Speech Enhancement, ...
- silence, chirps, speech, noise, diffuse bubble noise for 64 GB

(prof Gannot, ing. Tandeitnik)

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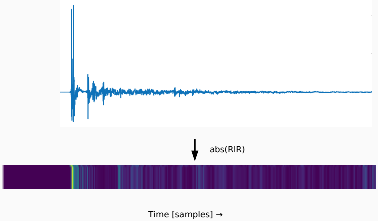
dEchorate: the skyline view



- each column correspond to the absolute values of one RIR

dEchorate: the skyline view

- each column correspond to the absolute values of one RIR
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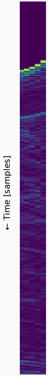
dEchorate: the skyline view



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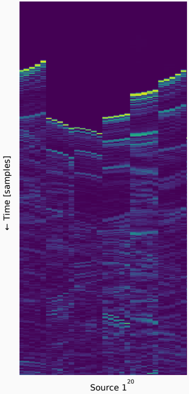

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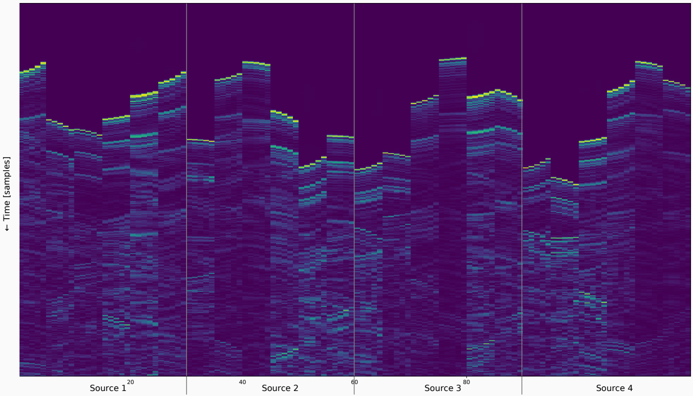

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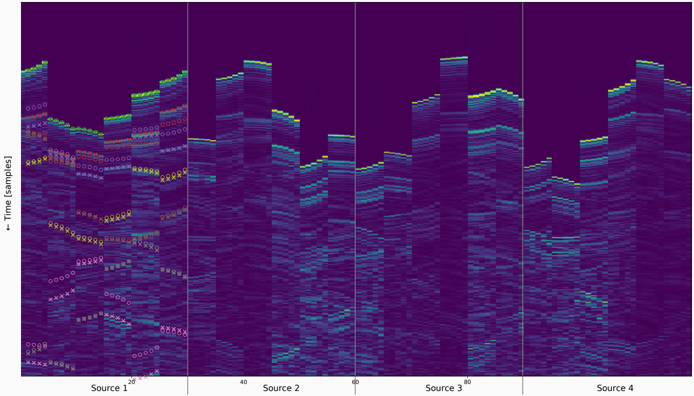

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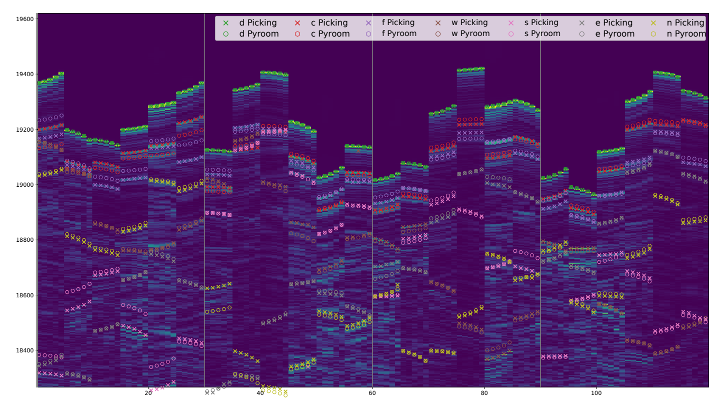

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Echo-aware Speech Enhancement with dEchorate

Speech Enhancement (SE)

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

interfering sources	+	noise	+	reverberation
$\downarrow$		$\downarrow$		$\downarrow$
source separation		denoising		dereverberation room equalization

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SE via **linear spatial filtering** in the STFT domain

$$\mathbf{x}[f,t] = \mathbf{h}[f]\mathbf{s}[f,t] + \mathbf{n}[f,t] \in \mathbb{C}^I \longrightarrow \quad \mathbf{w}^{\mathsf{H}}[f] \in \mathbb{C}^I \quad \longrightarrow \quad \mathbf{w}^{\mathsf{H}}[f]\mathbf{x}[f,t] \approx \mathbf{s}[f,t]$$

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- many variant, e.g. enhance or null multiple sources [Gannot et al., 2017]

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

Reducing output energy + distortionless ⇔ reduce any uncorrelated noise

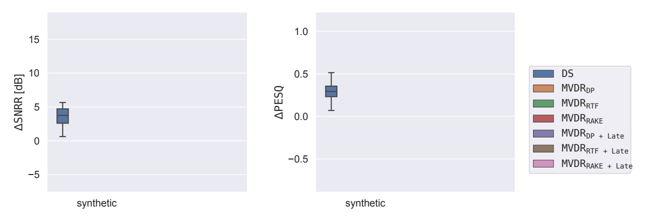
Echo-aware Speech Enhancement

Closed-form solution, but it requires:

	Noise covariance matrix	RIRs
DS	-	Direct Path (AOA)

Metrics: Signal to Noise and Reverberant Ratio (SNRR) and Speech Quality (PESQ)

Data: dEchorate dataset, RT60 = 600 ms)



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$\mathrm{MVDR}_{\mathrm{ReTF}}$	Noise	Relative Transfer Function

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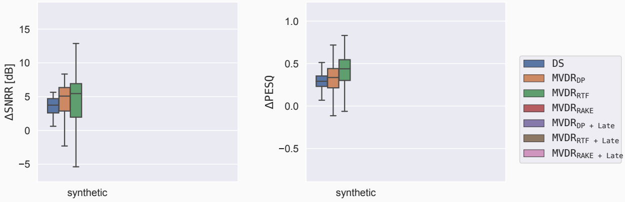

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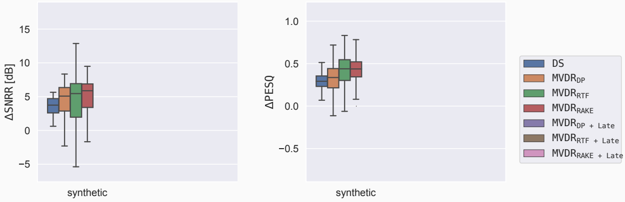

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$\mathrm{MVDR}_{\mathrm{Rake}}$	Noise	4 Early Echoes
$\mathrm{MVDR}_{\mathrm{DP+Late}}$	Noise + Late Diffusion	Direct Path (AOA)
$\mathrm{MVDR}_{\mathrm{ReTF+Late}}$	Noise + Late Diffusion	Relative Transfer Function
$\mathrm{MVDR}_{\mathrm{Rake+Late}}$	Noise + Late Diffusion	4 Early Echoes

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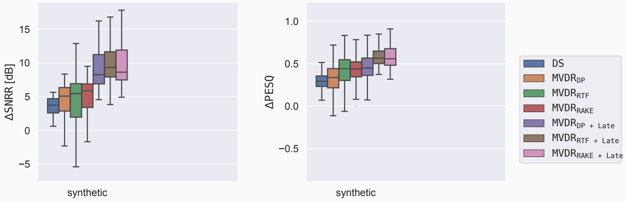

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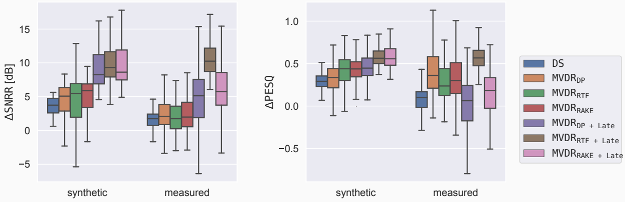

Conclusion

Summary of contributions

How to estimate them?

In passive stereo scenario:

- Learning-based method
  - off grid estimation
  - depends on source and # echoes
- Analytical method
  - estimation on first echo' TDOAs
  - only on synthetic data

How to use them?

- Source Localization
  - allow 2D DoA estimation with 2 mic
  - depends on the echo estimator
- Source Separation
- Speech Enhancement
  - in theory early echoes helps
  - needs to be accurately estimated
- Room Geometry Estimation

Where to find them?

- `dEchorate`
  Echo-aware database for both estimation and application
  - echo annotation $\Leftrightarrow$ geometry annotation
  - synthetic $\Leftrightarrow$ real RIRs

Echo-aware perspective

Directions for future work:

- on **estimation**
  - develop theoretical guaranties for off-grid acoustic echo retrieval
  - for DNN: extended physic-based learning or other learning paradigm (i.e., unfolding or curriculum learning)
- on **application**
  - other field of echoes: (Seismology, Underwater acoustic, Volcanology, Sniper Detection, etc.)
- on `dEchorate`
  - Synthetic to Real RIRs (style transfer, new types to acoustic simulators)
  - Benchmark for echo-aware algorithms
- **"close the loop":** audio analysis $\Leftrightarrow$ echo estimation
  in the thesis only the $\Rightarrow$ direction.

List of publications and artifacts

Publications

- Estimation
  - deep learning method in [Di Carlo et al., 2019]
  - `Blaster`— analytical method in [Di Carlo et al., 2020]
- Application
  - `Mirage`— sound source localization in [Di Carlo et al., 2019]
  - `Separake`— sound source separation in [Scheibler et al., 2018]
- Data
  - `dEchorate`— database (journal in progress)
- Other
  - Signal Processing CUP 2019 [Deleforge et al., 2019]
  - LOCATA Challenge 2019 [Lebarbenchon et al., 2018]
  - Collaboration with Honda on multichannel `Mirage`

Code

- `dEchorate`: GUI and code for `dEchorate`
- `Risotto`: library for ReTF estimation
- `Brioche`: library for Spatial filtering
- `pyMBSSLocate`: MBSSLocate in Python
- `Separake`: Multichannel NMF in Python

Thank you!

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