Echo-aware signal processing for audio scene analysis

Diego Di Carlo

December 3, 2020

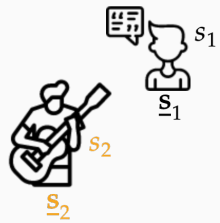
PhD supervisors: Antoine Deleforge
Nancy Bertin

Jury members: Renaud Seguier (president, examiner)
Simon Doclo (reviewer)
Laurent Girin (reviewer)
Fabio Antonacci (examiner)

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

Introduction

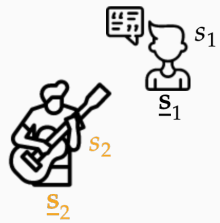
Echo-aware signal processing for audio scene analysis

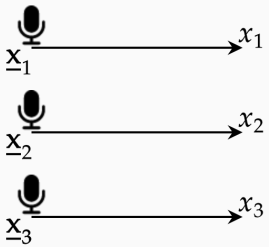


Sound

- produced by sources

Echo-aware signal processing for audio scene analysis

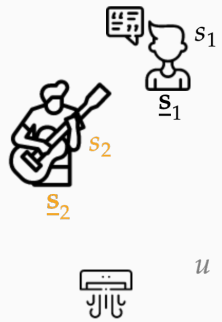


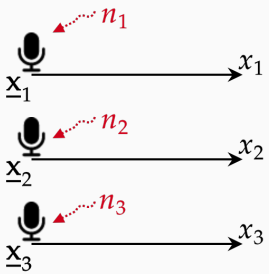


Sound

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

Echo-aware signal processing for audio scene analysis

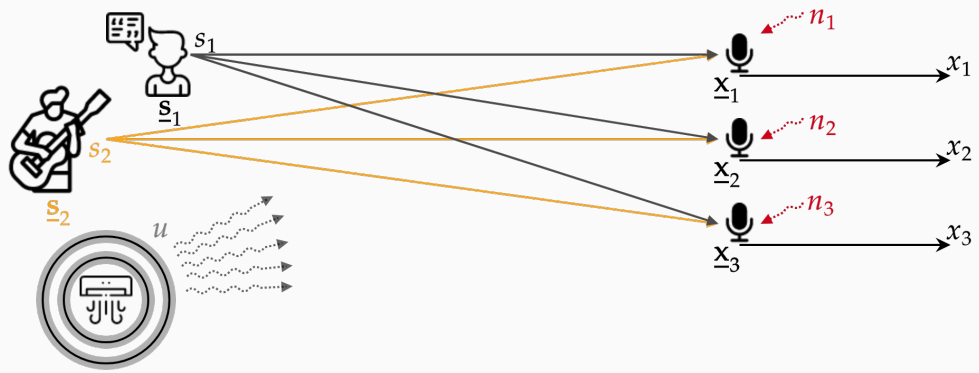




Sound

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

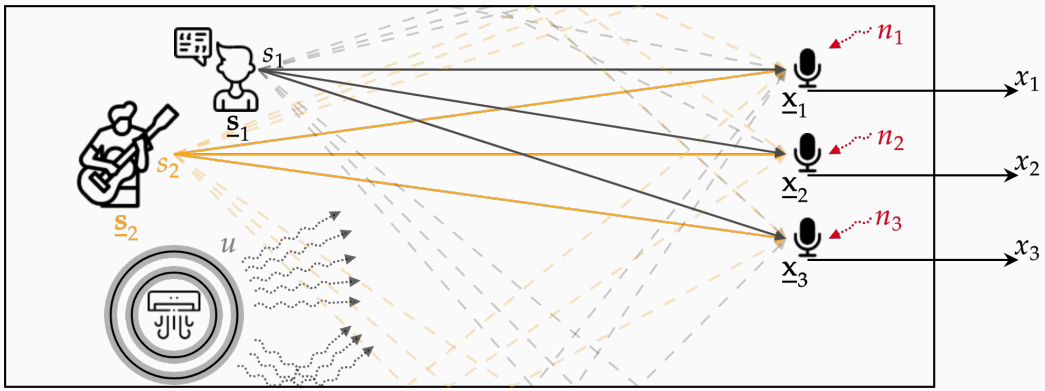
Echo-aware signal processing for audio scene analysis



Sound

- produced by sources
- recorded by (array of) microphones
- corrupted by noise
- propagates in the space

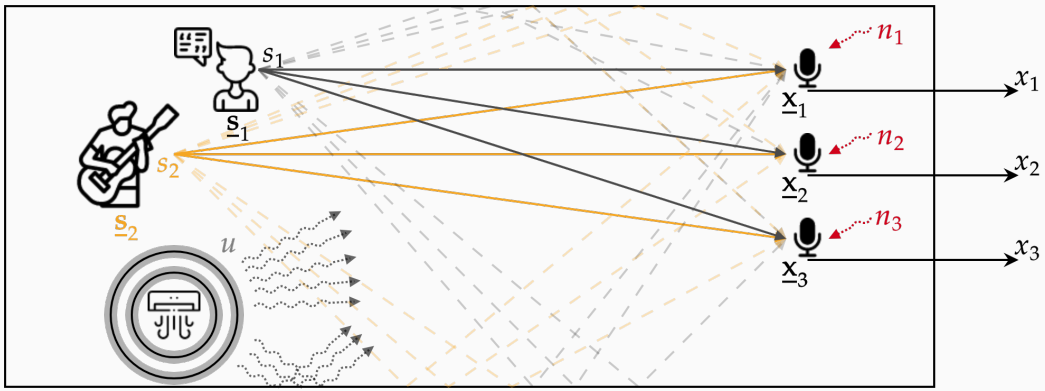
Echo-aware signal processing for audio scene analysis



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



Sound

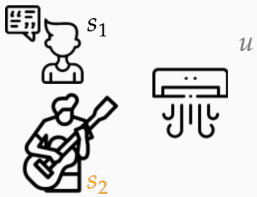
- produced by sources
- recorded by (array of) microphones
- corrupted by noise
- propagates in the space
- interacts with the room
  ↪ reverberation

$\sum$ = **Audio Scene**

Echo-aware signal processing for audio scene analysis

Echo-aware signal processing for audio scene analysis

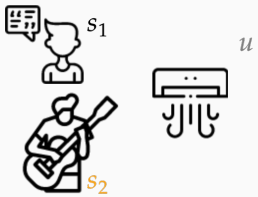
Semantic information



on nature and content

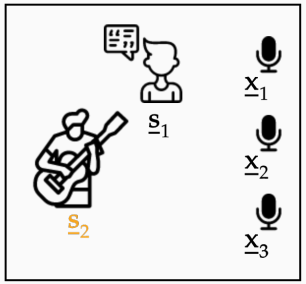
Echo-aware signal processing for audio scene analysis

Semantic information



on nature and content

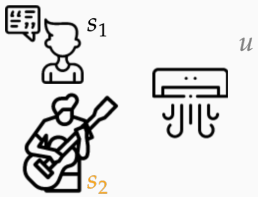
Spatial information



on position and geometry

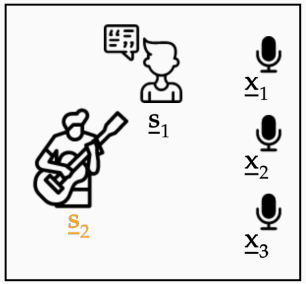
Echo-aware signal processing for audio scene analysis

Semantic information



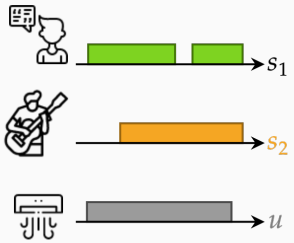
on nature and content

Spatial information



on position and geometry

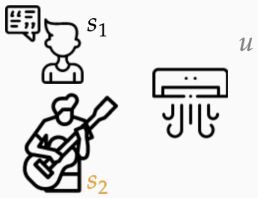
Temporal information



on events activity

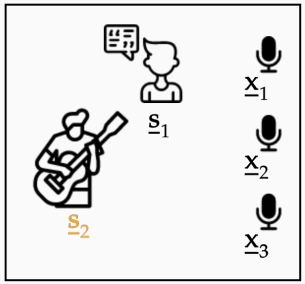
Echo-aware signal processing for audio scene analysis

Semantic information



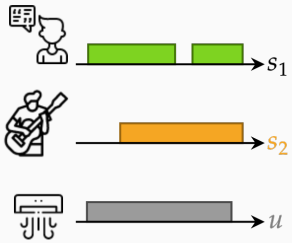
on nature and content

Spatial information



on position and geometry

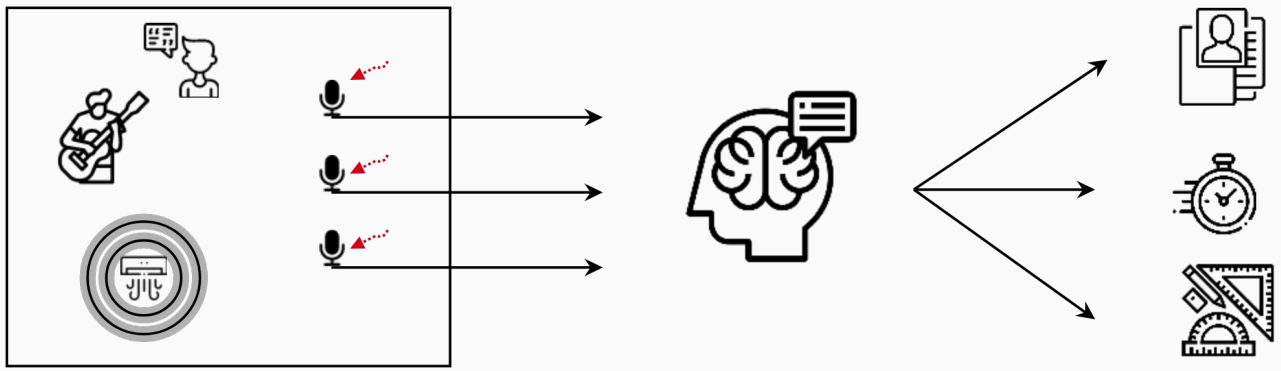
Temporal information



on events activity

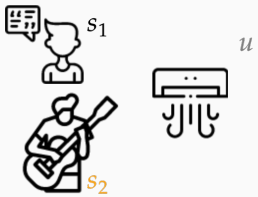
Audio Scene Analysis

Extraction and organization of all the information in the sound



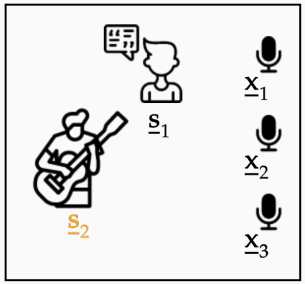
Echo-aware signal processing for audio scene analysis

Semantic information



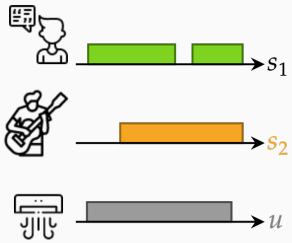
on nature and content

Spatial information



on position and geometry

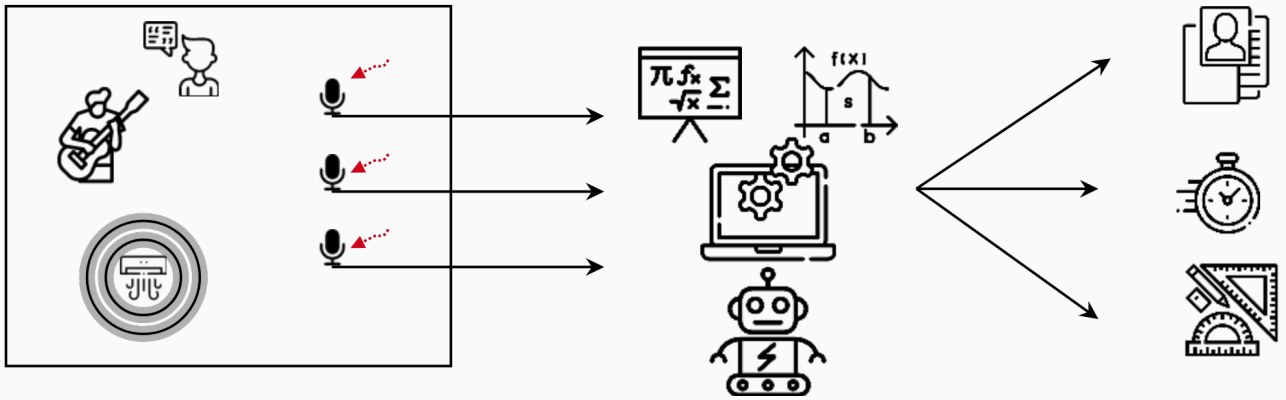
Temporal information



on events activity

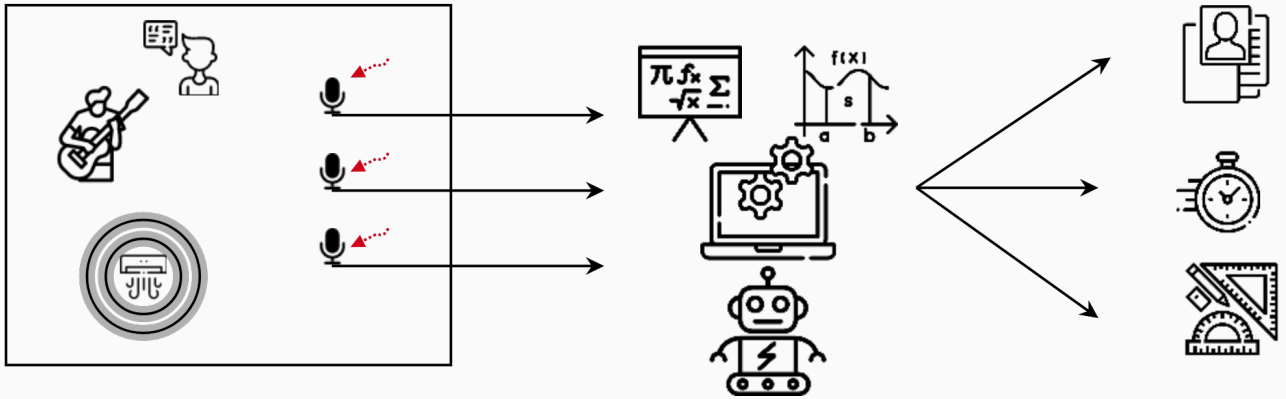
Audio Scene Analysis

Extraction and organization of all the information in the sound

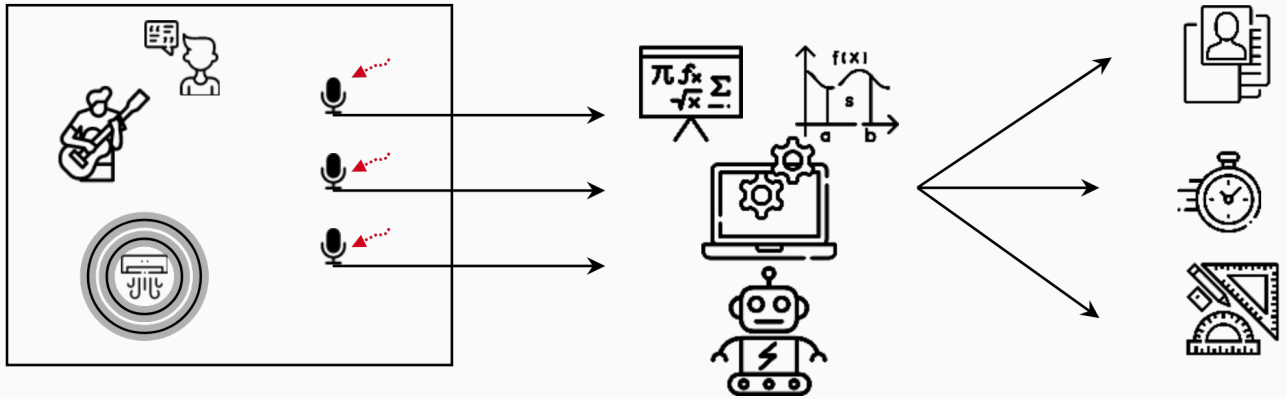


Can computers do it?

Echo-aware signal processing for audio scene analysis



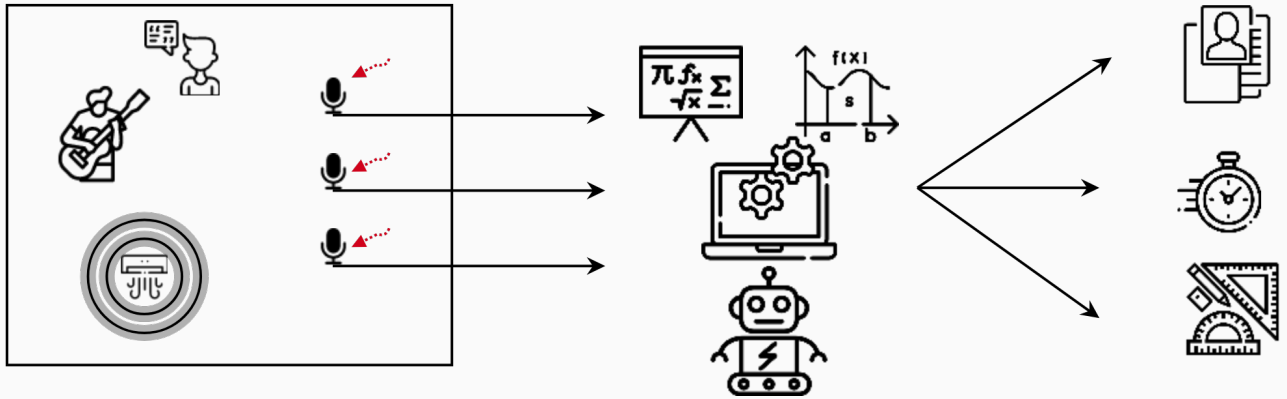
Echo-aware signal processing for audio scene analysis



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

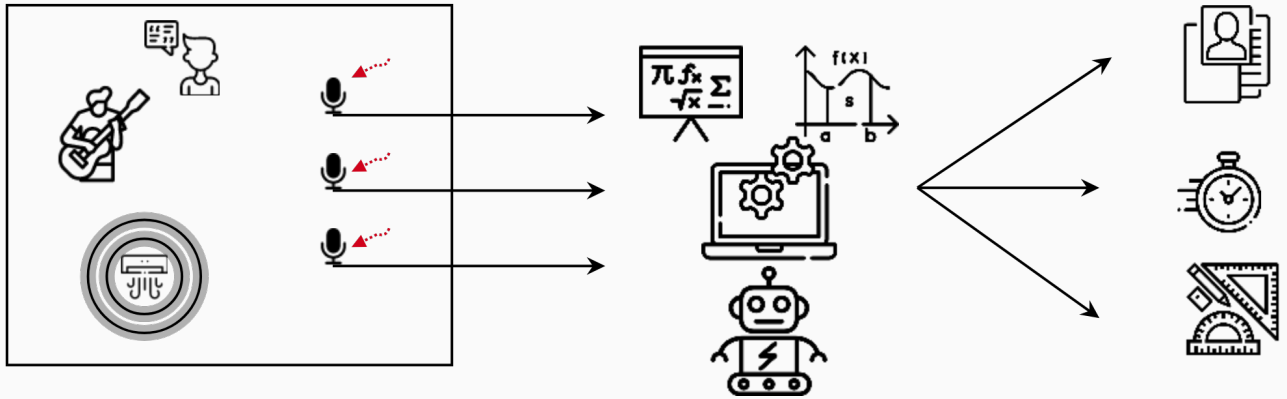
- Sound Source Separation
- Speech Enhancement
- Sound Source Localization
- Room Geometry Estimation

What? / Where?

- Voice Activity Detection
- Reverberation level estimation
- Acoustic Channel Estimation
- ...

When? / How?

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
- Sound Source Localization
- Room Geometry Estimation

What? / Where?

- Voice Activity Detection
- Reverberation level estimation
- Acoustic Channel Estimation
- ...

When? / How?

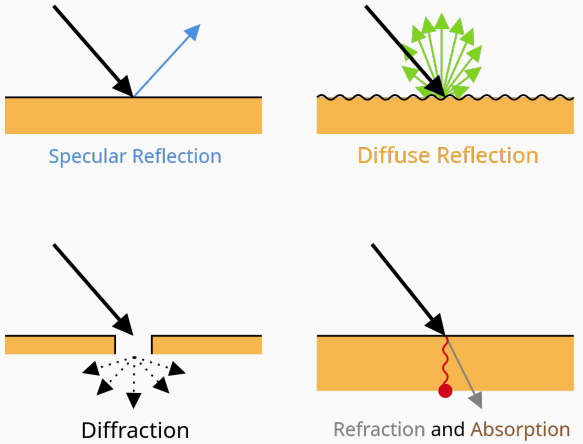
$$\text{HOW} \xrightarrow{\textit{helps}} \text{WHERE} \xrightarrow{\textit{helps}} \text{WHAT} \xrightarrow{\textit{helps}} \text{HOW} \xrightarrow{\textit{helps}} \ldots$$

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, etc.

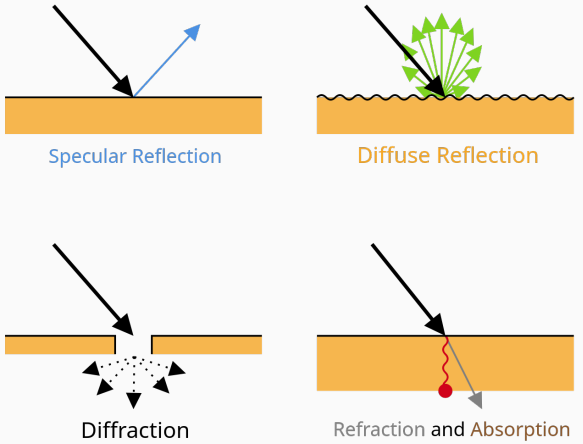


Echo-aware signal processing for audio scene analysis

Sound interacts with indoor environment:

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

} = reverberation

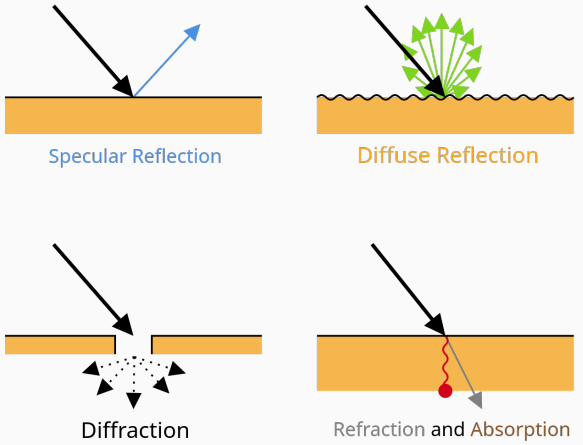


Echo-aware signal processing for audio scene analysis

Sound interacts with indoor environment:

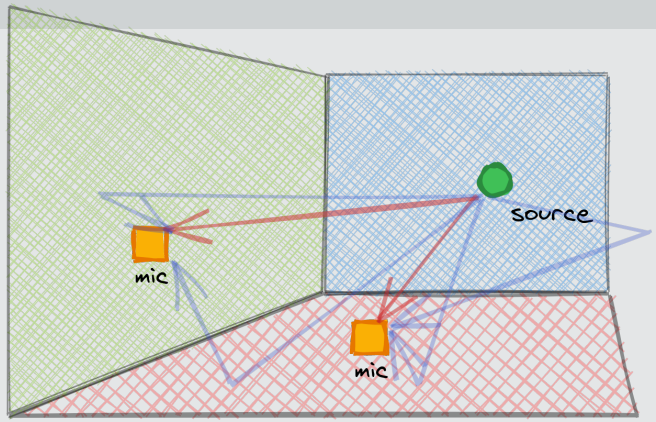
it is reflected specularly and diffusely
+ it is absorbed,
+ it is transmitted,
+ it is diffracted, etc.

} = reverberation



Acoustic Echoes: early specular reflection

- Reflections "standing out" w.r.t. reverberation
- Copy of a sound but later
  - same content
  - delay ⇔ travelled distance

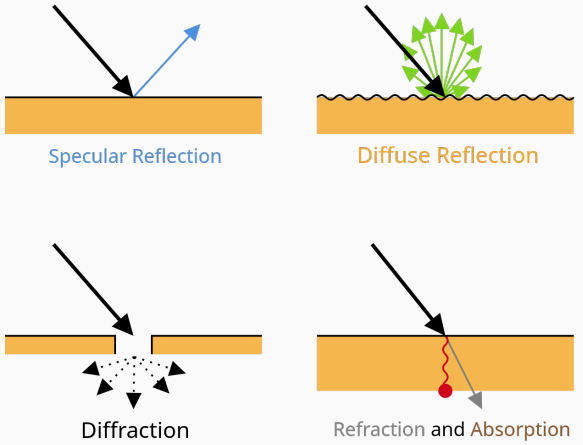


Echo-aware signal processing for audio scene analysis

Sound interacts with indoor environment:

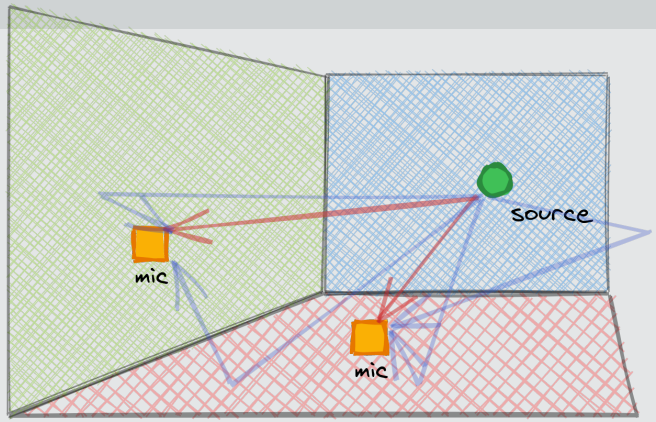
it is reflected specularly and diffusely
+ it is absorbed,
+ it is transmitted,
+ it is diffracted, etc.

} = reverberation



Acoustic Echoes: early specular reflection

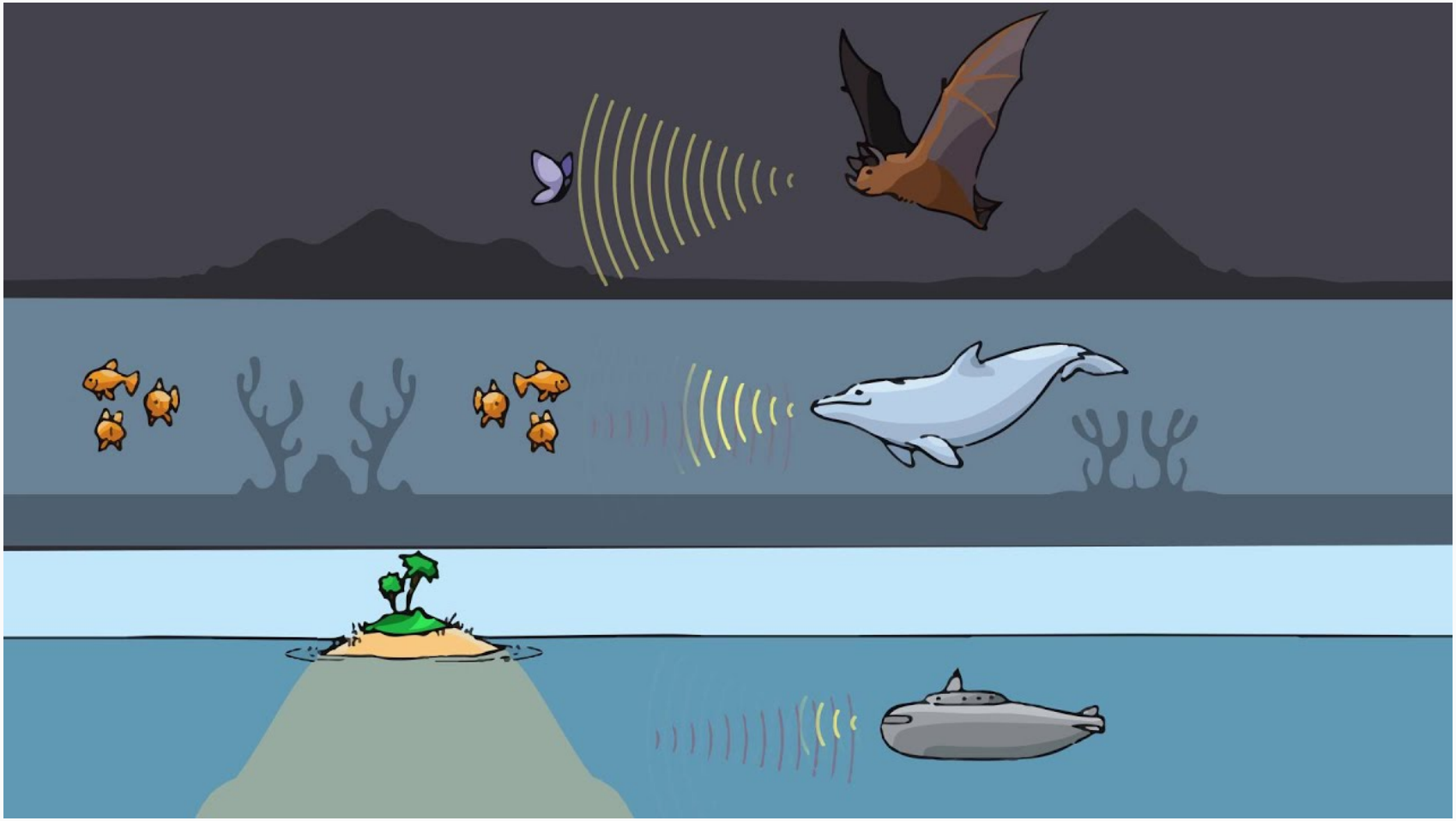
- Reflections "standing out" w.r.t. reverberation
- Copy of a sound but later
  - same content
  - delay ⇔ travelled distance



! idea: leverage this

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 $\Longrightarrow$ simple processing but reverberation is noise
- fully modeled and estimated $\Longrightarrow$ very challenging

Echo-aware signal processing for audio scene analysis

In audio signal processing, sound propagation is typically

- ignored $\Longrightarrow$ simple processing but reverberation is noise
- fully modeled and estimated $\Longrightarrow$ very challenging

Echo-aware methods

- explicitly account for some acoustic reflections to boost the performance
- attractive alternative between ignoring reverberation and modelling it entirely

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

[Ribeiro et al., 2010]

Outline and contributions

Thesis title:

Outline and contributions

Thesis title:

Echo-aware

↓

better processing

Outline and contributions

Thesis title:

Echo-aware → better processing

Signal Processing → models and frameworks

Outline and contributions

Thesis title:

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

Outline and contributions

Thesis title:

Echo-aware → better processing

Signal Processing → models and frameworks

for Audio Scene Analysis → context and problems

Thesis contribution:

1. How to estimate them?
2. How to use them?
3. Where to find them?

Outline and contributions

Thesis title:

Echo-aware → better processing

Signal Processing → models and frameworks

for Audio Scene Analysis → context and problems

Thesis contribution:

1. How to estimate them?
   - Learning-based method
   - Analytical method
2. How to use them?
3. Where to find them?

Outline and contributions

Thesis title:

Echo-aware → better processing

Signal Processing → models and frameworks

for Audio Scene Analysis → context and problems

Thesis contribution:

1. How to estimate them?
   - Learning-based method
   - Analytical method
2. How to use them?
   - Source Localization
   - Speech Enhancement
   - Source Separation(in the 📖)
   - Room Geometry Estimation(in the 📖)
3. Where to find them?

Outline and contributions

Thesis title:

Echo-aware → better processing

Signal Processing → models and frameworks

for Audio Scene Analysis → context and problems

Thesis contribution:

1. How to estimate them?
   - Learning-based method
   - Analytical method
2. How to use them?
   - Source Localization
   - Speech Enhancement
   - Source Separation(in the 📖)
   - Room Geometry Estimation(in the 📖)
3. Where to find them?
   - Echo-aware database

Problem Statement

Signal model

For one source and I microphones:

mic. signal ← $\tilde{x}_i(t) = (\tilde{h}_i * \tilde{s})(t) + \tilde{n}_i(t) \quad i \in I$ → source signal

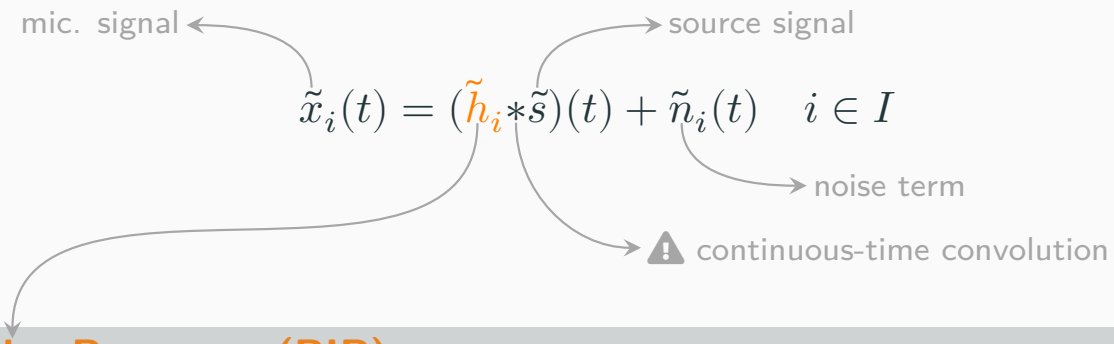
→ noise term

→ ⚠ continuous-time convolution

→ Room Transfer Function (RTF)

Signal model

For one source and I microphones:



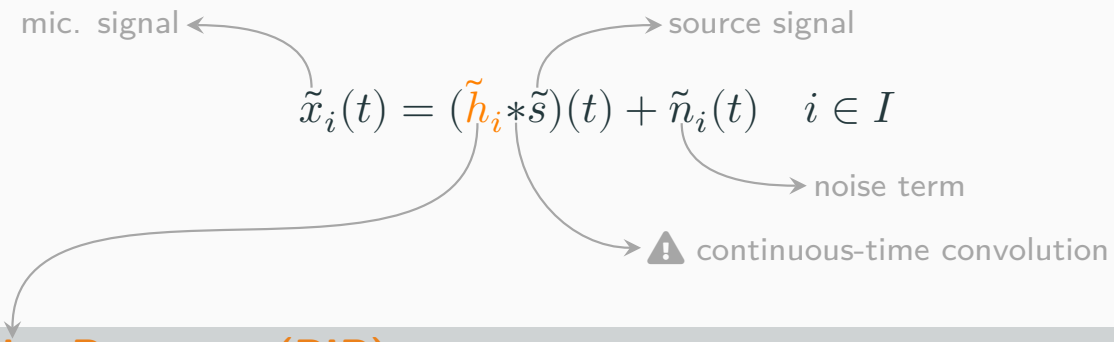
Room Impulse Response (RIR)

- 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)
  $\rightarrow$ one RIR for each microphone and source pair

Room Transfer Function (RTF)

Signal model

For one source and I microphones:



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)
  $\rightarrow$ one RIR for each microphone and source pair

In the Short Time Fourier Transform (STFT) domain:

$$X_i[f,t] = H_i[f]S[f,t] + N_i[f,t]$$

Room Transfer Function (RTF)

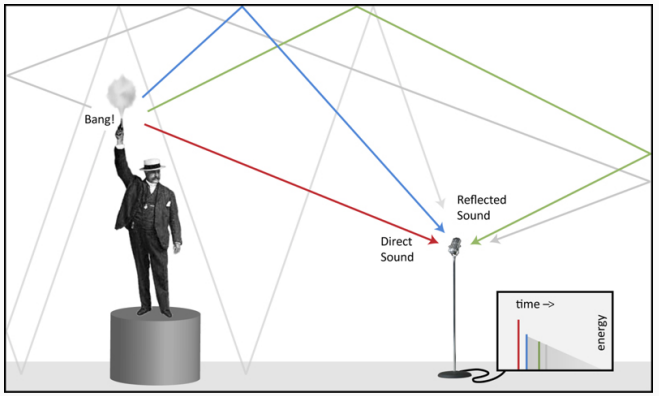
where $X[f,t], H[f,t], S[f,t], N[f,t] \in \mathbb{C}$

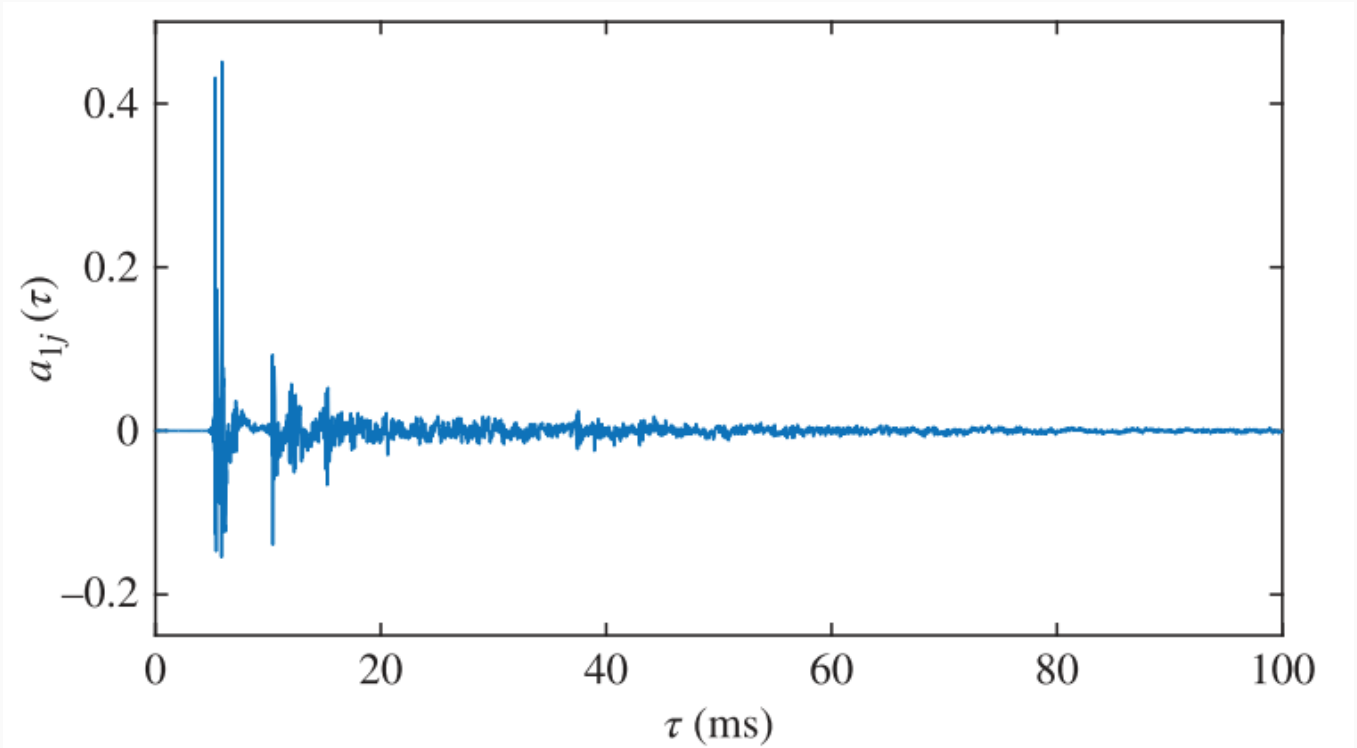
Elements of RIR

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

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

- $\tilde{h}_i^{\mathsf{d}}(t)$ = 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 functions:

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

$\varepsilon_i(t)$ → models later echoes, reverberation and other.

Problem Statement

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

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

$\varepsilon_i(t)$ → models later echoes, reverberation and other.

Goal: Acoustic Echo Retrieval (AER)

Estimate $\left\{\tau_i^{(r)}, \alpha_i^{(r)}{}_i\right\}_{i,r}$ from the microphone signals $\{x_i\}_i$

Problem Statement

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

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

$\varepsilon_i(t)$ → models later echoes, reverberation and other.

Goal: Acoustic Echo Retrieval (AER)

Estimate $\left\{\tau_i^{(r)}, \alpha_i^{(r)}{}_i\right\}_{i,r}$ from the microphone signals $\{x_i\}_i$

Challenges:

Problem Statement

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

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

$\varepsilon_i(t)$ → models later echoes, reverberation and other.

Goal: Acoustic Echo Retrieval (AER)

Estimate $\left\{\tau_i^{(r)}, \alpha_i^{(r)}{}_i\right\}_{i,r}$ from the microphone signals $\{x_i\}_i$

Challenges:

- RIRs depend on the scene geometry (room, source and mic position)

Problem Statement

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

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

$\varepsilon_i(t)$ → models later echoes, reverberation and other.

Goal: Acoustic Echo Retrieval (AER)

Estimate $\left\{\tau_i^{(r)}, \alpha_i^{(r)}{}_i\right\}_{i,r}$ from the microphone signals $\{x_i\}_i$

Challenges:

- RIRs depend on the scene geometry (room, source and mic position)
- Big under-modelling error (late reverberation and external noise)

Problem Statement

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

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

$\varepsilon_i(t)$ → models later echoes, reverberation and other.

Goal: Acoustic Echo Retrieval (AER)

Estimate $\left\{\tau_i^{(r)}, \alpha_i^{(r)}{}_i\right\}_{i,r}$ from the microphone signals $\{x_i\}_i$

Challenges:

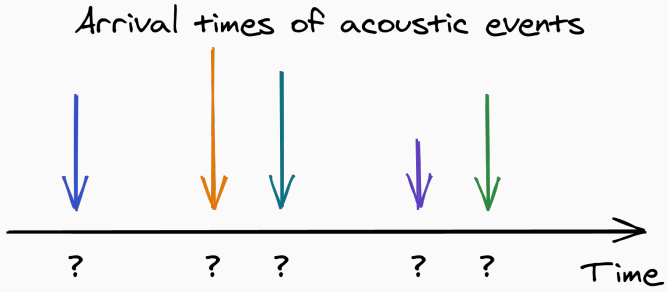
- RIRs depend on the scene geometry (room, source and mic position)
- Big under-modelling error (late reverberation and external noise)
- In reality: $\alpha_i^{(r)}\delta(t) \to (\alpha_i^{(r)} * \delta)(t)$ due to
  - frequency-dependent air attenuation, wall absorption, ...
  - sampling process

Acoustic Echo Estimation

Acoustic Echo Retrieval

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

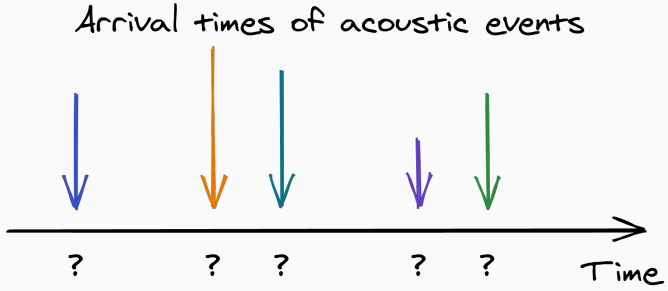
$$\{\tilde{x}_i\}_i \longrightarrow \{\tau_i^{(r)}, \alpha_i^{(r)}\}_{i,r}$$



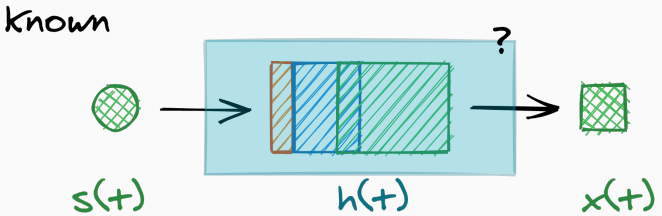
Acoustic Echo Retrieval

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

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



Two scenarios:

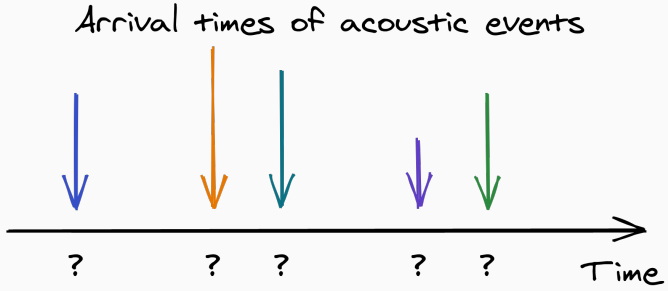


- **intrusive** or specific setups
- **non-blind** problem
  (**Applications:** sonar, measurements, etc.)

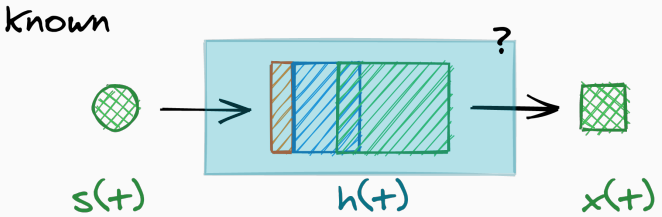
Acoustic Echo Retrieval

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

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

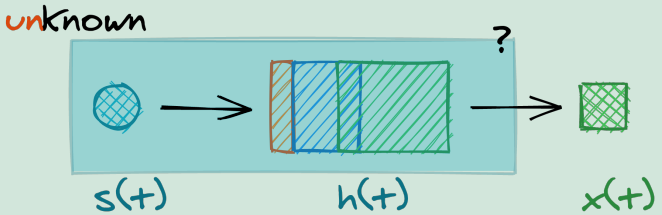


Two scenarios:



- **intrusive** or specific setups
- **non-blind** problem

(**Applications:** sonar, measurements, etc.)



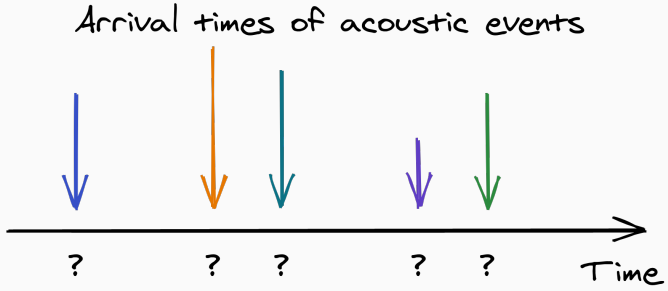
- **passive** and more common setups
- **blind inverse** problem (harder)

(**Applications:** recording on smart speakers, etc.)

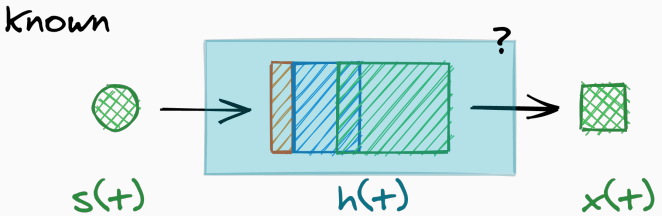
Acoustic Echo Retrieval

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

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

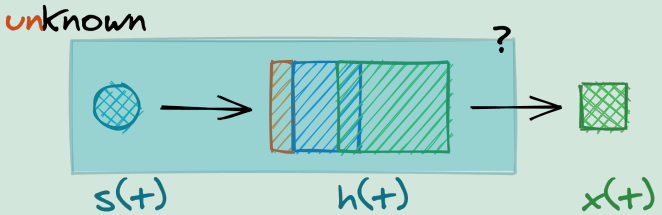


Two scenarios:



- **intrusive** or specific setups
- **non-blind** problem

(**Applications:** sonar, measurements, etc.)



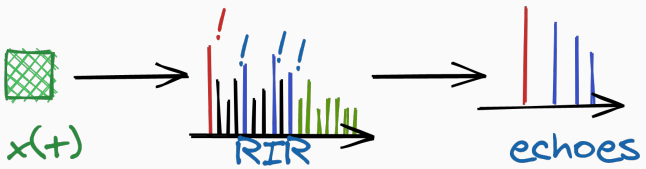
- **passive** and more common setups
- **blind inverse** problem (harder)

(**Applications:** recording on smart speakers, etc.)

Our case: one source and passive microphone array

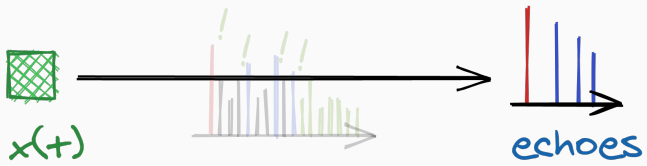
Passive Acoustic Echo Retrieval

RIR-based approaches



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

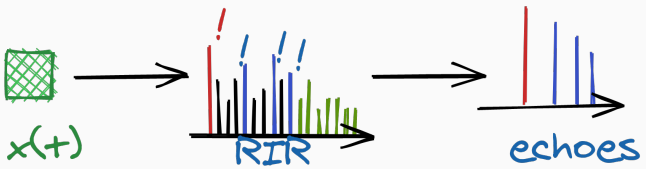
RIR-agnostic approaches



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

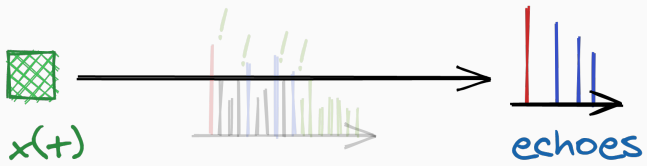
Passive Acoustic Echo Retrieval

RIR-based approaches



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

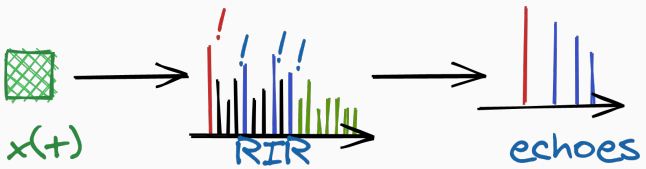
RIR-agnostic approaches



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

Passive Acoustic Echo Retrieval

RIR-based approaches



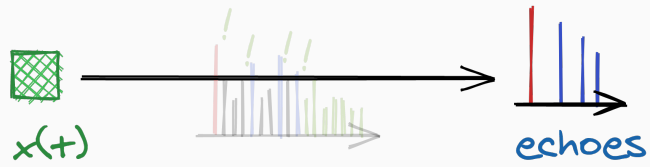
1. Discrete optimization $\Longrightarrow$ RIRs
2. Peak picking $\Longrightarrow$ Echoes

✓ BCE is well and known studied

✓ reasonably good for some application

[Crocco and Del Bue, 2016]

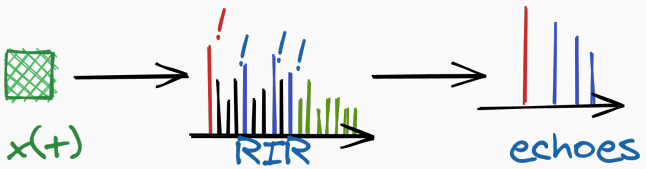
RIR-agnostic approaches



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

Passive Acoustic Echo Retrieval

RIR-based approaches



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

✓ BCE is well and known studied

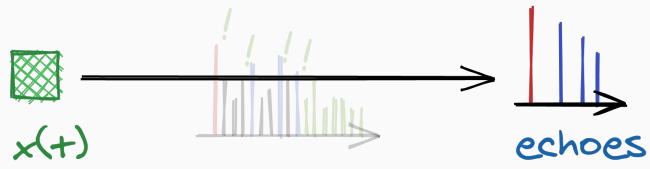
✓ reasonably good for some application
[Crocco and Del Bue, 2016]

✗ Full RIRs need to be estimated

✗ Peak picking has hyperparameters

✗ Issues due to *discrete* estimation

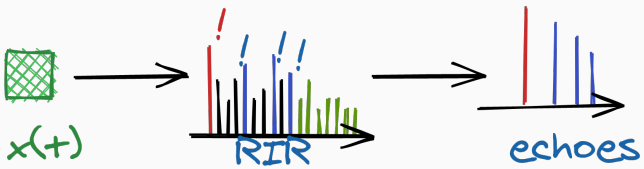
RIR-agnostic approaches



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

Passive Acoustic Echo Retrieval

RIR-based approaches



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

✓ BCE is well and known studied

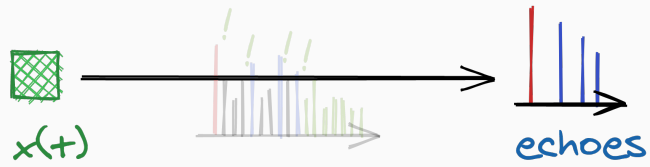
✓ reasonably good for some application
[Crocco and Del Bue, 2016]

✗ Full RIRs need to be estimated

✗ Peak picking has hyperparameters

✗ Issues due to *discrete* estimation

RIR-agnostic approaches



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

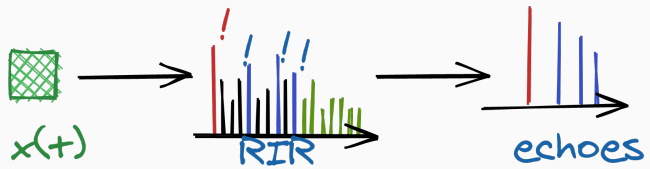
✓ No full RIRs & no peak picking

→ lower complexity
→ less hyperparameters

✗ exploratory
(few works on audio)

Passive Acoustic Echo Retrieval

RIR-based approaches



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

✓ BCE is well and known studied

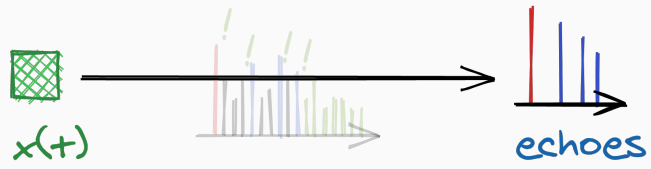
✓ reasonably good for some application
[Crocco and Del Bue, 2016]

✗ Full RIRs need to be estimated

✗ Peak picking has hyperparameters

✗ Issues due to *discrete* estimation

RIR-agnostic approaches



1. Direct 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

✗ exploratory
(few works on audio)

Proposed appoach RIR-agnostic & continuous:

1. Analytical approach
2. Learning-based approach

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

Key ingredient – *Cross relation identity*

Signal model

$$x_1 = h_1 \star x$$
$$x_2 = h_2 \star x$$

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

Key ingredient – *Cross relation identity*

Convolving with filters:

$$h_2 \star x_1 = h_2 \star h_1 \star x$$

$$h_1 \star x_2 = h_1 \star h_2 \star x$$

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

Key ingredient – *Cross relation identity*

Commutativity of convolution:

$$h_2 \star x_1 = h_2 \star h_1 \star x$$

$$h_1 \star x_2 = h_2 \star h_1 \star x$$

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

Key ingredient – *Cross relation identity*

Subtraction

$$\left.\begin{aligned} h_2 \star x_1 &= h_2 \star h_1 \star x \\ h_1 \star x_2 &= h_2 \star h_1 \star x \end{aligned}\right\} \rightarrow x_1 \star h_2 - x_2 \star h_1 = 0$$

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

Key ingredient – *Cross relation identity*

Subtraction

$$\left.\begin{aligned} h_2 \star x_1 &= h_2 \star h_1 \star x \\ h_1 \star x_2 &= h_2 \star h_1 \star x \end{aligned}\right\} \rightarrow x_1 \star h_2 - x_2 \star h_1 = 0$$

Ideas:

1. Echo TOAs $\propto$ sampling frequency
2. Find echoes $\rightarrow$ **find sparse non-negative vectors** h_1, h_2 of length L
3. Modeled as **Lasso**-like problem

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

Key ingredient – *Cross relation identity*

Subtraction

$$\left.\begin{aligned} h_2 \star x_1 &= h_2 \star h_1 \star x \\ h_1 \star x_2 &= h_2 \star h_1 \star x \end{aligned}\right\} \rightarrow x_1 \star h_2 - x_2 \star h_1 = 0$$

Ideas:

1. Echo TOAs $\propto$ sampling frequency
2. Find echoes $\rightarrow$ **find sparse non-negative vectors** h_1, h_2 of length L
3. Modeled as **Lasso**-like problem

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

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

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

$\mathcal{C}(h_1, h_2) \longrightarrow$ constraints e.g. nonnegativity, anchor

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

Key ingredient – *Cross relation identity*

Subtraction

$$\left.\begin{aligned} h_2 \star x_1 &= h_2 \star h_1 \star x \\ h_1 \star x_2 &= h_2 \star h_1 \star x \end{aligned}\right\} \rightarrow x_1 \star h_2 - x_2 \star h_1 = 0$$

Ideas:

1. Echo TOAs $\propto$ sampling frequency
2. Find echoes $\rightarrow$ **find sparse non-negative vectors** h_1, h_2 of length L
3. Modeled as **Lasso**-like problem

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

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

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

C. Elvira.

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

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

Proposed approach: analytical & continuous

C. Elvira.

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

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

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

Proposed approach: analytical & continuous

C. Elvira.

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

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

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

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

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

Proposed approach: analytical & continuous

C. Elvira.

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

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

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

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

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

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

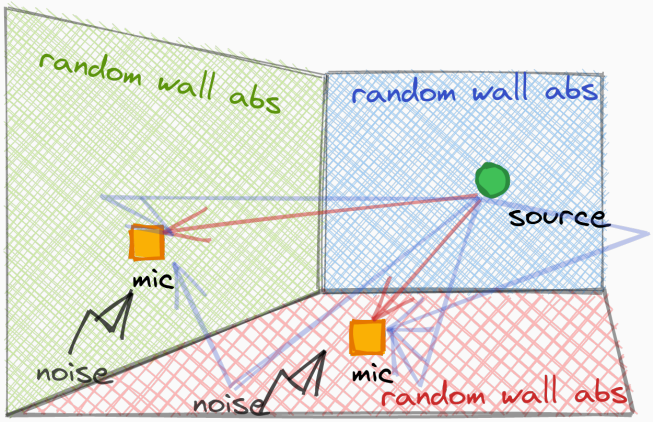
$\sim$ **Lasso**, but $\mathcal{F}h_i(f)$ is a continuous function $\rightarrow$ **BLasso** [Azais et al., 2015]

✓No huge matrix ✓ Solutions are trains of Dirac ✓ No peak picking ✓ Perfect in noiseless & synthetic case

Experimental results

Syntetic Dataset at 16 kHz

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



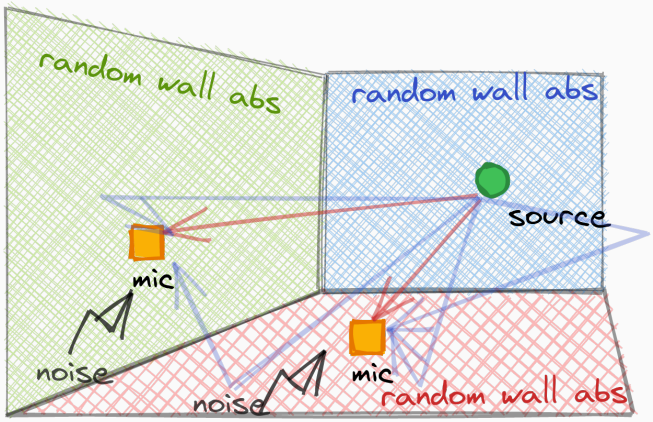
[1] [Lin et al., 2007]

[2] [Crocco and Del Bue, 2015]

Experimental results

Syntetic Dataset at 16 kHz

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



Baselines: discrete RIR-based methods based on LASSO

- BSN: Blind, Sparse and Non-negative[1]
- IL1C: iteratively-weighted ℓ_1 constraint[2] $\rightarrow$ State of the Art

hyperparameters and peak-picking tuned via cross-validation

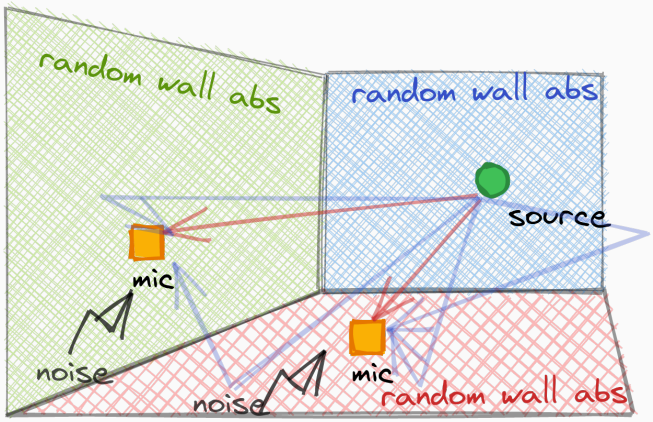
[1] [Lin et al., 2007]

[2] [Crocco and Del Bue, 2015]

Experimental results

Syntetic Dataset at 16 kHz

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



Baselines: discrete RIR-based methods based on LASSO

- BSN: Blind, Sparse and Non-negative[1]
- IL1C: iteratively-weighted ℓ_1 constraint[2] $\rightarrow$ State of the Art

hyperparameters and peak-picking tuned via cross-validation

Proposed method: Blind and Sparse Technique for Echo Retrieval (`Blaster`)

[1] [Lin et al., 2007]

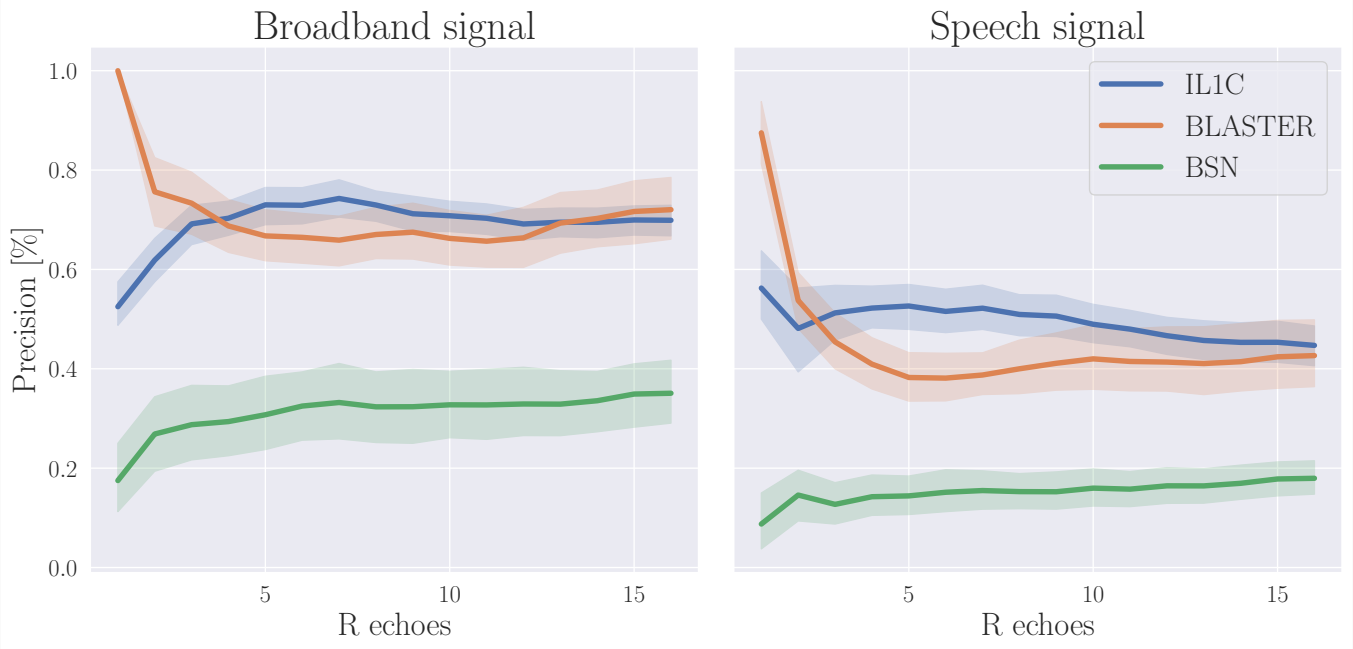
[2] [Crocco and Del Bue, 2015]

Precision per # of echoes

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

Precision per # of echoes

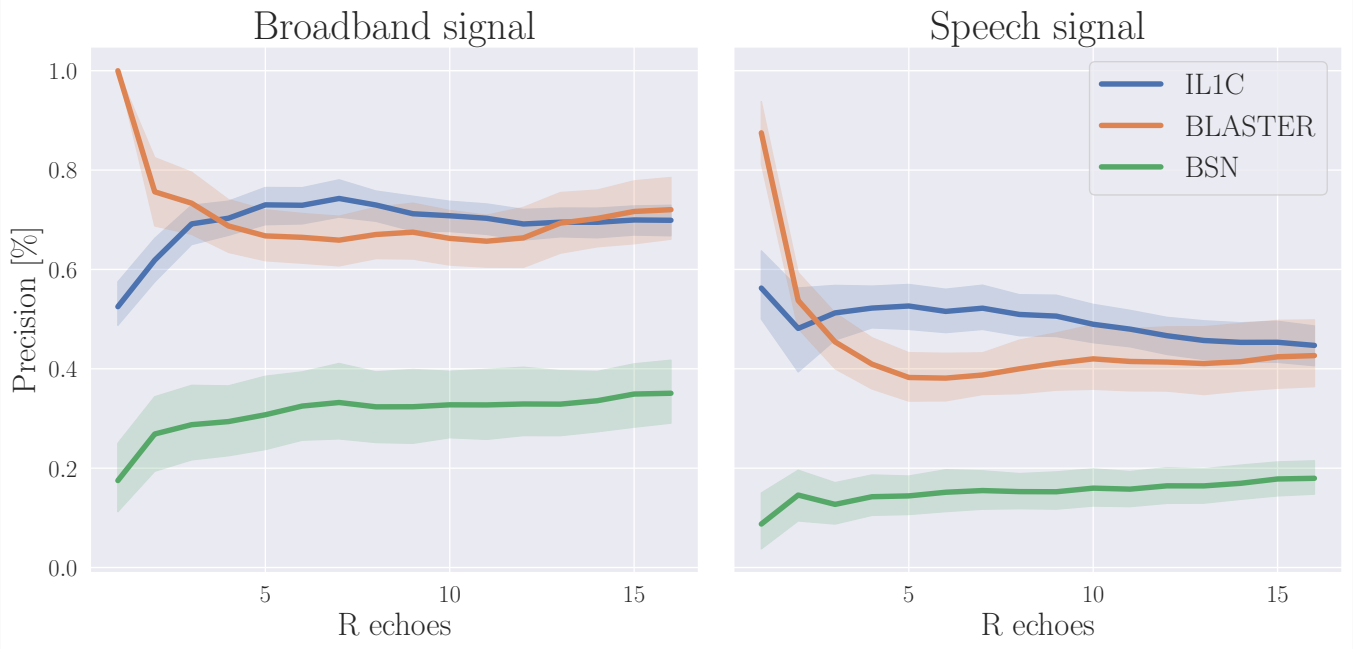
Metric: Precision = how many estimated echoes are correct (within 2 samples)



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

Precision per # of echoes

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



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

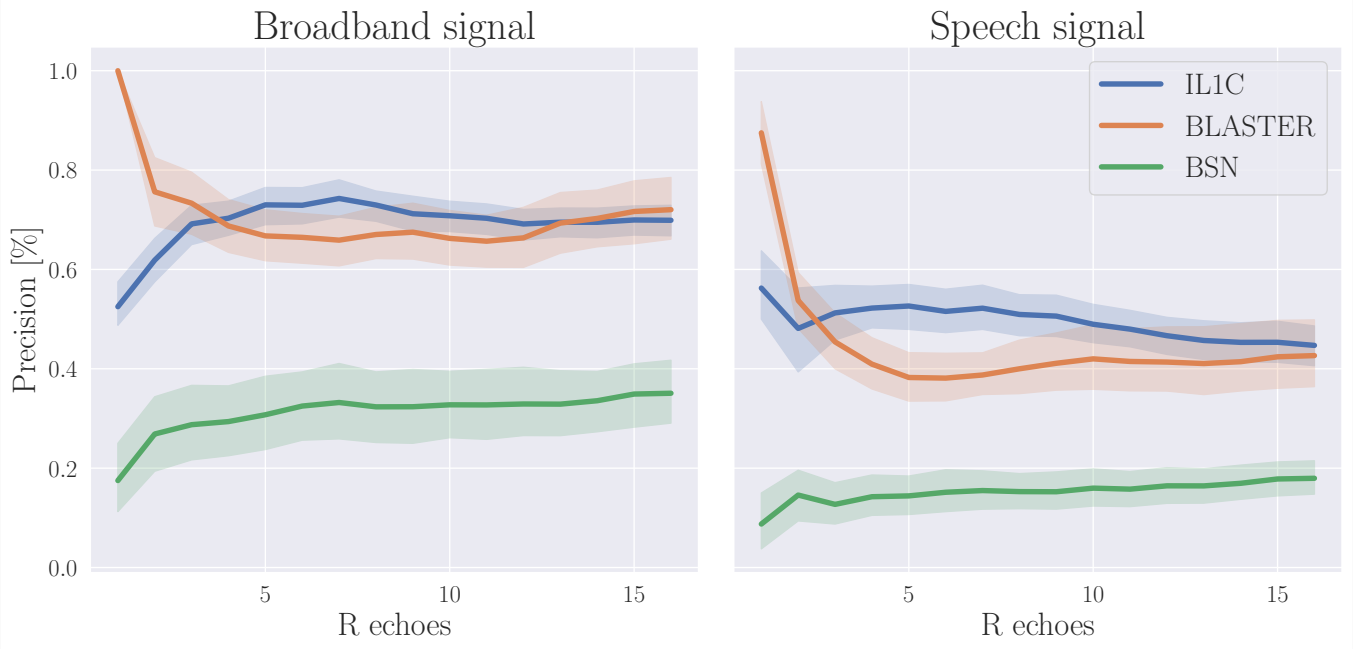
✗ Sensitive to # echoes

✗ Sensitive source signal

✓ Good for 2 echoes

Precision 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

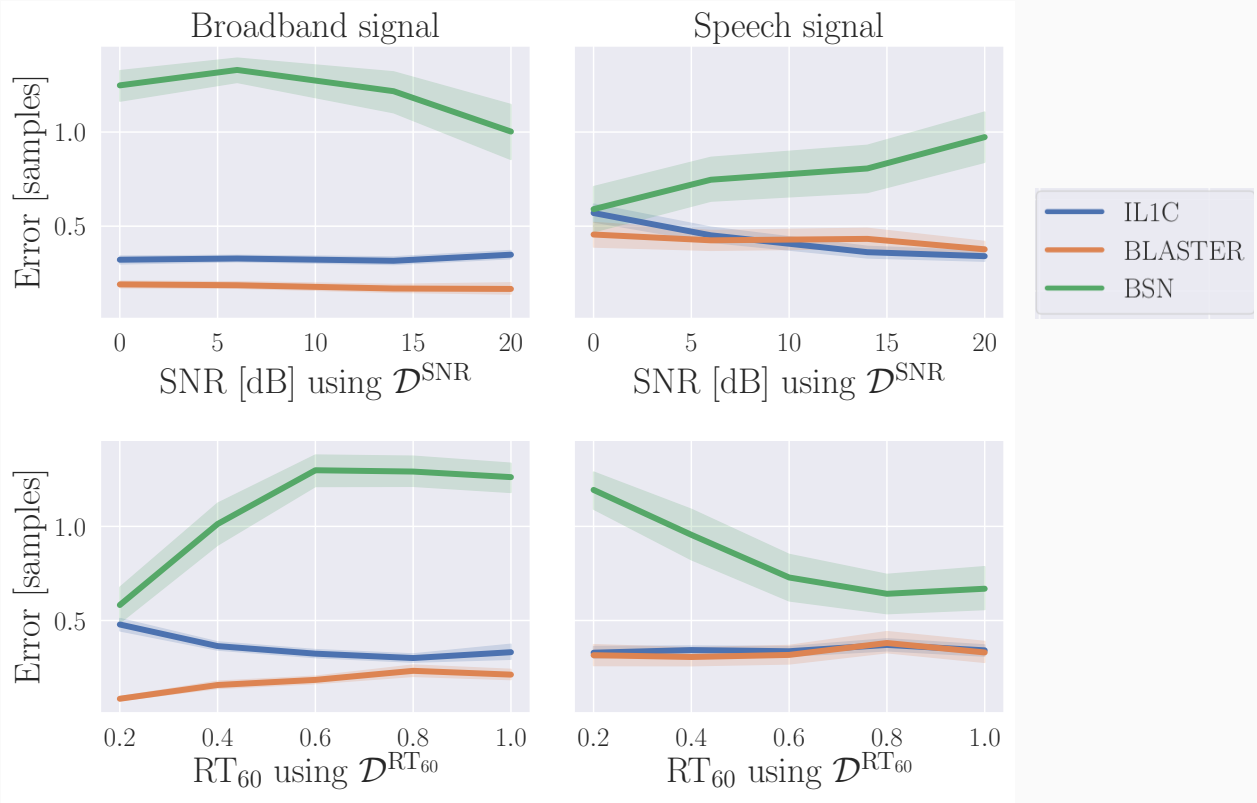
[Scheibler et al., 2018, Di Carlo et al., 2019]

Error per Dataset/Signal while recovering 7 echoes

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

Error per Dataset/Signal while recovering 7 echoes

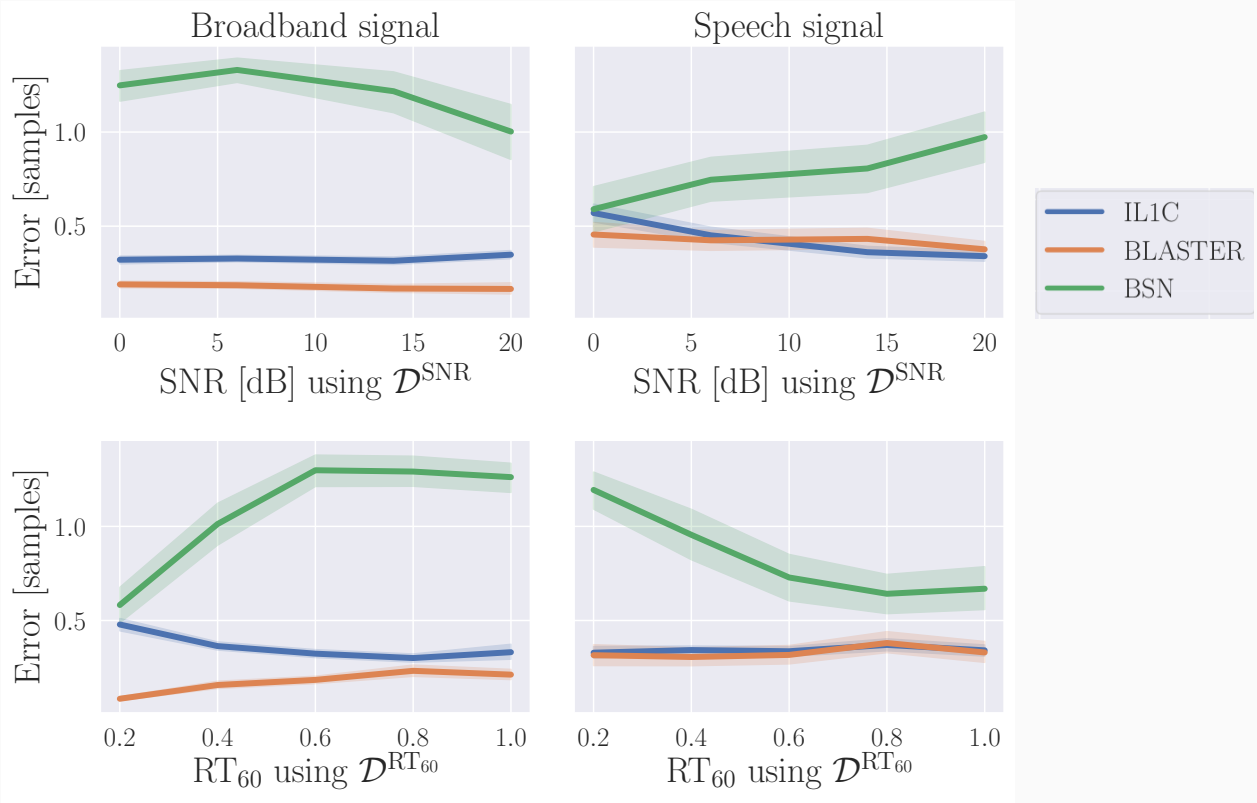
Metric: RMSE on matched echoes = error on the correct guess



(Fs = 16 kHz)

Error per Dataset/Signal while recovering 7 echoes

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



(Fs = 16 kHz)

✓Lower RMSE ✓ Robustness to SNR and RT_{60} ✗ Source signal dependent

Learning-based approach

Learning-based approach

Idea:

1. Use virtually supervised deep learning models
2. Estimate first echo (simple but important) (↰ used in the next section)
3. Only 2 microphones attending 1 sound source

Learning-based approach

Idea:

1. Use virtually supervised deep learning models
2. Estimate first echo (simple but important) (↰ used in the next section)
3. Only 2 microphones attending 1 sound source

Motivations:

- $x_i \rightarrow \tau_i^{(r)}$ is difficult, while $\tau_i^{(r)} \rightarrow x_i$ "is not"
  $\rightarrow$ acoustic simulators: mic/src/room geometry $\longrightarrow \left\{\tau_i^{(r)}, \alpha_i^{(r)}\right\}, \tilde{h}_i, \quad \tilde{x}_i$

Learning-based approach

Idea:

1. Use virtually supervised deep learning models
2. Estimate first echo (simple but important) (↰ used in the next section)
3. Only 2 microphones attending 1 sound source

Motivations:

- $x_i \rightarrow \tau_i^{(r)}$ is difficult, while $\tau_i^{(r)} \rightarrow x_i$ "is not"
  $\rightarrow$ acoustic simulators: mic/src/room geometry $\longrightarrow \left\{\tau_i^{(r)}, \alpha_i^{(r)}\right\}, \tilde{h}_i, \quad \tilde{x}_i$
- Acoustic simulator are "simple", versatile and fast
  $\rightarrow$ allow to create large dataset

Learning-based approach

Inputs:
Interchannel level and phase difference features 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

Learning-based approach

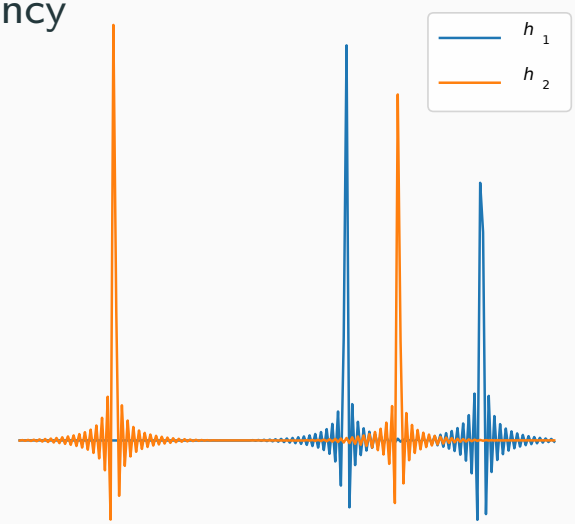
Inputs:
Interchannel level and phase difference features from

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

$\approx$ the relative transfer function $\rightarrow$ remove source dependency

Outputs:
Inter and intra Time Differences of Arrivals (TDOAs)

HP: close-surface scenario: first $\Leftrightarrow$ strongest echo



Learning-based approach

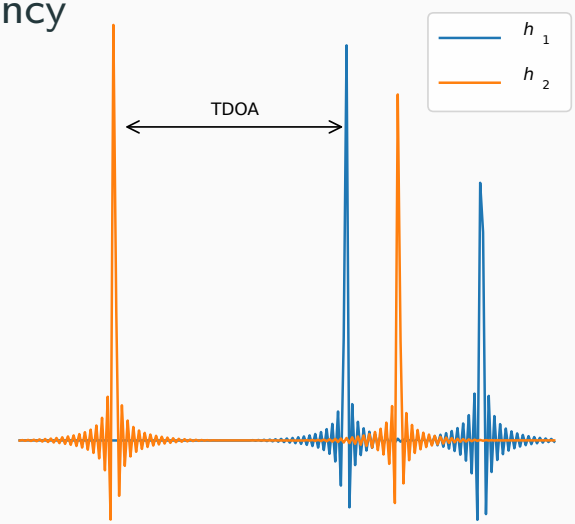
Inputs:
Interchannel level and phase difference features from

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

$\approx$ the relative transfer function $\rightarrow$ remove source dependency

Outputs:
Inter and intra Time Differences of Arrivals (TDOAs)

HP: close-surface scenario: first $\Leftrightarrow$ strongest echo



Learning-based approach

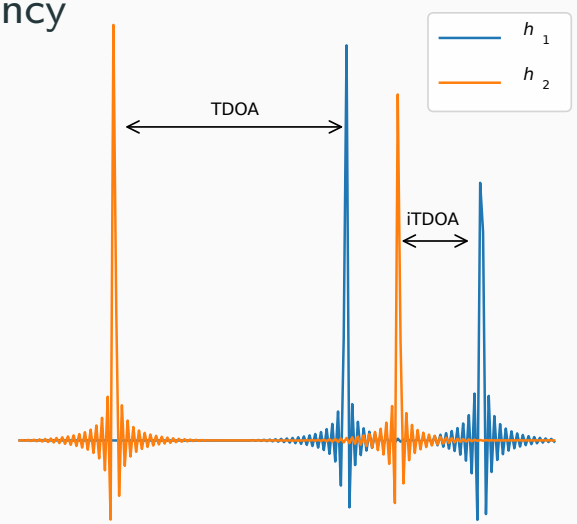
Inputs:
Interchannel level and phase difference features from

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

$\approx$ the relative transfer function $\rightarrow$ remove source dependency

Outputs:
Inter and intra Time Differences of Arrivals (TDOAs)

HP: close-surface scenario: first $\Leftrightarrow$ strongest echo



Learning-based approach

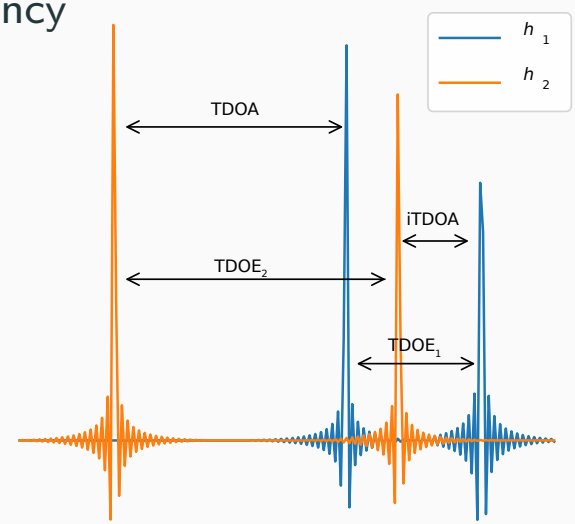
Inputs:
Interchannel level and phase difference features from

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

$\approx$ the relative transfer function $\rightarrow$ remove source dependency

Outputs:
Inter and intra Time Differences of Arrivals (TDOAs)

HP: close-surface scenario: first $\Leftrightarrow$ strongest echo



Learning-based approach

Inputs:
Interchannel level and phase difference features from

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

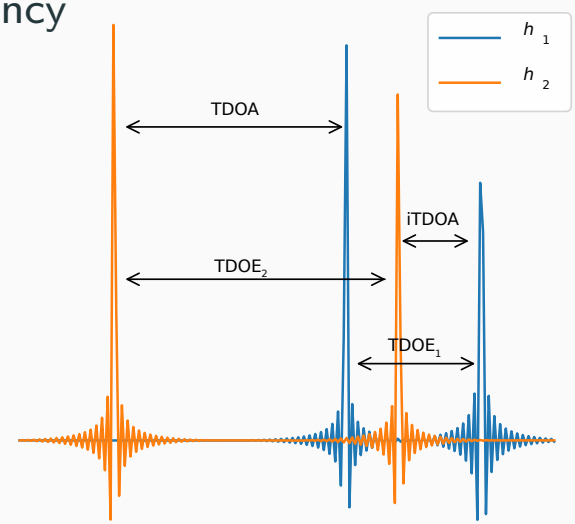
$\approx$ the relative transfer function $\rightarrow$ remove source dependency

Outputs:
Inter and intra Time Differences of Arrivals (TDOAs)

HP: close-surface scenario: first $\Leftrightarrow$ strongest echo

Loss Functions

1. RMSE (Multi-label regression) $\rightarrow$ TDOAs
2. Gaussian log-likelihood $\rightarrow \{\mu_\tau, \sigma_\tau^2\}\ \forall \tau \in$ TDOAs
3. Student log-likelihood $\rightarrow \{\mu_\tau, \lambda_\tau, \nu_\tau\}\ \forall \tau \in$ TDOAs



Learning-based approach

Inputs:
Interchannel level and phase difference features from

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

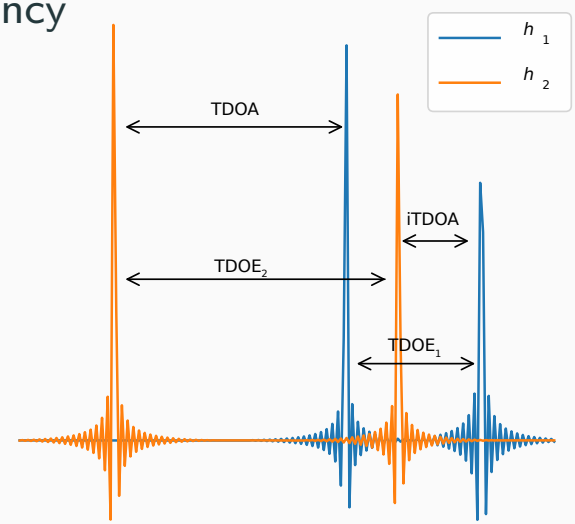
$\approx$ the relative transfer function $\rightarrow$ remove source dependency

Outputs:
Inter and intra Time Differences of Arrivals (TDOAs)

HP: close-surface scenario: first $\Leftrightarrow$ strongest echo

Loss Functions

1. RMSE (Multi-label regression) $\rightarrow$ TDOAs
2. Gaussian log-likelihood $\rightarrow \{\mu_\tau, \sigma_\tau^2\}\ \forall \tau \in$ TDOAs
3. Student log-likelihood $\rightarrow \{\mu_\tau, \lambda_\tau, \nu_\tau\}\ \forall \tau \in$ TDOAs



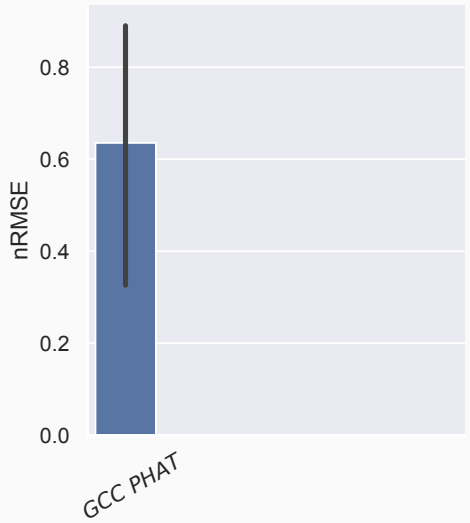
Architectures: MLP, CNN [Chakrabarty and Habets, 2017, Nguyen et al., 2018]

Experimental results

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

Baseline: GCC PHAT [Knapp and Carter, 1976]

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

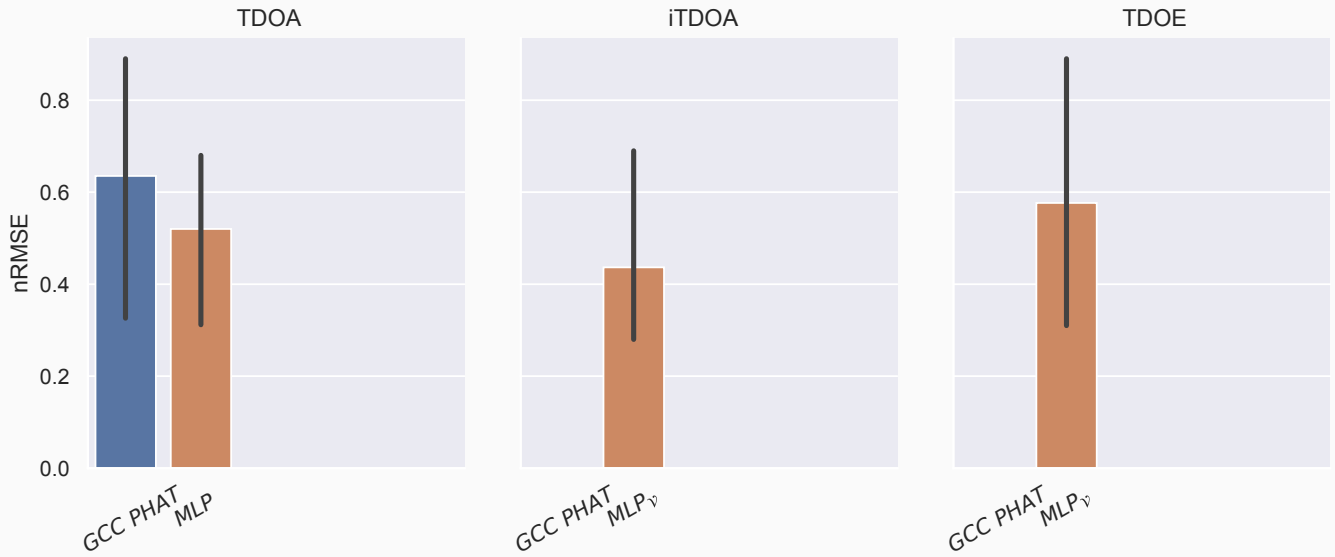


Experimental results

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

Baseline: GCC PHAT [Knapp and Carter, 1976]

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



Observation:

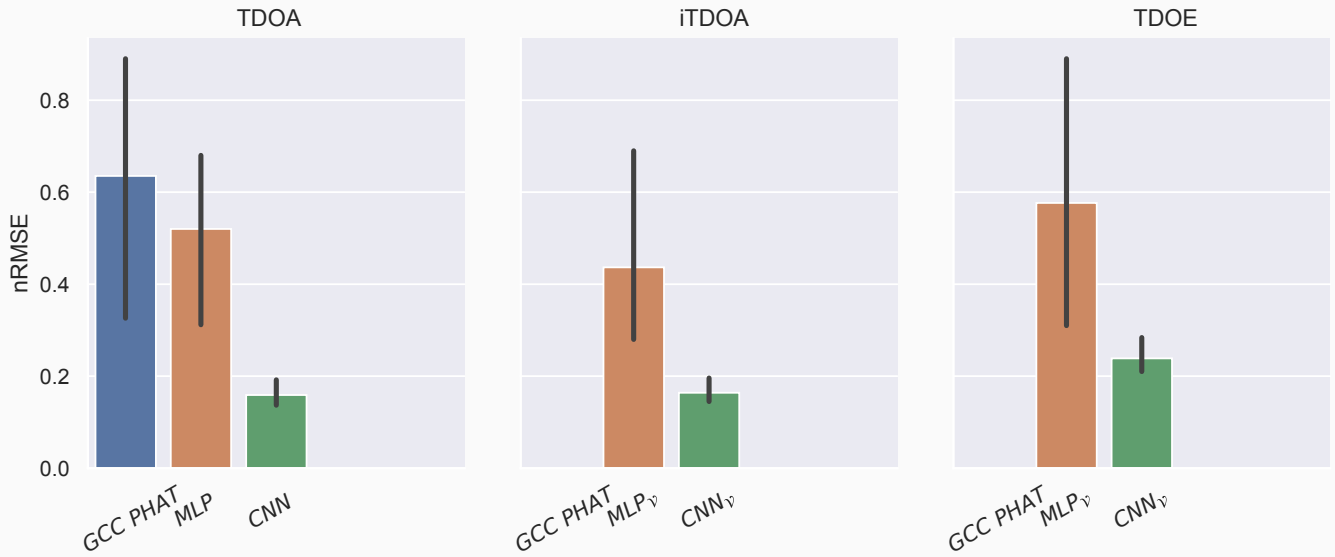
✓ MLP outperforms GCC PHAT on TDOA estimation

Experimental results

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

Baseline: GCC PHAT [Knapp and Carter, 1976]

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



Observation:

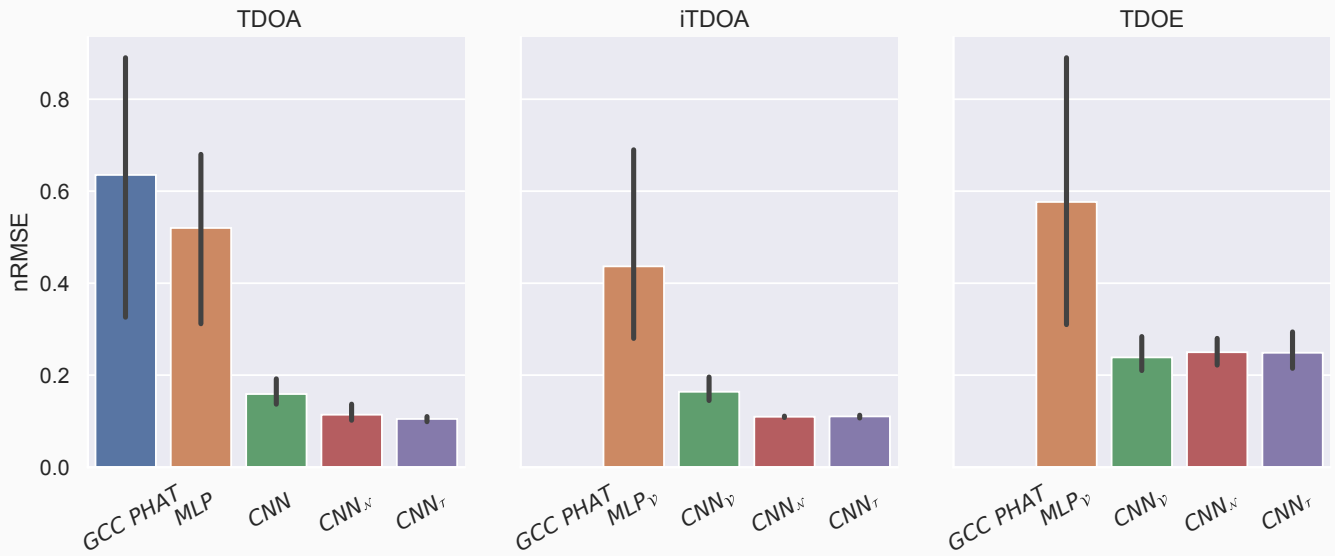
- ✓ MLP outperforms GCC PHAT on TDOA estimation
- ✓ CNN outperforms MLP (lower error and smaller variance)

Experimental results

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

Baseline: GCC PHAT [Knapp and Carter, 1976]

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



Observation:

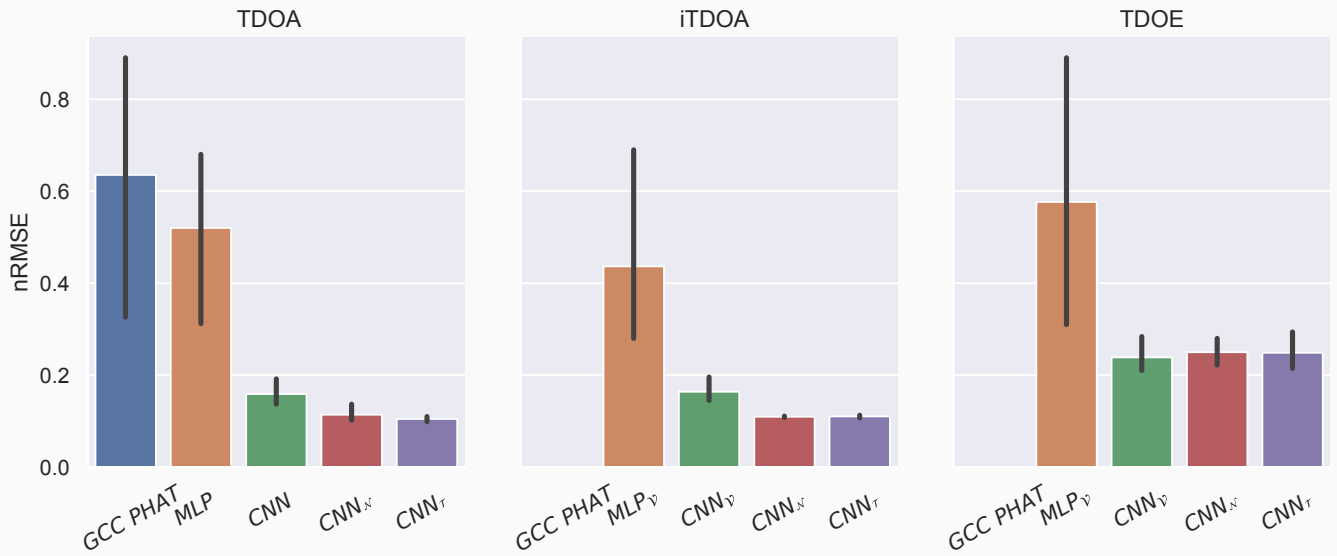
- ✓ MLP outperforms GCC PHAT on TDOA estimation
- ✓ CNN outperforms MLP (lower error and smaller variance)
- ✓ $\text{CNN}_{\mathcal{N}}$ and $\text{CNN}_{\mathcal{T}}$ outperform CNN (lower error and smaller variance)
- ✗ TDOA between DP and 1st echo more difficult

Experimental results

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

Baseline: GCC PHAT [Knapp and Carter, 1976]

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



Observation:

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

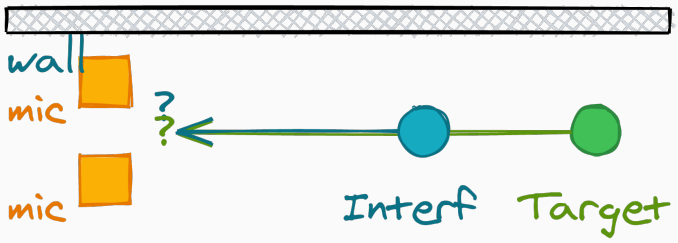
More echoes

Real data

Echo-aware Application

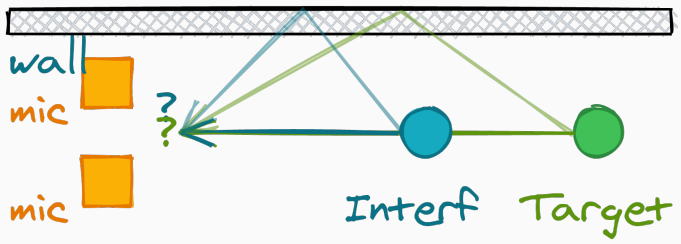
Echo-aware Applications

Echoes: same content, different time/direction



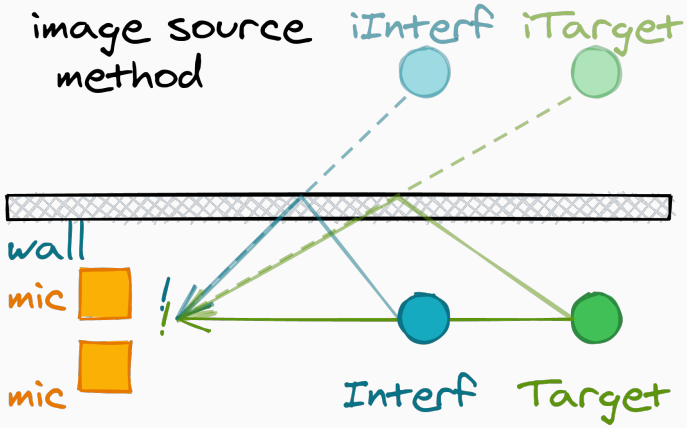
Echo-aware Applications

Echoes: same content, different time/direction



Echo-aware Applications

Echoes: same content, different time/direction



Echo-aware Applications

Echoes: same content, different time/direction

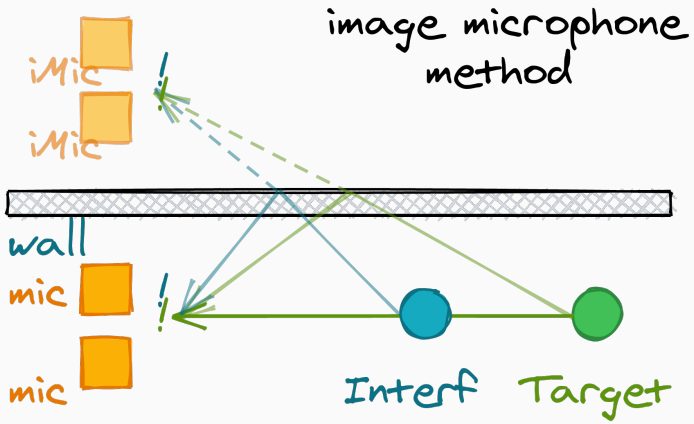


Image Source Model
⇔
Image Microphone Model

Echo-aware Applications

Echoes: same content, different time/direction

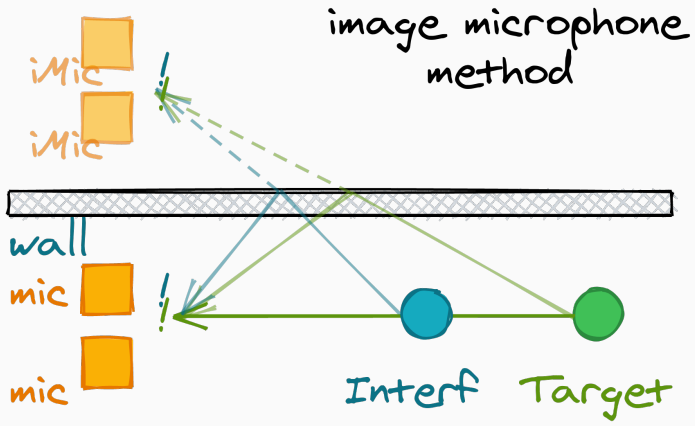


Image Source Model
⇔
Image Microphone Model

What?
Echoes = copy

- Sound Source Separation
  [Leglaive et al., 2016]
- Speech Enhancement
  [Flanagan et al., 1993,
  Dokmanić et al., 2015,
  Kowalczyk, 2019]

(In-depth literature review in .)

Echo-aware Applications

Echoes: same content, different time/direction

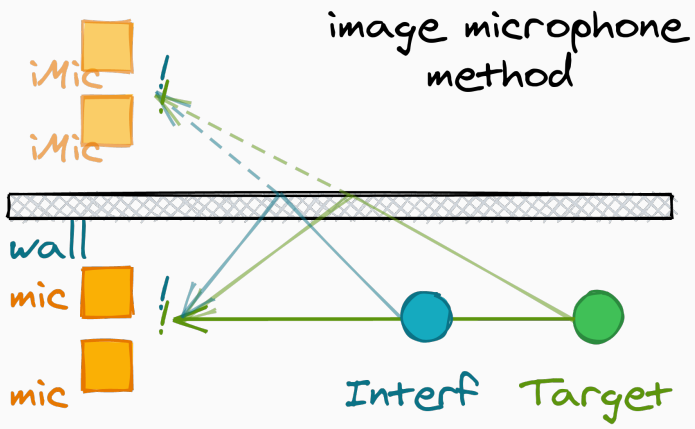


Image Source Model
⇔
Image Microphone Model

What?
Echoes = copy

- Sound Source Separation
  [Leglaive et al., 2016]
- Speech Enhancement
  [Flanagan et al., 1993, Dokmanić et al., 2015, Kowalczyk, 2019]

Where?
Echoes ← image

- Sound Source Localization
  [Ribeiro et al., 2010, Jensen et al., 2019]
- Room Geometry Estimation
  [Antonacci et al., 2012, Crocco et al., 2017]

(In-depth literature review in .)

Echo-aware Applications

Echoes: same content, different time/direction

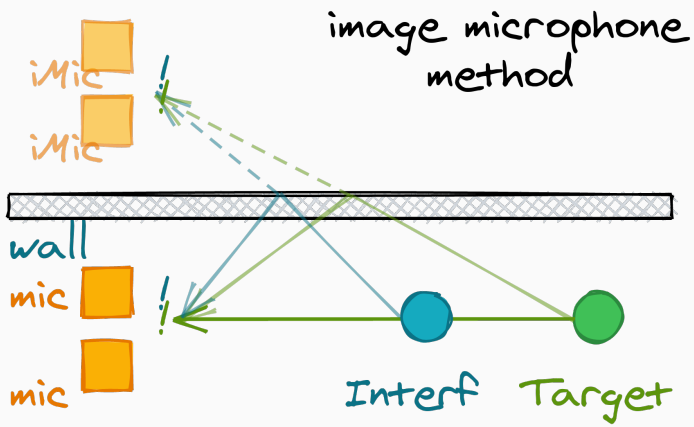


Image Source Model
⇔
Image Microphone Model

What?
Echoes = copy

- Sound Source Separation [Leglaive et al., 2016]
- Speech Enhancement [Flanagan et al., 1993, Dokmanić et al., 2015, Kowalczyk, 2019]

Where?
Echoes ← image

- Sound Source Localization [Ribeiro et al., 2010, Jensen et al., 2019]
- Room Geometry Estimation [Antonacci et al., 2012, Crocco et al., 2017]

How?
Echoes ∈ sound propagation

- Blind Channel Estimation [Lin et al., 2007, Crocco et al., 2017]
- Acoustic Measurements [Eaton et al., 2015, Kuttruff, 2016]

(In-depth literature review in .)

Echo-aware Applications

Echoes: same content, different time/direction

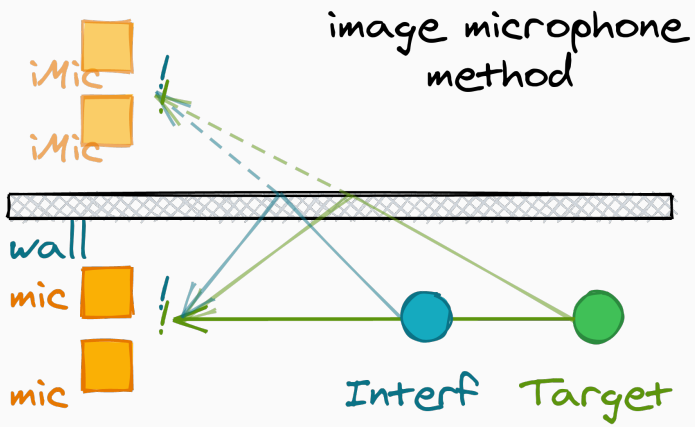


Image Source Model
⇔
Image Microphone Model

What?
Echoes = copy

- Sound Source Separation
  [Leglaive et al., 2016]
- Speech Enhancement
  [Flanagan et al., 1993, Dokmanić et al., 2015, Kowalczyk, 2019]

Where?
Echoes ← image

- Sound Source Localization
  [Ribeiro et al., 2010, Jensen et al., 2019]
- Room Geometry Estimation
  [Antonacci et al., 2012, Crocco et al., 2017]

How?
Echoes ∈ sound propagation

- Blind Channel Estimation
  [Lin et al., 2007, Crocco et al., 2017]
- Acoustic Measurements
  [Eaton et al., 2015, Kuttruff, 2016]

(In-depth literature review in .)

Echo-aware Applications

Echoes: same content, different time/direction

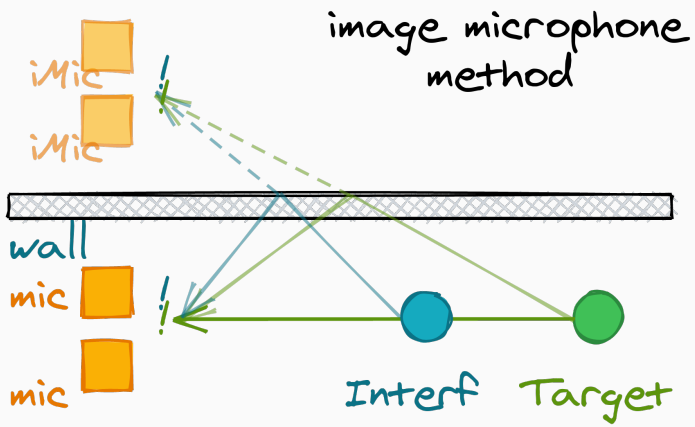


Image Source Model
⇔
Image Microphone Model

What?
Echoes = copy

- Sound Source Separation [Leglaive et al., 2016]
- Speech Enhancement [Flanagan et al., 1993, Dokmanić et al., 2015, Kowalczyk, 2019]

Where?
Echoes ← image

- Sound Source Localization [Ribeiro et al., 2010, Jensen et al., 2019]
- Room Geometry Estimation [Antonacci et al., 2012, Crocco et al., 2017]

How?
Echoes ∈ sound propagation

- Blind Channel Estimation [Lin et al., 2007, Crocco et al., 2017]
- Acoustic Measurements [Eaton et al., 2015, Kuttruff, 2016]

(In-depth literature review in .)

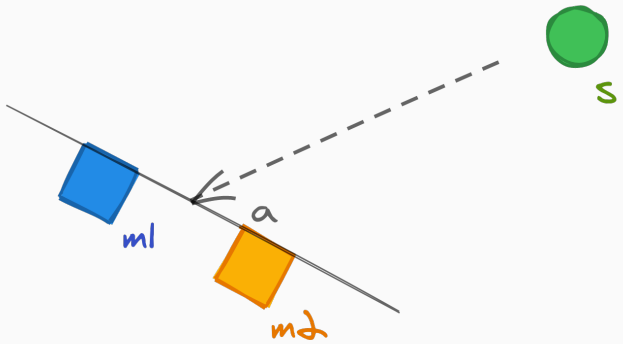
Sound Source Localization (SSL)

(common knowledge)

We do not consider here distance estimation.

SSL with 2 microphones

- Only one angle of arrival (AOA)
- Can be approximated from TDOA using e.g. GCC PHAT[1]
  (known limitation, but good in practice)[2]



[1] [Knapp and Carter, 1976]
[2] [DiBiase et al., 2001]
[3] [Lebarbenchon et al., 2018]

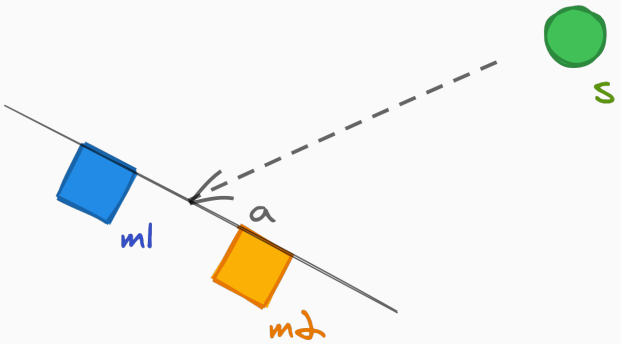
Sound Source Localization (SSL)

(common knowledge)

We do not consider here distance estimation.

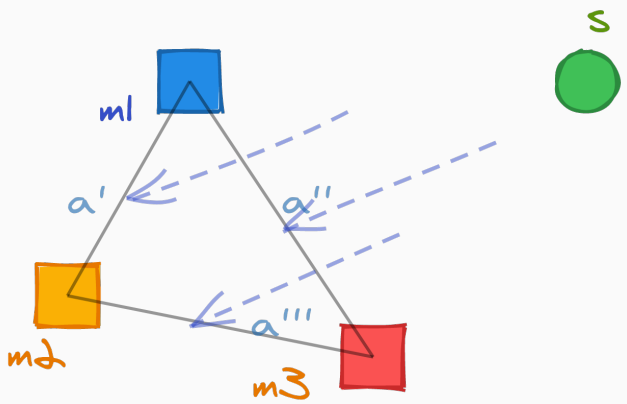
SSL with 2 microphones

- Only one angle of arrival (AOA) ⬈
- Can be approximated from TDOA using e.g. GCC PHAT[1]
  (known limitation, but good in practice)[2]



SSL with more microphones

- Two Direction of Arrival (DoA): azimuth (↔) and elevation (↕)
- AOA at each pair can be "fused" together
  (e.g., angular spectra in SRP-PHAT[2])
  (known limitation, but good in practice)[3]

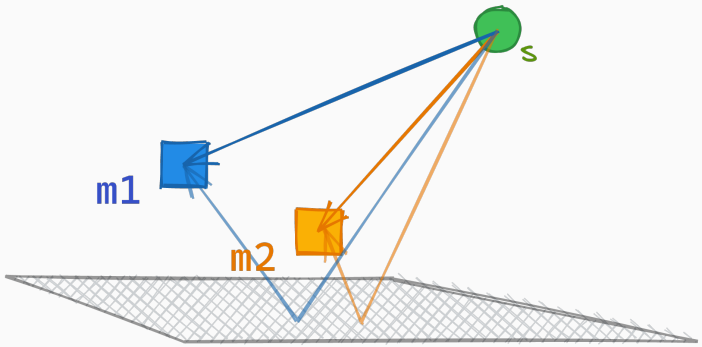


[1] [Knapp and Carter, 1976]
[2] [DiBiase et al., 2001]
[3] [Lebarbenchon et al., 2018]

Sound Source Localization with Echoes

The Picnic Scenario:

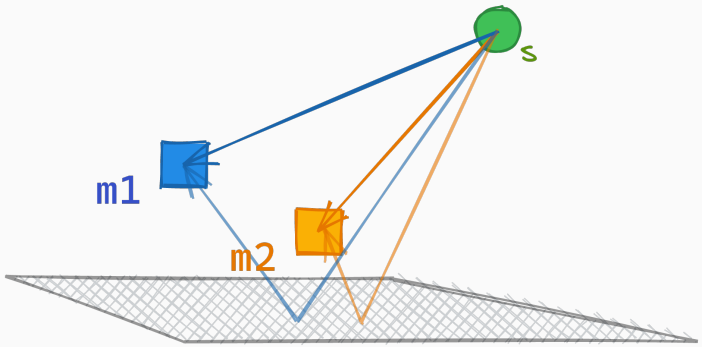
- One source
- Two microphones (10 cm spacing)
  - → passive scenario
  - → generalizable to any array geometry



Sound Source Localization with Echoes

The Picnic Scenario:

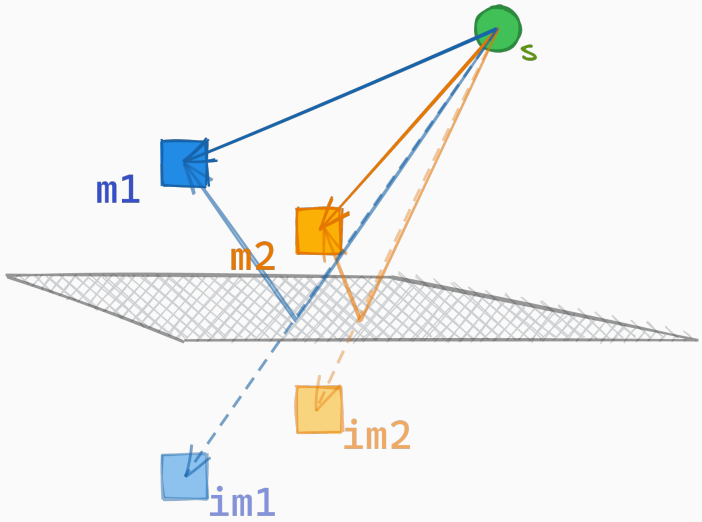
- One source
- Two microphones (10 cm spacing)
  - → passive scenario
  - → generalizable to any array geometry
- Close to a very reflective surface
  - → First echo = Strongest echo
  - → α_{picnic} const. $\forall f$
  - → table-top device



Sound Source Localization with Echoes

The Picnic Scenario:

- One source
- Two microphones (10 cm spacing)
  - → passive scenario
  - → generalizable to any array geometry
- Close to a very reflective surface
  - → First echo = Strongest echo
  - → α_{picnic} const. $\forall f$
  - → table-top device



Each pair is augmented with echoes

Mirage Array

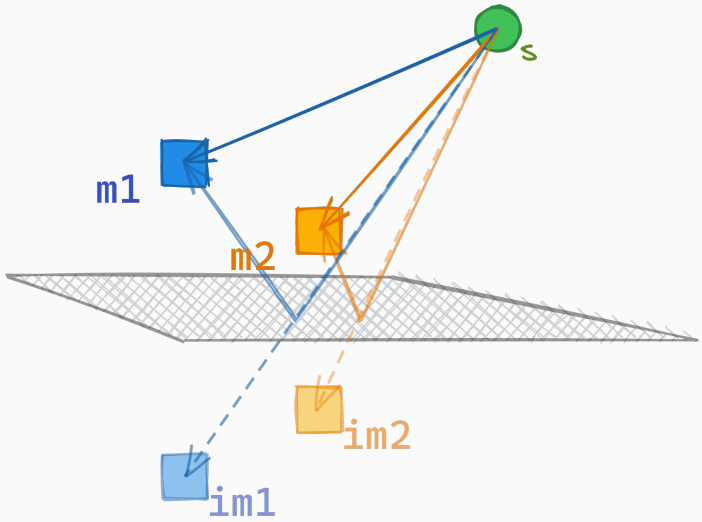
(Microphone Array Augmetation with Echoes)

How to access the *image* microphones?

Sound Source Localization with Echoes

The Picnic Scenario:

- One source
- Two microphones (10 cm spacing)
  - → passive scenario
  - → generalizable to any array geometry
- Close to a very reflective surface
  - → First echo = Strongest echo
  - → α_{picnic} const. $\forall f$
  - → table-top device

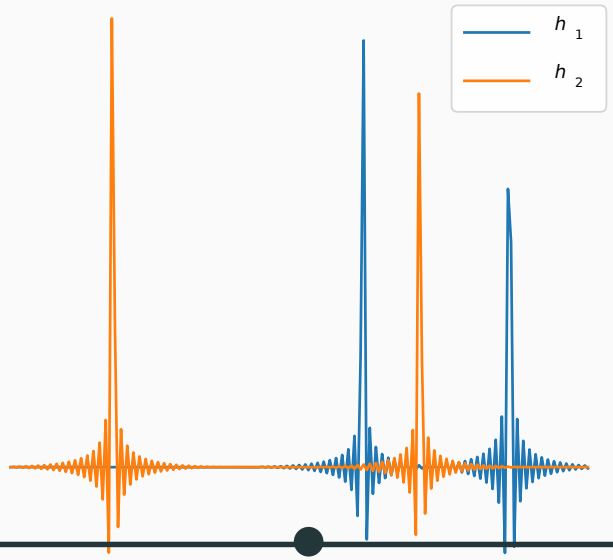


Each pair is augmented with echoes

Mirage Array

(Microphone Array Augmetation with Echoes)

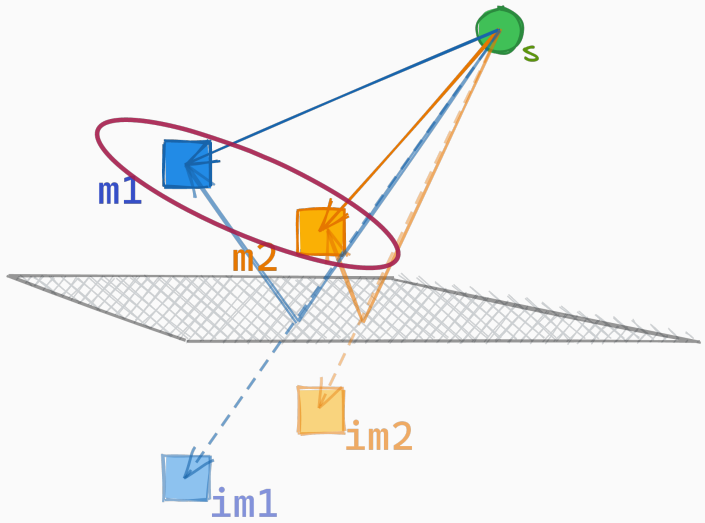
How to access the *image* microphones?



Sound Source Localization with Echoes

The Picnic Scenario:

- One source
- Two microphones (10 cm spacing)
  - → passive scenario
  - → generalizable to any array geometry
- Close to a very reflective surface
  - → First echo = Strongest echo
  - → α_{picnic} const. $\forall f$
  - → table-top device

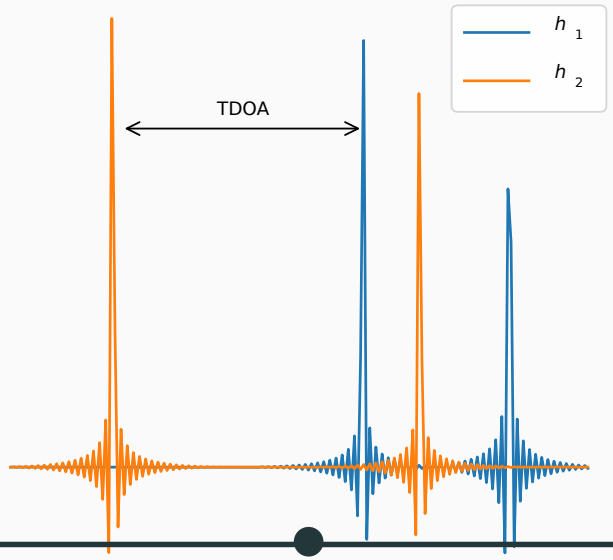


Each pair is augmented with echoes

Mirage Array

(Microphone Array Augmetation with Echoes)

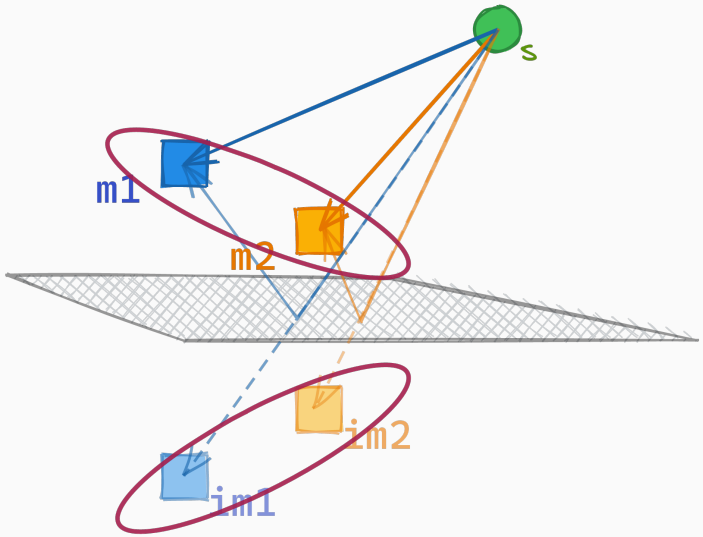
How to access the *image* microphones?



Sound Source Localization with Echoes

The Picnic Scenario:

- One source
- Two microphones (10 cm spacing)
  - → passive scenario
  - → generalizable to any array geometry
- Close to a very reflective surface
  - → First echo = Strongest echo
  - → α_{picnic} const. $\forall f$
  - → table-top device

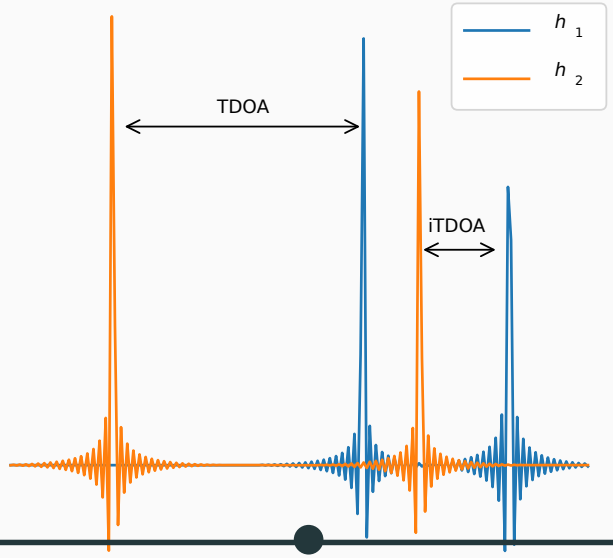


Each pair is augmented with echoes

Mirage Array

(Microphone Array Augmetation with Echoes)

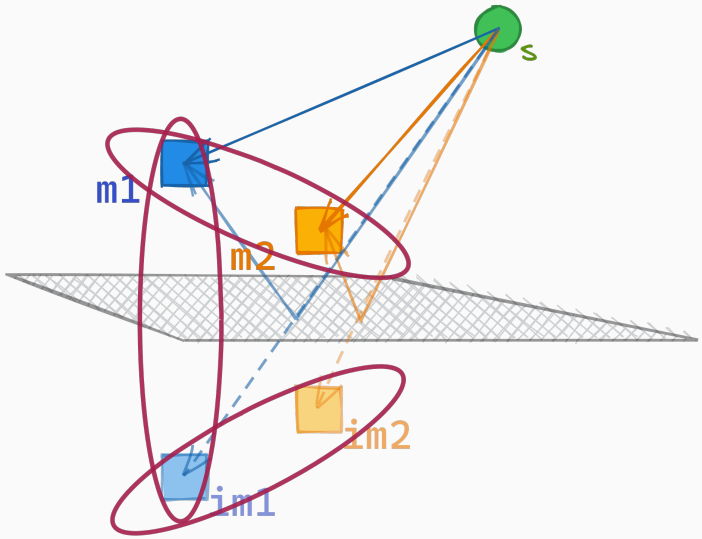
How to access the *image* microphones?



Sound Source Localization with Echoes

The Picnic Scenario:

- One source
- Two microphones (10 cm spacing)
  - → passive scenario
  - → generalizable to any array geometry
- Close to a very reflective surface
  - → First echo = Strongest echo
  - → α_{picnic} const. $\forall f$
  - → table-top device

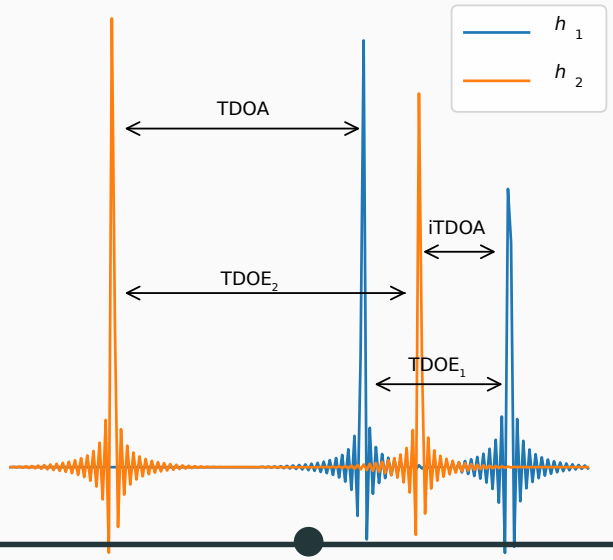


Each pair is augmented with echoes

Mirage Array

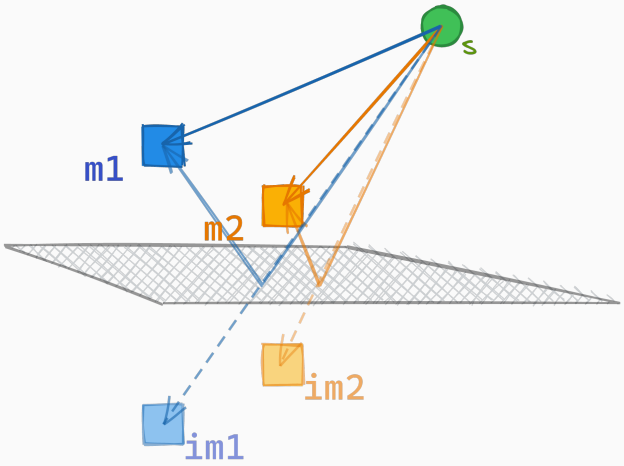
(Microphone Array Augmetation with Echoes)

How to access the *image* microphones?



Sound Source Localization with Echoes

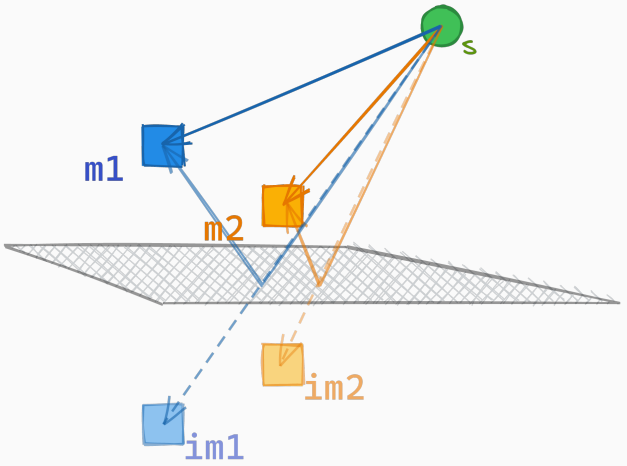
Idea: DoA estimate on the `Mirage` array
Recall: same TDOAs as for Learning-based method



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

Sound Source Localization with Echoes

Idea: DoA estimate on the Mirage array
Recall: same TDOAs as for Learning-based method



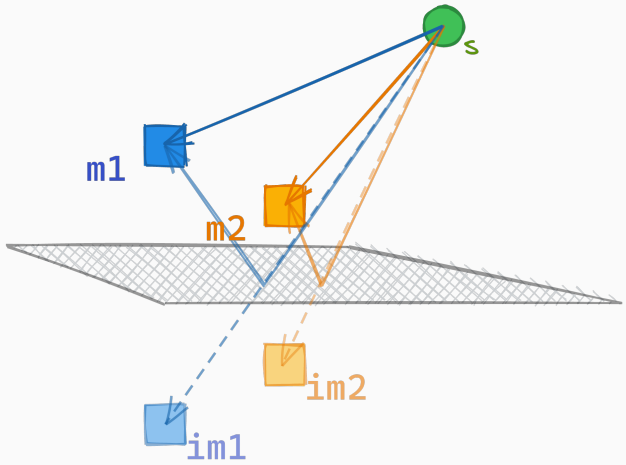
Proposed Approach:

1. estimate TDOAs using proposed learning-based approach (MLP)
2. fuse together the estimation (SRP-PHAT-like algorithm[1]),
   - the error on a validation set provides measure of uncertainty
   - microphone positions are known

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

Sound Source Localization with Echoes

Idea: DoA estimate on the `Mirage` array
Recall: same TDOAs as for Learning-based method



Proposed Approach:

1. estimate TDOAs using proposed learning-based approach (`MLP`)
2. fuse together the estimation (SRP-PHAT-like algorithm[1]),
   - the error on a validation set provides measure of uncertainty
   - microphone positions are known

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 MSE in the 📄)

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

Observation

✓ Comparable to baseline when white noise source in noiseless case

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 MSE in the 📄)

AOA ⬈	Input	ACCURACY $\alpha < 10°$	ACCURACY $\alpha < 20°$
`Mirage`	wn	77	97
`Mirage`	wn+n	26	54
`GCC PHAT`	wn	**81**	**97**
`GCC PHAT`	wn+n	65	83

Observation

✓ Comparable to baseline when white noise source in noiseless case

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 MSE in the 📄)

AOA ⬈	Input	ACCURACY $\alpha < 10°$	ACCURACY $\alpha < 20°$
`Mirage`	wn	77	97
`Mirage`	wn+n	26	54
`GCC PHAT`	wn	**81**	**97**
`GCC PHAT`	wn+n	65	83
`Mirage`	sp	63	82
`GCC PHAT`	sp	**82**	**97**

Observation

✓ Comparable to baseline when white noise source in noiseless case

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 MSE in the 📄)

AOA ⬈	Input	ACCURACY $\alpha < 10°$	ACCURACY $\alpha < 20°$
`Mirage`	wn	77	97
`Mirage`	wn+n	26	54
`GCC PHAT`	wn	**81**	**97**
`GCC PHAT`	wn+n	65	83
`Mirage`	sp	63	82
`Mirage`	sp+n	16	35
`GCC PHAT`	sp	**82**	**97**
`GCC PHAT`	sp+n	19	32

Observation

✓ Comparable to baseline when white noise source in noiseless case

✗ Does not generalize to noisy and speech data

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 MSE in the 📄)

AOA ⤢	Input	ACCURACY $\alpha < 10°$	ACCURACY $\alpha < 20°$
Mirage	wn	77	97
Mirage	wn+n	26	54
GCC PHAT	wn	**81**	**97**
GCC PHAT	wn+n	65	83
Mirage	sp	63	82
Mirage	sp+n	16	35
GCC PHAT	sp	**82**	**97**
GCC PHAT	sp+n	19	32

DoA ✣	Input	ACCURACY $< 10°$ θ↔	ACCURACY $< 10°$ ϕ↕	ACCURACY $< 20°$ θ↔	ACCURACY $< 20°$ ϕ↕
Mirage	wn	**59**	**71**	**79**	**88**
Mirage	wn+n	18	26	35	66
Mirage	sp	45	59	71	83
Mirage	sp+n	17	12	38	43

Observation

✓ Comparable to baseline when white noise source in noiseless case

✗ Does not generalize to noisy and speech data

✓ Takle “impossible” localization

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 MSE in the 📄)

AOA ⬈	Input	ACCURACY $\alpha < 10°$	ACCURACY $\alpha < 20°$
`Mirage`	wn	77	97
`Mirage`	wn+n	26	54
`GCC PHAT`	wn	**81**	**97**
`GCC PHAT`	wn+n	65	83
`Mirage`	sp	63	82
`Mirage`	sp+n	16	35
`GCC PHAT`	sp	**82**	**97**
`GCC PHAT`	sp+n	19	32

DoA ✥	Input	ACCURACY $< 10°$ θ↔	ACCURACY $< 10°$ ϕ↕	ACCURACY $< 20°$ θ↔	ACCURACY $< 20°$ ϕ↕
`Mirage`	wn	**59**	**71**	**79**	**88**
`Mirage`	wn+n	18	26	35	66
`Mirage`	sp	45	59	71	83
`Mirage`	sp+n	17	12	38	43

Observation

- ✓ Comparable to baseline when white noise source in noiseless case
- ✗ Does not generalize to noisy and speech data
- ✓ Takle "impossible" localization
- ⚠ Performance depending on echo estimator (work in progress)

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
- proper recording devices

dEchorate

Characteristics of dEchorate

- different room configurations and RT60 ($\rightarrow$ flipping wall panels)
- 6 array $\times$ 5 mics $\times$ 4 sources $\times$ 11 wall conf. $=$ **1320 annotated RIRs** at 48 kHz
- geometry annotation $\Leftrightarrow$ echo annotation in the RIRs
- real RIRs $\Leftrightarrow$ 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)

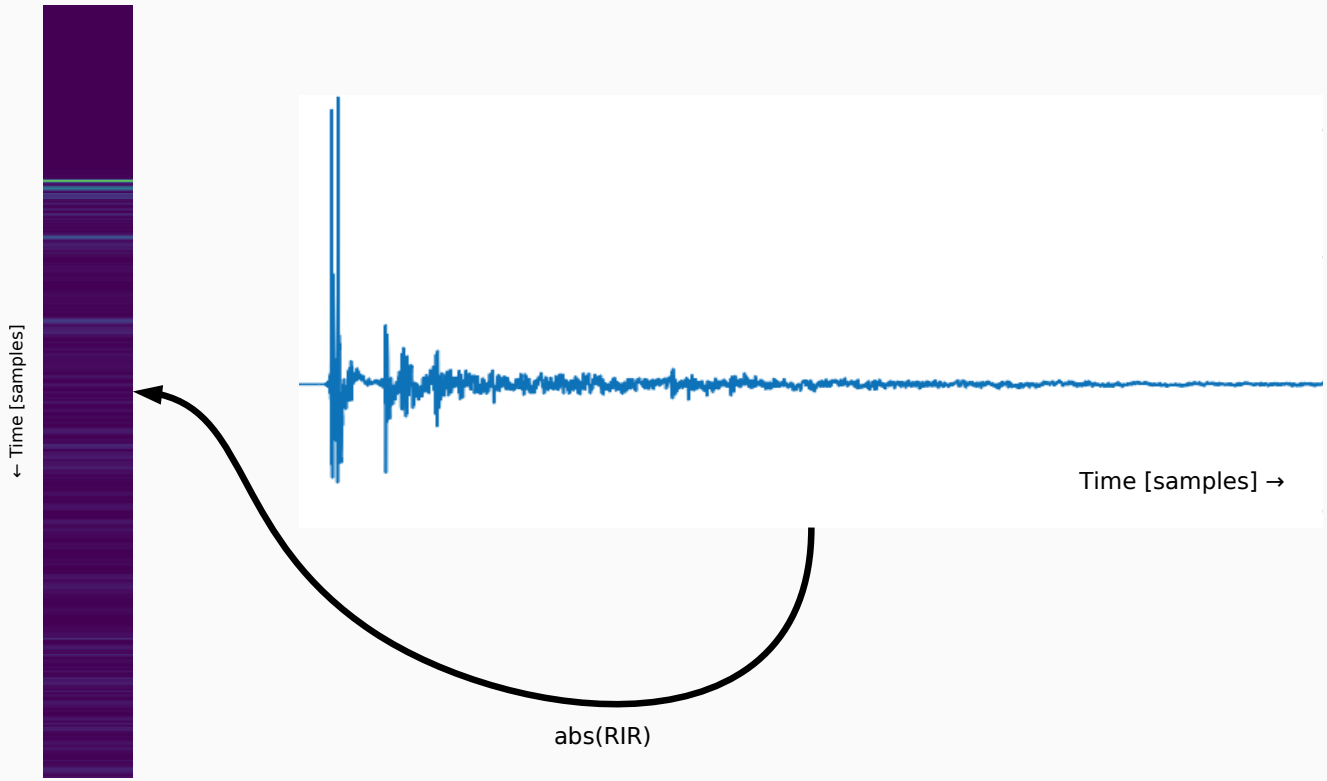
dEchorate

Characteristics of dEchorate

- different room configurations and RT60 ($\rightarrow$ flipping wall panels)
- 6 array $\times$ 5 mics $\times$ 4 sources $\times$ 11 wall conf. $=$ **1320 annotated RIRs** at 48 kHz
- geometry annotation $\Leftrightarrow$ echo annotation in the RIRs
- real RIRs $\Leftrightarrow$ 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)

dEchorate: the skyline view

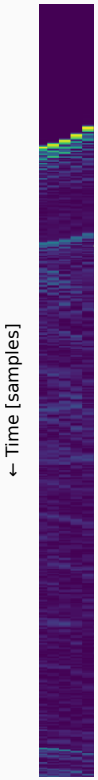


- each column correspond to the absolute values of one RIR

dEchorate: the skyline view

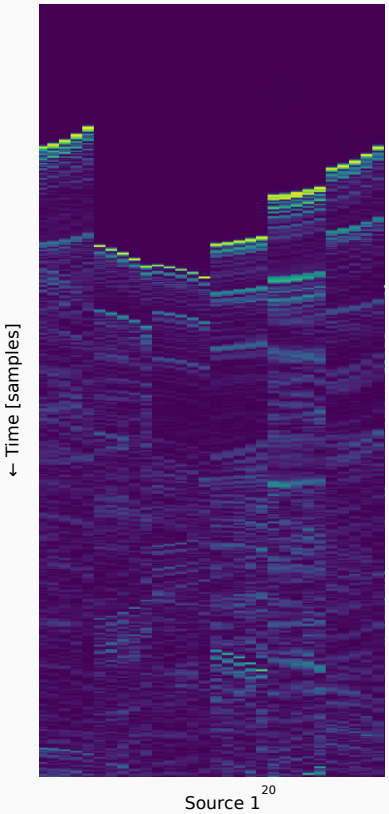
- each column correspond to the absolute values of one RIR

dEchorate: the skyline view



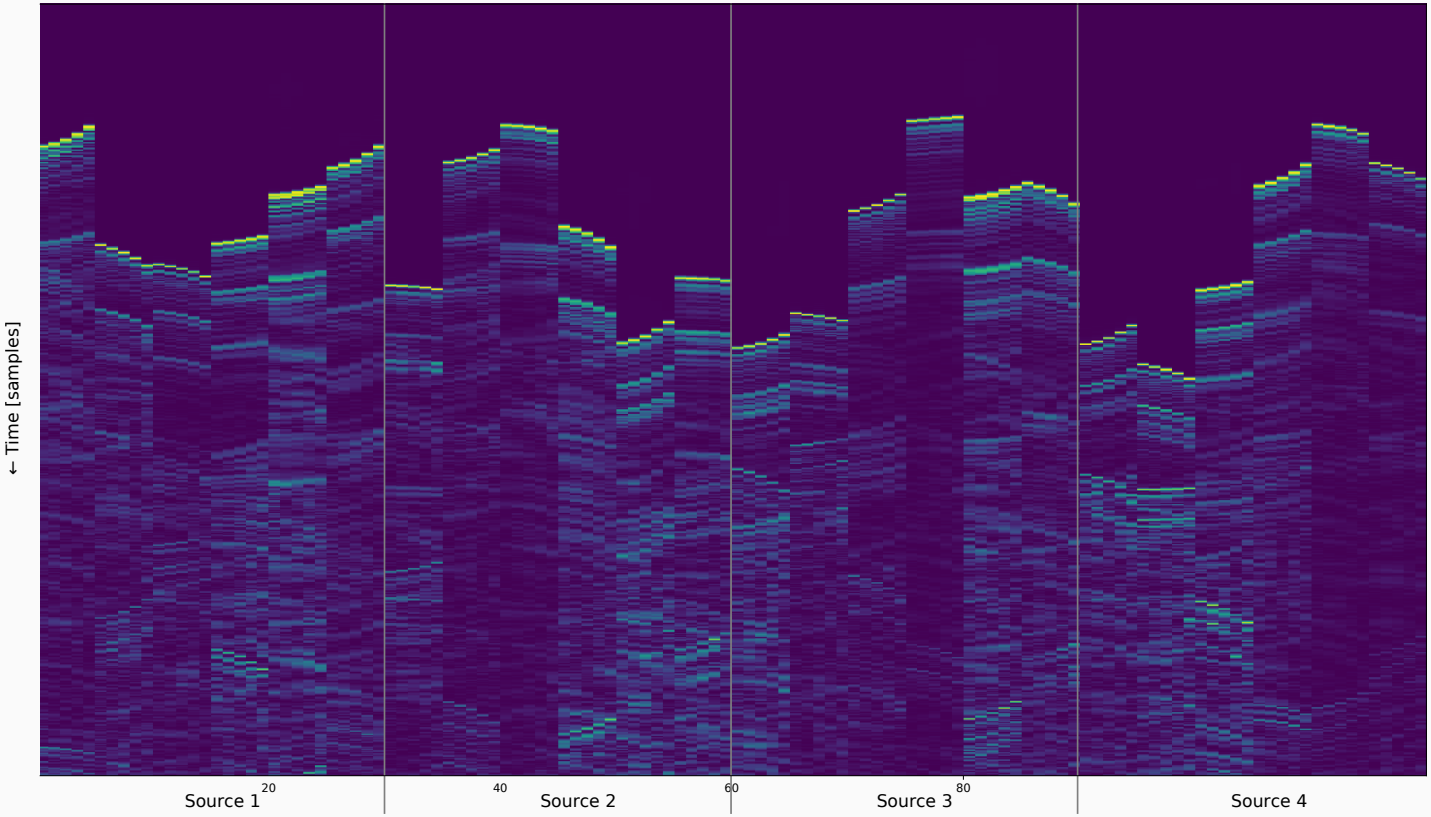
- each column correspond to the absolute values of one RIR
- a block of 5 columns corresponds to one array

dEchorate: the skyline view



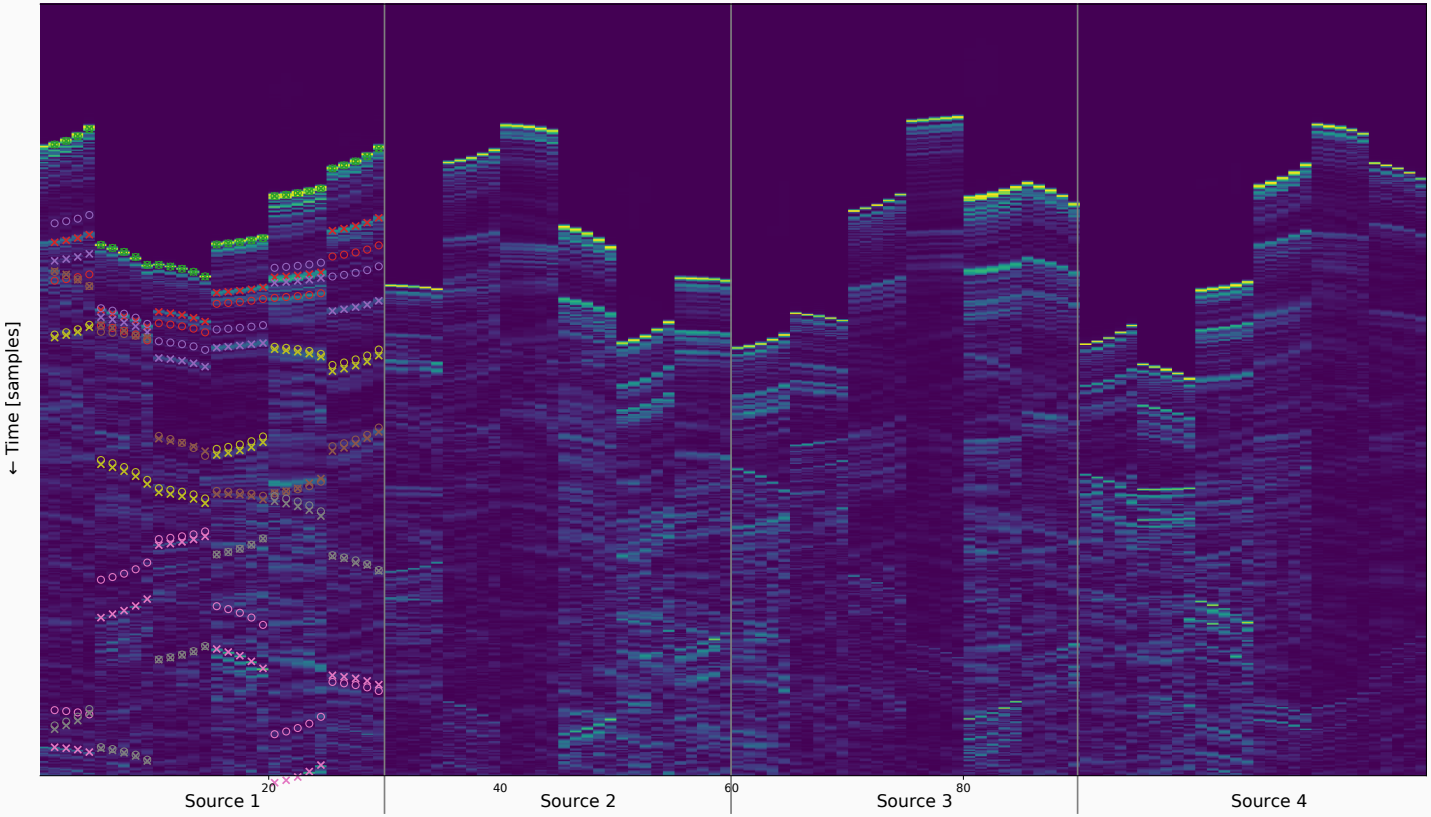
- each column correspond to the absolute values of one RIR
- a block of 5 columns corresponds to one array
- a block of 30 columns corresponds to 6 arrays for 1 sound source

dEchorate: the skyline view



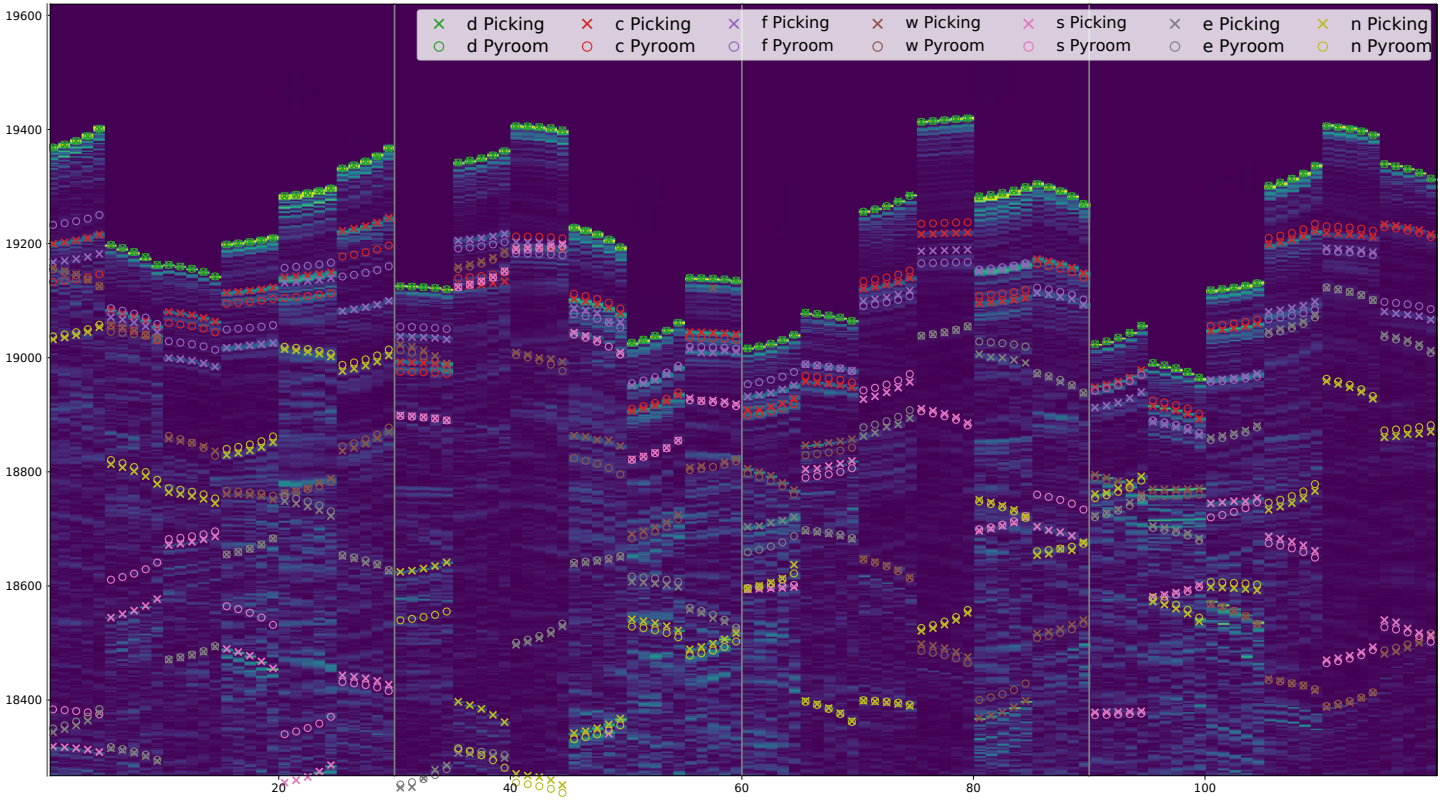
- each column correspond to the absolute values of one RIR
- a block of 5 columns corresponds to one array
- a block of 30 columns corresponds to 6 arrays for 1 sound source
- $\times$ corresponds to manual echo location, $\circ$ to geometric annotation

dEchorate: the skyline view



- each column correspond to the absolute values of one RIR
- a block of 5 columns corresponds to one array
- a block of 30 columns corresponds to 6 arrays for 1 sound source
- $\times$ corresponds to manual echo location, $\circ$ to geometric annotation

dEchorate: the skyline view



- each column correspond to the absolute values of one RIR
- a block of 5 columns corresponds to one array
- a block of 30 columns corresponds to 6 arrays for 1 sound source
- $\times$ corresponds to manual echo location, $\circ$ to geometric annotation

Speech Enhancement with dEchorate

Speech Enhancement (SE)

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

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

Speech Enhancement with dEchorate

Speech Enhancement (SE)

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

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

Speech Enhancement with dEchorate

Speech Enhancement (SE)

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

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

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

$$\mathbf{X}[f,t] = \mathbf{H}[f]\mathbf{S}[f,t] + \mathbf{N}[f,t] \in \mathbb{C}^I \quad \longrightarrow \quad \mathbf{W}^{\mathsf{H}}[f] \in \mathbb{C}^I \quad \longrightarrow \quad \mathbf{W}^{\mathsf{H}}[f]\mathbf{X}[f,t] \approx \mathbf{S}[f,t]$$

- **target is distortionless** (vs. Multichannel Wiener Filtering)
- many variant, e.g. enhance or null multiple sources [Gannot et al., 2017]

Speech Enhancement with dEchorate

Speech Enhancement (SE)

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

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

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

$$\mathbf{X}[f,t] = \mathbf{H}[f]\mathbf{S}[f,t] + \mathbf{N}[f,t] \in \mathbb{C}^I \quad \longrightarrow \quad \mathbf{W}^{\mathsf{H}}[f] \in \mathbb{C}^I \quad \longrightarrow \quad \mathbf{W}^{\mathsf{H}}[f]\mathbf{X}[f,t] \approx \mathbf{S}[f,t]$$

- **target is distortionless** (vs. Multichannel Wiener Filtering)
- many variant, e.g. enhance or null multiple sources [Gannot et al., 2017]

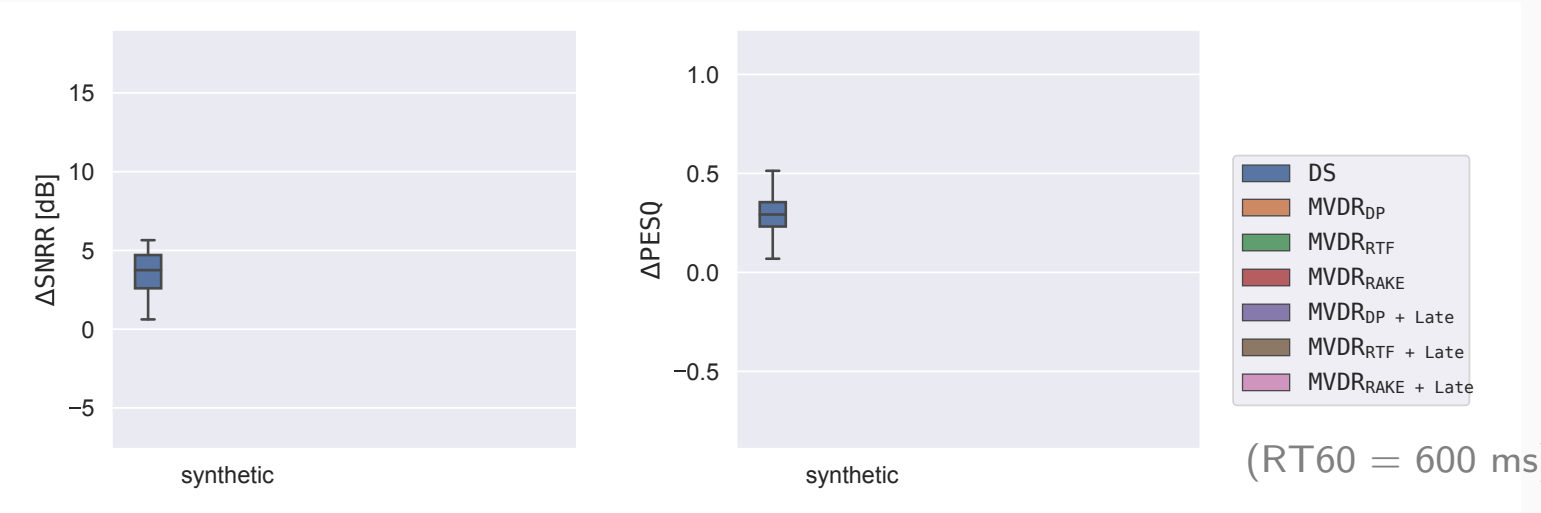
$$\widehat{\mathbf{W}} = \arg\min_{\mathbf{W}} \mathbb{E}\left\{ \left\| \mathbf{W}^{\mathsf{H}}\mathbf{X} \right\|_2^2 \right\} \quad \text{s.t.} \quad \mathbf{W}^{\mathsf{H}}\mathbf{H} = 1$$

Reducing output energy + distortionless $\Leftrightarrow$ reduce any uncorrelated noise

Speech Enhancement with dEchorate

Methods	Noise covariance matrix	RIRs
DS	-	Direct path (AOA)

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

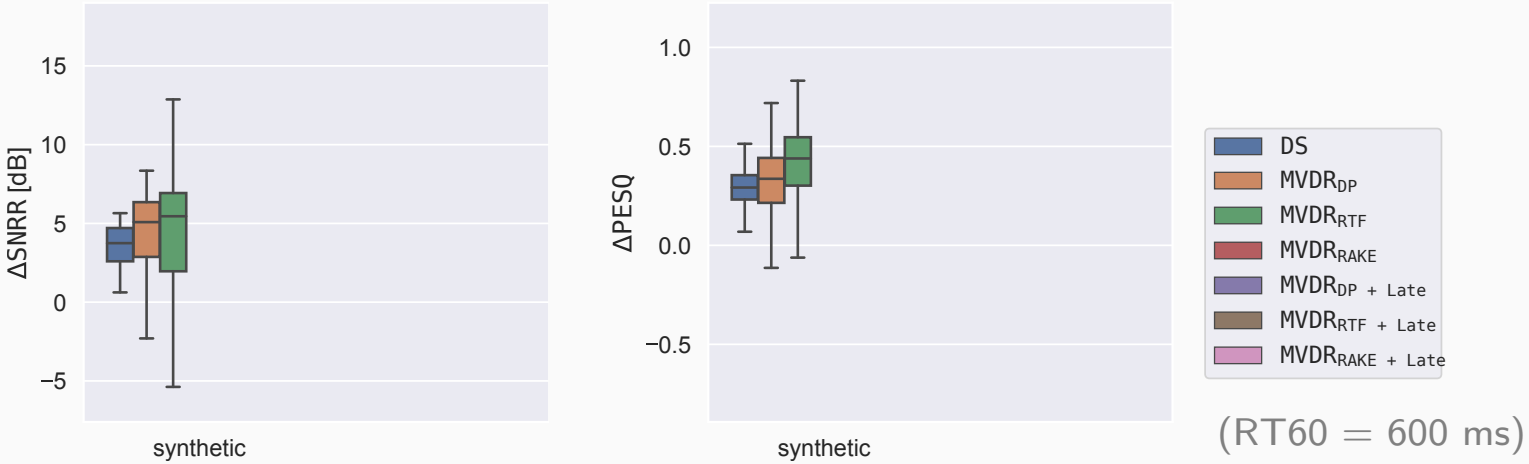


(RT60 = 600 ms)

Speech Enhancement with dEchorate

Methods	Noise covariance matrix	RIRs
DS	-	Direct path (AOA)
MVDR_{DP}	Noise	Direct path (AOA)
$\text{MVDR}_{\text{ReTF}}$ [1]	Noise	Relative Transfer Function

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



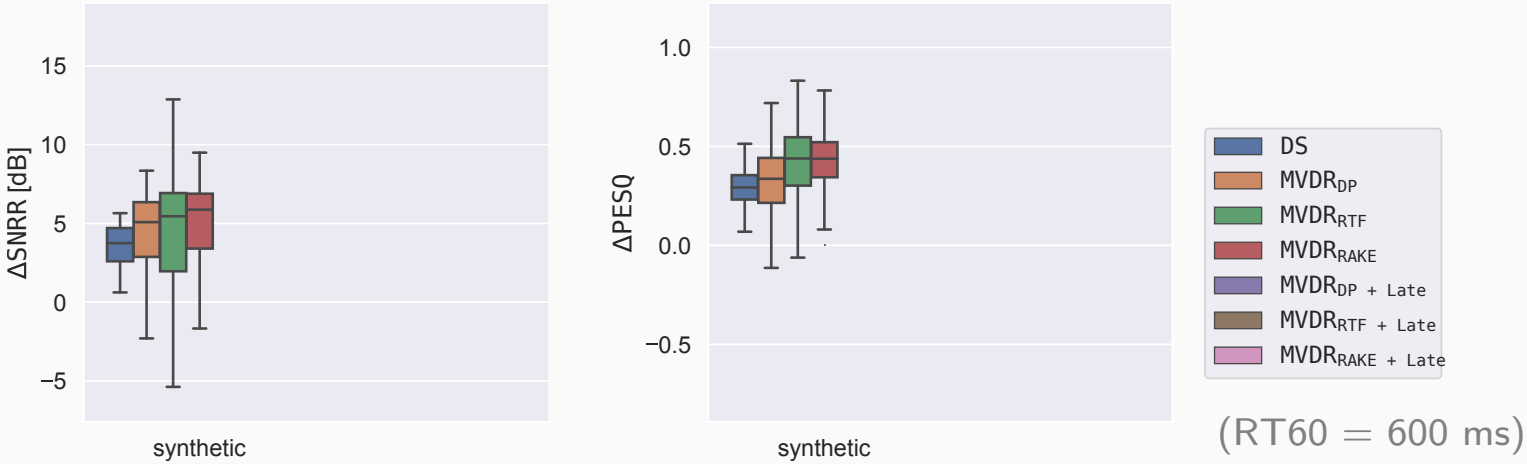
(RT60 = 600 ms)

[1] Using [Markovich-Golan et al., 2018],

Speech Enhancement with dEchorate

Methods	Noise covariance matrix	RIRs
DS	-	Direct path (AOA)
MVDR_{DP}	Noise	Direct path (AOA)
$\text{MVDR}_{\text{ReTF}}$ [1]	Noise	Relative Transfer Function
$\text{MVDR}_{\text{Rake}}$ [2]	Noise	4 strongest echoes per channel

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



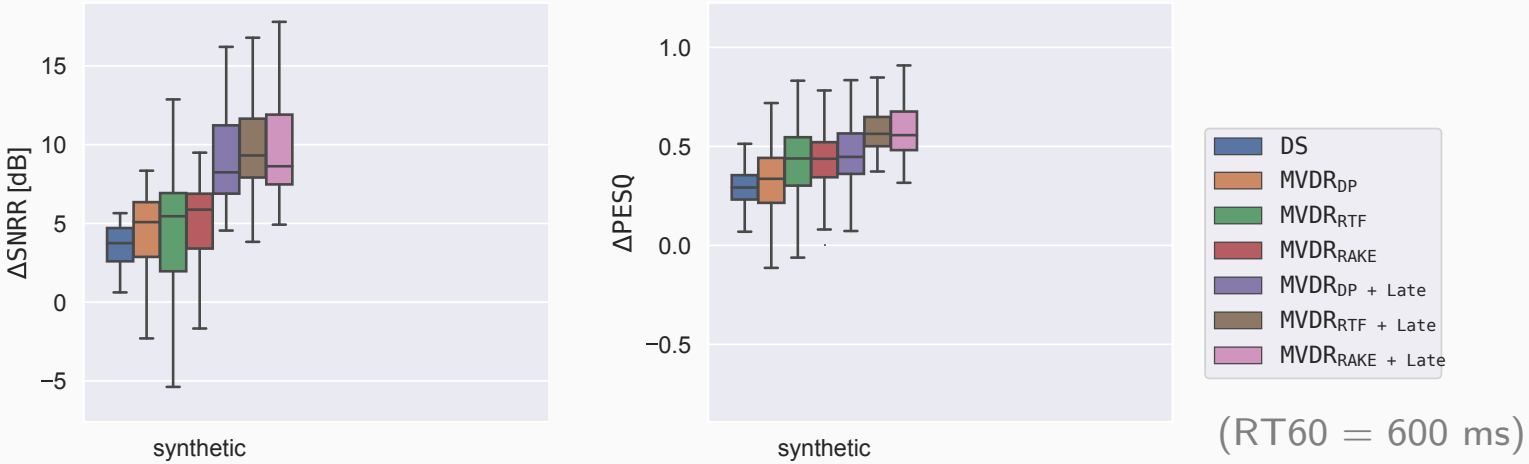
(RT60 = 600 ms)

[1] Using [Markovich-Golan et al., 2018], [2] Using [Kowalczyk, 2019],

Speech Enhancement with dEchorate

Methods	Noise covariance matrix	RIRs
DS	-	Direct path (AOA)
MVDR_{DP}	Noise	Direct path (AOA)
$\text{MVDR}_{\text{ReTF}}$ [1]	Noise	Relative Transfer Function
$\text{MVDR}_{\text{Rake}}$ [2]	Noise	4 strongest echoes per channel
$\text{MVDR}_{\text{DP+Late}}$	Noise + Late Diffusion [3]	Direct path (AOA)
$\text{MVDR}_{\text{ReTF+Late}}$ [1]	Noise + Late Diffusion [3]	Relative Transfer Function
$\text{MVDR}_{\text{Rake+Late}}$ [2]	Noise + Late Diffusion [3]	4 strongest echoes per channel

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



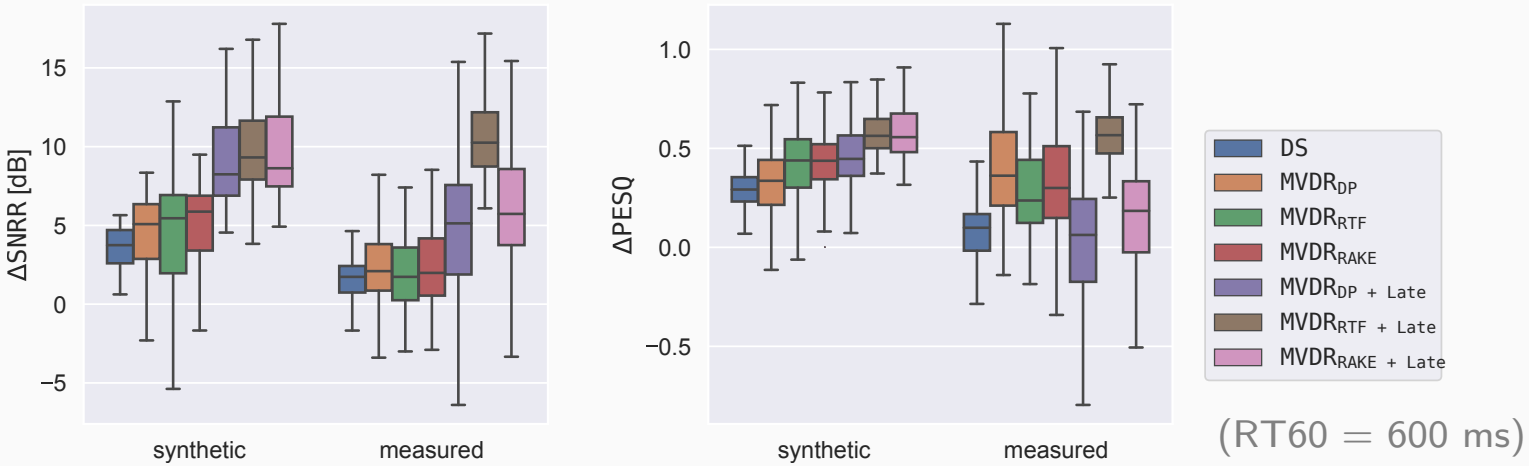
(RT60 = 600 ms)

[1] Using [Markovich-Golan et al., 2018], [2] Using [Kowalczyk, 2019], [3] Using [Schwartz et al., 2016],

Speech Enhancement with dEchorate

Methods	Noise covariance matrix	RIRs
DS	-	Direct path (AOA)
MVDR_{DP}	Noise	Direct path (AOA)
$\text{MVDR}_{\text{ReTF}}$ [1]	Noise	Relative Transfer Function
$\text{MVDR}_{\text{Rake}}$ [2]	Noise	4 strongest echoes per channel
$\text{MVDR}_{\text{DP+Late}}$	Noise + Late Diffusion [3]	Direct path (AOA)
$\text{MVDR}_{\text{ReTF+Late}}$ [1]	Noise + Late Diffusion [3]	Relative Transfer Function
$\text{MVDR}_{\text{Rake+Late}}$ [2]	Noise + Late Diffusion [3]	4 strongest echoes per channel

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



(RT60 = 600 ms)

[1] Using [Markovich-Golan et al., 2018], [2] Using [Kowalczyk, 2019], [3] Using [Schwartz et al., 2016],

Conclusion

Echoes of contributions

Echoes of contributions

How to estimate them?

In passive stereo scenario:

- Analytical method
  - ✓ direct estimation
  - ✗ depends on source and # echoes
- Learning-based method
  - ✓ estimation of first echo' TDOAs
  - ✗ only on synthetic data and noise source

Echoes of contributions

How to estimate them?

In passive stereo scenario:

- Analytical method
  - ✓ direct estimation
  - ✗ depends on source and # echoes
- Learning-based method
  - ✓ estimation of first echo' TDOAs
  - ✗ only on synthetic data and noise source

How to use them?

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

Echoes of contributions

How to estimate them?

In passive stereo scenario:

- Analytical method
  - ✓ direct estimation
  - ✗ depends on source and # echoes
- Learning-based method
  - ✓ estimation of first echo' TDOAs
  - ✗ only on synthetic data and noise source

How to use them?

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

3. Where to find them?

- `dEchorate`
  Echo-aware database for both estimation and application
  - ✓ echo annotation ⇔ geometry annotation
  - ✓ synthetic ⇔ real RIRs

Echo-aware perspective

Directions for future work:

Echo-aware perspective

Directions for future work:

- on **estimation**
  - develop theoretical guaranties for off-grid acoustic echo retrieval
  - for DNN: extended physics-based learning or other learning paradigm

Echo-aware perspective

Directions for future work:

- on **estimation**
  - develop theoretical guaranties for off-grid acoustic echo retrieval
  - for DNN: extended physics-based learning or other learning paradigm

- on **application**
  - other field of echoes: Seismology, Underwater acoustic, Volcanology, etc.

Echo-aware perspective

Directions for future work:

- on **estimation**
  - develop theoretical guaranties for off-grid acoustic echo retrieval
  - for DNN: extended physics-based learning or other learning paradigm
- on **application**
  - other field of echoes: Seismology, Underwater acoustic, Volcanology, etc.
- on `dEchorate`
  - Benchmark data for echo-aware algorithms
  - Synthetic to Real RIRs (style transfer, new type of acoustic simulator)

Echo-aware perspective

Directions for future work:

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

List of publications and assets

- On estimation
  - deep learning method in [Di Carlo et al., 2019]
  - `Blaster`: analytical method in [Di Carlo et al., 2020]
- On applications
  - `Mirage`: sound source localization in [Di Carlo et al., 2019]
  - `Separake`: sound source separation in [Scheibler et al., 2018]
- On 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 Research Group on multichannel `Mirage`

Code

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

List of publications and assets

- On estimation
  - deep learning method in [Di Carlo et al., 2019]
  - `Blaster`: analytical method in [Di Carlo et al., 2020]
- On applications
  - `Mirage`: sound source localization in [Di Carlo et al., 2019]
  - `Separake`: sound source separation in [Scheibler et al., 2018]
- On 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 Research Group on multichannel `Mirage`

Code

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

Thank you!

References i


Aissa-El-Bey, A. and Abed-Meraim, K. (2008).
Blind simo channel identification using a sparsity criterion.
In *2008 IEEE 9th Workshop on Signal Processing Advances in Wireless Communications*, pages 271–275. IEEE.


Antonacci, F., Filos, J., Thomas, M. R., Habets, E. A., Sarti, A., Naylor, P. A., and Tubaro, S. (2012).
Inference of room geometry from acoustic impulse responses.
IEEE Transactions on Audio, Speech, and Language Processing, 20(10):2683–2695.


Azais, J.-M., De Castro, Y., and Gamboa, F. (2015).
Spike detection from inaccurate samplings.
Applied and Computational Harmonic Analysis, 38(2):177–195.


Chakrabarty, S. and Habets, E. A. (2017).
Broadband doa estimation using convolutional neural networks trained with noise signals.
In *2017 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA)*, pages 136–140. IEEE.

References ii


Crocco, M. and Del Bue, A. (2015).
Room impulse response estimation by iterative weighted l 1-norm.
In *2015 23rd European Signal Processing Conference (EUSIPCO)*, pages 1895–1899. IEEE.


Crocco, M. and Del Bue, A. (2016).
Estimation of tdoa for room reflections by iterative weighted l 1 constraint.
In *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3201–3205. IEEE.


Crocco, M., Trucco, A., and Del Bue, A. (2017).
Uncalibrated 3d room geometry estimation from sound impulse responses.
Journal of the Franklin Institute, 354(18):8678–8709.


Deleforge, A., Di Carlo, D., Strauss, M., Serizel, R., and Marcenaro, L. (2019).
Audio-based search and rescue with a drone: Highlights from the ieee signal processing cup 2019 student competition [sp competitions].
IEEE Signal Processing Magazine, 36(5):138–144.

References iii


Di Carlo, D., Deleforge, A., and Bertin, N. (2019).
Mirage: 2d source localization using microphone pair augmentation with echoes.
In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 775–779. IEEE.


Di Carlo, D., Elvira, C., Deleforge, A., Bertin, N., and Gribonval, R. (2020).
Blaster: An off-grid method for blind and regularized acoustic echoes retrieval.
In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 156–160. IEEE.


DiBiase, J. H., Silverman, H. F., and Brandstein, M. S. (2001).
Robust localization in reverberant rooms.
In *Microphone Arrays*, pages 157–180. Springer.


Dokmanić, I., Scheibler, R., and Vetterli, M. (2015).
Raking the cocktail party.
IEEE journal of selected topics in signal processing, 9(5):825–836.

References iv


Eaton, J., Gaubitch, N. D., Moore, A. H., and Naylor, P. A. (2015).
The ace challenge—corpus description and performance evaluation.
In *2015 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA)*, pages 1–5. IEEE.


Flanagan, J. L., Surendran, A. C., and Jan, E.-E. (1993).
Spatially selective sound capture for speech and audio processing.
Speech Communication, 13(1-2):207–222.


Gannot, S., Vincent, E., Markovich-Golan, S., and Ozerov, A. (2017).
A consolidated perspective on multimicrophone speech enhancement and source separation.
IEEE/ACM Transactions on Audio, Speech, and Language Processing, 25(4):692–730.


Jensen, J. R., Saqib, U., and Gannot, S. (2019).
An em method for multichannel toa and doa estimation of acoustic echoes.
In *2019 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA)*, pages 120–124. IEEE.

References v


Knapp, C. and Carter, G. (1976).
The generalized correlation method for estimation of time delay.
IEEE transactions on acoustics, speech, and signal processing, 24(4):320–327.


Kowalczyk, K. (2019).
Raking early reflection signals for late reverberation and noise reduction.
The Journal of the Acoustical Society of America, 145(3):EL257–EL263.


Kowalczyk, K., Habets, E. A., Kellermann, W., and Naylor, P. A. (2013).
Blind system identification using sparse learning for tdoa estimation of room reflections.
IEEE Signal Processing Letters, 20(7):653–656.


Kuttruff, H. (2016).
***Room acoustics*.**
CRC Press.

References vi

Lebarbenchon, R., Camberlein, E., Di Carlo, D., Gaultier, C., Deleforge, A., and Bertin, N. (2018).
Evaluation of an open-source implementation of the srp-phat algorithm within the 2018 locata challenge.
Proc. of LOCATA Challenge Workshop-a satellite event of IWAENC.

Leglaive, S., Badeau, R., and Richard, G. (2016).
Multichannel audio source separation with probabilistic reverberation priors.
IEEE/ACM Transactions on Audio, Speech, and Language Processing, 24(12):2453–2465.

Lin, Y., Chen, J., Kim, Y., and Lee, D. D. (2007).
Blind sparse-nonnegative (bsn) channel identification for acoustic time-difference-of-arrival estimation.
In *2007 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, pages 106–109. IEEE.

References vii


Lin, Y., Chen, J., Kim, Y., and Lee, D. D. (2008).
Blind channel identification for speech dereverberation using l1-norm sparse learning.
In *Advances in Neural Information Processing Systems*, pages 921–928.


Markovich-Golan, S., Gannot, S., and Kellermann, W. (2018).
Performance analysis of the covariance-whitening and the covariance-subtraction methods for estimating the relative transfer function.
In *2018 26th European Signal Processing Conference (EUSIPCO)*, pages 2499–2503. IEEE.


Nguyen, Q., Girin, L., Bailly, G., Elisei, F., and Nguyen, D.-C. (2018).
Autonomous sensorimotor learning for sound source localization by a humanoid robot.


Ribeiro, F., Ba, D., Zhang, C., and Florêncio, D. (2010).
Turning enemies into friends: Using reflections to improve sound source localization.
In *2010 IEEE International Conference on Multimedia and Expo*, pages 731–736. IEEE.

References viii


Scheibler, R., Di Carlo, D., Deleforge, A., and Dokmanić, I. (2018).
Separake: Source separation with a little help from echoes.
In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6897–6901. IEEE.


Schwartz, O., Gannot, S., and Habets, E. A. (2016).
Joint estimation of late reverberant and speech power spectral densities in noisy environments using frobenius norm.
In *2016 24th European Signal Processing Conference (EUSIPCO)*, pages 1123–1127. IEEE.


Tong, L., Xu, G., and Kailath, T. (1994).
Blind identification and equalization based on second-order statistics: A time domain approach.
IEEE Transactions on information Theory, 40(2):340–349.