# Echo-aware signal processing for audio scene analysis


Diego Di Carlo

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Simon Doclo (reviewer)
Laurent Girin (reviewer)
Fabio Antonacci (examiner)

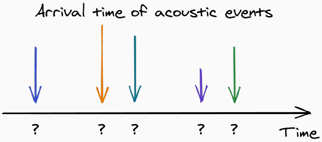
Université de Rennes 1, IRISA/INRIA, Panama research group

# Acoustic Echo Estimation

# Acoustic Echo Retrieval

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

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



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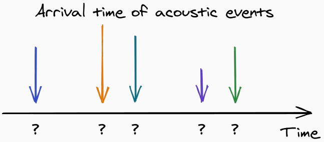
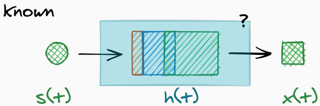



**Two scenarios:**




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

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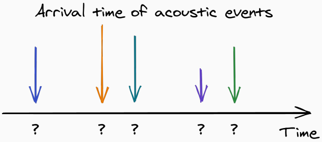


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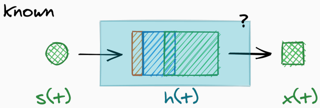


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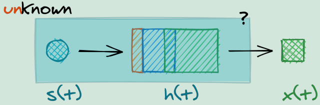


- **passive** and more common setups
- **blind inverse** problem (harder)

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

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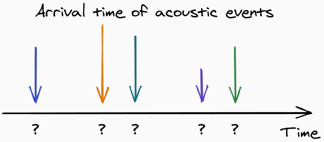


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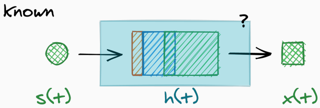


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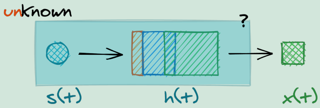


**passive** and more common setups

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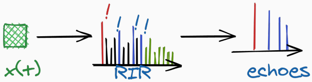
**Our case:** signal source and passive microphone array

# Passive Acoustic Echo Retrieval

### RIR-based approaches

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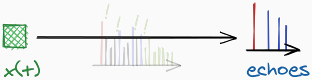

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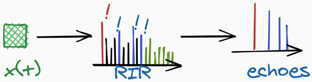


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2. Peak picking $\implies$ Echoes

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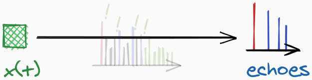


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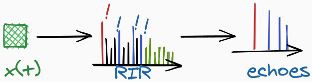


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✓ reasonably good for some application
[Crocco and Del Bue, 2016]

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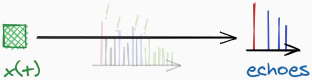


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→ lower complexity
→ less hyperparameters

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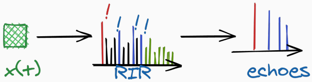


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✗ Peak picking has hyperparameters

✗ Issues due to *discrete* estimation

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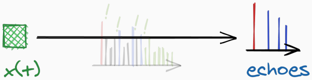


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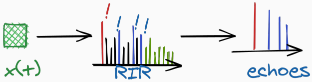


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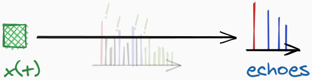


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✗ exploratory
(no standard solver, few works on audio)

**Proposed appoach** RIR-agnostic & continuous:

1. Learning-based approach
2. Analytical approach

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

### Key ingredient – *Cross relation identity*

Signal model

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

### 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

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

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

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

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

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

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Convolving with filters:

$$h_2 \star x_1 = h_2 \star h_1 \star x$$
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Commutativity of convolution:

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

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Subtraction

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

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## Proposed approach: analytical & continuous

C. Elvira.

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

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

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

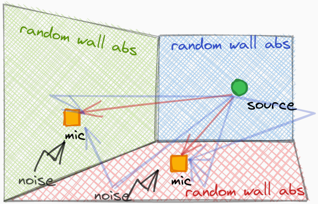
$\sim$ **Lasso**, but $\mathcal{F}h_i(f)$ is a continuous function $\rightarrow$ **BLasso** [Azais et al., 2015]

✓No huge matrix ✓ Solutions is a train 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
- $\mathcal{D}^{\mathrm{SNR}}$: $\mathtt{SNR} \in [0, 20]$ dB, $\mathtt{RT}_{60} = 400$ ms
- $\mathcal{D}^{\mathrm{RT}60}$: $\mathtt{RT}_{60} = [100, 1000]$ ms, $\mathtt{SNR} = 20$ dB




**Baselines:** discrete RIR-based methods based on LASSO

- BSN: Blind, Sparse and Non-negative[1]
- IL1C: iteratively-weighted $\ell_1$ constraint[2] $\rightarrow$ State of the Art

hyperparameters and peak-picking tuned via cross-validation

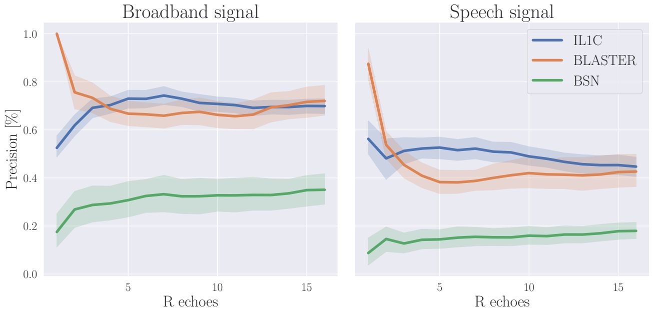
**Proposed method:** Blind and Sparse Technique for Echo Retrieval (Blaster)

[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)




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

✗ Sensitive kto # echoes

✗ Sensitive source signal

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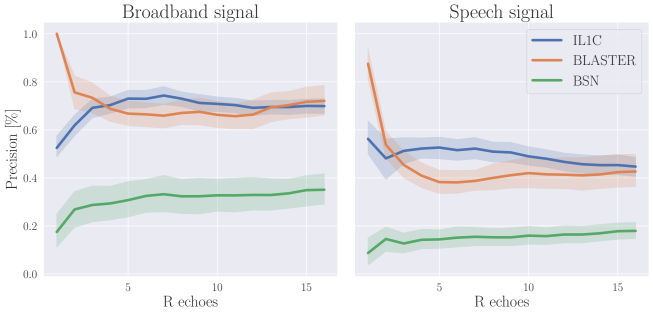


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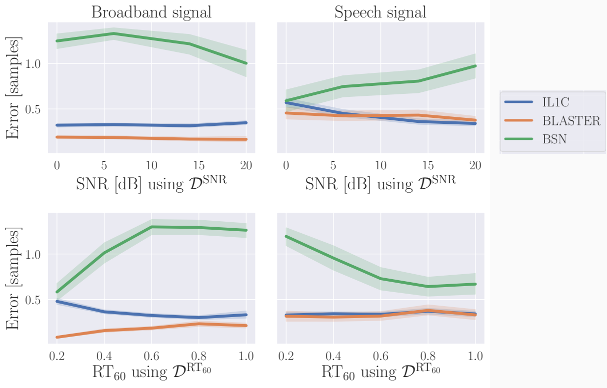
# Error per Dataset/Signal while recovering 7 echoes

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




(Fs = 16 kHz)

✓Lower RMSE

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

✗ Source signal dependent

## 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:**

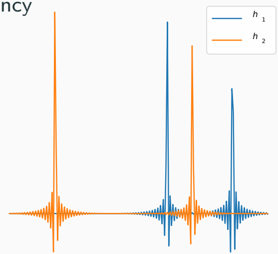
- $x_i \to \tau_i^{(r)}$ is difficult, while $\tau_i^{(r)} \to x_i$ "is not"
  $\to$ acoustic simulators: mic/src/room geometry $\longrightarrow \left\{\tau_i^{(r)}, \alpha_i^{(r)}\right\}, \tilde{h}_i, \quad \tilde{x}_i$
- Acoustic simulator are "simple", versatile and fast
  $\to$ allow to create large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




**Outputs:**
Inter and intra Time Difference of Arrivals (TDOAs)

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

**Loss Function**

1. RMSE (Multi-label regression) $\rightarrow$ TDOAs
2. Gaussian log-likelihood $\rightarrow \{\mu_\tau, \sigma_\tau^2\}\ \forall \tau \in$ TDOAs
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**Architecture:** MLP, CNN [Chakrabarty and Habets, 2017, Nguyen et al., 2018]

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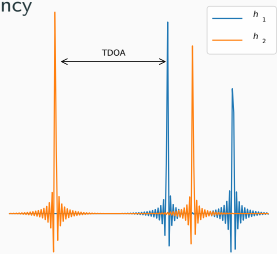


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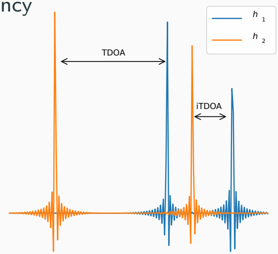


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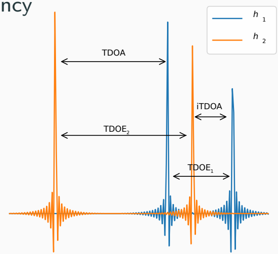
2. Gaussian log-likelihood $\rightarrow \{\mu_\tau, \sigma_\tau^2\}\ \forall \tau \in$ TDOAs
3. Student log-likelihood $\rightarrow \{\mu_\tau, \lambda_\tau, \nu_\tau\}\ \forall \tau \in$ TDOAs



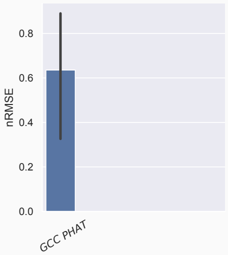

**Architecture:** MLP, CNN [Chakrabarty and Habets, 2017, Nguyen et al., 2018]

# 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)



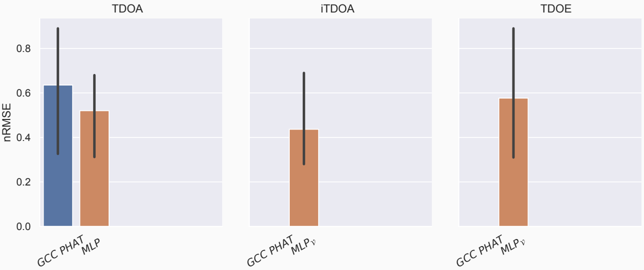

More echoes
Real data

# Experimental results

**Proposed Method:** `MLP`, `CNN`, $\texttt{CNN}_{\mathcal{N}}$, $\texttt{CNN}_{\mathcal{T}}$

**Baseline:** `GCC PHAT` [Knapp and Carter, 1976]

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




**Observation:**

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

More echoes

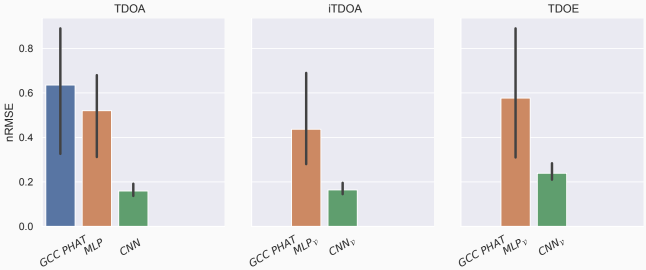
Real data

# Experimental results

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

**Baseline:** GCC PHAT [Knapp and Carter, 1976]

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




**Observation:**

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

More echoes

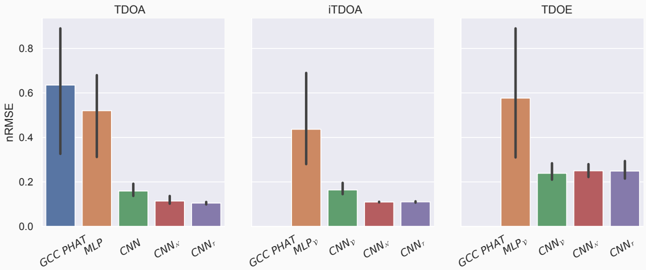
Real data

# 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

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