Echo-aware signal processing for audio scene analysis

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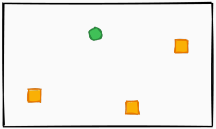
Acoustic Echo Estimation

State of the Art

Key ingredient – *Cross relation identity*



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

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Ideas:

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

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

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

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

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

✓ [Tong et al., 1994] ✓ [Lin et al., 2008] ✓ [Aissa-El-Bey and Abed-Meraim, 2008]
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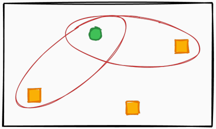

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Proposed approach: analytical & off-grid

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

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

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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**

$$\mathbf{X}_i = \mathtt{DFT}(x_i) \simeq \mathcal{F}x_i(nF_s) \qquad n = 0 \ldots N-1$$

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Idea: Recover echoes by matching a finite number of frequencies

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$\sim$ **Lasso** problem, but $\mathcal{F}h_2(f)$ is a continuous function.

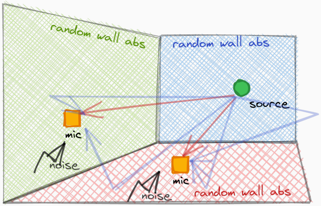
Instance of a **BLasso** problem [Bredies and Carioni, 2020]

Solved with Sliding Frank-Wolfe algorithm [Denoyelle et al., 2019]

Experimental results

Methods

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



Baseline method are xvalidated on other dataset

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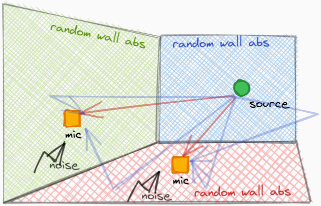

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Dataset

- $\mathcal{D}^{\text{SNR}}$: $SNR \in [0, 20]$ dB, $\text{RT}_{60} = 400$ ms
- $\mathcal{D}^{\text{RT60}}$: $\text{RT}_{60} = [100, 1000]$ ms, $SNR = 20$ dB

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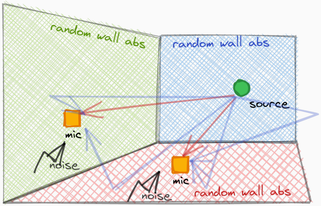

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Metrics

Performance per # of echoes

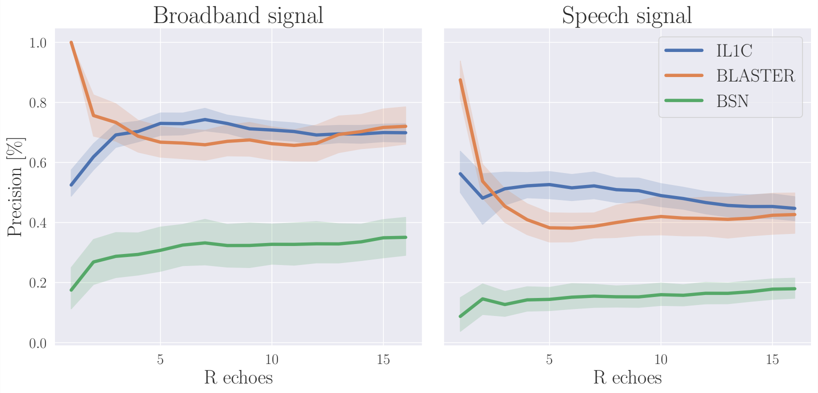


Figure 1: $\mathrm{RT}_{60} = 400$ ms and SNR $= 20$ dB.

✗ Sensitive to # echoes

✗ Sensitive source signal

✓ Good for 2 echoes

Performance per # of echoes

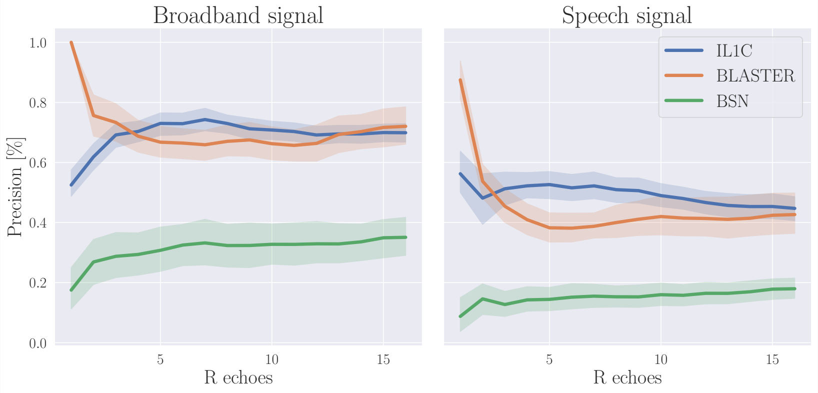


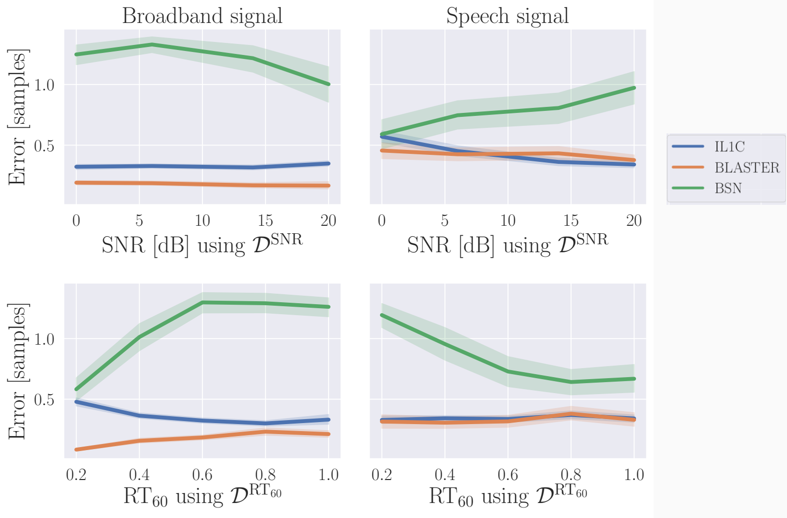
Figure 1: $\mathrm{RT}_{60} = 400$ ms and SNR $= 20$ dB.

✗ Sensitive to # echoes

✗ Sensitive source signal

✓ Good for 2 echoes [Scheibler et al., 2018,

Error per Dataset/Signal while recovering 7 echoes



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

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