BLASTER

An off-grid method for blind and regularized acoustic echoes retrieval

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Introduction

Introduction

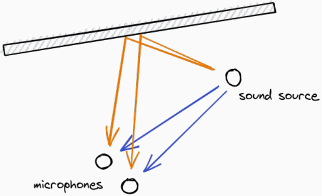
Proposed Approach

Results

Echoes help acoustic processing

Audio Speech Signal Processing

- **suffers** in real non-anechoic environments
- **early reflections** and **reverberation**
  - … breaks the *free-field* assumption
  - … are considered as *foes*



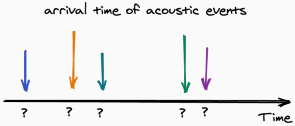
Echo-aware Audio Processing turns them into friends

- for **speech enhancement**
  [Ribeiro et al., 2010, Dokmanić et al., 2015, Scheibler et al., 2018]
- for 3D **room geometry estimation** from sound
  [Antonacci et al., 2012, Dokmanić et al., 2015, Crocco et al., 2017]

The acoustic echoes retrieval (AER) problem

Estimating early (strong) acoustic reflections:

- their time of arrivals → TOAs Estimation
- their amplitude



We consider the scenario

1. BLIND: Source signal is unknown
2. SIMO: Single input and multiple outputs (here only stereophonic recordings)

Room Impulse Response, h_i

The linear filtering effect due to the propagation of sound from a source to a microphone in a indoor space

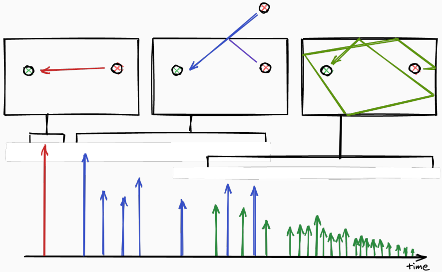
$$x_i(t) = (h_i * s)(t) + n_i(t)$$

with Image Source Model:

as stream of Diracs:

$$h_i(t) = \sum_{r=0}^{R} \alpha_{i,r} \delta(t - \tau_{i,r})$$

$$\Longleftrightarrow$$



Key ingredient – *Cross relation identity*

$$x_i = h_i * s$$

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

Ideas

1. Sampled version of x_1, x_2 are available $(\mathbf{x}_1, \mathbf{x}_2)$
2. Assume echoes belong to multiples of the sampling frequency
3. Identify echoes $\rightarrow$ find sparse vectors $\mathbf{h}_1, \mathbf{h}_2$
4. Lasso-like problem

$$\widehat{\mathbf{h}}_1, \widehat{\mathbf{h}}_2 \in \underset{\mathbf{h}_1, \mathbf{h}_2 \in \mathbb{R}^n}{\arg\min} \|\mathbf{x}_1 * \mathbf{h}_2 - \mathbf{x}_2 * \mathbf{h}_1\|_2^2 + \lambda Reg(\mathbf{h}_1, \mathbf{h}_2)$$

$Reg(\mathbf{h}_1, \mathbf{h}_2) \longrightarrow$ sparse promoting regularizer

✓ [Lin et al., 2007] ✓ [Aïssa-El-Bey and Abed-Meraim, 2008]
✓ [Kowalczyk et al., 2013] ✓ [Crocco and Del Bue, 2015]

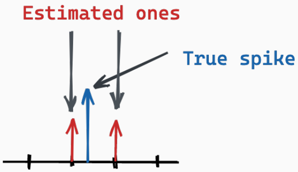
Limitations / bottleneck

Limitations

- Echoes are not necessarily "on grid"
- *Body guard* effect [Duval and Peyré, 2017]

  $\longrightarrow$ low recall $\Longrightarrow$ low accuracy

  $\longrightarrow$ slow convergence



Increase the sampling frequency, F_s

$\longrightarrow$ Increase Precision

Computational bottleneck

- Bigger vectors and matrices

  $\longrightarrow$ memory usage

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

  $\longrightarrow$ slow convergence

State of the Art approach

State Of The Art

1. discrete (sparse)
   Blind Channel Estimation
   (BCE)
2. Peak-picking

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$\Longrightarrow$ however

- Full channel
  so lot of memory
- Echoes are “off-grid”

State of the Art approach

State Of The Art

1. discrete (sparse) Blind Channel Estimation (BCE)
2. Peak-picking

$\Longrightarrow$ **we propose**

1. BCE + Continuous Dictionary
2. Greedy-like approach
3. Inputs:
   - mic recordings
   - # echoes

$\Longrightarrow$ **however**

- Full channel so lot of memory
- Echoes are “off-grid”

Acoustic Echoes Retrieval as off-grid Spike Retrieval Problem

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Off-the-grid acoustic echo retrieval

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

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

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

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

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

Idea: Recover echoes by matching a finite number of frequencies

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

Instance of a **BLasso** problem [Bredies and Pikkarainen, 2013]

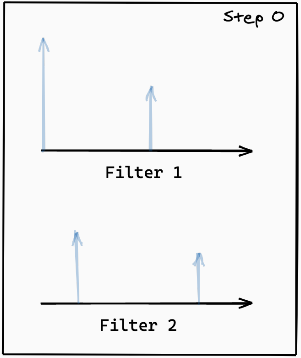
✓ no Toeplitz matrix

✓ Solutions is a train of Dirac

✓ anchor prevents trivial solution

Algorithm

Problem is **convex** with respect to the filters h_1 and h_2
$\longrightarrow$ Sliding Frank-Wolfe algorithm [Denoyelle et al., 2019]

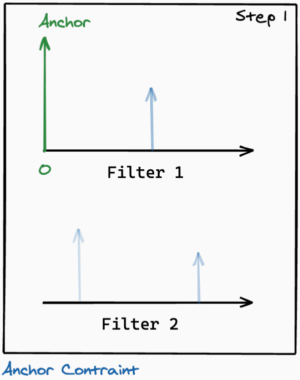


Initialization

Problem is **convex** with respect to the filters h_1 and h_2

$\longrightarrow$ Sliding Frank-Wolfe algorithm [Denoyelle et al., 2019]

1. Start from the anchor



Algorithm

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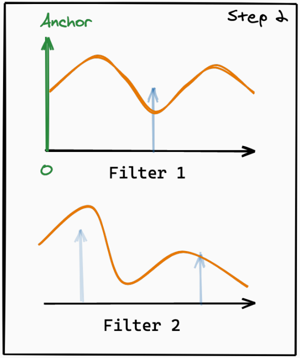
1. Start from the anchor
2. Compute the *local* cost based on Cross-relation



Local Const

Algorithm

Problem is **convex** with respect to the filters h_1 and h_2
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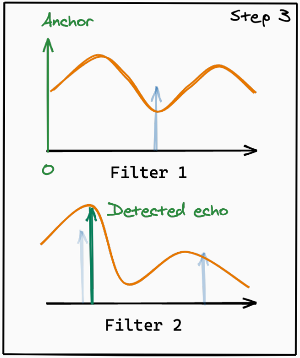
1. Start from the anchor
2. Compute the *local* cost based on Cross-relation
3. Find the maximizer



Detected echo

Algorithm

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1. Start from the anchor
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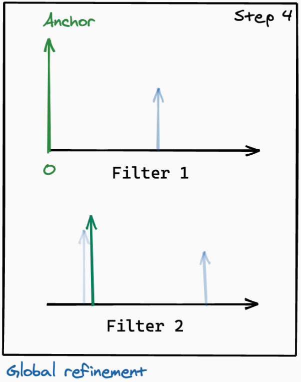
3. Find the maximizer
4. Update weight (Lasso-like)



Algorithm

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1. Start from the anchor
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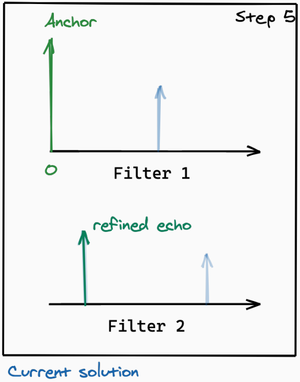
3. Find the maximizer
4. Update weight (Lasso-like)
5. Joint refinement



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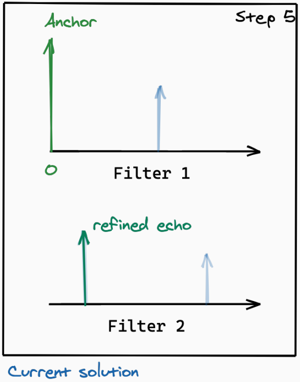
5. Joint refinement

Repeat until optimality conditions are met



Numerical Results

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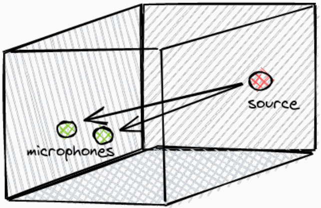
Experimental Setup

Condition

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



Considered Methods

- BSN: Blind Sparse and Non-negative BCE [Lin et al., 2007]

$$\underset{\mathbf{h}=[\mathbf{h}_1,\mathbf{h}_2]}{\arg\min} \ \|\mathcal{T}(\mathbf{x}_1)\mathbf{h}_2 - \mathcal{T}(\mathbf{x}_2)\mathbf{h}_1\|_2^2 + \lambda\|\mathbf{h}\|_1 \quad \text{s.t.} \quad \mathbf{h}[0] = 1, \mathbf{h} \geq 0$$

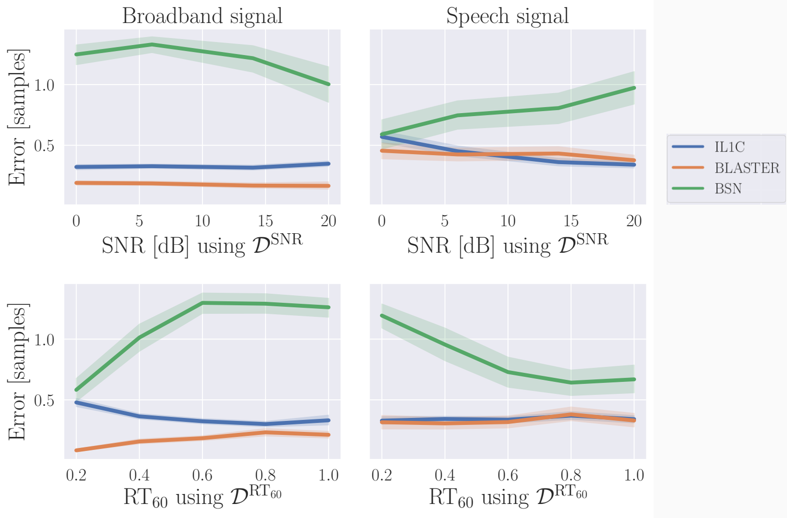
- IL1C: Iterative ℓ_1 Constraint BCE [Crocco and Del Bue, 2015]

$$\underset{\mathbf{h}=[\mathbf{h}_1,\mathbf{h}_2]}{\arg\min} \ \|\mathcal{T}(\mathbf{x}_1)\mathbf{h}_2 - \mathcal{T}(\mathbf{x}_2)\mathbf{h}_1\|_2^2 + \|\mathbf{h}\|_1 \quad \text{s.t.} \quad \mathbf{h}^\top \mathbf{p}^{(z)} = 1, \mathbf{h} \geq 0$$

- BLASTER: Off-grid BCE

$$\underset{h_1,h_2 \in \text{measure}}{\arg\min} \ \|X_1 \cdot \mathcal{F}h_2(f) - X_2 \cdot \mathcal{F}h_1(f)\|_2^2 + \lambda\|h_1 + h_2\|_{\mathrm{TV}} \quad \text{s.t.} \quad h_1(\{0\}) = 1, h_l \geq 0$$

Error per Dataset/Signal while recovering 7 echoes



✓Lower RMSE

✓ Robustness to SNR and RT_{60}

✗ Source signal dependent

Precision per threshold in typical scenario

	Precision [%]									
	R = 2 echoes					R = 7 echoes				
τ_{thr} [samples]	0.5	1	2	3	10	0.5	1	2	3	10
BSN	8	9	27	46	62	5	8	38	54	73
IL1C	51	55	55	56	58	42	53	55	56	58
BLASTER	**68**	**73**	**74**	**75**	**75**	46	53	56	57	61

Table 1: $RT_{60} = 200$ ms and SNR = 20 dB.

✓ Invariant
to threshold

✗ Sensitive
to # echoes

Performance per # of echoes

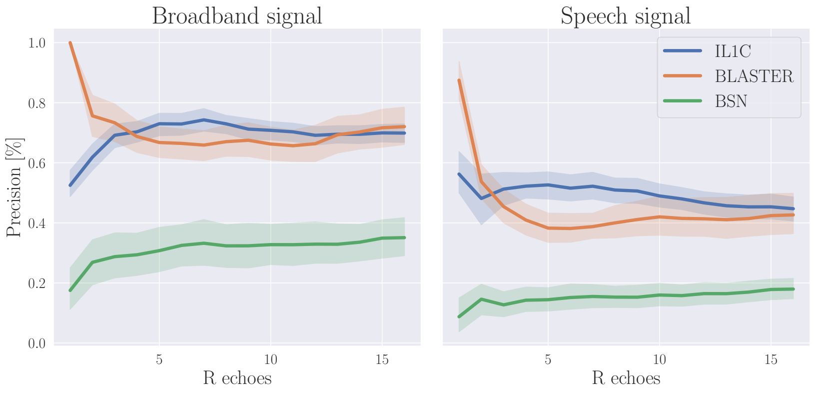


Figure 1: $RT_{60} = 400$ ms and SNR = 20 dB.

✗ Sensitive to # echoes

✗ Sensitive source signal

✓ Good for 2 echoes

Performance per # of echoes

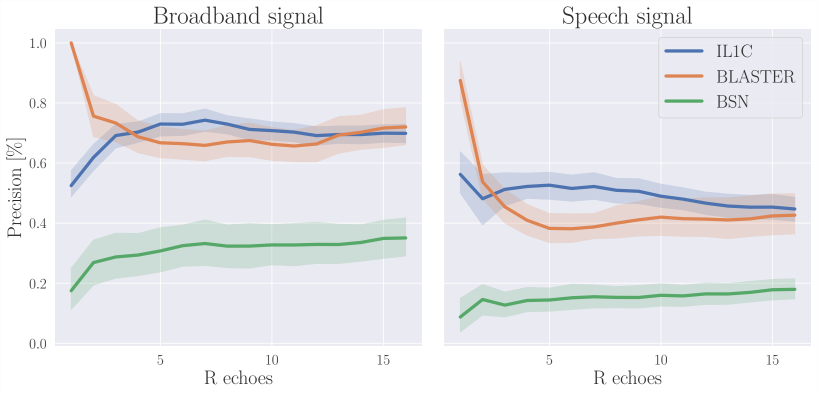


Figure 1: $RT_{60} = 400$ ms and SNR = 20 dB.

✗ Sensitive to # echoes

✗ Sensitive source signal

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

Conclusion

1. Introduction
    - Echoes helps indoor processing
    - On-grid method suffer of pathological problem when off-grid problem
2. BLASTER
    - Super resolution can be applied to SIMO BCE
    - Dirac modeled in closed-from
3. Experiments
    - Smaller RMSE due to super-resolution
    - Better performances for smaller # echoes
    - Performances are source-dependent

Future Work

- Extension to multichannel recording
- Test on real data recordings

Thank you!

https://gitlab.inria.fr/panama-team/blaster

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