

# Gridless 3D Recovery of Image Sources from Room Impulse Responses

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## 1. Introduction

1. The problem
2. Image source model

## 2. Image source reconstruction

## 3. Numerical resolution

1. Adapted Sliding-Frank-Wolfe algorithm
2. Experiments and results

# Outline

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# Problem formulation

**Can one hear the shape of a room ?**

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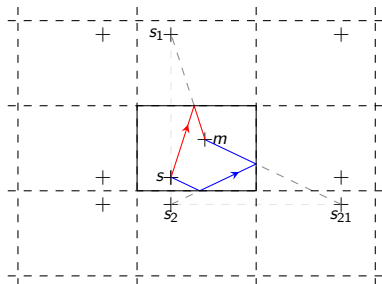
More precisely, given:

- an initial **sound impulse** (Dirac in time and 3D space)
- discrete-time, multichannel, low-pass measurements of the **room impulse response (RIR)**

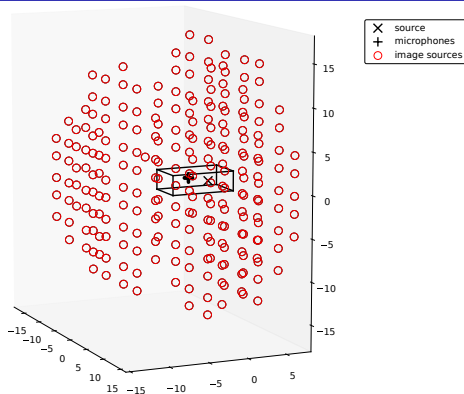
can we reconstruct the positions of the walls, floor and ceiling ?



# Image Sources



(a) First and second order IS



(b) 3D view of an IS point cloud

- the image sources contain the information about the **acoustic properties** of the room
- in particular, room geometry is given by the locations of the source and the **first order** image sources

# Model

Using the **image source model** [2], the approximated pressure field  $p(\mathbf{r}, t)$  is solution to an inhomogeneous free-field wave equation given by :

$$\frac{1}{c^2} \frac{\partial^2}{\partial t^2} p(\mathbf{r}, t) - \Delta p(\mathbf{r}, t) = \sum_{k=0}^{\infty} a_k \delta(\mathbf{r} - \mathbf{r}_k^{\text{src}}) \delta(t) \quad (1)$$

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The general solution of 1 is given by:

$$p(\mathbf{r}, t) = \sum_{k=0}^{\infty} a_k \frac{\delta(t - \|\mathbf{r} - \mathbf{r}_k^{\text{src}}\|_2 / c)}{4\pi \|\mathbf{r} - \mathbf{r}_k^{\text{src}}\|_2}. \quad (2)$$



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## Hypotheses:

- 1 rectangular cuboid rooms
- 2 frequency-independent walls, floor and ceiling
- 3 omnidirectional sources and receivers
- 4 specular reflections
- 5 one point source emitting a perfect impulse at  $t = 0$
- 6 fixed source and receiver responses: ideal low-pass filters

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- we only have access to a vector of observations via a linear operator  $\Gamma$  (with kernel  $\gamma$ ) :  
 $\mathbf{x} = \Gamma(\psi) = \int_r \gamma(r) d\psi(r) \in \mathbb{R}^{N_{\text{obs}}}$

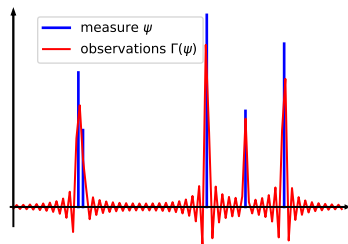


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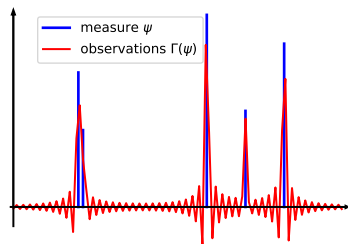


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**Idea:** consider a **relaxed** optimization problem over the entire space of **Radon measures** [3] of  $\mathbb{R}^d$ :

$$\min_{\psi \in \mathcal{M}(\mathbb{R}^d)} \underbrace{\frac{1}{2} \|\mathbf{x} - \Gamma(\psi)\|_2^2}_{\text{data compliance}} + \underbrace{\lambda \|\psi\|_{\text{TV}}}_{\text{regularization}} \quad (\text{BLASSO})$$

# Room Response

We start by relaxing the source distribution in space:

$$\frac{1}{c^2} \frac{\partial^2}{\partial t^2} p(\mathbf{r}, t) - \Delta p(\mathbf{r}, t) = \sum_{k=0}^{\infty} a_k \delta(\mathbf{r} - \mathbf{r}_k^{\text{src}}) \delta(t) \quad (1)$$

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For a given source distribution  $\psi$ , the solution to the wave equation (3) is given by

$$p(\mathbf{r}, t) = \int_{r'} \frac{\delta(t - \|\mathbf{r} - \mathbf{r}'\|_2 / c)}{4\pi \|\mathbf{r} - \mathbf{r}'\|_2} \psi(\mathbf{r}') d\mathbf{r}'. \quad (4)$$



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The **multi-channel response**  $\mathbf{x}$  measured by the microphones is:

$$x_{m,n} := (\kappa * p(\mathbf{r}_m^{\text{mic}}, \cdot))(n/f_s) = \int_{\mathbf{r} \in \mathbb{R}^3} \frac{\kappa(n/f_s - \|\mathbf{r}_m^{\text{mic}} - \mathbf{r}\|_2 / c)}{4\pi \|\mathbf{r}_m^{\text{mic}} - \mathbf{r}\|_2} \psi(\mathbf{r}) d\mathbf{r} \quad (5)$$

where  $\kappa : t \mapsto \text{sinc}(\pi f_s t)$  is the ideal low-pass filter at the microphones frequency of sampling.

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We define the linear operator

$$\Gamma : \begin{array}{l} \mathcal{M}(\mathbb{R}^3) \longrightarrow \mathbb{R}^{N \times M} \\ \psi \longmapsto \mathbf{x} = \left( \int_{\mathbf{r} \in \mathbb{R}^3} \frac{\kappa (n_j/f_s - \|r - r_{m_j}^{\text{mic}}\|_2 / c)}{4\pi \|r - r_{m_j}^{\text{mic}}\|_2} d\psi(r) \right)_{1 \leq j \leq N \times M} \end{array} \quad (6)$$

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In particular, if  $\psi = \sum_{k=0}^K a_k \delta_{\mathbf{r}_k^{\text{src}}}$  (the measure defined by the image sources),  $\mathbf{x} = \Gamma(\psi)$  is the multichannel RIR.

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# Adapted Sliding-Frank-Wolfe algorithm [1]

## Algorithm:

- find a new source by maximizing  $\mathbf{r} \mapsto \frac{1}{\lambda} \Gamma^*(\mathbf{x} - \Gamma \psi^k)(\mathbf{r})$
- optimize over the amplitudes  $a_k$

## Last step:

local non-convex optimization of the cost function with regards to the amplitudes and positions  $(a_k, \mathbf{r}_k)_k$

## Simulated experimental setup:

- compact spherical array of 32 microphones (scaled eigenmike with radius  $4.2\text{cm}$ ,  $8.4\text{cm}$ , etc.)
- random room sizes ( $2 \times 2 \times 2\text{m} \rightarrow 10 \times 10 \times 5\text{m}$ ), random sources and microphone locations
- synthetic noisy RIR cut at  $50\text{ms}$  for the observations
- study the impact of the sampling frequency, the noise, the array radius



# Numerical results

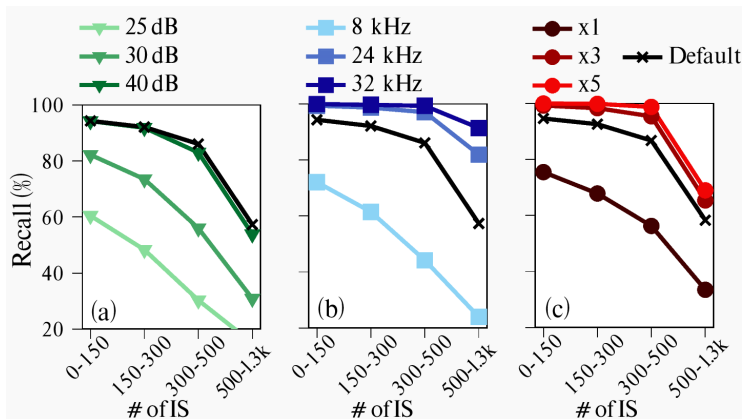


Figure: Recall over a room dataset for varying noise ratios (PSNR), sampling frequencies and spherical microphone array diameter

**Default parameters:** noiseless,  $f_s = 16\text{kHz}$ ,  $d = 16.8\text{cm}$

# Conclusion

The proposed method offers significant advantages for room geometry reconstruction :

- **gridless**, direct estimation of continuous 3D source positions from discrete RIRs
- high precision recovery of low order image sources
- robustness to noise
- requires no prior information on the room properties



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Some of the areas that remain to explore :

- estimating room parameters
- generalization to non-rectangular room shapes
- application to real data
- joint estimation of the source-microphone response  $\kappa \dots$

- [1] J. B. Allen and D. A. Berkley, “Image method for efficiently simulating small-room acoustics,” *Journal of the Acoustical Society of America*, vol. 65, pp. 943–950, 1976.
- [2] V. Duval and G. Peyré, “Exact Support Recovery for Sparse Spikes Deconvolution,” *Foundations of Computational Mathematics*, vol. 15, no. 5, pp. 1315–1355, 2015.
- [3] Q. Denoyelle, V. Duval, G. Peyré, and E. Soubies, “The Sliding Frank-Wolfe Algorithm and its Application to Super-Resolution Microscopy,” *Inverse Problems*, 2019.