ECHO-AWARE signal processing for audio scene analysis

Diego DI CARLO

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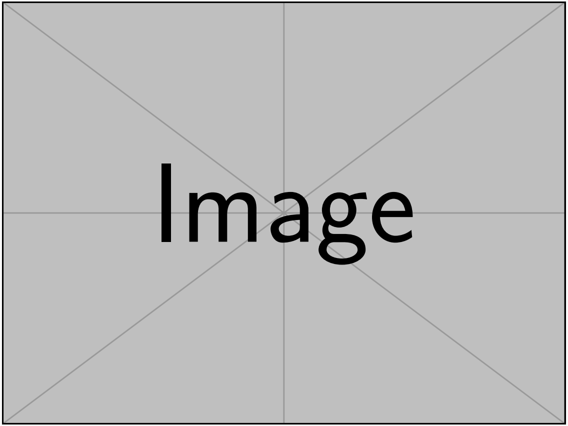
INRIA IRISA

Introduction

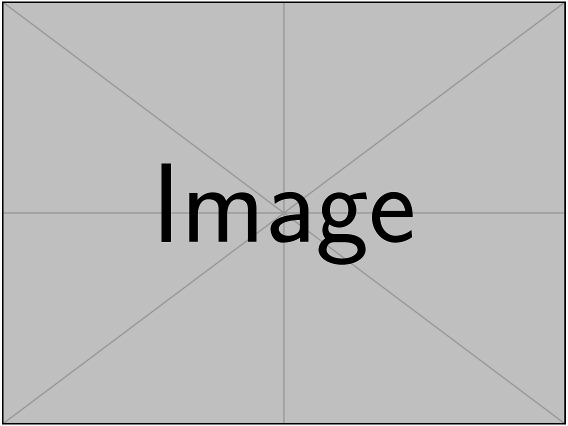
Scenario



Sound

- produced by sources

Scenario



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- produced by sources
- recorded by microphones

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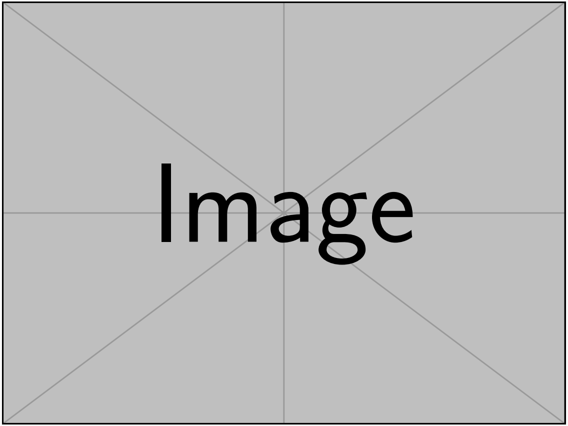

Sound

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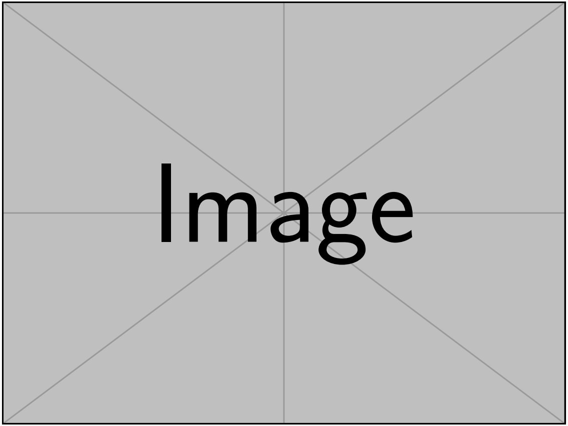
- corrupted by noise

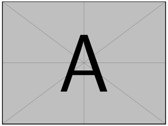


Sound

- produced by sources
- recorded by microphones
- corrupted by noise
- propagates in the room
  $\hookrightarrow$ reverberation

Microphones recordings carries

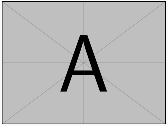
Semantic information about source nature and semantic content

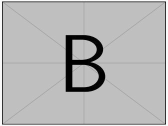


Echo-aware signal processing for audio scene analysis

Microphones recordings carries

- **Semantic** information about source nature and semantic content
- **Spatial** information about due to *sound propagation*





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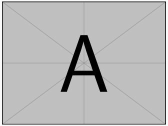

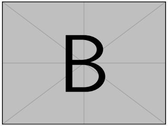

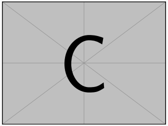

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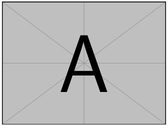
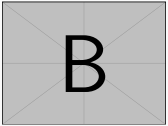
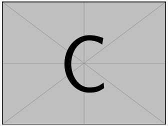
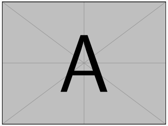






Audio Scene Analysis

is the extraction and organization of all the information in the sound



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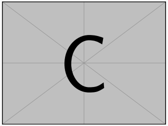

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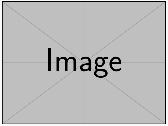
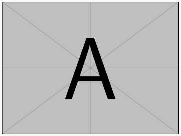


Echo-aware signal processing for audio scene analysis

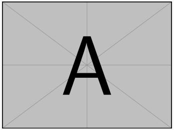
Typical problems

- What?
  - *Sound Source Separation*
  - *Speech Enhancement*
    (denoising, dereverberation)
  - *Automatic Speech Recognition*



Echo-aware signal processing for audio scene analysis

Sounds as signals, recording as process



- a

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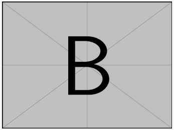

- a
- b

Signal Processing

Offer mathematical models, frameworks and tools to tackle such ASA problems

Echo-aware signal processing for audio scene analysis

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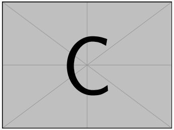

- a
- b
- c

Signal Processing

Offer mathematical models, frameworks and tools to tackle such ASA problems

General Pipeline

- (Mathematical Models)
- Signal representation (STFT, Features)
- Enhancement (denoising, dereverberation)
- Parameter Estimation (DOA, Localization)
- Adaptive Processing (Filtering)

Echo-aware signal processing for audio scene analysis

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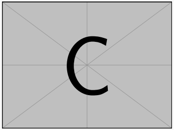

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Acoustic Echoes

- Product of the sound propagation
- Sound repetition
  - “same” content: can be integrated
  - “different” sounds: carry info about the reflection
  - different direction of arrival: spatial information

Echo-aware processing
is between anechoic processing and reverberant processing
Anechoic processing

- short processing

✓ sound field tends to be diffuse

✗ sound reflection as interferences
neglect most of the sound energy
ignore the correlation between the direct sound and its reflection and consequently may result in a distorted output

✗ coherent processing becomes impossible

Echo-processing

- Middle processing perceive coming from all directions [?]

Turning echoes into friends

Typically reverberation is considered as ”foe” for the processing.

Thesis objective

1. provide new methodologies and data to process and estimate acoustic echoes
2. extend previous classical methods for audio scene analysis

1D Outline

Echo-aware signal processing
for audio scene analysis

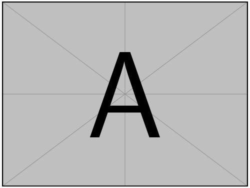
Modeling

Echoes and Room Acoustics

Sound propagates and interacts with space

- it travels with a certain speed and it is attenuated;
- it is absorbed and reflected by surfaces;
- and it is scattered, diffracted, etc.

This is describe by the so called RIRs



Elements of reverberation
[?, ?, ?, ?]

- Direct path
- Early Echoes
- Reverberation tails

Early Echoes

Echoes and Room Impulse Response

RIRs can be modeled with the Image Methods

- specular reflection only
- “playing billiard in a concert hall”
- for shoebox room it is is the solution for physics
- in frequency domain it writes as

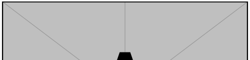
RIRs accounts for
the geometry of the room

- Room shape and size
- Mic and Source position
- presence of objects

the acoustic properties of the audio scene

- surface materials
- objects materials

examples



Room Impulse Response

$$\tilde{x}_i = (\tilde{h}_i * \tilde{s})(t) \longrightarrow \tilde{X}_i(f) = \tilde{H}_{ij}(f)\tilde{S}(f)$$

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

Observation
Our vision is limited both in time (finite and discrete) and in frequency (finite and discrete)

$$x_i[n] = ... \tag{1}$$

Signal model in the frequency domain

$$x_i = (h_i * s)(t) \ \longrightarrow \ X(f) = H_i(f)S(f)$$

Approximations

- Narrowband Approximation
- DTFT echo model in the DFT

Interim Conclusion I

Approximations

- Echoes are well described by specular reflection
- Echoes are off-grid by nature
- Sampling and quantization make them hard
- Processing in the discrete frequency domain, but with continuous time echo model

Acoustic Echo Estimation

Acoustic Echo Retrieval

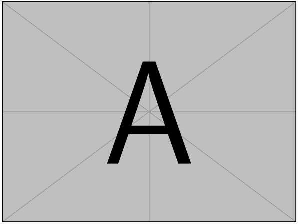
Given the echo model

$$H_{ij}(f) = \sum_{r=0}^{R} \alpha e^{2\pi},$$

The acoustic echoes retrieval (AER) problem

Estimating early (strong) acoustic reflections:

- their time of arrivals $\rightarrow$ TOAs Estimation
- their amplitude
  $\hookrightarrow$ closed-from knowing τ [?]



Note that an order of r

Taxonomy of Acoustic Echo Estimation

- based on the emitted signal knowledge:

Active approaches

- Signal is emitted and known
- Intrusive
- Single channel
- Methods: Least-Square estimation, Inverse Filtering (Equalization)
- Application: measurements, calibration, sonars, slam

Passive approaches

- Emitted signal is not known
- Not intrusive (for passive listening)
- Multichannel
- Methods:
  blind deconvolution problem *ill*-posed and *ill*-conditioned
  ↪ statistics, *sparsity* etc
- Application:
  Robot hearing (Table Top Scenario), Pre-processing step

Taxonomy of Acoustic Echo Estimation

- based on the estimated filter:

RIR-based approaches

1. RIRs are first estimated as SIMO BCE problem
2. Echoes extracted from first part of the RIRs with peak picking and disambiguation

Pros

- SIMO BCE is well studied (elegant framework)
- It works well is some scenarios and in practice
  $\hookrightarrow$ if not limitation

Cons

- Full RIR
- dependent of manually tuned peak picking
- Pathological issue (sampling and body-guard
- Complexity
- Non-negativity and sparsity not true

RIRs-agnostic approaches

1. Estimation directly in the echoes parameters space $\{\tau, \alpha\}$
   and direction of arrivals can be used instead

Performed with

- Cross-correlation
  on-grid, eg. EM, Acoustic Cameras
- Cross-relation with super-resolution
  off-grid, [?, ?]

Pro

- No need for full RIRs
- Sub-sampling accuracy
- Low complexity
- Sparsity and Non-negativity are respected

Cons

- Exploratory

AER as discrete SIMO BCE

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

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

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

5. Pick picking

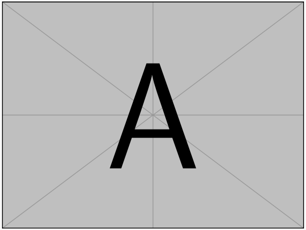
✓ [?] ✓ [?]
✓ [?] ✓ [?]

Limitations / bottleneck

Limitations

- Echoes are not necessarily “on grid”
- *Body guard* effect [**?**]

  $\longrightarrow$ low recall $\implies$ 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

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

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

Idea: Recover echoes by matching a finite number of frequencies

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

Instance of a **BLasso** problem [?] (Sliding Frank-Wolfe algorithm)

no Toeplitz matrix

Solutions is
a train of Dirac

anchor prevents
trivial solution

Experiments

- simulation data with ISM with Pyroomacoustics
- 1 source, 2 microphones, random room geometry
- Full RIRs
- 2 sources: broadband and speech
- 2 datasets: different SNR, different RT60

Methods

- BSN: Blind Sparse and Nonnegative SIMO BCE [?]
- IL1C: Iteratively-weighted ℓ_1 Constraint SIME BCE [?]
- Blaster: Proposed off-grid approach

Metrics

- RMSE
- Precision

Blaster- Results

Observation 1: Mapping from observation to echo is extremely difficult
Later echoes are not considered, may help

Observation 2: We have acoustic simulators
Acoustic simulators based on ISM

source position, room $\leftarrow$ reverberation elements $\leftarrow$

annotation for free

Observation 3: (Deep) Learning-based methods successful for localization
Echoes are strongly related to the source position

Idea: Use Deep Learning for AER

- Extend previous work on source localization for Echo Estimation
- Estimate the first echo TOA
  $\hookrightarrow$ simple case, but with important application in SSL

Lantern- Data & Models

Data

- train:
  ↪ artificially generated RIR
  ↪ white noise + noise
  ↪ instantaneous RTF
- test:
  ↪ artificially generated RIR
  ↪ white noise, speech + noise
  ↪ instantaneous RTF

Architecture

- models: MLP, CNN
- loss: Multi-class regression problem
  ↪ RMSE
  ↪ Gaussian regression + uncertainty
  ↪ Student Regression + uncertainty

Experiments

1. MLP
2. CNN
3. CNN + Noise
4. CNN + Gaussian
5. CNN + Student

Results

1. MLP
2. CNN
3. CNN + Noise
4. CNN + Gaussian
5. CNN + Student

Interim conclusion (2/4)

on Acoustic Echo Retrieval:

- Most of the literature is on Passive and RIR-based, with on-grid approaches
- On-grid approaches suffers by the off-grid nature of the echoes (complexity, sampling)

on Blaster:

✓ off-grid parameter-free which exploit dirac closed-form model (non negativity and sparsity)

✓ smaller RMSE due to super-resolution, better for small # of echoes

✗ source dependent and on number of echoes

✗ validate only on synthetic data

→ Multichannel and RTF-based extention

on Lantern:

✓ promising results for first echo estimation

✓ direct application for table top application

✗ difficult extention

✗ need for real data validation

Echo-aware Application

Audio signal processing and sound propagation

Sound propagation is [?]

$$x_i(t) = (h * s)(t)$$
$$h(t) = h^d(t) + h^e(t) + h^r(t)$$
$$H(f) = \sum_{r=0}^{R} \alpha_i^{(r)}(f) \mathrm{e}^{-\mathrm{i}2\pi\tau_i^{(r)} f_k}$$

- completely ignored
  $\hookrightarrow h(t) = 1$
- assumed direct path (*anechoic* case)
  $\hookrightarrow h(t) = h^d(t) + \varepsilon(t)$
- fully modeled (*reverberant* case)
  $\hookrightarrow h(t) = h^d(t) + h^e(t) + h^l(t) + \varepsilon(t)$
- early echoes (*multipath* case)
  $\hookrightarrow h(t) = h^d(t) + h^e(t) + \varepsilon(t)$

$\Leftarrow$ strong early reflection and strong reverberation level

- detrimentally affect typical Audio Scene Analysis algorithm
- undesired interfering source
- undesired position of the true sources (TDOA disambiguation)

What: echoes as sound repetition

- Sound Source Separation
- Speech Enhancement
  ↪ Dereverberation, Denoising, Room Equalization
- Speaker Verification

Where: echoes as new sound direction

- Sound Source Localization
- Microphone Calibration
- Room Geometry Reconstruction

How: echoes as element of sound propagation

- Blind Acoustic Channel Estimation
  as initialization for other methods
- Acoustic Measurements

Echo-aware Application

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The Picnic Scenario:

- Microphone close to a surface (table-top scenario)
- Clear definition of the echo
- One source

Mirage Array
How to access the *image* microphone

Each pair is augmented with echoes

1D SSL

- Estimate the TDOA between two microphones signals with GCC
- Map the TDOA to angles knowing the array geometry

2D SSL

- For each pair:
  1D-SSL
- Compute a global angular spectrum by “fusing” together the estimation of each pairs

Baseline:
GCC-PHAT on true microphones

Proposed Approach:
Using DNN-based TDOA estimation
problem: real value not estimation

Interim conclusion (3/4)

Echo-aware Audio Scene Analysis

- ✓ vast gamma of problems
  ↪ not limited to audio (e.g., seismology, medical imaging, astrophysics, etc.)
- ✓ between anechoic and reverberant propagation
- ✓ physical-interpretation (with virtual microphones)
- ✗ performance depending on the quality of the echo-estimation
  still very challenging task
- ✗ ....

`Mirage` & echo-aware SSL

- ✓ impossible 2D localization with only 2 microphones

`Separake` & echo-aware SSS

- nice

Echo-aware Dataset

Echo-aware Datasets

Data in audio signal processing

1. are necessary for validating (and learning) models
2. collecting real data is a not always possible
   annotation and recording require expertise, equipment and time
3. dataset of real data cannot be easily shared
   they do not generalize to different use-cases and scenarios (array, recording scenario)
4. simulated data are used instead: quantity, versatility, annotation easiness and "quality"

Echo-aware Data in audio signal processing

For SE : strong echoes, but not annotated
[?, ?, ?]

For RooGE : good geo. annotation, but no variety of acoustic scenarios
[?, ?, ?]

Echo Annotation

1. RIR estimation with ESS [?]
2. IPS with beacon
3. GUI for echo annotation
   Skyline, Matched Filter, Assisted Peak Picking
4. Refined position with Least Square optimization
5. iterate including ceiling (perfectly flat)

dEchorate realization

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TABLE RESULTS

dEchorate realization

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IMAGE SKYLINE

Room Geometry Estimation

Estimating the room geometry: shape, volume or reflector position)
from signal or form TOAs and labels

If TOAs annotation (label and value) are available, RooGE as Image Source Inversion:
For each wall/label:

1. TOA $\rightarrow$ image source position via 3D multilateration
2. image source position $\rightarrow$ reflector estimation via geometric reasoning

Other methods differs for prior knowledge and setup [?, ?, ?]

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IMAGE EXAMPLE HERE

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TABLES RESULTS HERE

Speech Enhancement

Improve the quality of a *target* sound source with respect:

- interferences, i.e. form other sources $\rightsquigarrow$ sound source separation
- background noise $\rightsquigarrow$ denoising
- reverberation $\rightsquigarrow$ dereverberation, room equalization

Spatial filtering via Beamformers

- Is a speech enhancement techniques for multichannel
- vs. Wiener Filtering, the target is distortionless
- in anechoic case, it correspond to delay-and-sum beamformer
- physical interpretation with steering vector based on DOA
- both in time and frequency domain

Echo-aware Speech Enhancement

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Beamforming: Delay and Sum

$$\mathbf{y}[l,k] = \mathbf{W}^{\mathsf{H}}\mathbf{x}[l,k]$$

STFT Signal Model

$$\mathbf{x}[l,k] = \mathbf{H}[k]\mathbf{s}[l,k] + \mathbf{n}[l,k]$$

Beamforming: Filter and Sum

$$\mathbf{y}[l,k] = \mathbf{W}^{\mathsf{H}}\mathbf{x}[l,k]$$

Beamforming in the STFT domain: apply filter and sum independently at each frequency bin

The PSD of various components
asd

Different Criteria and Solution

- DS
- MVDR - DP
- MVDR ReTF

IMAGE RESULTS

Interim conclusion (3/4)

`dEchorate` dataset for echo-aware signal processing

- designed for AER, SE and RooGE
- Geometrical annotation $\longleftrightarrow$ image source annotation $\longleftrightarrow$ Signal Annotation
- Measured Real RIRs and equivalent synt RIR
- also speech, noise, babble noise and different room conf (+fornitures)
- GUI, tools and code

Application
Echo Estimation

- Huge difference between real and simulated data

Room Geometry Reconstruction

- some annotation inconsistencies are noticed (but manually corrected)

Echo-aware Speech Enhancement

- a
- b

Conclusion

2D Outline

Thesis outline with projects