Linear and Parametric Microphone Array Processing

Part 1 - Introduction

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ICASSP 2013, Vancouver, Canada

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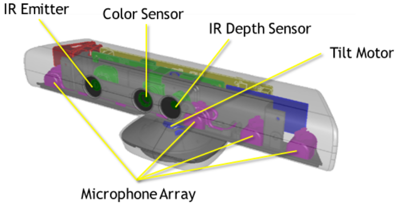

IR Emitter
Color Sensor
IR Depth Sensor
Tilt Motor
Microphone Array

Overview

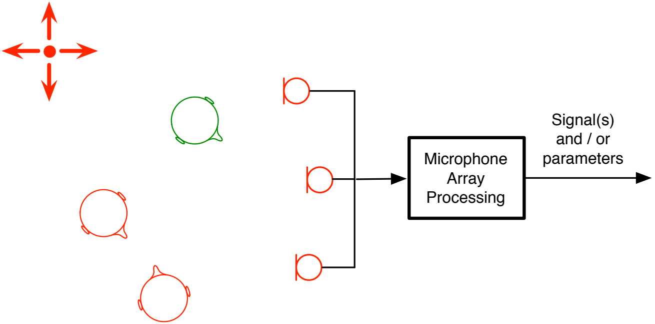
1. Introduction and Motivation

Problems we can (potentially) solve using microphone array processing:

- Extract desired sounds that are corrupted by interfering sounds
  - **Noise reduction**
  - **Reverberation reduction**
  - Echo reduction
- Localize sound sources
- Determine the number of (active) sound sources

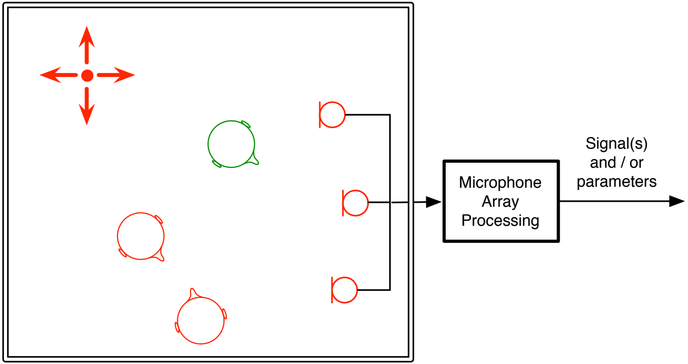
Applications:

- Hands-free communication systems
- Hands-free human-machine interfaces (e.g., TVs, smartphones)
- Teleconferencing systems
- Hearing-aid devices
- Assistive listening devices
- ...



Interferers:

- Spatially coherent noise (e.g., used to model sound sources)
- Spatially incoherent noise (e.g., used to model sensor noise)
- Diffuse noise (e.g., used to model reverberation, car noise, cocktail-party noise and babble noise)



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Why is microphone array processing so different from antenna array processing?

Challenges (to name a few):

- Speech signals are wideband and highly non-stationary
- Noise often has the same spectral characteristics as the desired sounds
- Room reverberation / diffuse sound field
- Time-varying spatial characteristics
- Number of sensors and placement is usually restricted
- The human ear has a very high dynamic range
- Knowing what is desired and what is undesired

AUDIO LABS

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Overview

2. Spatial Processing Approaches

We can divide existing approaches into three categories:

- **Linear Spatial Processing** A linear filter is applied to the observed microphone signals. The filter is based on, for example, the estimated second-order statistics of the observed and noisy signals. In many cases, estimates of the (relative) acoustic transfer functions are employed. Can be applied in both centralized and distributed manner.
- **Parametric Spatial Processing** A perceptually or physically motivated parametric sound field model is assumed. The model parameters such as the direction-of-arrival, position and signal-to-diffuse ratio are estimated using multiple microphones. Based on these parameters, a time and frequency dependent gain is computed and applied to a reference signal (e.g., one of the microphones or fixed beamformer).
- **Informed Spatial Processing** The main idea behind informed spatial filtering is to incorporate relevant information about the specific problem into the design of spatial filters and the estimation of the required statistics and/or propagation vector(s).

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Outline of today's tutorial:

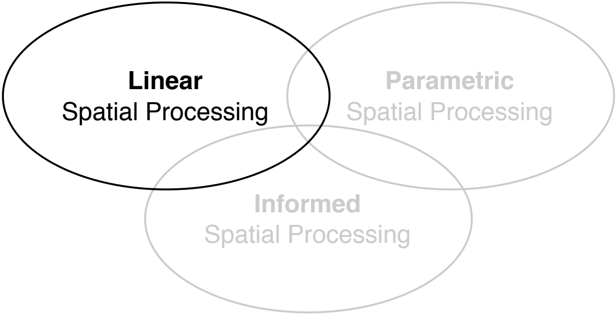

Figure: Different spatial processing approaches.

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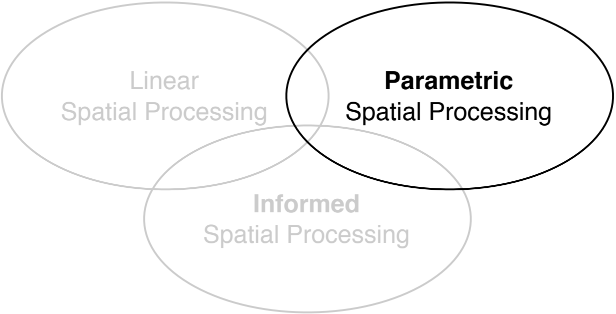

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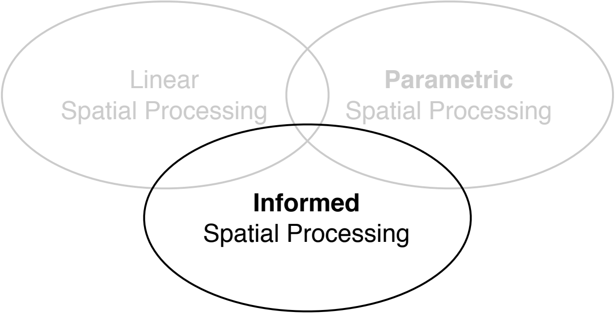

Figure: Different spatial processing approaches.

2. Spatial Processing Approaches

Different **objectives**:

- Estimate the anechoic signal as received by one of the microphones.
- Estimate the reverberant signal as received by one of the microphones (See, for example, [Gannot et al., 2001, Benesty et al., 2008, Benesty et al., 2011]).
- Estimate the signal provided by a *signal-independent beamformer* or *single-channel/multichannel equalizer* (See, for example, [Habets et al., 2010, Habets and Benesty, 2013]).
- ...

Different **optimization criteria**:

- Minimum mean squared error → Multichannel Wiener filter (MWF).
- Constrained minimization → Parametric MWF (a.k.a. speech-distortion weighted MWF).
- Constrained minimization → Minimum variance distortionless response (MVDR) beamformer.
- Constrained minimization → Linearly constrained minimum variance (LCMV) beamformer.

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Some important facts:

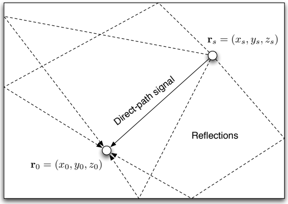
- All filters (expect for the LCMV) maximize the subband output signal-to-noise ratio.
- All filters (expect for the LCMV) are equal up to a frequency-dependent scaling factor.
- All filters are different in terms of the amount of noise reduction and speech distortion.
- Depending on the assumed propagation model, we can find different filter expressions such as, for example, the rank-1 multichannel Wiener filter.

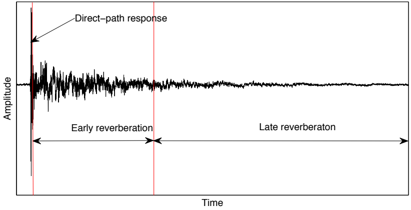
Overview

3.1 Room Impulse Response

Room impulse responses consist of:

- Direct path
- Early reflections → Haas effect, precedence effect and coloration
- Late reflections → can reduce speech intelligibility





Further reading: [Kuttruff, 2000].

3.1 Room Impulse Response

- Room impulse response:

$$h_{(\mathbf{r}_\mathrm{o},\mathbf{r}_\mathrm{s})}(t) = \sum_{i=1}^{\infty} g_i(t) * \delta(t - \tau_i),$$

  where τ_i denotes the time-of-arrival of the i-th reflection and $g_i(t)$ denotes the impulse response of the i-th reflection.

- Room transfer function:

$$H_{(\mathbf{r}_\mathrm{o},\mathbf{r}_\mathrm{s})}(\omega) = \sum_{i=1}^{\infty} G_i(\omega) \exp(-j\omega\tau_i).$$

  where $G(\omega)$ denotes the Fourier transform of $g_i(t)$.

- Statistical models have been proposed to model the RIR in [Polack, 1988, Jot et al., 1997] and the RTF in [Schroeder, 1962, Schroeder, 1987].

3.1 Room Impulse Response

One popular way to simulate RIRs is to use image sources [Allen and Berkley, 1979]:

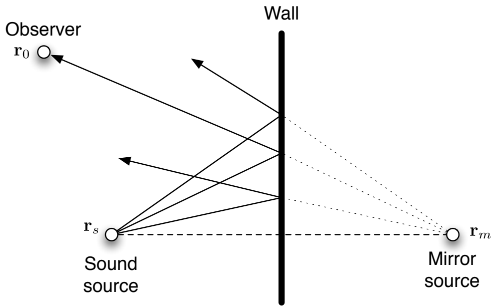


Figure: Source image method.

An implementation is available at:
`http://home.tiscali.nl/ehabets/rir_generator.html`

The energy decay curve (EDC) is defined as:

$$\mathrm{EDC}(t) = \int_{t}^{\infty} h^2_{(\mathbf{r}_\mathrm{O},\mathbf{r}_\mathrm{S})}(t')\,\mathrm{d}t'.$$

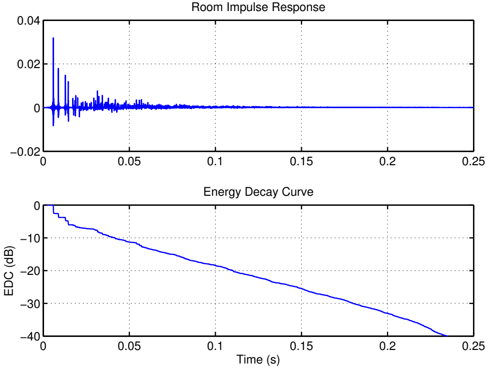


Figure: Example of an energy decay curve.

3.2 Reverberation Time

- The reverberation time quantifies the severity of reverberation within a room, and is often denoted by RT_{60}.
- It is defined as the time that is necessary for a 60 dB decay of the sound energy after switching off a sound source.

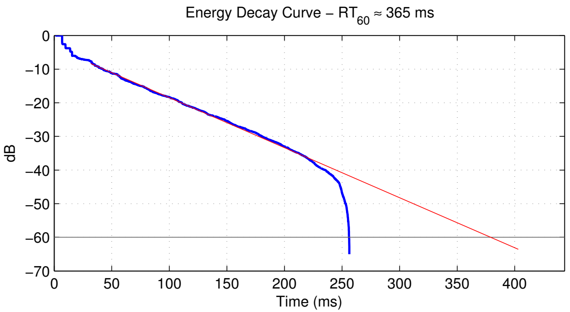


Figure: Determining the reverberation time.

3.3 Spatial Coherence

Definition of the (complex) spatial coherence:

$$\Gamma_{X_1X_2}(\omega) = \frac{\int_{\mathbb{A}} P_{X_1X_2}(\omega)\ d\mathbb{A}}{\int_{\mathbb{A}} \sqrt{P_{X_1}(\omega)P_{X_2}(\omega)}\ \mathrm{d}\mathbb{A}}.$$

The mean-squared coherence is given by $|\Gamma_{X_1X_2}(\omega)|^2$.

Coherent sound field:

$$\Gamma_{X_1X_2}(\omega) = \frac{P_{X_1X_2}(\omega)}{\sqrt{P_{X_1}(\omega)P_{X_2}(\omega)}} = e^{-j\,\frac{\omega}{c}\,d\cos(\phi)},$$

where $P_{X_1} = P_{X_2}$ and $P_{X_1X_2} = P_{X_1}e^{-j\,\frac{\omega}{c}\,d\cos(\phi)}$.

Incoherent sound fields:

$$\Gamma_{X_1X_2}(\omega) = 0,$$

because $P_{X_1X_2} = 0$.

Cylindrically isotropic sound field (2D diffuse) with $\mathrm{d}\mathbb{A} = r\ \mathrm{d}\phi$ and $A = 2\pi r$:

$$\Gamma_{X_1 X_2}(\omega) = \frac{1}{2\pi}\int_0^{2\pi} e^{-j\frac{\omega}{c}d\cos\phi}\ \mathrm{d}\phi$$
$$= J_0(\omega d/c),$$

where $J_0(\,\cdot\,)$ is the zero-order Bessel function of the first kind.

Spherically Isotropic sound field (3D diffuse) with $\mathrm{d}\mathbb{A} = r^2 sin(\phi)\ \mathrm{d}\phi\ \mathrm{d}\theta$ and $A = 4\pi r^2$:

$$\Gamma_{X_1 X_2}(\omega) = \frac{1}{4\pi r^2}\int_0^{2\pi}\int_0^{\pi} e^{-j\frac{\omega}{c}d\cos\phi} r^2 \sin(\phi)\ \mathrm{d}\phi\ \mathrm{d}\theta$$
$$= \frac{\sin(\omega d/c)}{\omega d/c}.$$

3.4 Simulators

- RIR generator:
  http://home.tiscali.nl/ehabets/rir_generator.html

- Signal generator (time-varying RIRs):
  http://home.tiscali.nl/ehabets/signal_generator.html

- Spherical microphone array RIR generator: [Jarrett et al., 2012]:
  http://home.tiscali.nl/ehabets/smirgen.html

  Note: This simulator can also be used as a mouth simulator!

- Spherical and cylindrical isotropic noise generator [Habets and Gannot, 2007]:
  http://home.tiscali.nl/ehabets/publications/Habets2007b.html

- Generating nonstationary multisensor signals (such as babble speech) that exhibit a pre-defined spatial coherence [Habets et al., 2008]:
  http://home.tiscali.nl/ehabets/publications/Habets2008.html

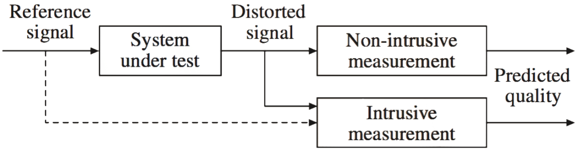
Overview

4. Evaluation

Quality assessment by:

1. **Subjective listening test**
   - Extremely valuable but time consuming and expensive.
   - The test needs to be carefully designed.

2. **Objective quality measures**
   - Quantify the quality by measuring a “distance” between the original and processed signals.
   - Objective measure are most useful when there is a high correlation with subjective listening test results.
   - For that reason, many objective measures exploit aspects of the auditory system.



4.1 Subjective Listening Test

The mean opinion score (MOS) is a widely used and accepted criterion for speech coder assessment. Although not very suitable for the evaluation of speech enhancement algorithms it is often used.

Rating	Speech Quality	Level of Distortion
5	Excellent	Imperceptible
4	Good	Just perceptible, but not annoying
3	Fair	Perceptible and slightly annoying
2	Poor	Annoying, but not objectionable
1	Bad	Very annoying and objectionable

Table: Mean opinion score scale

4.1 Subjective Listening Test

ITU-T P.835 was recommended specifically for the evaluation of speech enhancement algorithms.

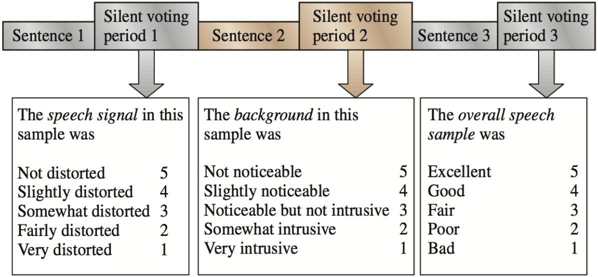


Figure: The ITU-T P-835's scheme for evaluating the subjective quality of speech enhancement algorithms. Each test sample is comprised of three subsamples, where each subsample is followed by a silent voting period.

4.2 Intrusive Objective Quality Measures

For noise reduction:

- Mean-squared error (MSE)
- Signal to noise ratio (SNR)
- Segmental SNR - average SNR in dB across frames (geometric mean)
- Log-spectral distance (LSD)
- Itakura-Saito (IS) - based on linear prediction coefficients
- Noise reduction factor
- Speech reduction factor
- ...

In the context of array processing (subband/fullband):

- Array gain
- Directivity factor
- Directivity index
- White noise gain (be careful - higher values are better!)
- ...

These measures are often computed over short-time frames and subsequently averaged across frames.

4.2 Intrusive Objective Quality Measures

Perceptually motivated quality measures:

- Weighted segmental SNR (computed in the frequency-domain)
- Weighted spectral slope (WSS)
- Bark spectral distortion (BSD)
- Perceptual evaluation of speech quality (PESQ)
  ITU Recommendation ITU-T P.862
- Perceptual speech quality measure (PSQM)
  ITU Recommendation ITU-T P.861
- Perceptual evaluation of audio quality (PEAQ)
  ITU Recommendation BS.1387
- Low complexity speech quality assessment (LCQA)
- ...

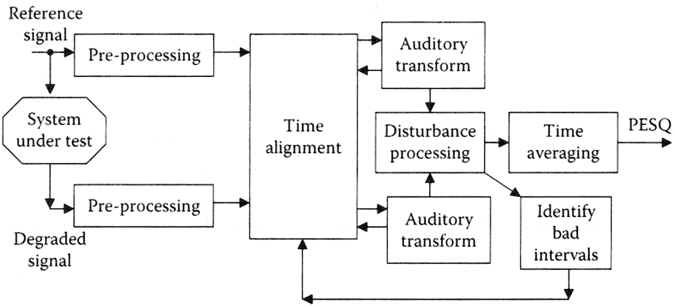


Figure: Block diagram PESQ measure [Loizou, 2007]

4.2 Intrusive Objective Quality Measures

Designed to evaluate how much reverberation is present / reduced.

Signal-based:

- Signal to reverberation ratio
- Segmental signal to reverberation ratio [Naylor et al., 2010]
- Reverberation decay tail (RDT) [Wen and Naylor, 2006]
- Speech to reverberation modulation energy ratio (SRMER) [Falk et al., 2010]
- ...

Channel-based:

- Reverberation time
- Direct to reverberation ratio
- Early decay time (RT_{60} measured over the first 10 dB of the decay)
- Early to late reverberation ratio (a.k.a. Clarity or Klarheitsmass)
- Early to total energy ratio (a.k.a. Definition or Deutlichkeit)
- ...

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