Linear and Parametric Microphone Array Processing

Part II: Linear Spatial Processing

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Outline

Linear Spatial Noise Reduction Techniques I

Families of Methods

1. Fixed beamforming Combine the microphone signals using a time-invariant filter-and-sum operation (data-independent)

   [Jan and Flanagan, 1996]; [Doclo and Moonen, 2003].

2. Blind Source Separation (BSS) Considers the received signals at the microphones as a mixture of all sound sources filtered by the RIRs. Utilizes Independent Component Analysis (ICA) techniques

   [Makino et al., 2007]; TRINICON, [Buchner et al., 2004].

3. Adaptive Beamforming Combine the spatial focusing of fixed beamformers with adaptive suppression of (spectrally and spatially time-varying) background noise

   General reading: [Cox et al., 1987]; [Van Veen and Buckley, 1988]; [Van Trees, 2002].

Linear Spatial Noise Reduction Techniques II

Some Criteria

1. Adaptive optimization [Sondhi and Elko, 1986]; [Kaneda and Ohga, 1986]; [Brandstein and Ward, 2001].
2. Minimum variance distortionless response (MVDR) and GSC [Van Compernolle, 1990]; [Affes and Grenier, 1997]; [Nordholm et al., 1993]; [Hoshuyama et al., 1999]; [Gannot et al., 2001]; [Herbordt, 2005]; [Gannot and Cohen, 2008].
3. Minimum mean square error (MMSE) - GSVD based spatial Wiener filter [Doclo and Moonen, 2002a].
4. Speech distortion weighted multichannel Wiener filter (SDW-MWF) [Doclo and Moonen, 2002b]; [Spriet et al., 2004]; [Doclo et al., 2005].
5. Maximum signal to noise ratio (SNR) [Warsitz and Haeb-Umbach, 2007].
6. Linearly constrained minimum variance (LCMV) [Markovich et al., 2009].

Linear Spatial Noise Reduction Techniques III

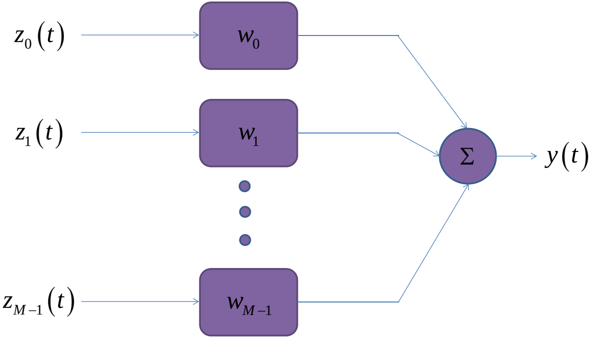
Some Books

1. Acoustic signal processing for telecommunication [Gay and Benesty, 2000].
2. Microphone Arrays: Signal Processing Techniques and Applications [Brandstein and Ward, 2001].
3. Speech Enhancement [Benesty et al., 2005].
4. Blind speech separation [Makino et al., 2007].
5. Microphone Array Signal Processing [Benesty et al., 2008a].
6. Springer handbook of speech processing [Benesty et al., 2008b].
7. Handbook on array processing and sensor networks [Haykin and Liu, 2010].
8. Speech processing in modern communication: Challenges and perspectives [Cohen et al., 2010].

Spatial Filters

Beamforming: Filter and Sum

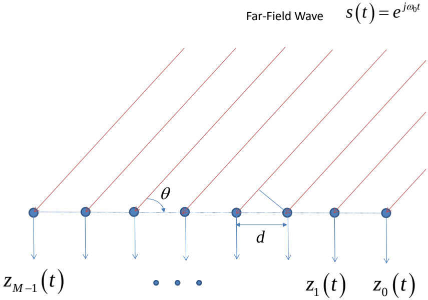
$$y(t) = \mathbf{w}^H(t)\mathbf{z}(t).$$



$\mathbf{w}$: $M \times 1$ beamforming vector of filters (or just gains).

Array Processing

Preliminaries



Narrow-band Signal

$$
\begin{aligned}
y(t) &= \sum_{m=0}^{M-1} w_m^* e^{j\omega_0(t-\tau_m)} \\
&= e^{j\omega_0 t} \sum_{m=0}^{M-1} w_m^* e^{-j\omega_0 \left(\frac{d\cos(\theta)}{c}\right)m} \\
&= e^{j\omega_0 t} \sum_{m=0}^{M-1} w_m^* e^{-j2\pi \frac{d}{\lambda_0}\cos(\theta)m}
\end{aligned}
$$

Beampattern is the DTFT of the weights

$$
y(t) = e^{j\omega_0 t} W\left(\frac{d}{\lambda_0}; \cos(\theta)\right)
$$

The Delay & Sum Beamformer

Uniform Linear Array (ULA)

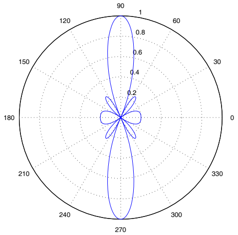
- $w_m = \frac{1}{M};\ m = 0, \ldots, M-1.$
- For simplicity, assume symmetric array.
- Steered to $\cos(\theta_0)$.
- Beampattern:

$$B(\theta) = \frac{1}{M} \cdot \frac{\sin\left(\frac{M}{2} 2\pi \frac{d}{\lambda_0}(\cos(\theta) - \cos(\theta_0))\right)}{\sin\left(\frac{1}{2} 2\pi \frac{d}{\lambda_0}(\cos(\theta) - \cos(\theta_0))\right)}$$

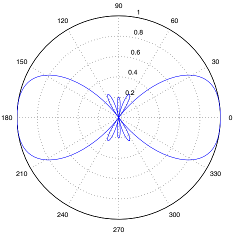
Beamformers

- Discriminate between angles.
- Can be steered by setting $\mathbf{w}$.
- Depends on the ratio $\frac{d}{\lambda_0}$.

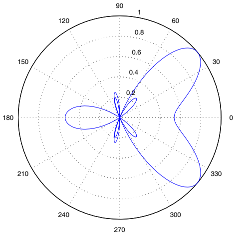
Beampattern



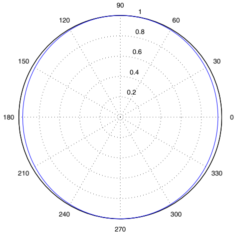
(a) $\theta_0 = 90^o$; $\frac{d}{\lambda_0} = \frac{1}{2}$



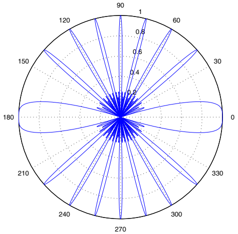
(b) $\theta_0 = 0^o$; $\frac{d}{\lambda_0} = \frac{1}{2}$



(c) $\theta_0 = 40^o$; $\frac{d}{\lambda_0} = \frac{1}{2}$

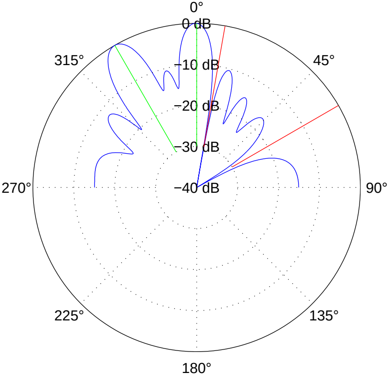


(d) $\theta_0 = 90^o$; $\frac{d}{\lambda_0} = \frac{1}{32}$



(e) $\theta_0 = 90^o$; $\frac{d}{\lambda_0} = \frac{4}{1}$

Additional Control on the Beampattern



- 10 microphone uniform linear array.
- 2 Desired sources in green and 2 interfering sources in red.
- Can be obtained by applying the LCMV criterion.

Directivity and White Noise Gain (WNG) [Van Trees, 2002] I

Definitions

- Propagation vector: $\mathbf{u} = \left[\, \sin(\theta)\cos(\phi)\ \sin(\theta)\sin(\phi)\ \cos(\theta) \,\right]^T$.
- Beampattern: $B(\phi, \theta)$.
- Beampower: $P(\phi, \theta) = |B(\phi, \theta)|^2$.

Directivity

- Assume that desired response is normalized: $P(\phi_0, \theta_0) = 1$.
- $D = \left(\frac{1}{4\pi} \int_0^{\pi} \int_0^{2\pi} \sin(\theta) P(\phi, \theta) d\phi d\theta \right)^{-1}$.
- Directivity Index: $DI = 10 \log_{10}(D)[\text{dB}]$.
- Maximum Directivity for ULA with $d = \frac{\lambda}{2}$ is M. It is achieved by the delay & sum beamformer.

Directivity and White Noise Gain (WNG) [Van Trees, 2002] II

White Noise Gain

- SNR improvement for spatially white input: $A_{\mathbf{w}} = \frac{\mathrm{SNR_{out}}}{\mathrm{SNR_{in}}} = \|\mathbf{w}\|^{-2}$.
- Sensitivity to array weight imperfections and sensor misalignment is $T_{se} = \frac{1}{A_{\mathbf{w}}} = \|\mathbf{w}\|^2$ (hence, large WNG is better).

Maximum Directivity [Parsons, 1987]

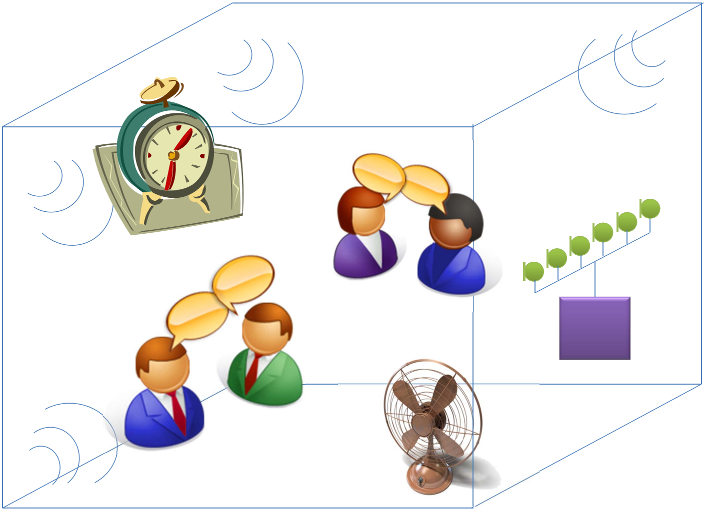
- MVDR criterion for diffuse noise field: super-directive beamformer.
- Obtained for linear endfire array with vanishingly small inter-sensor distance ($d \to 0$)!
- Maximum achievable directivity is M^2.
- In that case $T_{se} \to \infty$ [Gilbert and Morgan, 1955] (see extention AASP-L4, Levin, Gannot and Habets).
- Robust design limiting the sensitivity exists [Cox et al., 1986].
- Forms the basis of differential microphone arrays [Elko, 1996].

From Geometry to Linear Algebra

Array Design for Speech Propagating in Acoustic Environments

- Beampatterns:
  Array response as a function of the angle of arrival (AoA).
- In reverberant environments (especially for low DRR), sound propagation is more involved than merely the AoA.
- The steering vector (comprised of the AoA) generalizes to acoustic transfer function (ATF).
- The ATF summarizes all arrivals of the speech signals.
- The vector of received signals is treated as a vector in an abstract linear space.
- Linear Algebra methods are utilized to construct beamformers.
- AoA becomes less prominent.

A Noisy Example



Multiple Wideband Signals (e.g. Speech)

Short-Time Fourier Transform (STFT) - Multiplicative Transfer Function (MTF) Approximation

$t \overset{\text{STFT}}{\Longrightarrow} \{\ell, k\}$; Convolution $\overset{\text{STFT}}{\Longrightarrow}$ Multiplication (for long enough frames).

Microphone Signals ($m = 0, \ldots, M-1$):

$$z_m(\ell, k) = \sum_{j=1}^{P_d} s_j^d h_{jm}^d + \sum_{j=1}^{P_i} s_j^i h_{jm}^i + \sum_{j=1}^{P_n} s_j^n h_{jm}^n + n_m$$

Vector Formulation

$$\mathbf{z}(\ell, k) = \mathbf{H}^d \mathbf{s}^d + \mathbf{H}^i \mathbf{s}^i + \mathbf{H}^n \mathbf{s}^n + \mathbf{n} \triangleq \mathbf{H}\mathbf{s} + \mathbf{n}.$$

$$P = P_d + P_i + P_n \ \leq M$$

Beamforming in the STFT Domain

Apply filter & sum beamforming independently for each frequency bin.

Power Spectral Density (PSD)

Microphone Signals

$$\mathbf{z}(\ell, k) = \mathbf{H}^d \mathbf{s}^d + \mathbf{H}^i \mathbf{s}^i + \mathbf{H}^n \mathbf{s}^n + \mathbf{n} \triangleq \mathbf{H}\mathbf{s} + \mathbf{n}$$

The PSD of the Various Components:

- Stationary Sources: $\mathbf{\Phi}_{zz}^{\mathrm{stat}} = \mathbf{H}^n \mathbf{\Phi}_{s^n s^n} \left(\mathbf{H}^n\right)^H + \mathbf{\Phi}_{nn}$.
- Constraints Sources:

$$\mathbf{H}\mathbf{\Phi}_{ss}\mathbf{H}^H \triangleq \mathbf{H}^d \mathbf{\Phi}_{s^d s^d} \left(\mathbf{H}^d\right)^H + \mathbf{H}^i \mathbf{\Phi}_{s^i s^i} \left(\mathbf{H}^i\right)^H + \mathbf{H}^n \mathbf{\Phi}_{s^n s^n} \left(\mathbf{H}^n\right)^H.$$

- Microphone Signals: $\mathbf{\Phi}_{zz}(\ell, k) = \mathbf{H}\mathbf{\Phi}_{ss}\mathbf{H}^H + \mathbf{\Phi}_{nn}$.
- Noise+Interference Sources:

$$\mathbf{\Phi}_{vv}(\ell, k) \triangleq \mathbf{H}^i \mathbf{\Phi}_{s^i s^i} \left(\mathbf{H}^i\right)^H + \mathbf{H}^n \mathbf{\Phi}_{s^n s^n} \left(\mathbf{H}^n\right)^H + \mathbf{\Phi}_{nn}$$

Linearly Constrained Minimum Variance Beamformer

[Er and Cantoni, 1983]; [Van Veen and Buckley, 1988]

LCMV Criterion

- $y(\ell, k) = \mathbf{w}^H(\ell, k)\mathbf{z}(\ell, k)$.
- Let $\mathbf{\Phi}_{nn} = E\{\mathbf{n}\mathbf{n}^H\}$ be the $M \times M$ correlation matrix of the unconstraint sources.
- Minimize noise power $\mathbf{w}^H \mathbf{\Phi}_{nn} \mathbf{w}$
  Such that a linear constraint set is satisfied: $\mathbf{C}^H\mathbf{w} = \mathbf{g}$.
- $\mathbf{C}$: $M \times P$ constraints matrix.
- $\mathbf{g}$: $P \times 1$ response vector.

Closed-form Solution

$$\mathbf{w}(\ell, k) = \mathbf{\Phi}_{nn}^{-1}\mathbf{C}\left(\mathbf{C}^H\mathbf{\Phi}_{nn}^{-1}\mathbf{C}\right)^{-1}\mathbf{g}$$

Linearly Constrained Minimum Power (LCMP) Beamformer

[Van Trees, 2002]

LCMV vs. LCMP

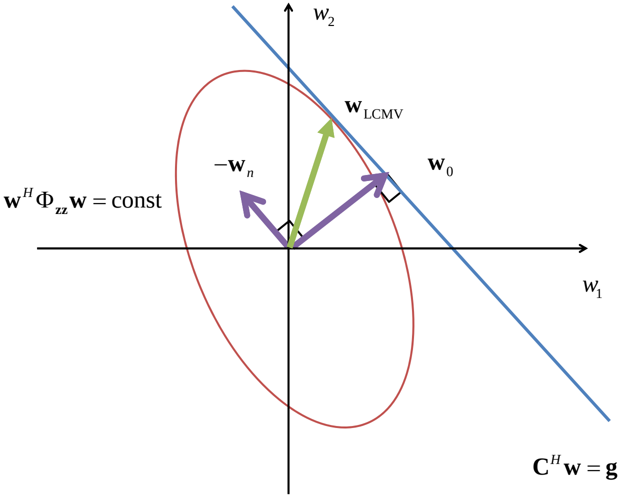
- Assume $\mathbf{C} = \mathbf{H}$ (all directional signals constrained).

$$\begin{aligned}
\mathbf{w}_{\mathrm{LCMP}} &= \underset{\mathbf{w}}{\operatorname{argmin}}\{\mathbf{w}^H \boldsymbol{\Phi}_{zz}\mathbf{w} \text{ s.t. } \mathbf{H}^H\mathbf{w} = \mathbf{g}\} \\
&= \underset{\mathbf{w}}{\operatorname{argmin}}\{\mathbf{w}^H (\mathbf{H}\boldsymbol{\Phi}_{ss}\mathbf{H}^H + \boldsymbol{\Phi}_{nn})\mathbf{w} \text{ s.t. } \mathbf{H}^H\mathbf{w} = \mathbf{g}\} \\
&= \underset{\mathbf{w}}{\operatorname{argmin}}\{\mathbf{g}^H \boldsymbol{\Phi}_{ss}\mathbf{g} + \mathbf{w}^H \boldsymbol{\Phi}_{nn}\mathbf{w} \text{ s.t. } \mathbf{H}^H\mathbf{w} = \mathbf{g}\} \\
&= \underset{\mathbf{w}}{\operatorname{argmin}}\{\mathbf{w}^H \boldsymbol{\Phi}_{nn}\mathbf{w} \text{ s.t. } \mathbf{H}^H\mathbf{w} = \mathbf{g}\} = \mathbf{w}_{\mathrm{LCMV}}
\end{aligned}$$

- If $\mathbf{H}$ is not accurately estimated, the LCMP beamformer exhibits self-cancellation and hence severe speech distortion.
- It is quite common in the literature to use only the term LCMV for both beamformers.

LCMV Minimization

Graphical Interpretation [Frost III, 1972]



The Minimum Variance Distortionless Beamformer

[Affes and Grenier, 1997]; [Hoshuyama et al., 1999]; [Gannot et al., 2001]

Beamformer Design:

- One desired signal $\Rightarrow$ Single constraint ($P = 1$).
- "Steer a beam" to desired source and minimize other directions.
- $\mathbf{C} = \mathbf{h}^d; \quad \mathbf{g} = 1.$

Closed-form Solution (MPDR eq. MVDR):

$$\mathbf{w}(\ell, k) = \frac{\mathbf{\Phi}_{zz}^{-1}\mathbf{h}^d}{(\mathbf{h}^d)^H \mathbf{\Phi}_{zz}^{-1}\mathbf{h}^d} = \frac{\mathbf{\Phi}_{nn}^{-1}\mathbf{h}^d}{(\mathbf{h}^d)^H \mathbf{\Phi}_{n}^{-1}\mathbf{h}^d}$$

Output signal:

$$y = s^d + \text{residual noise and interference signals}$$

Multiple Speech Distortion Weighted Multichannel Wiener Filter (MSDW-MWF)[Markovich-Golan et al., 2012b]

Notation (Reminder)

- Received signals: $\mathbf{z}(\ell, k) = \mathbf{H}\mathbf{s} + \mathbf{n}$.
- $P < M$ constrained sources: $\mathbf{s}(\ell, k) \triangleq \begin{bmatrix} s_1 & \cdots & s_P \end{bmatrix}^T$ and respective ATFs: $\mathbf{H}(\ell, k) \triangleq \begin{bmatrix} \mathbf{h}_1 & \cdots & \mathbf{h}_P \end{bmatrix}$.
- Sources covariance matrix: $\mathbf{\Phi}_{ss} = \text{diag}\left\{\phi_{s_1 s_1}, \ldots, \phi_{s_P s_P}\right\}$.
- Microphones covariance matrix: $\mathbf{\Phi}_{zz} \triangleq \mathbf{H}\mathbf{\Phi}_{ss}\mathbf{H}^\dagger + \mathbf{\Phi}_{nn}$.

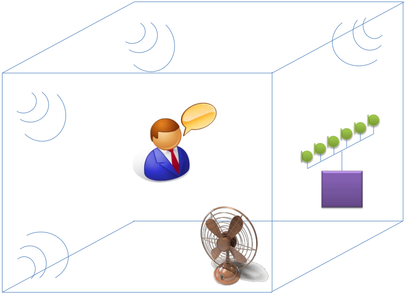
MSDW-MWF

- Control the distortion of each individual source.
- Minimize the weighted mean square error (MSE).
- Desired response for all constrained signals: $d(\ell, k) \triangleq \mathbf{g}^H \mathbf{s}(\ell, k)$.
- The beamformer output: $y(\ell, k) = \mathbf{w}^H \mathbf{z}(\ell, k)$.
- MSE: $\mathrm{E}\left\{|d(\ell) - y(\ell)|^2\right\}$.

Speech enhancement with a Single Source I

Speech Distortion Weighted Multichannel Wiener Filter (SDW-MWF)

[Doclo and Moonen, 2002b]; [Spriet et al., 2004]; [Doclo et al., 2005]



Speech enhancement with a Single Source II

Speech Distortion Weighted Multichannel Wiener Filter (SDW-MWF)

[Doclo and Moonen, 2002b]; [Spriet et al., 2004]; [Doclo et al., 2005]

The Multichannel Wiener Filter (MWF) Criterion

$$J_w \triangleq \mathrm{E}\left\{ |d(\ell) - y(\ell)|^2 \right\} = \left| g - (\mathbf{h}^d)^H \mathbf{w} \right|^2 \phi_{s^d s^d} + \mathbf{w}^H \mathbf{\Phi}_{nn} \mathbf{w}$$

The Speech Distortion Weighted (SDW)-MWF Criterion

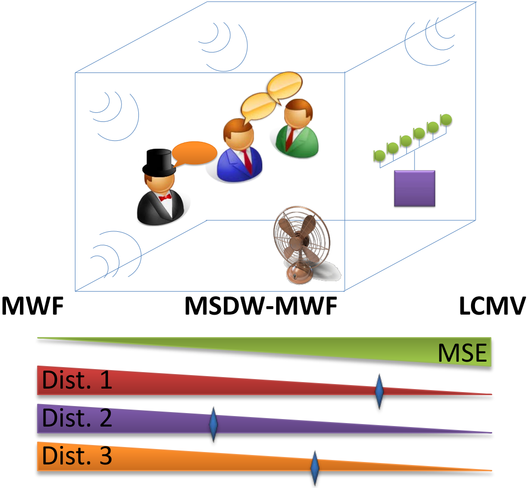
$$J_{\text{SDW-MWF}} = \left| g - (\mathbf{h}^d)^H \mathbf{w} \right|^2 \phi_{s^d s^d} + \mu \mathbf{w}^H \mathbf{\Phi}_{nn} \mathbf{w}$$

The Speech Distortion Weighted (SDW)-MWF Solution

$$\mathbf{w} = \frac{\phi_{s^d s^d} \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d}{\mu + \phi_{s^d s^d} (\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d} g$$

Speech Enhancement with Multiple Sources I

[Markovich-Golan et al., 2012b]



Speech Enhancement with Multiple Sources II

[Markovich-Golan et al., 2012b]

The MSDW-MWF Criterion

$$J_{\text{MSDW-MWF}} \triangleq \left(\mathbf{g} - \mathbf{H}^H \mathbf{w}\right)^H \mathbf{\Lambda} \mathbf{\Phi}_{ss} \left(\mathbf{g} - \mathbf{H}^H \mathbf{w}\right) + \mathbf{w}^H \mathbf{\Phi}_{nn} \mathbf{w}$$

- Diagonal weights matrix: $\mathbf{\Lambda} \triangleq \text{diag}\left\{\lambda_1, .., \lambda_P\right\}$.

MSDW-MWF Beamformer

$$\mathbf{w} \triangleq \left(\mathbf{H} \mathbf{\Lambda} \mathbf{\Phi}_{ss} \mathbf{H}^H + \mathbf{\Phi}_{nn}\right)^{-1} \mathbf{H} \mathbf{\Lambda} \mathbf{\Phi}_{ss} \mathbf{g}$$

Special Cases of $\boldsymbol{\Lambda}$

MWF

- $\boldsymbol{\Lambda} = \mathbf{I}$.
- $\mathbf{w} = \boldsymbol{\Phi}_{zz}^{-1}\mathbf{H}\boldsymbol{\Phi}_{ss}\mathbf{g}$.

SDW-MWF (Reminder: Single Source of Interest)

- $\boldsymbol{\Lambda} = \mu^{-1}$.
- $\mathbf{w} = \left(\mathbf{h}^d \phi_{s^d s^d} (\mathbf{h}^d)^H + \mu \boldsymbol{\Phi}_{nn}\right)^{-1} \mathbf{h}^d \phi_{s^d s^d} g$.
- $\lim_{\mu\to 0} \mathbf{w} = \frac{\boldsymbol{\Phi}_{nn}^{-1}\mathbf{h}^d}{(\mathbf{h}^d)^H \boldsymbol{\Phi}_{nn}^{-1}\mathbf{h}^d} g$ (MVDR eq. MPDR).

LCMV

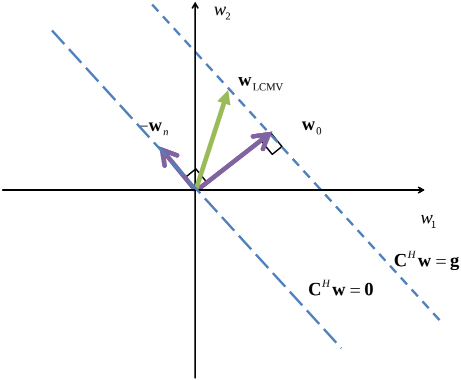
- $\boldsymbol{\Lambda} = \mu^{-1}\boldsymbol{\Phi}_{ss}^{-1}$.
- $\lim_{\mu\to 0} \mathbf{w} = \boldsymbol{\Phi}_{nn}^{-1}\mathbf{H}\left(\mathbf{H}^H\boldsymbol{\Phi}_{nn}^{-1}\mathbf{H}\right)^{-1}\mathbf{g}$ (LCMV eq. LCMP).

The Generalized Sidelobe Canceller Implementation

For Constrained Minimization [Griffiths and Jim, 1982]

Split the Beamformer

- $\mathbf{w} = \mathbf{w}_0 - \mathbf{w}_n$.
- Constraints Subspace: $\mathbf{w}_0 \in \mathrm{Span}\{\mathbf{C}\}$.
- Null Subspace: $\mathbf{w}_n \in \mathcal{N}\{\mathbf{C}\}$.
- $\mathbf{w}_n \triangleq \mathbf{Bq}$.
- $\mathbf{B}$: $M \times (M - P)$ matrix. Spans the Null Subspace.
- $\mathbf{q}$: vector of $M - P$ filters.
- $\Rightarrow \mathbf{w} = \mathbf{w}_0 - \mathbf{Bq}$.



The Generalized Sidelobe Canceller Implementation

GSC Output

$$y = \mathbf{w}_0^H \mathbf{z} - \mathbf{q}^H \underbrace{\mathbf{B}^H \mathbf{z}}_{\mathbf{u}(\ell,k)}$$

Constraints Subspace ($\mathbf{w}_0 \in \mathrm{Span}\{C\}$):

$$\mathbf{w}_0(\ell, k) \triangleq \mathbf{C}\left(\mathbf{C}^H \mathbf{C}\right)^{-1} \mathbf{g}$$

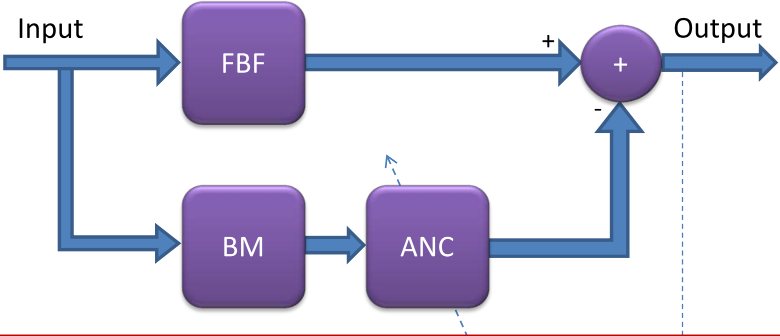
Null Subspace (columns of **B** span $\mathcal{N}\{C\}$):

$$\mathbf{B}(\ell, k) \triangleq \mathbf{I}_{\mathrm{M}\times\mathrm{M}} - \mathbf{C}\left(\mathbf{C}^H \mathbf{C}\right)^{-1} \mathbf{C}^H; \ (\text{verify } \mathbf{B}^H \mathbf{C} = \mathbf{0}).$$

Noise Cancelling Filters (orthogonality principle):

$$E\left\{\mathbf{u}\left(\mathbf{z}^H \mathbf{w}_0 - \mathbf{u}^H \mathbf{q}\right)\right\} \Rightarrow \mathbf{q}(\ell, k) = \left(\mathbf{B}^H \mathbf{\Phi}_{zz} \mathbf{B}\right)^{-1} \mathbf{B}^H \mathbf{\Phi}_{zz} \mathbf{w}_0$$

The GSC Structure [Griffiths and Jim, 1982]



GSC Blocks

- Fixed beamformer (FBF) - satisfies the constraints ($\mathbf{w}_0$).
- Blocking matrix (BM) - generates $M - P$ unconstrained signals ($\mathbf{B}$).
- Noise canceller (ANC) - adaptively (LMS) suppresses the residual noise utilizing $M - P$ degrees of freedom (DoF) ($\mathbf{q}$) [Widrow et al., 1975]; [Shynk, 1992].

GSC Implementation of the MVDR Beamformer

Blocks [Griffiths and Jim, 1982]:

$$\mathbf{w}_0(\ell, k) = \frac{\mathbf{h}^d}{\|\mathbf{h}^d\|^2}$$

$$\mathbf{B}(\ell, k) \triangleq \mathbf{I}_{\mathrm{M}\times\mathrm{M}} - \frac{\mathbf{h}^d \left(\mathbf{h}^d\right)^H}{\|\mathbf{h}^d\|^2}$$

$$\mathbf{q}(\ell, k) = \left(\mathbf{B}^H \mathbf{\Phi}_{zz} \mathbf{B}\right)^{-1} \mathbf{B}^H \mathbf{\Phi}_{zz} \mathbf{w}_0$$

$\mathbf{q}(\ell, k)$ can be recursively updated using the LMS algorithm [Shynk, 1992].

The Relative Transfer Function GSC (TF-GSC)

Relax Dereverberation Requirement [Gannot et al., 2001]

Modified Constraint Set:

$$\mathbf{C}(\ell, k) = \mathbf{h}^d(\ell, k); \quad \tilde{\mathbf{g}}(\ell, k) = (h_0^d(\ell, k))^*$$

$$\Rightarrow (\mathbf{h}^d(\ell, k))^H \mathbf{w} = (h_0^d(\ell, k))^*$$

Equivalent to:

$$\tilde{\mathbf{C}}(\ell, k) = \tilde{\mathbf{h}}^d(\ell, k) \triangleq \frac{\mathbf{h}^d}{h_0^d} = \left[1 \ \frac{h_1^d}{h_0^d} \ \ldots \ \frac{h_{M-1}^d}{h_0^d} \right]^T$$

$$\mathbf{g}(\ell, k) = 1.$$

The Relative Transfer Function

$\tilde{\mathbf{h}}^d(\ell, k)$ - The ratio of all ATFs to the reference ATF (#0 in this case).

The Transfer Function GSC utilizing RTF I

[Gannot et al., 2001]

FBF:

$$\mathbf{w}_0(\ell, k) = \tilde{\mathbf{h}}^d / \|\tilde{\mathbf{h}}^d\|^2$$

Blocking matrix

- Noise reference signals: $\mathbf{u} = \mathbf{B}^H \mathbf{z}$.
- Efficient implementation of the BM with $M - 1$ filters exists.

$$\mathbf{B}(\ell, k) = \begin{bmatrix} -(\tilde{h}_1^d)^* & -(\tilde{h}_2^d)^* & \dots & -(\tilde{h}_{M-1}^d)^* \\ 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ & \dots & \ddots & \\ 0 & 0 & \dots & 1 \end{bmatrix}$$

Compactly, $u_0 = 0$; $u_m = z_m - \tilde{h}_m^d z_0$, $m \neq 0$.

The Transfer Function GSC utilizing RTF II

[Gannot et al., 2001]

Output signal:

$$y(\ell, k) = \underbrace{h_0^d s^d}_{\tilde{s}_0^d(\ell,k)} + \text{residual noise and interference signals}$$

Tradeoff:

Noise reduction is sacrificed if dereverberation is required [Habets et al., 2010].

Multi-Constraint Beamformer

Based on LCMV Beamforming [Markovich et al., 2009]

Applications:

- Conference call scenario with multiple participants.
- Hands-free cellular phone conversation in a car environment with several passengers.
- Cocktail Party scenario, in which desired conversation blend with many simultaneous conversations.

Problem Formulation (Reminder):

$$\mathbf{z} = \mathbf{H}^d \mathbf{s}^d + \mathbf{H}^i \mathbf{s}^i + \mathbf{H}^n \mathbf{s}^n + \mathbf{n}$$

GSC Formulation

GSC Implementation of the LCMV (exists [Breed and Strauss, 2002])

$$\mathbf{w} = \mathbf{w}_0 - \mathbf{B}\mathbf{q}$$

Fixed Beamformer (in Constraints Subspace)

$$\mathbf{w}_0 = \mathbf{C}\left(\mathbf{C}^H\mathbf{C}\right)^{-1}\mathbf{g}$$

Blocking Matrix (in Constraints Null Subspace)

$$\mathbf{B} = \mathbf{I}_{M\times M} - \mathbf{C}\left(\mathbf{C}^H\mathbf{C}\right)^{-1}\mathbf{C}^H$$

Can be efficiently implemented: $(M-P)\times P$ filters [Markovich-Golan et al., 2012a].

Noise Canceler

$$\mathbf{q} = \left(\mathbf{B}^H\mathbf{\Phi}_{zz}\mathbf{B}\right)^{-1}\mathbf{B}^H\mathbf{\Phi}_{zz}(\ell,k)\mathbf{w}_0$$

The Constraints Set

Original

$$\mathbf{C} \triangleq \mathbf{H} = \left[\mathbf{H}^d \ \mathbf{H}^i \ \mathbf{H}^n \right]$$

$$\mathbf{g} \triangleq \left[\underbrace{1 \ \ldots \ 1}_{P_d} \ \underbrace{0 \ \ldots \ 0}_{P-P_d} \right]^T$$

LCMV output

Since all directional signals are constrained, $\mathbf{q} = 0$ if $\mathbf{\Phi}_{nn}$ is spatially-white.

$$y = \sum_{j=1}^{P_d} s_j^d + \text{noise components}$$

An Equivalent Constraints Set

An orthonormal basis $\mathbf{Q}$:

- Noise+Interference Sources PSD (no desired sources):

$$\mathbf{\Phi}_{vv}(\ell,k) \triangleq \mathbf{H}^i \mathbf{\Phi}_{s^i s^i} \left(\mathbf{H}^i\right)^H + \mathbf{H}^n \mathbf{\Phi}_{s^n s^n} \left(\mathbf{H}^n\right)^H + \mathbf{\Phi}_{nn}$$

- Eigenvalue decomposition: $\mathbf{\Phi}_{vv}(\ell,k) = \mathbf{E}\mathbf{\Lambda}\mathbf{E}^H$.
- Replace $\left[\, \mathbf{H}^i \;\; \mathbf{H}^n \,\right]$ with $\mathbf{Q}$, comprised of the eigenvectors that correspond to the significant eigenvaleues (# of significant eigenvaleues is, hopefully, $P_i + P_n$).

$$\dot{\mathbf{C}}^H \mathbf{w} = \mathbf{g}$$

$$\dot{\mathbf{C}} \triangleq \left[\, \mathbf{H}^d \;\; \mathbf{Q} \,\right]$$

A Modified Constraints Set

Relax the dereverberation requirements using RTFs:

$$\tilde{\mathbf{g}} \triangleq \Big[\underbrace{(h_{10}^d)^* \ \ldots \ (h_{P_d 0}^d)^*}_{P_d} \ \underbrace{0 \ \ldots \ 0}_{P-P_d} \Big]^T$$

$$\Rightarrow \tilde{\mathbf{h}}_j^d \triangleq \mathbf{h}_j^d / h_{j0}^d; \quad \mathbf{g} \triangleq \Big[\underbrace{1 \ \ldots \ 1}_{P_d} \ \underbrace{0 \ \ldots \ 0}_{P-P_d} \Big]^T$$

Hence, a modified constraints set: $\tilde{\mathbf{C}} \triangleq \left[\tilde{\mathbf{H}}^d \ \mathbf{Q} \right]$.

LCMV output:

$$y = \sum_{j=1}^{P_d} h_{j0}^d s_j^d + \text{noise components}$$

LCMV and MVDR Beamformers using ATFs & RTFs

Features & Drawbacks of the Proposed Beamformers

+ No need for sensor position calibration.
+ Beamformer components estimated from the received signals.
+ High amount of noise and interference reduction.
+ Low speech distortion.
- Number of filter coefficients to be estimated tends to be very large.
- Hence frame length tends to be large as well (can be mitigated at the expense of increased complexity. See CTF approximation).
- Limited performance in diffuse noise fields (can be mitigated by using postfiltering).

Performance Analysis

Theoretical and practical comparison of MVDR and LCMV beamformers can be found in [Markovich et al., 2008]; [Habets et al., 2009].

Objective Performance Measures

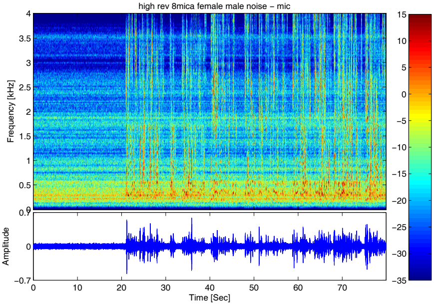
Desired > nonstationary by 6dB; Desired > stationary by 13dB

T_{60}	Source	FBF SIR			Total SIR			SSNR	LSD
		s_1^i	s_2^i	s_1^n	s_1^i	s_2^i	s_1^n		
150ms	s_1^d	18.8	22.4	19.1	18.5	21.7	24.0	9.6	1.1
	s_2^d	18.7	22.3	19.1	18.7	21.9	24.2	10.2	1.7
200ms	s_1^d	18.1	20.6	19.5	18.3	21.3	24.7	7.2	1.5
	s_2^d	18.1	20.7	19.6	18.9	21.9	25.2	8.4	2.0
250ms	s_1^d	18.5	19.8	19.9	18.4	20.9	24.5	7.0	1.8
	s_2^d	18.5	19.8	19.9	19.4	22.0	25.6	7.7	2.4
300ms	s_1^d	17.6	17.6	19.5	18.3	19.3	23.6	6.9	2.2
	s_2^d	17.4	17.5	19.3	18.6	19.7	24.0	7.7	1.8

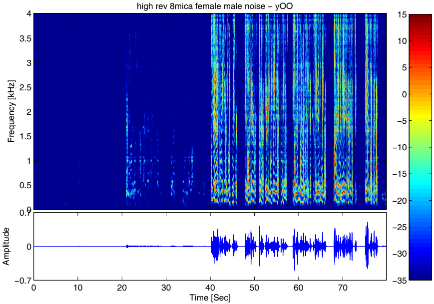
Table: 2 desired sources, 2 competing speakers, 1 stationary noise source. The desired signal at the input is larger than the competing signal by 6dB and larger than the stationary noise by 13dB. 10 microphones simulated environment. LSD & SSNR are the distortion measures between desired signal components at the output and at the input microphone #1.

Single Desired Speaker

Directional Noise Field



(a) Noisy at mic. #1

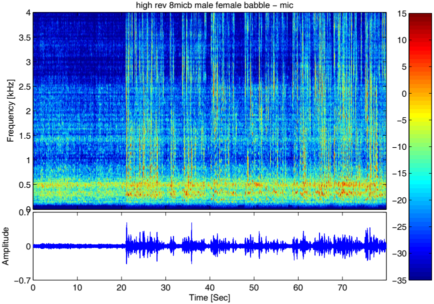


(b) Enhanced signal

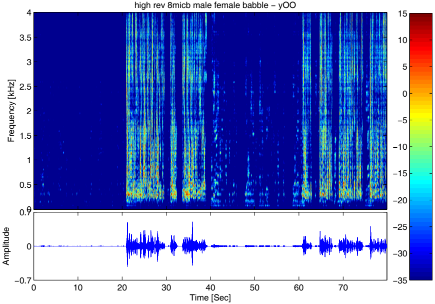
Figure: Female (desired) and male (interference) with Directional noise. 8 microphones recorded at BIU acoustic lab set to $T_{60} = 300$ms.

Single Desired Speaker

Pseudo-Babble Noise Field



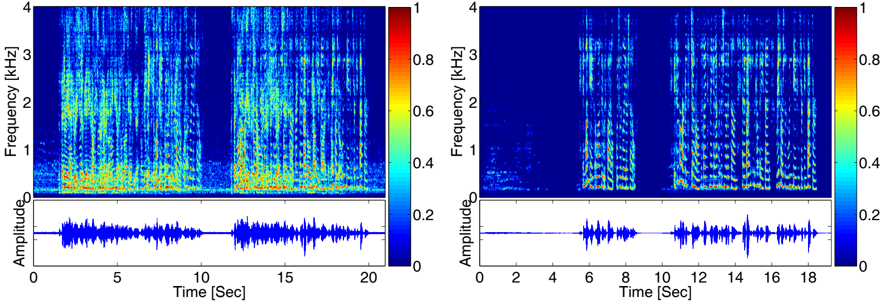
(a) Noisy at mic. #1



(b) Enhanced signal

Figure: Male (desired) and Female (interference) contaminated by pseudo-babble noise. 8 microphones recorded at BIU acoustic lab set to $T_{60} = 300$ms.

Multi-Speaker

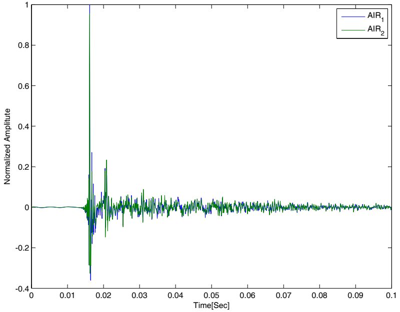


(a) Noisy at mic. #1 (b) Enhanced signal

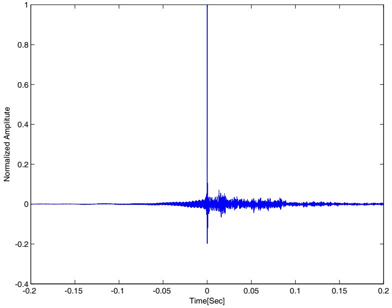
Figure: 1 desired source and 3 competing speakers. 8 microphones recorded at BIU acoustic lab set to $T_{60} = 300$ms.

Approximately 20dB SIR and SNR improvement.

The Importance of the RTF



(a) Room Impulse Responses



(b) Relative Impulse Response

Features

- Generalizes the time difference of arrival (TDOA) to ratio of ATFs.
- Usually exhibits "better behaviour" than the ATF.
- RTF is equivalent to Interaural Transfer Function (ITF).
- Drawback: Non-causal (in severe cases can cause "pre-echo").

Relative Transfer Function Estimation

Single Desired Source with Stationary Noise

System Perspective:

$$z_m(\ell, k) = \tilde{h}_m^d(\ell, k)(\ell, k) z_0(\ell, k) + u_m(\ell, k)$$

System Identification:

$$\hat{\Phi}_{z_m z_0}(\ell, k) = \tilde{h}_m^d(\ell, k) \hat{\Phi}_{z_0 z_0}(\ell, k) + \Phi_{u_m z_0}(\ell, k) + \varepsilon_m(\ell, k)$$

Estimation is Biased:

$u_m(\ell, k)$ and $z_0(\ell, k)$ are correlated $\Rightarrow$ Biased estimator for $\tilde{h}_m^d(\ell, k)$.

Relative Transfer Function Estimation I

Based on Speech Non-stationarity [Shalvi and Weinstein, 1996]; [Gannot et al., 2001]

Assumptions:

- System is Time-Invariant.
- Noise has only stationary components.
- Speech is non-stationary (use frames ℓ_i, $i = 1, \ldots, I$).

$$\begin{bmatrix} \hat{\Phi}_{z_m z_0}(\ell_1, k) \\ \hat{\Phi}_{z_m z_0}(\ell_2, k) \\ \vdots \\ \hat{\Phi}_{z_m z_0}(\ell_I, k) \end{bmatrix} = \begin{bmatrix} \hat{\Phi}_{z_0 z_0}(\ell_1, k) & 1 \\ \hat{\Phi}_{z_0 z_0}(\ell_2, k) & 1 \\ \vdots & \\ \hat{\Phi}_{z_0 z_0}(\ell_I, k) & 1 \end{bmatrix} \begin{bmatrix} \tilde{h}_m^d(k) \\ \Phi_{u_m z_0}(k) \end{bmatrix} + \begin{bmatrix} \varepsilon_m(\ell_1, k) \\ \varepsilon_m(\ell_2, k) \\ \vdots \\ \varepsilon_m(\ell_I, k) \end{bmatrix}$$

Relative Transfer Function Estimation II

Based on Speech Non-stationarity [Shalvi and Weinstein, 1996]; [Gannot et al., 2001]

Solution

For $m = 1, \ldots, M-1$:

$$\hat{\tilde{h}}_m^d(k) = \frac{< \hat{\Phi}_{z_m z_0} \hat{\Phi}_{z_0 z_0} > (k) - < \hat{\Phi}_{z_m z_0} > (k) < \hat{\Phi}_{z_0 z_0} > (k)}{< \hat{\Phi}^2_{z_0 z_0} > (k) - < \hat{\Phi}_{z_0 z_0} >^2 (k)}$$

where, T_i the length of segment T_i and

$$< \Psi > (k) = \frac{\sum_{i=1}^{I} T_i \Psi(\ell_i, k)}{\sum_{i=1}^{I} T_i}.$$

An extension to two nonstationary sources in stationary noise exists [Reuven et al., 2008].

Alternative Estimation Procedures

- Assume direct-path model for the RIR and use TDOA estimation.
- Use speech presence probability and spectral subtraction [Cohen, 2004].
- ...

Subspace tracking [Affes and Grenier, 1997]

- Normalize by the, assumed to be known, norm:

$$\mathbf{z} = \mathbf{h}_d s^d + \mathbf{n} = \frac{\mathbf{h}_d}{\|\mathbf{h}_d\|}(\|\mathbf{h}_d\| s^d) + \mathbf{n} \triangleq \bar{\mathbf{h}}_d \bar{s}^d + \mathbf{n}$$

- Use PASTd [Yang, 1995] to recursively track the rank-1 eigenvector:

$$\hat{\bar{\mathbf{h}}}_d(\ell+1) = \hat{\bar{\mathbf{h}}}_d(\ell) + \mu(\ell)\mathbf{u}(\ell)\bar{y}^*_{\mathrm{FBF}}(\ell)$$

where, $\bar{y}_{\mathrm{FBF}} = \bar{\mathbf{h}}_d^H \mathbf{z}$. $\hat{\mathbf{h}}_d$ is obtained by using the ATF norm.

- Related to robust GSC [Hoshuyama et al., 1999].

Multi-Sources Case [Markovich et al., 2009]

Implementing the GSC Necessitates:

- Desired sources RTFs, $\tilde{\mathbf{H}}^d(\ell, k)$.
- Interferences subspace basis, $\mathbf{Q}(\ell, k)$.

Assumptions and Observations

- The ATFs are slowly-time varying.
- Segments with non-overlapping activity of desired and interference speakers are available.
- Double-talk within the group is allowed.
- Stationary sources are always active.

Interferences Subspace Estimation

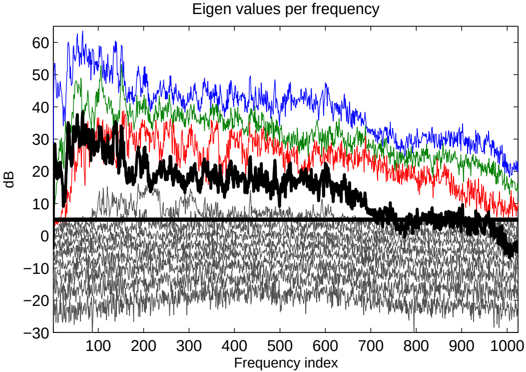
Step 1

EVD and Pruning

- Estimate the signals subspace at each time segment without any desired sources active

$$\hat{\mathbf{\Phi}}_{zz}(\ell_i, k) = \bar{\mathbf{E}}_i \mathbf{\Lambda}_i \bar{\mathbf{E}}_i^H$$

- All eigenvectors corresponding to "weak" eigenvalues are discarded



Interferences Subspace Estimation

Step 2

Union of Estimates

- Straightforward:

$$\mathbf{E}(k) \triangleq \bigcup_{i=1}^{N_{seg}} \bar{\mathbf{E}}_i(k)$$

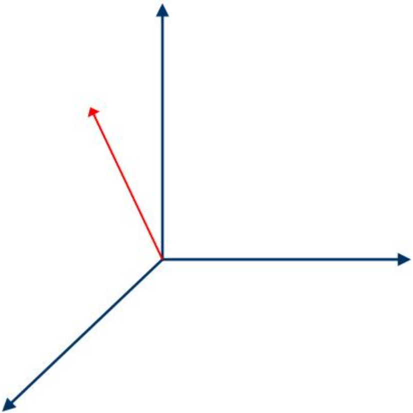
- Practical use QRD

$$\left[\bar{\mathbf{E}}_1(k)\bar{\mathbf{\Lambda}}_1^{\frac{1}{2}}(k) \ \ldots \ \bar{\mathbf{E}}_{N_{seg}}(k)\bar{\mathbf{\Lambda}}_{N_{seg}}^{\frac{1}{2}}(k) \right] \mathbf{P}(k) = \mathbf{Q}(k)\mathbf{R}(k)$$

- Discard vectors from the basis $\mathbf{Q}(k)$ that correspond to “weak” coefficients in $\mathbf{R}(k)$.

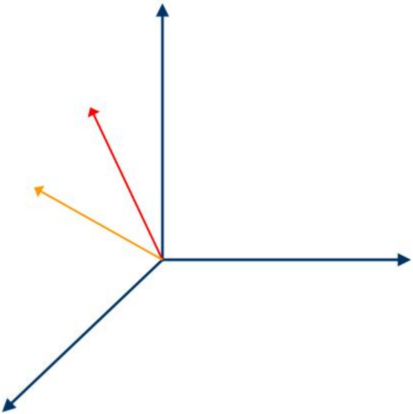
EVD per Frame - Graphical Interpretation

Frame 1, strong eigenvectors



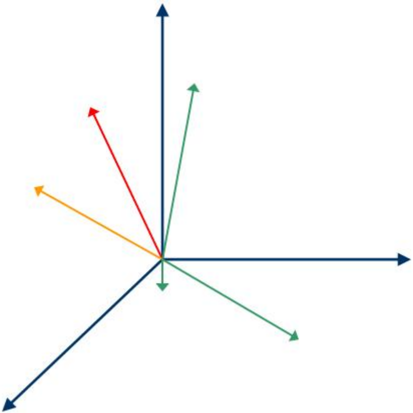
EVD per Frame - Graphical Interpretation

Frame 2, strong eigenvectors



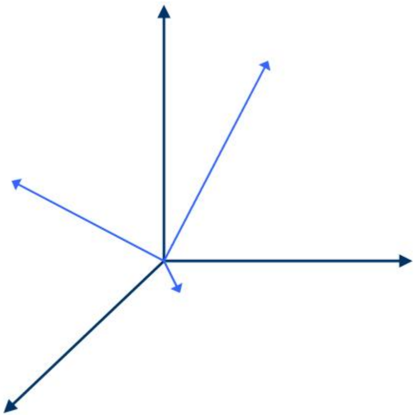
EVD per Frame - Graphical Interpretation

Frame 3, strong eigenvectors



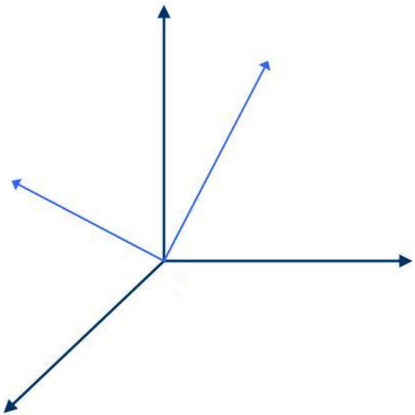
QRD Calculation

Graphical Interpretation



QRD Pruning

Graphical Interpretation



Desired Sources RTF Estimation

One Concurrent Desired Speaker

PSD Estimation

- Stationary noise PSD:

$$\mathbf{\Phi}_{zz}^{\mathrm{stat}} = \mathbf{H}^n \mathbf{\Phi}_{s^n s^n} \left(\mathbf{H}^n\right)^H + \mathbf{\Phi}_{nn}$$

- One desired source (i_0), no non-stationary source:

$$\hat{\mathbf{\Phi}}_{zz}^{d,i_0} \approx \phi_{i_0}^d \mathbf{h}_{i_0}^d \left(\mathbf{h}_{i_0}^d\right)^H + \mathbf{\Phi}_{zz}^{\mathrm{stat}}$$

Largest Generalized Eigenvector

$$\hat{\mathbf{\Phi}}_{zz}^{d,i_0} \mathbf{f}_{i_0} = \lambda_{i_0} \mathbf{\Phi}_{zz}^{\mathrm{stat}} \mathbf{f}_{i_0} \Rightarrow \hat{\tilde{\mathbf{h}}}_{i_0}^d \triangleq \frac{\mathbf{\Phi}_{zz}^{\mathrm{stat}} \mathbf{f}_{i_0}}{\left(\mathbf{\Phi}_{zz}^{\mathrm{stat}} \mathbf{f}_{i_0}\right)_0}$$

Multichannel Post-filtering (for single desired source)

Using matrix inversion lemma [Simmer et al., 2001]; [Doclo et al., 2010]

Why Postfiltering?

- In diffuse noise field multichannel processing is not enough!
- For nonstationary signals advanced single microphone spectral enhancement methods are beneficial [Cohen and Gannot, 2008].

MWF for estimating speech component at reference microphone (#0)

$$\mathbf{w}_{\text{SDW-MWF}} = \frac{\phi_{s^d s^d} \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d}{\mu + \phi_{s_d s_d} (\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d} (h_0^d)^* = \underbrace{\frac{\mathbf{\Phi}_{nn}^{-1} \tilde{\mathbf{h}}^d}{(\tilde{\mathbf{h}}^d)^H \mathbf{\Phi}_{nn}^{-1} \tilde{\mathbf{h}}^d}}_{\text{MVDR}} \times \underbrace{\frac{\phi_{y_s y_s}}{\phi_{y_s y_s} + \mu \phi_{y_n y_n}}}_{\text{SDW-SWF}}$$

where, $\phi_{y_s y_s} = |h_0^d|^2 \phi_{s^d s^d}$ is the desired speech component at the MVDR output and $\phi_{y_n y_n}$ is the respective noise output.

Zelinski Postfilter [Zelinski, 1988]

Assumptions

- Distortionless beamformer $\phi_{y_s y_s} = \phi_{s^d s^d}$.
- Spatially white noise field, $\mathbf{\Phi}_{nn} = \phi_{nn}\mathbf{I}$ (no other interference sources).
- Hence, $\phi_{z_i z_j} = \phi_{s^d s^d}$; $i \neq j$ & $\phi_{z_i z_i} = \phi_{s^d s^d} + \phi_{nn}$.

Estimated Wiener Postfilter

- Recursive estimation of the auto- and cross-spectra: $\hat{\phi}_{z_i z_j}(\ell) = \alpha \hat{\phi}_{z_i z_j}(\ell - 1) + (1 - \alpha) z_i(\ell) z_j^*(\ell)$.
- Zelinski's postfilter:

$$w_{\mathrm{Zel}}(\ell, k) = \frac{\frac{2}{M(M-1)} \sum_{i=0}^{M-2} \sum_{j=i+1}^{M-1} \Re(\hat{\phi}_{z_i z_j}(\ell, k))}{\frac{1}{M} \sum_{i=0}^{M-1} \hat{\phi}_{z_i z_i}(\ell, k)}$$

- Combined with Spectral Subtraction [Meyer and Simmer, 1997].
- Further developed and analyzed [Marro et al., 1998].

McCowan & Bourlard Postfilter [McCowan and Bourlard, 2003]

Further Assumptions

- Noise field with known and isotropic coherence function, $\phi_{n_i n_j} = \phi_{nn}\Gamma_{n_i n_j}$ (no other interference sources).
- Hence, $\phi_{z_i z_j} = \phi_{s^d s^d} + \phi_{nn}\Gamma_{n_i n_j}$; $i \neq j$ & $\phi_{z_i z_i} = \phi_{z_j z_j} = \phi_{s^d s^d} + \phi_{nn}$.
- Diffuse noise field is usually assumed $\Gamma_{n_i n_j}(\omega) = \mathrm{Sinc}(\frac{\omega d_{ij}}{c})$.

Estimated Wiener Postfilter

- McCowan & Bourlard postfilter:

$$\hat{\phi}_{s_i^d s_j^d}(\ell, k) = \frac{\Re(\hat{\phi}_{z_i z_j}) - 0.5\Re(\Gamma_{n_i n_j})(\hat{\phi}_{z_i z_i} + \hat{\phi}_{z_j z_j})}{1 - \Re(\Gamma_{n_i n_j})}$$

$$w_{\mathrm{MB}}(\ell, k) = \frac{\frac{2}{M(M-1)} \sum_{i=0}^{M-2} \sum_{j=i+1}^{M-1} \hat{\phi}_{s_i^d s_j^d}}{\frac{1}{M} \sum_{i=0}^{M-1} \hat{\phi}_{z_i z_i}} \triangleq \frac{\hat{\phi}_{s^d s^d}}{\frac{1}{M} \sum_{i=0}^{M-1} \hat{\phi}_{z_i z_i}}$$

Improved Noise PSD Estimation

Noise Over-estimation

Both postfilters [Zelinski, 1988] and [McCowan and Bourlard, 2003] use over-estimated noise PSD, since they use the input signals rather than the beamformer output.

Noise PSD at beamformer output [Leukimmiatis et al., 2006]

Replace the denominator by:

$$\hat{\phi}_{n_i n_j}(\ell, k) = \frac{0.5(\hat{\phi}_{z_i z_i} + \hat{\phi}_{z_j z_j}) - \Re(\hat{\phi}_{z_i z_j})}{1 - \Re(\Gamma_{n_i n_j})}$$

$$\hat{\phi}_{nn}(\ell, k) = \frac{2}{M(M-1)} \sum_{i=0}^{M-2} \sum_{j=i+1}^{M-1} \hat{\phi}_{n_i n_j}(\ell, k)$$

$$w_{\mathrm{Leuk}}(\ell, k) = \frac{\hat{\phi}_{s^d s^d}}{\hat{\phi}_{s^d s^d} + \hat{\phi}_{nn} \mathbf{w}_{\mathrm{MVDR}}^H \mathbf{\Gamma}_{nn} \mathbf{w}_{\mathrm{MVDR}}}$$

Nonlinear Postfilter [Balan and Rosca, 2002] I

Motivation

- Nonlinear processing has many advantages in speech enhancement.
- A plethora of nonlinear algorithms for single microphone speech enhancement exist.
- An extension to the multichannel case can derived.

Sufficient Statistics

- Conditional p.d.f.:

$$P_r(\mathbf{z}|s^d; \phi_{s^d s^d}, \mathbf{\Phi}_{nn}, \mathbf{h}^d) = \frac{1}{\pi \mathbf{\Phi}_{nn}} \exp\{-(\mathbf{z} - \mathbf{h}^d s^d)^H \mathbf{\Phi}_{nn}^{-1} (\mathbf{z} - \mathbf{h}^d s^d)\}$$

- MVDR output is sufficient statistics for s_d: $T(\mathbf{z}) = \frac{(\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1} \mathbf{z}}{(\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d}$
- $P_r(\rho(s^d)|\mathbf{z}) = P_r(\rho(s^d)|T(\mathbf{z}))$

Nonlinear Postfilter [Balan and Rosca, 2002] II

Log Spectral Amplitude Estimator extending [Ephraim and Malah, 1985]

- Beamformer output: $y = s + \frac{(\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1}}{(\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d} \mathbf{n}$.
- LSA criterion:

$$|\hat{s}^d| = \exp\{E\{\log(|s^d|)|\mathbf{z}\}\} = \exp\{E\{\log(|s^d|)|\,T(\mathbf{z})\}\}$$

- Estimator:

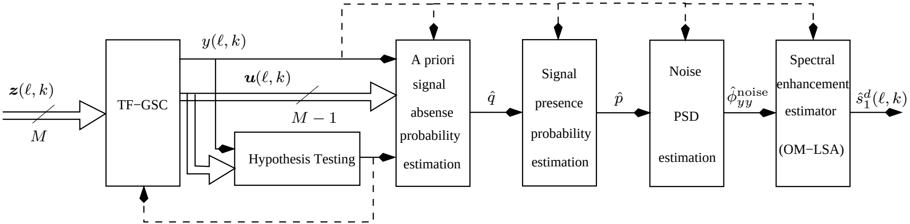
$$|\hat{s}^d| = \frac{\xi}{1+\xi} \exp\left\{\frac{1}{2}\int_v^\infty \frac{e^{-t}}{t} dt\right\} |y|$$

where $\xi \triangleq \phi_{s^d s^d} (\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d$ is the a priori SNR,
$\gamma \triangleq |y|^2 (\mathbf{h}^d)^H \mathbf{\Phi}_{nn}^{-1} \mathbf{h}^d$ is the a posteriori SNR and $v = \frac{\xi\gamma}{1+\xi}$.

- Final estimator is obtained by $\hat{s}^d = |\hat{s}^d| e^{\angle(y)}$.
- Gives motivation to the algorithm presented next.

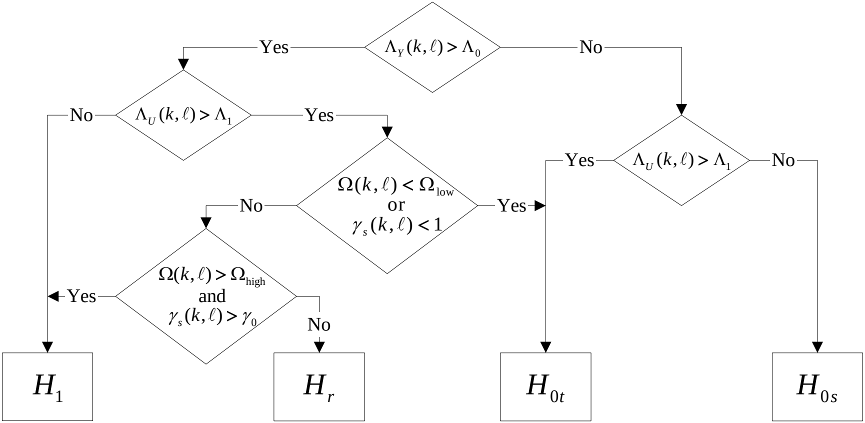
GSC & Speech Presence Probability based Postfiltering

[Cohen et al., 2003]; [Gannot and Cohen, 2004]



- Use main output and reference noise signals to update the speech presence probability.
- Feed backward the decision to update GSC parameters.
- Use the speech presence probability to update the OM-LSA [Cohen and Berdugo, 2001] algorithm for residual noise reduction.

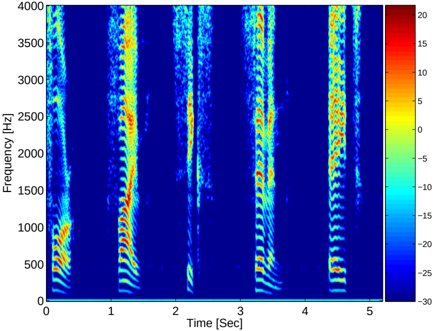
Hypothesis Test



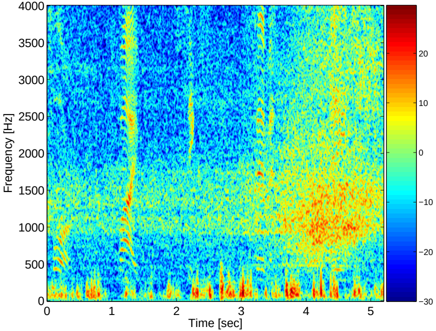
- Λ_Y - local non-stationarity at beamformer output.
- Λ_U - local non-stationarity at noise reference signals.
- Ω - The transient beam-to-reference ratio (TBRR).
- γ_s - a posteriori SNR at the beamformer output.

Experimental Study I

Car Scenario



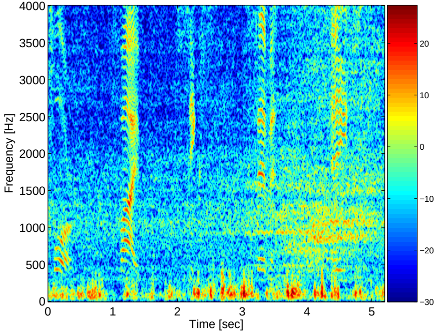
(a) Clean speech



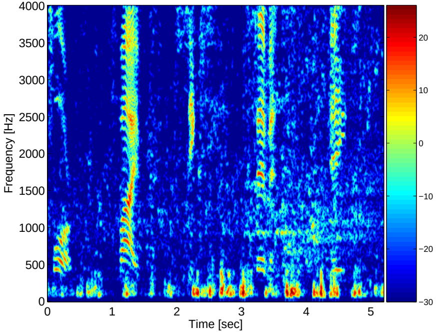
(b) Noisy at mic. #1

Experimental Study II

Car Scenario



(c) TF-GSC output



(d) Multichannel postfiltering

Figure: Speech utterance: "Dial: One, Two, Three, Four, Five, Six, Seven, Eight". Car with open windows equipped with 4 microphones.

The Convolutive TF-GSC [Talmon et al., 2009a] I

Motivation

The GSC [Griffiths and Jim, 1982]

Implemented in time-domain and assumes delay-only propagation. Hence speech distortion is expected.

The TF-GSC [Gannot et al., 2001]

- The RTFs are incorporated into the GSC beamformer.
- Adaptation to reverberant environments obtained by time-frequency implementation.
- For high T_{60}:
  - The RIRs and the respective relative RIRs become very long.
  - Multiplication in frequency-domain (MTF approximation) is only valid if the time frames are significantly larger than the relative RIR.
  - In practice, short frames are used, resulting in inaccurate representation of the RTF and hence performance degradation.

The Convolutive TF-GSC [Talmon et al., 2009a] II

Motivation

Time-Domain MVDR [Chen et al., 2008]

- Full relative RIR is taken into account.
- Theoretically, optimal MVDR in reverberant environment.
- The full-length RTF estimation requires:
  - Very long observations, limiting the ability to work in dynamic environments and to track time-variations.
  - Large computational complexity.
- In practice, the speech source RIRs are modelled as shorter filters.

STFT Implementation [Talmon et al., 2009a] Enables:

- Short frames.
- Long relative RIRs.

CTF-GSC

Objectives

In the STFT Domain:

- Formulate the problem using system representation in the STFT domain [Avargel and Cohen, 2007].
- Build a GSC scheme (a TF-GSC extension).
- Suggest practical solutions using approximations. Specifically, show solutions under the MTF and CTF approximations.
- Incorporate the RTF identification based on the CTF model [Talmon et al., 2009b] and compare experimental results with the TF-GSC.
- Currently, applicable only to single desired source.

Signal Model I

Time Domain

$$z_m(t) = s^d(t) * h_m^d(t) + n_m(t) = \tilde{s}^d(t) * \tilde{h}_m^d(t) + n_m(t)$$

- $\tilde{s}^d(t) = s^d(t) * h_1^d(t)$ - Desired signal component at microphone #1.
- $\tilde{h}_m^d(t)$ - relative RIR between microphone #1 and microphone $\#m$.

STFT Domain

$$z_m(\ell, k) = \sum_{k'=0}^{N_{\mathrm{FFT}}-1} \sum_{p'} \tilde{h}_m(\ell', k', k)\tilde{s}_d(\ell - \ell', k') + n_m(\ell, k)$$

Concatenating successive signal frames:

$$\mathbf{z}_m(k) = \sum_{k'=0}^{N_{\mathrm{FFT}}-1} \tilde{\mathbf{H}}_m(k', k)\tilde{\mathbf{s}}_d(k') + \mathbf{n}_m(k) \overset{\mathrm{CTF}}{\approx} \tilde{\mathbf{H}}_m(k)\tilde{\mathbf{s}}_d(k) + \mathbf{n}_m(k)$$

Signal Model II

Beamforming in the STFT Domain

$$\hat{\hat{\mathbf{s}}}_d(k) = \sum_{m=1}^{M} \sum_{k'=0}^{N_{\mathrm{FFT}}-1} \mathbf{W}_m^H(k',k)\mathbf{z}_m(k') \overset{\mathrm{CTF}}{\approx} \sum_{m=1}^{M} \mathbf{W}_m^H(k)\mathbf{z}_m(k)$$

MVDR & GSC

- Constrained power minimization (MVDR) can be defined.
- GSC structure exists (# of constraints $<$ # of measurements).
- Similarly to the TF-GSC, $\tilde{\mathbf{H}}_m(k', k)$ can be identified [Talmon et al., 2009b].

Setup

Comparing the proposed method to the TF-GSC:

- Image method ([Allen and Berkley, 1979], implemented by [Habets, 2006]).
- Array of 5 microphones.
- Reverberation time $T_{60} = 0.5$s.
- TF-GSC:
  - Frame length - $N = 512$.
  - RTF length - 500.
  - Noise Canceller length - 450.
- CTF-GSC:
  - In FBF and BM - $N = 512, 50\%$ overlap.
  - In adaptive NC - $N = 512, 75\%$ overlap.
  - RTF length - 5 frames.

Signal Blocking

The signal blocking factor (SBF) is defined by:

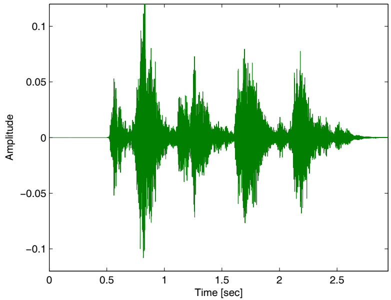
$$\mathbf{SBF} = 10 \log_{10} \frac{E\left\{(\tilde{s}^d(t))^2\right\}}{\mathrm{Mean}_m E\left\{u_m^2(t)\right\}}$$

where $u_m(t)$; $m = 2, \ldots, M$ are the blocking matrix outputs.

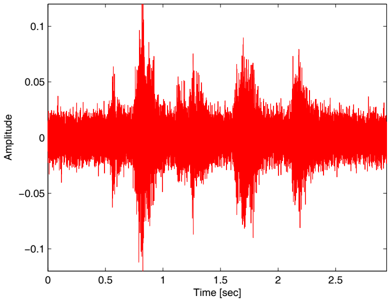
The blocking ability [dB] (known RTF)

	mic. 2	mic. 3	mic. 4	mic. 5
TF	17	12	14	8
CTF	22	17	18	13

Known RTF, Input SNR=0dB I

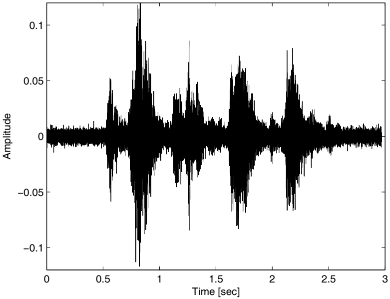


(a) Reverberated speech at microphone #1.

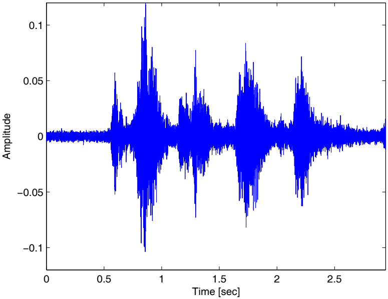


(b) Noisy signal at microphone #1.

Known RTF, Input SNR=0dB II



(c) TF-GSC output.

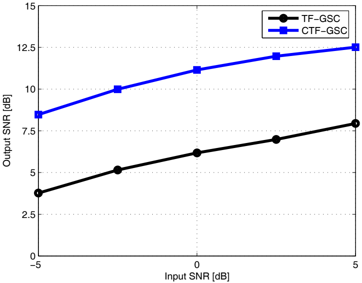


(d) CTF-GSC output.

Summary

Output SNR and Noise Reduction [dB] for known RTF

In SNR	SNR		NR	
	TF-GSC	CTF-GSC	TF-GSC	CTF-GSC
-5	3.8	8.5	-5.9	-10.9
-2.5	5.2	10.0	-6.2	-10.9
0	6.2	11.2	-6.2	-10.9
2.5	7.0	12.0	-6.7	-10.9
5	7.9	12.5	-6.1	-10.9



Estimated RTF

Signal Blocking

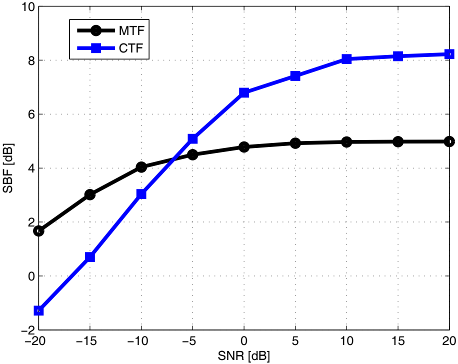
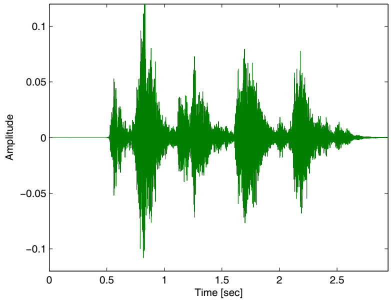
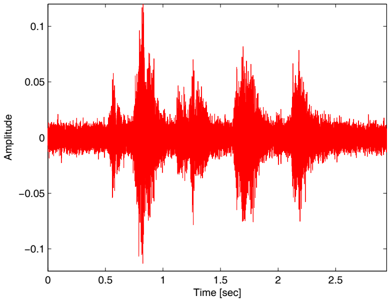


Figure: SBF curves obtained by the RTF identification method based on the MTF and CTF models.

Identified RTF, Input SNR=5dB I

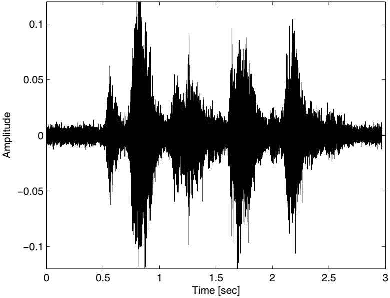


(a) Reverberated speech at microphone #1.

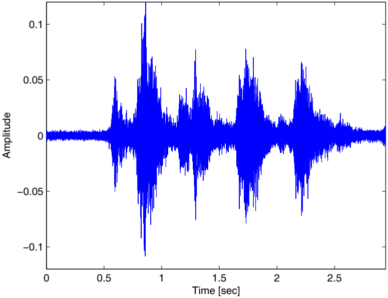


(b) Noisy signal at microphone #1.

Identified RTF, Input SNR=5dB II

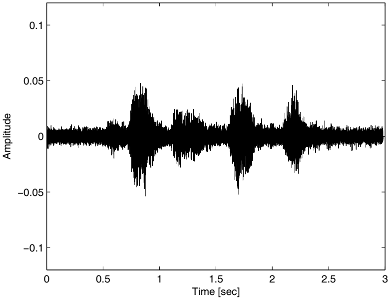


(c) TF-GSC output.

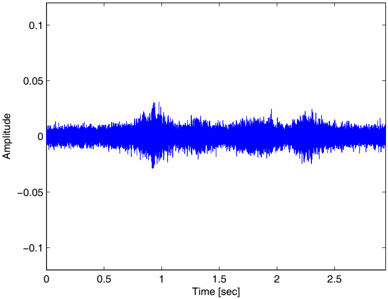


(d) CTF-GSC output.

Identified RTF, Input SNR=5dB III



(e) BM output TF-GSC.

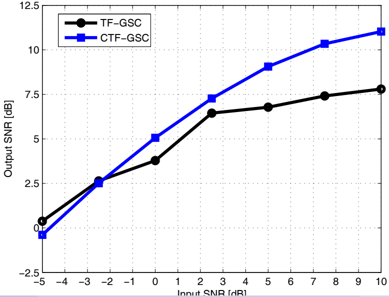


(f) BM output CTF-GSC.

Summary

Output SNR and Noise Reduction [dB] for estimated RTF

In SNR	SNR		NR	
	TF-GSC	CTF-GSC	TF-GSC	CTF-GSC
-5	0.9	-0.4	-2.2	-4.7
-2.5	2.6	2.5	-2.9	-5.3
0	3.8	5.1	-3.2	-6.0
2.5	6.5	7.3	-4.0	-6.8
5	6.8	9.1	-4.3	-7.7
7.5	7.4	10.3	-4.8	-8.4
10	7.8	11.0	-5.5	-9.1



Dynamic Scenario [Markovich-Golan et al., 2010]

Subspace tracking of Multiple Sources

Goal

Extract desired moving speakers from a mixture of speakers using the LCMV beamformer.

Working hypothesis

- Activity indicator for desired speech signals is available.
- Availability of time segments with nonconcurrent desired and interfering speakers.
- "Stable" subspaces represent static speakers with high probability.

Features

- Tracking ability using projection approximation subspace tracking deflation (PASTd) [Yang, 1995].
- Double talk within group allowed during estimation.
- "Expiry time" for outdated basis vectors.

LCMV beamformer

Definitions (Reminder)

$$\mathbf{w} = \mathbf{\Phi}_{zz}^{-1}\mathbf{C}\left(\mathbf{C}^{\dagger}\mathbf{\Phi}_{zz}^{-1}\mathbf{C}\right)^{-1}\mathbf{g}$$

Straightforward Constraints Set

$$\mathbf{C} = \left[\, \mathbf{H}^{d} \;\; \mathbf{H}^{i} \,\right] \qquad \mathbf{g} = \left[\, \mathbf{1}_{1\times P_d} \;\; \mathbf{0}_{1\times P_i} \,\right]^{T}$$

Modified Constraints Set

$$\tilde{\mathbf{C}} = \left[\, \mathbf{Q}^{d} \;\; \mathbf{Q}^{i} \,\right] \qquad \tilde{\mathbf{g}} = \left[\, \left(Q^{d}_{1,1}\right)^{*} \cdots \left(Q^{d}_{P_d,1}\right)^{*} \;\; \mathbf{0}_{1\times P_i} \,\right]^{T}$$

where $\mathbf{Q}^{d}$, $\mathbf{Q}^{i}$ - bases for desired and interfering subspaces.

Output

$$y(\ell, k) = \sum_{j=1}^{P_d} h^{d}_{j,1}(\ell, k) s^{d}_{j}(\ell, k) + \text{residual noise}$$

Tracking Scheme I

Forgetting Factor Consideration

- Tracking $\mathbf{Q}^d$ and $\mathbf{Q}^i$ is a variant of the PASTd algorithm [Yang, 1995] with pre-whitening.
- Forgetting factor β controls the adaptation, with $N_\beta = \frac{1}{1-\beta}$ the algorithm's memory length.
- Standard PASTd suffers from contradicting requirements for β:
  - Fast adaptation $\Rightarrow$ small β.
  - Long memory $\Rightarrow$ large β.
- The contradicting requirements can be mitigated by combined tracking scheme.

Tracking Scheme II

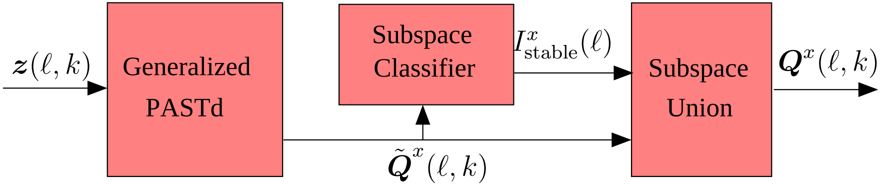
Short & Long Memory

- Use short memory PASTd for fast adaptation of the instantaneous subspace of the xth group of signals, $\tilde{\mathbf{Q}}^x(\ell, k)$.
- Declare stable subspaces, $\mathbf{Q}^x(\ell, k)$, if the basis is valid for more than pre-defined number of frames.
  $I^x_{\mathrm{stable}}(\ell)$ - Indicator for stable subspace of the xth group.
- Subspace union of the valid stable subspaces and the instantaneous subspace using QRD.
- Attribute an expiration time for each stable subspace.

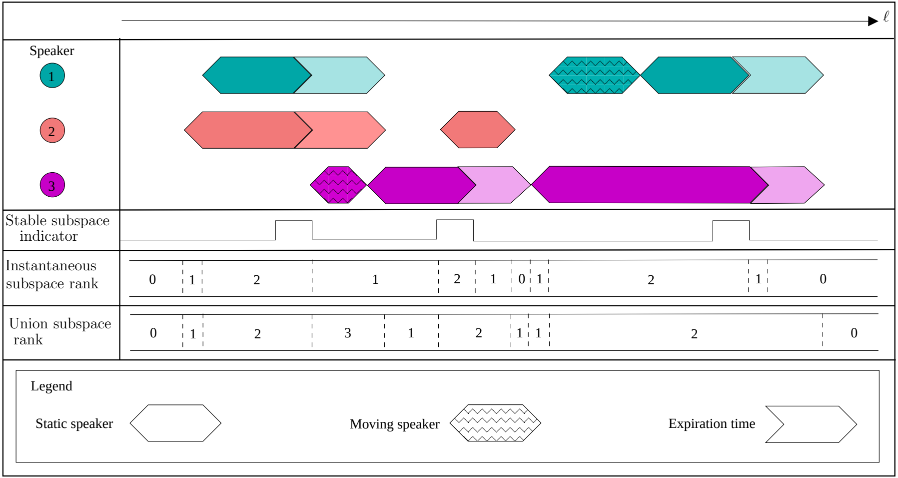
Tracking Scheme III

Classification of Subspace Stability

- The energy of the projected signals onto the instantaneous subspace $\tilde{\mathbf{Q}}^x(\ell, k)$ (integrated over past N_β frames) consists of most of the signals' energy.
- $I^x_{\mathrm{stable}}(\ell) = 1$ if the aggregated energy of the projected signals onto the instantaneous subspace (integrated over past $N_{\mathrm{stable}} \gg N_\beta$ frames) consists of most of the signals' energy.

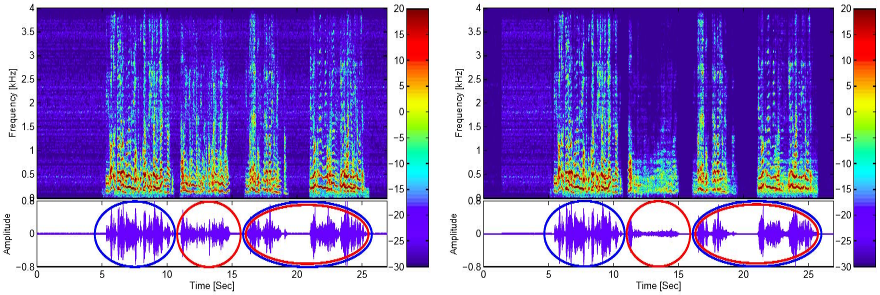


Tracking Example



Experimental Study

Results



(a) Noisy at mic. #1 (b) Enhanced signal

Figure: 2 concurrent desired speakers and 2 competing speakers. 8 microphones recorded at BIU acoustic lab set to $T_{60} = 300$ms.

Binaural LCMV Beamformer

Hadad, Gannot, Doclo, 2012

Motivation

- Duplicate the LCMV beamformer at both ears utilizing all microphones.
- The concept of RTF can be extended and used for preservation of binaural cues (ILD & ITD).
- Efficient implementation by block sharing.

Problem Formulation

Microphone Signals

$$\mathbf{z} = \mathbf{H}^d \mathbf{s}^d + \mathbf{H}^i \mathbf{s}^i + \mathbf{v}$$

Left & Right Reference Microphones

$$z_\ell = \mathbf{e}_\ell^H \mathbf{z}; \quad z_r = \mathbf{e}_r^H \mathbf{z}$$

where

$$\mathbf{e}_\ell = \begin{cases} 1 & m = m_\ell \\ 0 & \text{otherwise} \end{cases} \qquad \mathbf{e}_r = \begin{cases} 1 & m = m_r \\ 0 & \text{otherwise} \end{cases}$$

Binaural Spatial Filters

$$y_\ell = \mathbf{w}_\ell^H \mathbf{z}; \quad y_r = \mathbf{w}_r^H \mathbf{z}.$$

Double LCMV Criterion

Two BFs Utilizing All Microphones

$$\mathbf{w}_\ell = \mathrm{LCMV}(\mathbf{z}; \mathbf{C}, \mathbf{g}_\ell); \quad \mathbf{w}_r = \mathrm{LCMV}(\mathbf{z}; \mathbf{C}, \mathbf{g}_r)$$

Orthonormal Basis for the ATFs

$$\{\mathbf{H}_d = \mathbf{Q}_d \boldsymbol{\Theta}_d; \quad \mathbf{H}_i = \mathbf{Q}_i \boldsymbol{\Theta}_i\} \Rightarrow \mathbf{C} = \begin{bmatrix} \mathbf{Q}_d & \mathbf{Q}_i \end{bmatrix}$$

Left & Right Response Vectors

Apply dereverberation relaxation utilizing RTFs.

Cue Gain Factors:

Desired response $0 < \eta \approx 1$; Interference response $0 < \mu \ll 1$

Interaural Signal Ratio (ISR)

Input ISR

$$\mathrm{ISR}^{in} = \frac{z_\ell}{z_r} = \frac{\mathbf{e}_\ell^\dagger\left(\mathbf{H}_d\mathbf{s}_d + \mathbf{H}_i\mathbf{s}_i\right)}{\mathbf{e}_r^\dagger\left(\mathbf{H}_d\mathbf{s}_d + \mathbf{H}_i\mathbf{s}_i\right)}.$$

Output ISR (in our implementation)

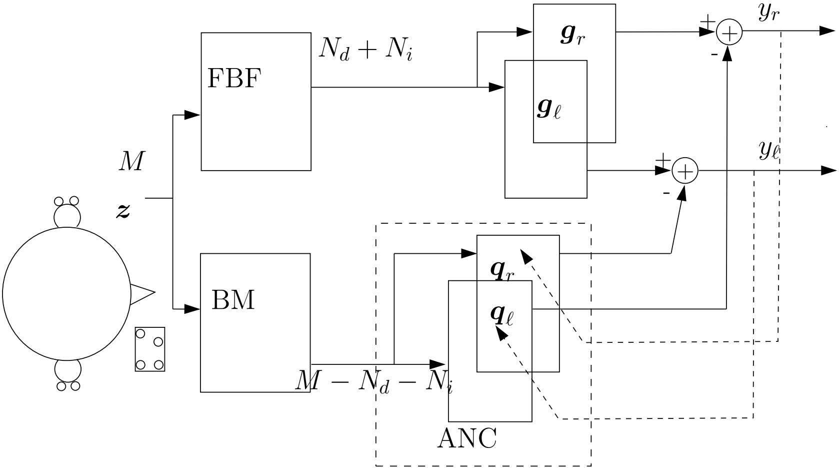
$$\mathrm{ISR}^{out} = \frac{y_\ell}{y_r} = \frac{\mathbf{e}_\ell^\dagger\left(\eta\mathbf{H}_d\mathbf{s}_d + \mu\mathbf{H}_i\mathbf{s}_i\right)}{\mathbf{e}_r^\dagger\left(\eta\mathbf{H}_d\mathbf{s}_d + \mu\mathbf{H}_i\mathbf{s}_i\right)}.$$

ISR vs. ITF

Properties

- Single source case: $\mathrm{ISR}^{out} = \mathrm{ISR}^{in}$ and ISR identifies with the ITF.
- Only one group is active $\Rightarrow$ spatial cues of the group maintained.
- Speech sparsity in STFT domain $\Rightarrow$ cues are preserved also for arbitrary activity pattern.
- Binaural cue preservation is only guaranteed for the constrained sources.
- Unconstrained stationary noise sources and residual (constrained) interference sources will "inherit" the input cues of the dominant source.
- $0 < \mu \ll 1$ will mask the artifacts resulting from leakage.

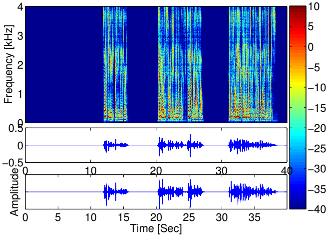
Block Diagram



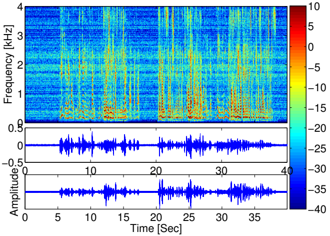
Setup

- Hearing device:
  - 2 hearing aid devices mounted on B&K HATS, with 2 microphones, 2cm inter-distance.
  - A 9×5 utility device with 4 mics. at the corners, average distance 3.5cm. The device placed on a table at a distance of 0.5m.
- Signals:
  - 1 desired speaker, $\theta_d = 30^o$, 1m (constrained).
  - 1 interference speaker at $\theta_i = -70^o$, 1m (constrained).
  - 1 directional stationary noise, $\theta_n = -40^o$, 2.5m (unconstrained).
  - SIR=0dB, SNR=14dB.
- Acoustic lab:
  - Dimensions $6 \times 6 \times 2.4$; Controllable reverb. time $T_{60} = 0.3s$.
- STFT:
  - Sampling frequency 8kHz, 4096 points, 75% overlap.
- Algorithm Cue gain factors:
  - Desired speech - $\eta = 1$.
  - Interference speech - $\mu = 0.1$ (20dB attenuation).

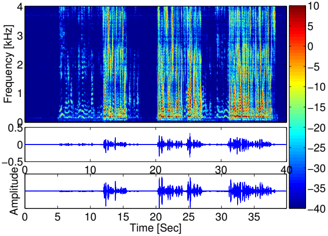
Sonograms



(a) Desired speaker, reference mic.

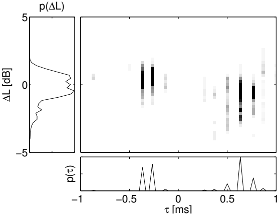


(b) Received reference microphones

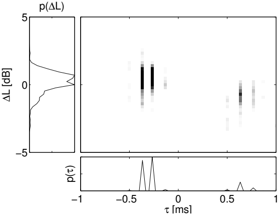


(c) BLCMV outputs

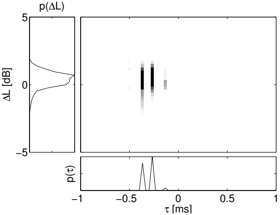
ILD & ITD Preservation (Faller and Merimaa, 2004) I



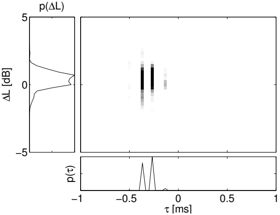
(a) Noisy input



(b) Enhanced output

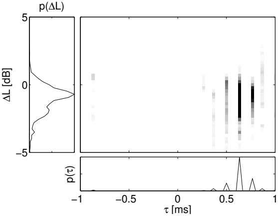


(c) Desired input

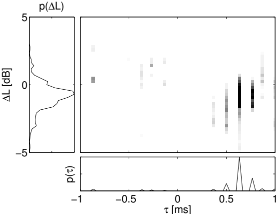


(d) Desired output

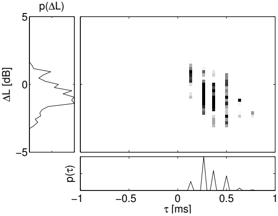
ILD & ITD Preservation (Faller and Merimaa, 2004) II



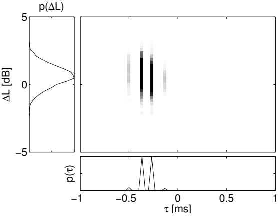
(e) Interference input



(f) Interference output



(g) Stationary input



(h) Stationary output

Audio Samples

Available at:

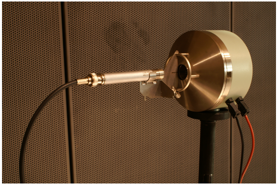
http://www.eng.biu.ac.il/gannot/speech-enhancement/

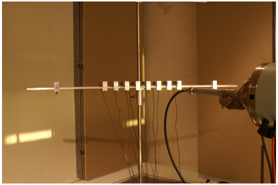
Acoustics Lab, Bar-Ilan University

Features

- Controlled and acoustically isolated environment.
- 60 double-sided panels control the reverberation time.
- Equipped with microphone arrays, loudspeakers, measurement and acquisition equipment.
- Enables fast testing, implementation and verification of algorithms.

BIU Acoustics Lab: Picture Gallery





Thanks to my Collaborators

1. Shmulik Markovich-Golan
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3. Prof. Ronen Talmon
4. David Levin
5. Prof. Emanuël Habets
6. Elior Hadad
7. Prof. Jacob Benesty
8. and many more...

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