MULTICHANNEL JOINT DEREVERBRATION AND NOISE REDUCTION IN THE STFT DOMAIN

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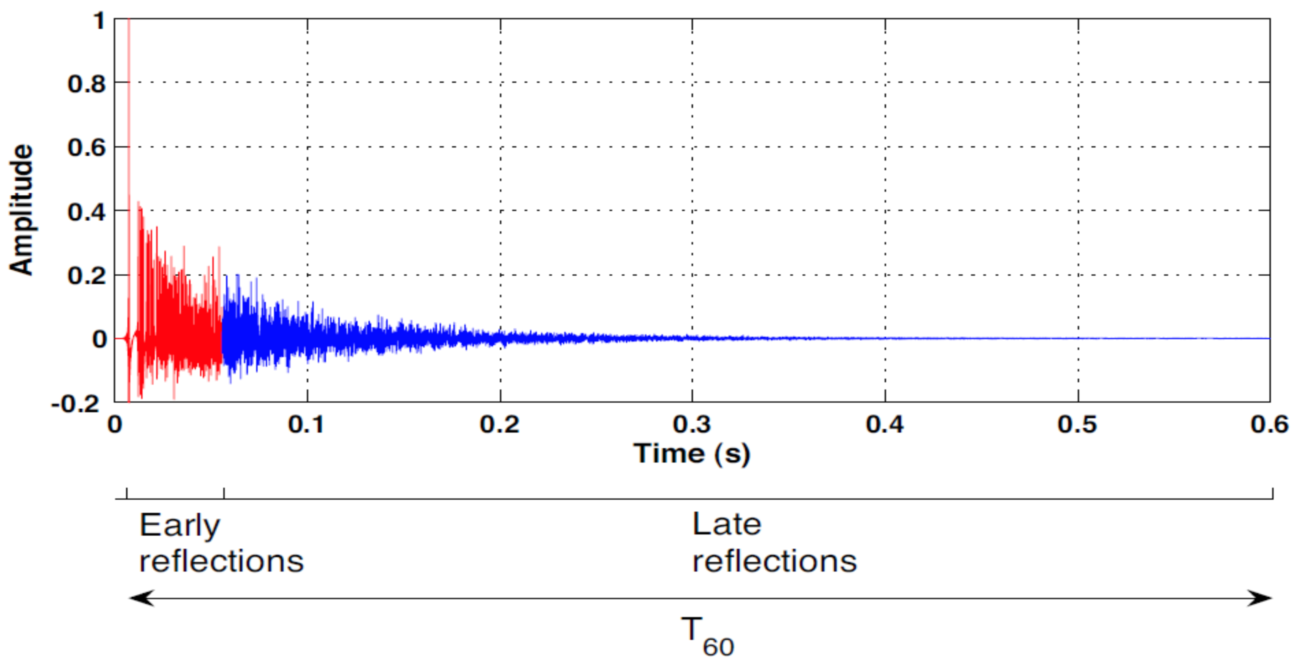
Outline

1. Problem definition, previous work and main contributions
2. Optimal Beamformers for the JDNR problem
3. Reverberation Blockage beamformers
4. Summary and conclusions

Problem Definition

- In a typical environment the received speech signals are degraded by room reverberation and background noise.
- Noise is mostly additive and uncorrelated with the speech signal.
- Reverberations are the correlated delayed reflections of the source signal.
- The room impulse response (RIR) describes the linear relation between the speaker and the microphone.
- The RIR can be divided into late and early reflections.

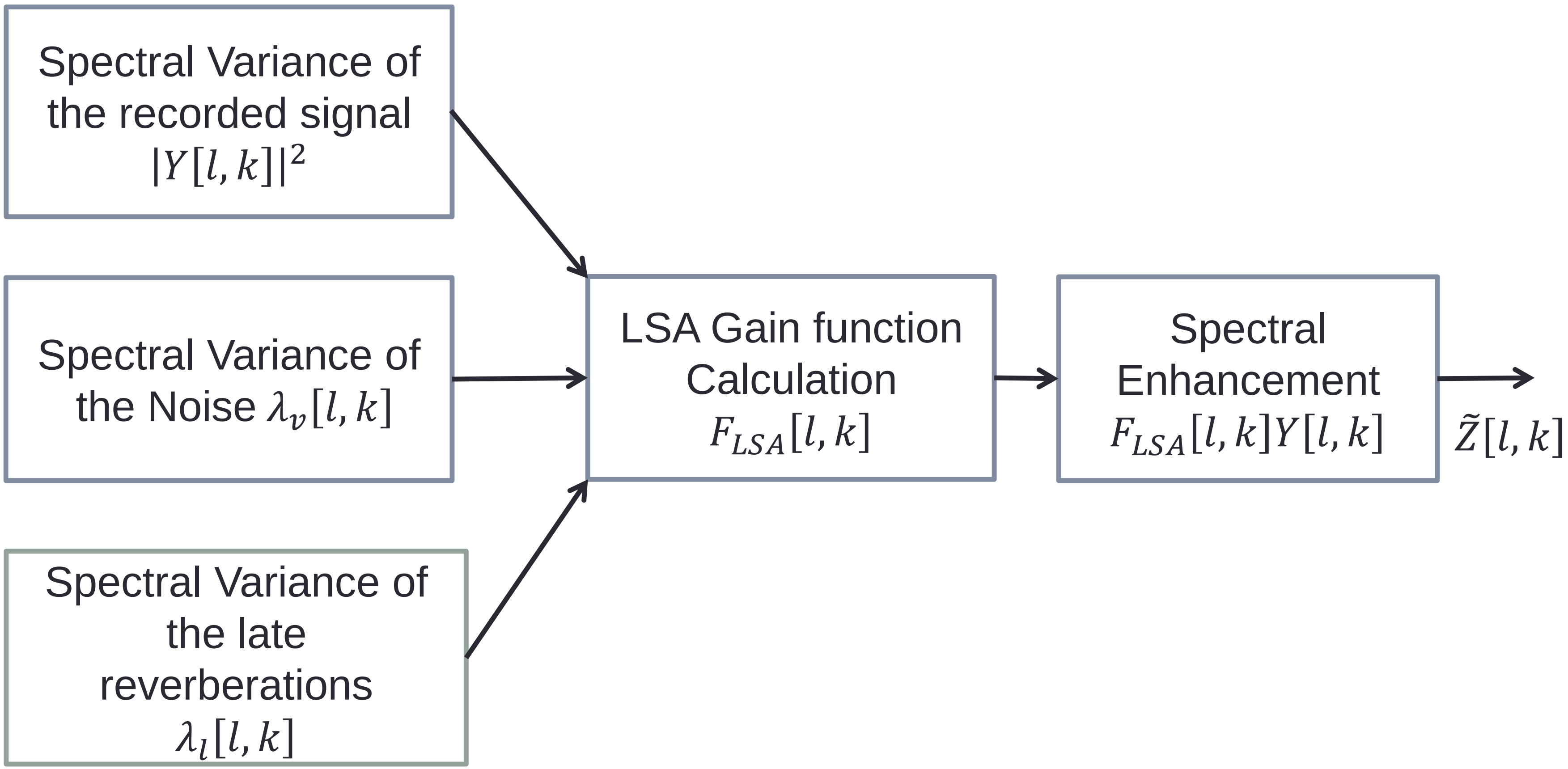


clean

Noise + Rev

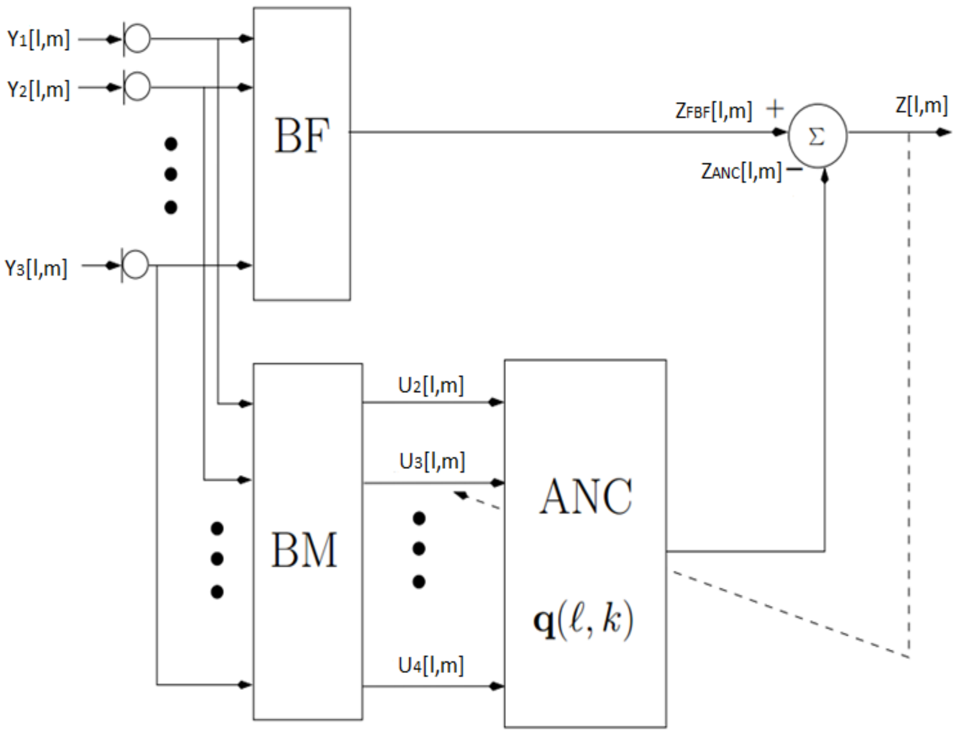
Dereverberation by Spectral Subtraction

E.A.P. Habets, S. Gannot and I. Cohen, “Late reverberant spectral variance estimation based on a statistical model,” IEEE Signal Processing Letters, vol. 16, pp. 770-773, Sept.2009



TF-GSC

S. Gannot, D. Burshtein and E. Weinstein, “Signal enhancement using beamforming and nonstationarity with applications to speech”, IEEE Trans Aug. (2001)



- The first block is a fixed beamformer, designed to satisfy the constraint.
- The second block is a blocking matrix, which blocks the desired signal and produces noise-only reference signals.
- The third block is an unconstrained adaptive algorithm that aims at canceling the residual noise at the fixed beamformer output

Drawbacks of previous dereverberation algorithms

- In most of the beamforming algorithms the focus was set on noise reduction.
- GSC based beamformers are sensitive to RTF/RIR estimation error which are common in reverberant environments → usually causes leakage.
- Most beamformers were designed to extract the clean but reverberant signal at the reference channel
- Reverberation at the look direction of the beamformer, are disregarded.
- The reverberation reduction problem is not addressed directly in the optimization scheme.

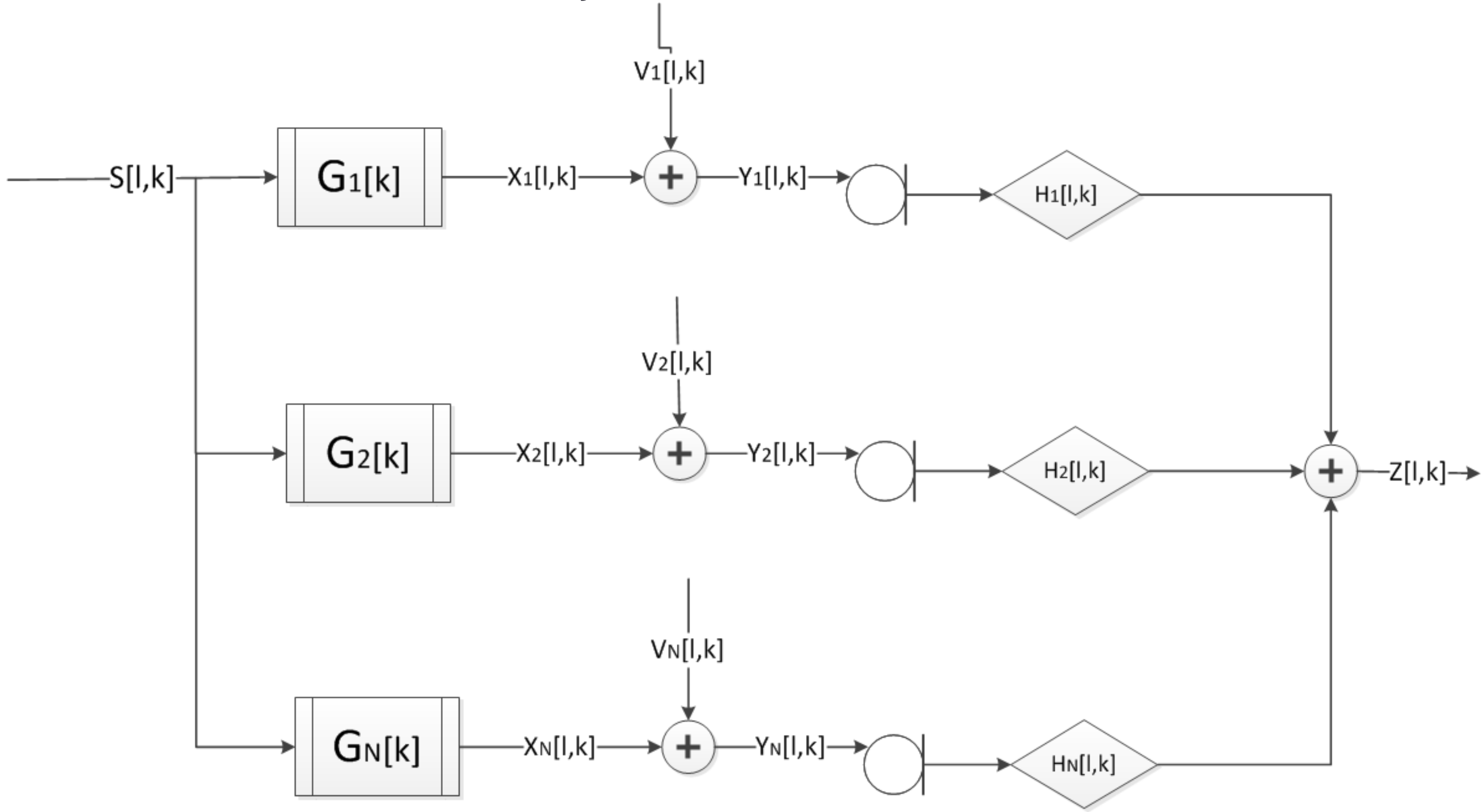
Main Contributions

- Propose an algorithm for the estimation of the full to early relative transfer function $\frac{\bar{G}\,[k]}{G_{1,e}[k]}$
- Use the full to early RTF estimator to adjust known beamformers to the problem of joint dereverberation and noise reduction.
- We neglect the GSC scheme and use close form solutions
- Propose an new signal decomposition model for the array observation vector.
- Use the model to design beamformers that address dereverberation directly in the optimization scheme

OPTIMAL BEAMFORMERS FOR THE JDNR PROBLEM

STFT Beamforming

- Applying a complex weight to the output of each sensor, and summing across the aperture
  - $Y_j[l,k] = G_j[k]S[l,k] + V_j[l,k], \quad j = 1 \dots N$
  - $Z[l,k] = \sum_{j=1}^{N} Y_j[l,k]H_j[l,k]$



Signal Decomposition

- The vector $\bar{Y}[l,k]=\bar{G}[k]S[l,k]+\bar{V}[l,k]$ can be written as a function of the desired signal.
- $\bar{Y}[l,k]=\overline{d}_{\bar{x},X_{1,c}}[k]X_{1,c}[l,k]+\bar{V}[l,k]$
- $\bar{d}_{\bar{x},X_{1,c}}[k]$ is the array's Steering Vector, constructed out of the full to early RTF vector
- $\bar{d}_{\bar{x},X_{1,c}}[k]=\left[\frac{G_1[k]}{G_{1,c}[k]},\frac{G_2[k]}{G_{1,c}[k]},\dots,\frac{G_N[k]}{G_{1,c}[k]}\right]$ $=\frac{G_1[k]}{G_{1,c}[k]}x\underbrace{\left[1,\frac{G_2[k]}{G_1[k]},\dots,\frac{G_N[k]}{G_1[k]}\right]}_{Estimators\ exists}$
- We suggest an algorithm to estimate $\frac{G_1[k]}{G_{1,c}[k]}$

MSE criteria

- The Subband MSE criterion is defined as:
- $J\left[\bar{h}[l,k]\right] = E\left\{\left|\bar{h}^H[l,k]\bar{Y}[l,k] - X_{1,c}[l,k]\right|^2\right\}$
- Can be divided into two uncorrelated parts
- $J_d\left[\bar{h}[l,k]\right] = \phi_{X_{1,c}}[l,k]\left|\bar{h}^H[l,k]\bar{d}_{\bar{x},X_{1,c}}[k] - 1\right|^2$
- $J_r\left[\bar{h}[l,k]\right] = \bar{h}^H[l,k]\Phi_{vv}[l,k]\bar{h}[l,k]$
- Goal → extract $X_{1,c}[l,k]$ from $\bar{Y}[l,k]$ using:
- $Z[l,k] = \bar{h}^H[l,k]\bar{Y}[l,k]$
- $\bar{h}[l,k]$ is chosen to either minimize $J\left[\bar{h}[l,k]\right]$ or minimize $J_d\left[\bar{h}[l,k]\right]$ or $J_r\left[\bar{h}[l,k]\right]$ subject to some constraint.

Performance Measures

- We Analyze the Beamformer performance by 3 criteria:

1. Noise Reduction.

$$OSNR = \frac{1}{N_T}\sum_{l=0}^{N_T}\frac{\sum_{k=0}^{M}\phi_{X1,c}[l,k]\left|\bar{h}^H[l,k]\bar{d}_{\bar{x},X_{1,c}}[k]\right|^2}{\sum_{k=0}^{M}\bar{h}^H[l,k]\Phi_{vv}[l,k]\bar{h}[l,k]}$$

2. Speech Distortion.

$$\nu_{sd} = \frac{1}{N_T}\sum_{l=0}^{N_T}\sum_{k=0}^{M}\phi_{X1,c}[l,k]\left|\bar{h}^H[l,k]\bar{d}_{\bar{x},X_{1,c}}[k]-1\right|^2$$

3. Reverberation suppression

$$LSD[l] = \sqrt{\frac{1}{K}\sum_{k=0}^{K-1}\left|\mathcal{L}\{Z[l,k]\}-\mathcal{L}\{X_{1,c}[l,k]\}\right|^2 dB}$$

Wiener MVDR and Trade-off Beamformers

- The Wiener beamformer minimizes $J\left[\bar{h}[l,k]\right]$.
- The MVDR beamformer minimizes $J_r\left[\bar{h}[l,k]\right]$, under no distortion constraint $J_d\left[\bar{h}[l,k]\right] = 0$.
- The Trade-off beamfomer minimizes $J_d\left[\bar{h}[l,k]\right]$,with the constraint $J_r\left[\bar{h}[l,k]\right] = \beta\phi_{V_1}[l,k]$ 1>β>0

Trade-off Beamformer

- The Trade-off Beamformer solves the constraint minimization problem
- $\bar{h}_{\mathrm{T},\mu}[l,k] = \underbrace{min}_{\bar{h}} J_d\left[\bar{h}[l,k]\right],\ \mathrm{S.T}\ J_r\left[\bar{h}[l,k]\right] = \beta\phi_{V_1}[l,k]$

  β>0, for a Lagrange multiplier $\mu > 0$
- $\bar{h}_{\mathrm{T},\mu}[l,k] = \frac{\phi_{X_{1,c}}[l,k]\Phi_{\bar{v}\bar{v}}^{-1}[l,k]\bar{d}_{\bar{x},X_{1,c}}[k]}{\mu+\phi_{X_{1,c}}[l,k]\bar{d}_{\bar{x},X_{1,c}}^{H}\Phi_{\bar{v}\bar{v}}^{-1}[l,k]\bar{d}_{\bar{x},X_{1,c}}[k]}$
- When $\mu = 0 \rightarrow$ MVDR $\mu = 1 \rightarrow$ Wiener
- When $0 < \mu < 1 \rightarrow$ trade off between the MVDR and the Wiener beamformers.
- When $\mu > 1 \rightarrow$ Strong noise reduction, high speech distortion

Relative Transfer function Estimation

- Estimation of the classical RTFs have been suggested in:
- I. Cohen, Relative Transfer Function Identification Using Speech Signals Special Issue of the IEEE Trans – using a recursive normalized WLMS scheme
- A. Krueger, E. Warsitz, and R. Haeb-Umbach, Speech enhancement with a GSC-like structure employing eigenvector-based transfer function ratios estimation- using GEVD on the noise correlation matrix
- E. Habets and J. Benesty, A perspective on frequency-domain beamformers in room acoustics- using $\frac{\{\Phi_{xx}[l,k]\}_{1:N}}{\{\Phi_{xx}[l,k]\}_{1,1}}$

Relative Transfer function Estimation

- Similar to the work in - I. Cohen “Relative Transfer Function Identification Using Speech Signals Special”, Issue of the IEEE Trans.
- From the signal model
- $\Phi_{Y_1,Y_1}[l,k] = \phi_{X_{1,c},X_1}[l,k] d_{X_{1,c},X_1}[l,k] + \phi_{V_1,V_1}[l,k]$
- For every frequency bin k we define L equations
- $$\begin{bmatrix} \hat{\phi}_{Y_1,Y_1}[1,k] - \hat{\phi}_{V_1,V_1}[1,k] \\ \vdots \\ \hat{\phi}_{Y_1,Y_1}[L,k] - \hat{\phi}_{V_1,V_1}[L,k] \end{bmatrix} = \begin{bmatrix} \hat{\phi}_{X_{1,c},X_1}[1,k] \\ \vdots \\ \hat{\phi}_{X_{1,c},X_1}[L,k] \end{bmatrix} \hat{d}_{X_{1,c},X_1}[k] + \begin{bmatrix} \bar{\epsilon}_1[1,k] \\ \vdots \\ \bar{\epsilon}_1[L,k] \end{bmatrix}$$

Relative Transfer function Estimation

- Use recursive normalized LMS solution :
- $\hat{d}_{X_1,X_{1,c}}[l,k] = \hat{d}_{X_1,X_{1,c}}[l-1,k]$
  $+ \mu_{RTF} \frac{\bar{\bar{I}}[k]}{\widehat{\phi}_{X_{1,c},X_1}[l,k]} \bar{\epsilon}_1[l,k]$
- $I[l,k] = \begin{cases} 1 \ if \ p[l,k] \geq p_0 \\ 0 \qquad otherwise \end{cases}$, p_0 is a predefine threshold
- μ_{RTF} is the LMS Update step
- $\bar{\epsilon}_1[l,k] = \widehat{\phi}_{Y_1,Y_1}[l,k] - \widehat{\phi}_{V_1,V_1}[l,k] - \widehat{\phi}_{X_{1,c},X_1}[l,k]\hat{d}_{X_1,X_{1,c}}[l-1,k]$
- This estimator is known as the minimum variance estimator.

PSD estimation

- The cross PSD Φ_{yy} is estimated by applying a first order recursive smoothing approach:
- $\Phi_{yy}[l,k] = \alpha_y \Phi_{yy}[l-1,k] + (1$

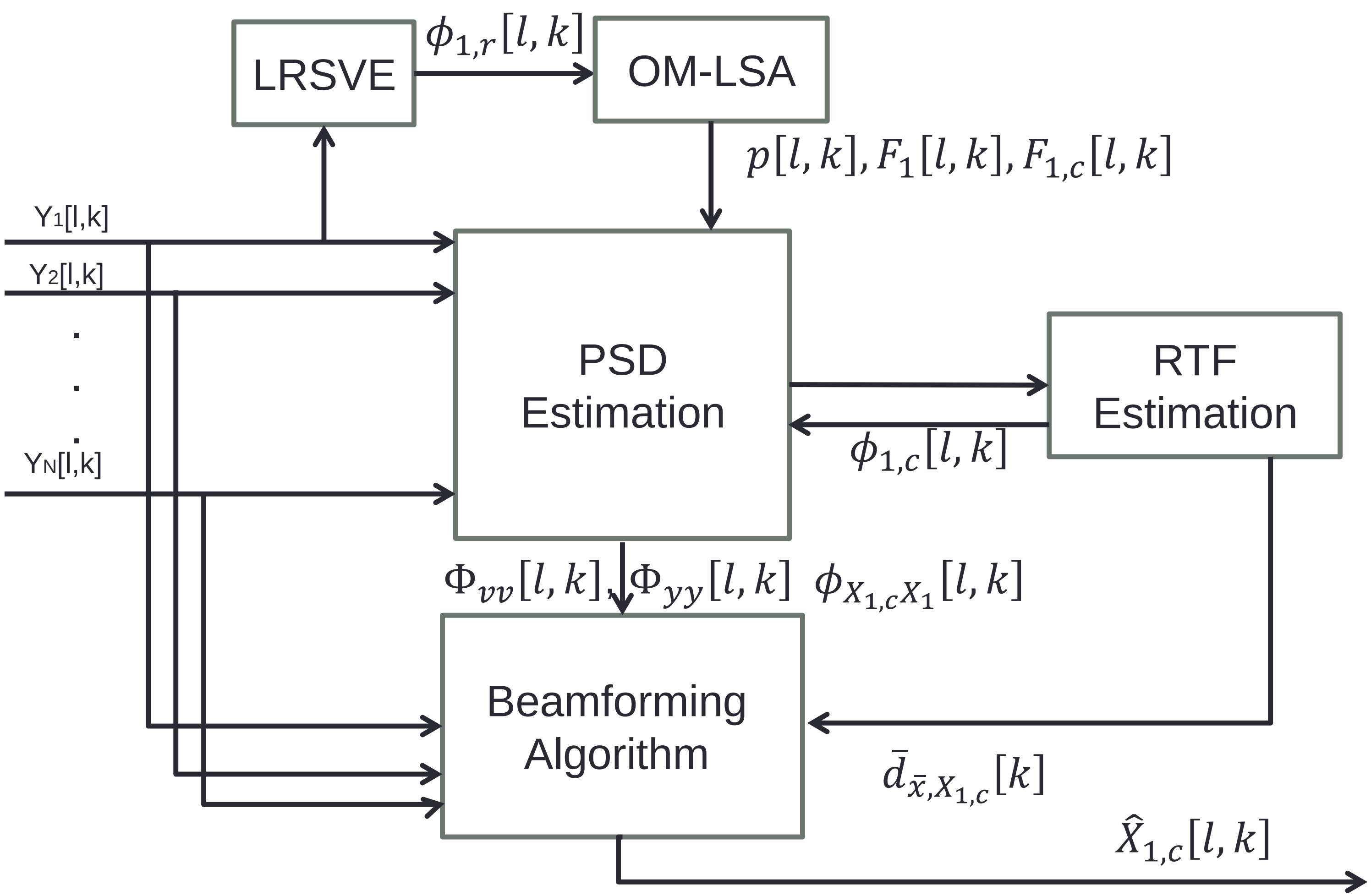
Desired and reverberant cross signal PSD Estimation

- $\Phi_{x1,x1_c}$ is calculated using two log-spectral amplitude gain functions
- $\Phi_{x1,x1_c}[l,k] = \alpha_y \Phi_{x1,x1_c}[l-1,k] + (1$

Desired signal PSD Estimation

- Using the estimate for $\Phi_{x1,x1_c}$ we use it to find an estimate for full to early RTF $d_{X_{1,c},X_1}[l,k]$.
- We incorporate $d_{X_{1,c},X_1}[l,k]$ into an estimator for the desired signal PSD
- $\Phi_{x1_c}[l,k] = \alpha_y \Phi_{x1_c}[l-1,k] + (1$

System flow

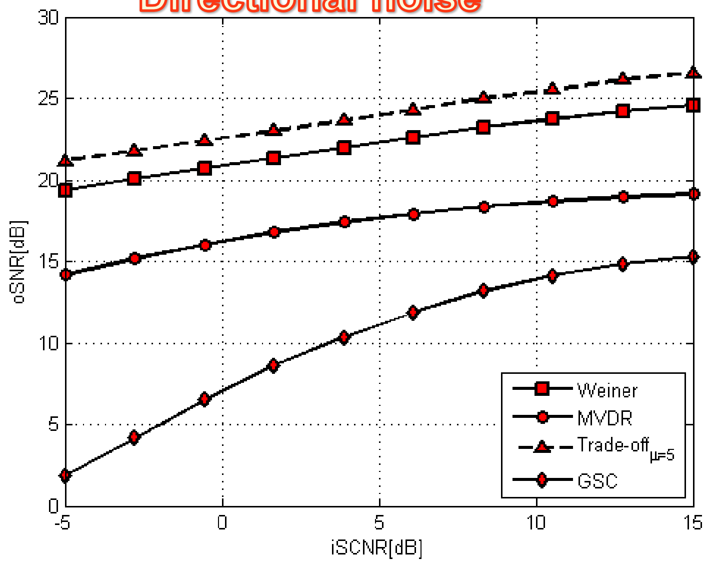

LRSVE
$\phi_{1,r}[l,k]$
OM-LSA
$p[l,k], F_1[l,k], F_{1,c}[l,k]$
Y1[l,k]
Y2[l,k]
YN[l,k]
PSD Estimation
RTF Estimation
$\phi_{1,c}[l,k]$
$\Phi_{vv}[l,k], \Phi_{yy}[l,k]$ $\phi_{X_{1,c}X_1}[l,k]$
Beamforming Algorithm
$\bar{d}_{\bar{x},X_{1,c}}[k]$
$\hat{X}_{1,c}[l,k]$

Simulation Description

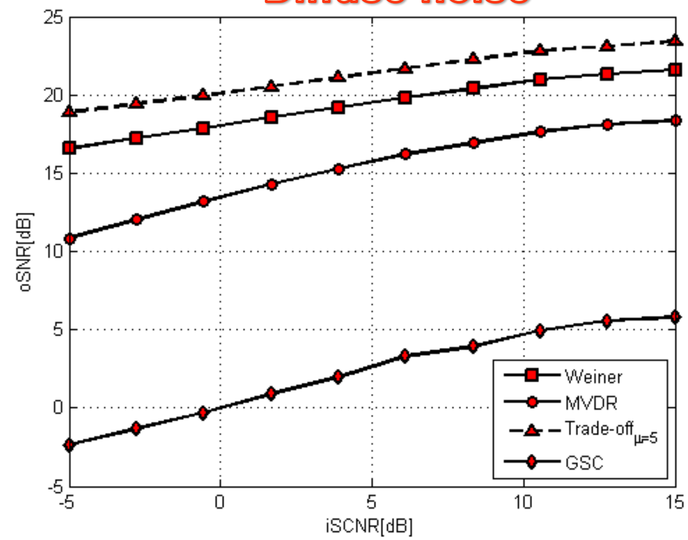
- The system is constructed out of 7 narrow band microphones array.
- The distance between each to microphones was set to 5[cm].
- The room dimensions were set to $[6\text{x}6\text{x}4][m]^{3}$
- The source was placed in $[X, Y, Z] = [3{,}3{,}2][m]$
- The reverberation time T_{60} is adaptable
- A noise source was placed at $[X, Y, Z] = [4{,}4{,}2][m]$ from the speaker, with an adaptable - iSCNR.
- To simulate the microphones thermal noise, white noise with 20[dB] SNR was added to each
- TF-GSC without post filter, BM was constructed out of the estimated RTF.

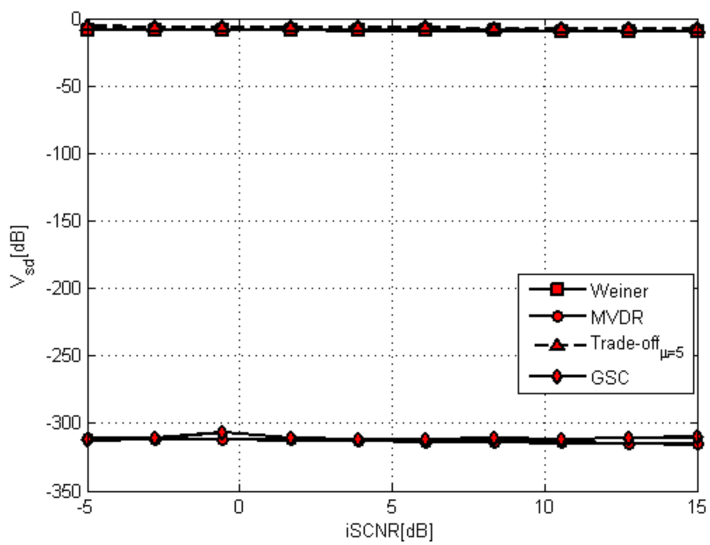
Influence of iSCNR T60=0.8[sec]

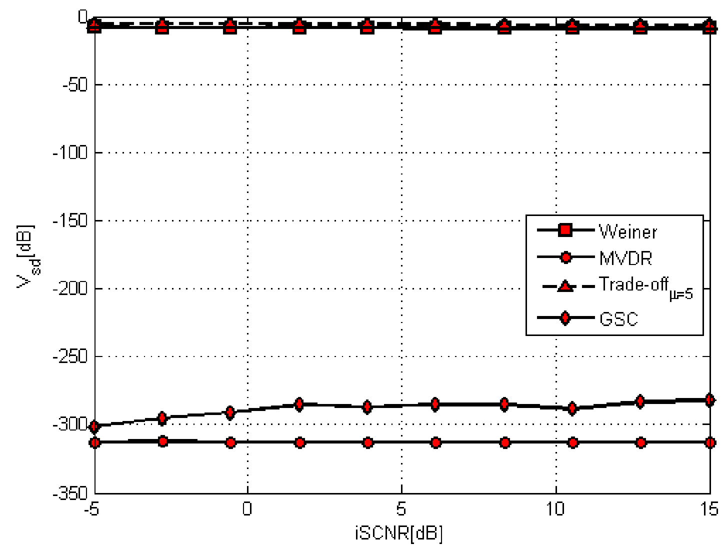
Directional noise



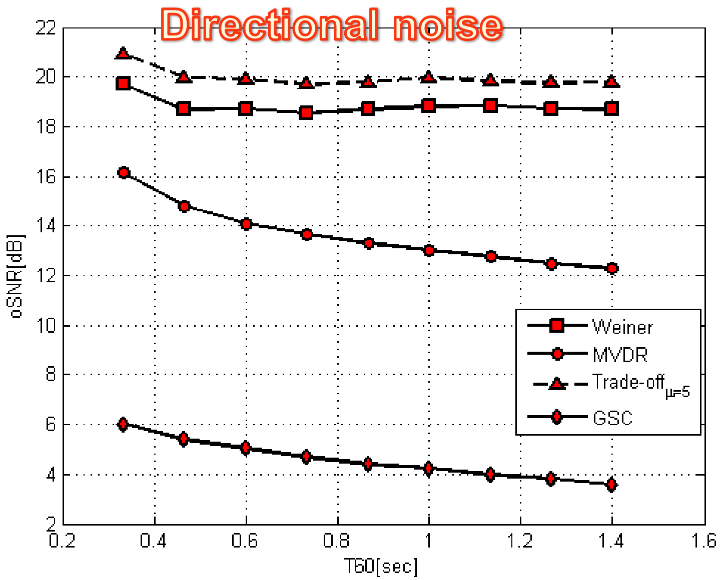
Diffuse noise

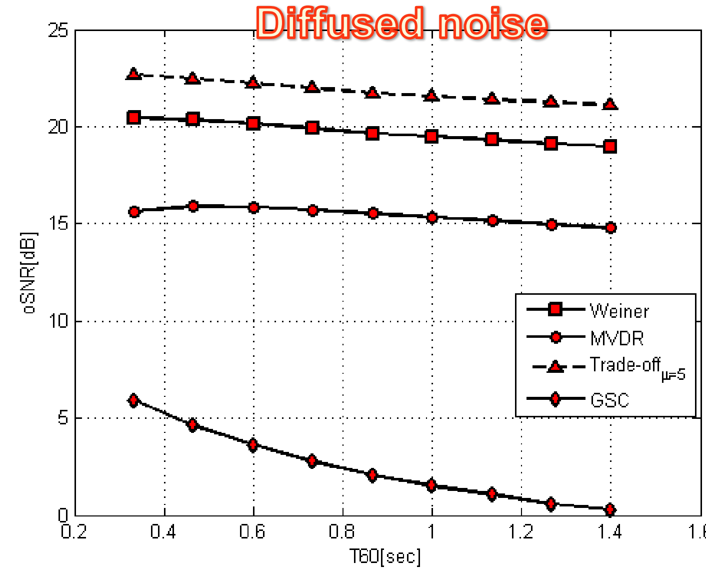


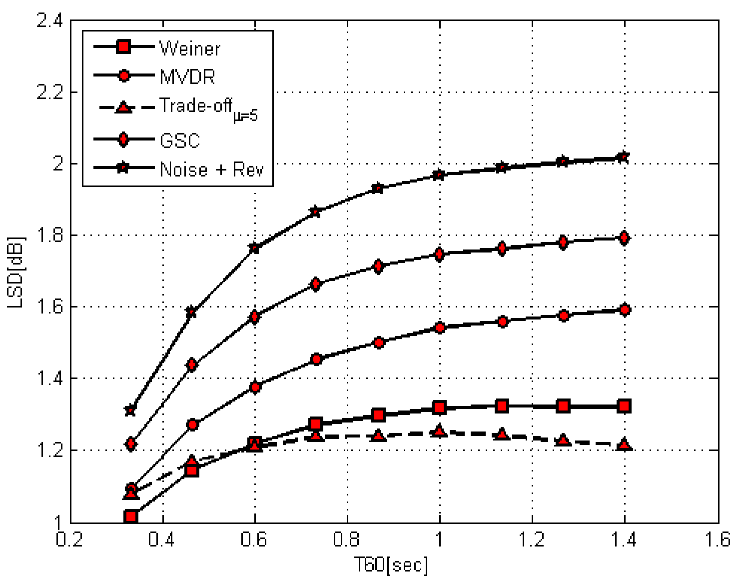


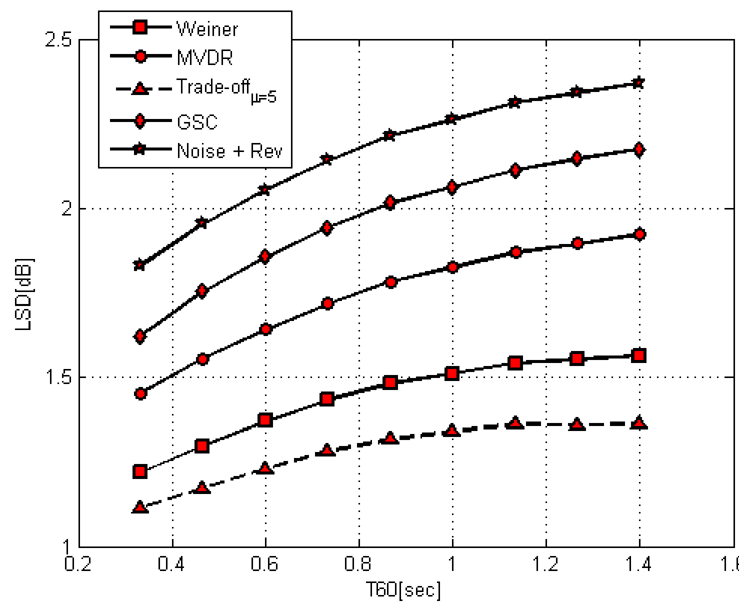


Influence of T60 iSCNR = 5[db]









REVERBERATION BLOCKAGE BEAMFORMERS

New Signal decomposition

- We preform a simple manipulation on the signal model
- $\bar{Y}[l,k] = \bar{r}[k]X_{1,c}[l,k] + i_N X_{1,c}[l,k] + \bar{V}[l,k]$
- $\bar{r}[k]$ is the a vector holding the ratio between the unwanted parts of the RIR to the desired part
- $\bar{r}[k] = \bar{d}_{X_1,X_{1,c}}[k] - i_N = \left[\frac{G_1[k]}{G_{1,c}[k]} - 1, \frac{G_2[k]}{G_{1,c}[k]} - 1, \dots, \frac{G_N[k]}{G_{1,c}[k]}\right.$

MSE criteria

- The Sub band MSE criterion is defined as:
- $J\left[\bar{h}[l,k]\right] = \phi_{X_{1,c}}[l,k]\left[\left|\bar{h}^H[l,k]i_N - 1\right|^2 + 2Re\left\{\left(\bar{h}^H[l,k]i_N\right.\right.\right.$

Performance Measures

- We Analyze the Beamformer performance using the following broadband measures

1. Noise Reduction + rev suppression

$$oSNR_{BB}[l] = \frac{\sum_{k=0}^{M} \phi_{X1,c}[l,k] \left| \bar{h}^H[l,k] i_N \right|^2}{\sum_{k=0}^{M} \bar{h}^H[l,k] \Phi_{tt}[l,k] \bar{h}[l,k]}$$

$$iSNR_{BB}[l] = \frac{\sum_{k=0}^{M} \phi_{X1,c}[l,k]}{\sum_{k=0}^{M} \phi_{X1,c}[l,k] \left[\left| \bar{r}_1 \quad [k] \right|^2 + 2RE\{ \bar{r}_1 \quad [k] \} \right] + \phi_{V1}[l,k]}$$

$$A_{BB} = \frac{1}{N_T} \sum_{l=0}^{N_T} \frac{oSNR_{BB}}{iSNR_{BB}}$$

Performance Measures

- We Analyze the Beamformer performance using the following broadband measures

1. Speech Distortion. ν_{sd}

$$= \frac{1}{N_T} \sum_{l=0}^{N_T} \frac{\sum_{k=0}^{M} \phi_{X1,c}[l,k] \left| \bar{h}^H[l,k] \bar{d}[k] \ -1 \right|^2}{\sum_{k=0}^{M} \phi_{X1,c}[l,k]}$$

2. Reverberation suppression index

$$\nu_{sr} = \frac{1}{N_T} \sum_{l=0}^{N_T} \frac{\sum_{k=0}^{M} \phi_{X1,c}[l,k] \left| \bar{h}^H[l,k] \bar{r}[k] \right|^2}{\sum_{k=0}^{M} \phi_{X1,c}[l,k]}$$

The Reverberation Block Wiener Beamformer

- The RBW Beamformer solves the constraint minimization problem
- $\bar{h}_{RBW}[l,k] = \underbrace{min}_{\bar{h}}\left\{J_d\left[\bar{h}[l,k]\right] + J_{rn}\left[\bar{h}[l,k]\right]\right\}$

$$\mathrm{S.T}\ \bar{h}^H[l,k]\bar{r} = 0$$

- $\bar{h}_{RBW}[l,k] = \phi_{X_{1,c}}[l,k]\Phi_{pp}^{-1}[l,k]\left[I_{NxN} - \frac{\bar{r}[k]\bar{r}^H[k]\Phi_{pp}^{-1}[l,k]}{\bar{r}^H[k]\Phi_{pp}^{-1}[l,k]\bar{r}[k]}\right] i_N$
- $\Phi_{pp}^{-1}[l,k] = \Phi_{vv}^{-1}[l,k] - \frac{\phi_{X_{1,c}}[l,k]\Phi_{vv}^{-1}[l,k]\ i_N i_N^T \Phi_{vv}^{-1}[l,k]}{1+\phi_{X_{1,c}}[l,k] i_N^T \Phi_{vv}^{-1}[l,k] i_N}$
- The RBW Beamformer takes the reverberation suppression index to 0

Normalized MVDR Beamformer

- The NMVDR Beamformer solves the constraint minimization problem
- $\bar{h}_{NMVDR}[l,k] = \underbrace{min}_{\bar{h}}\left\{J_{rn}\left[\bar{h}[l,k]\right] + J_{rc}\left[\bar{h}[l,k]\right]\right\}$

$$\mathrm{S.T}\ \bar{h}^{H}[l,k]i_N = 1$$

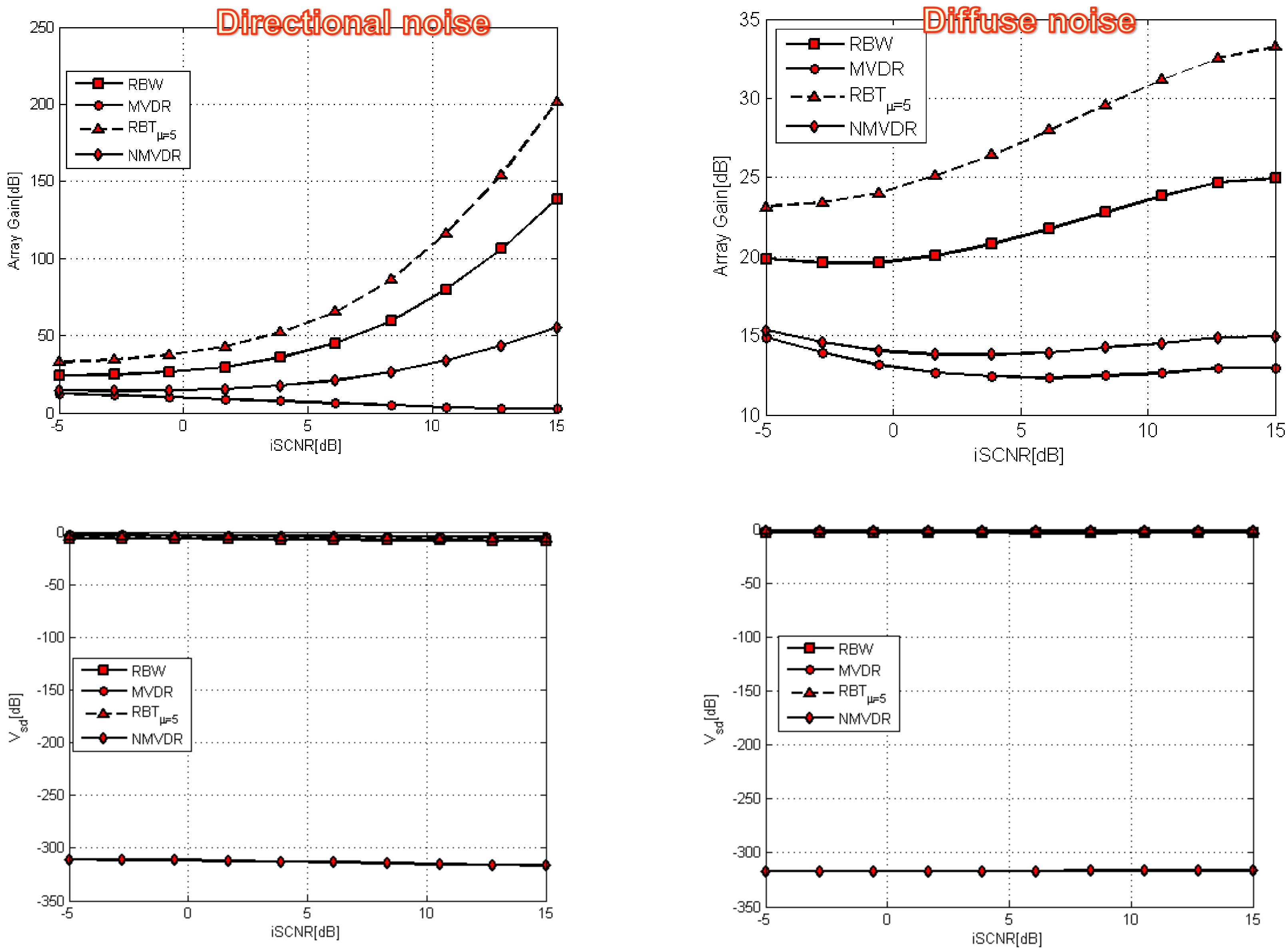
$$\bar{h}_{NMVDR}[k,l] = \frac{\Phi_{tt}^{-1}[l,k]i_N}{{i_N}^{T}\Phi_{tt}^{-1}[l,k]i_N}$$

- $\nu_{sd}\left[\bar{h}_{NMVDR}[l,k]\right] = 0$
- Special case of the NLCMV beamformer.
- The NLCMV enforces both reverberation blockage and no distortion.

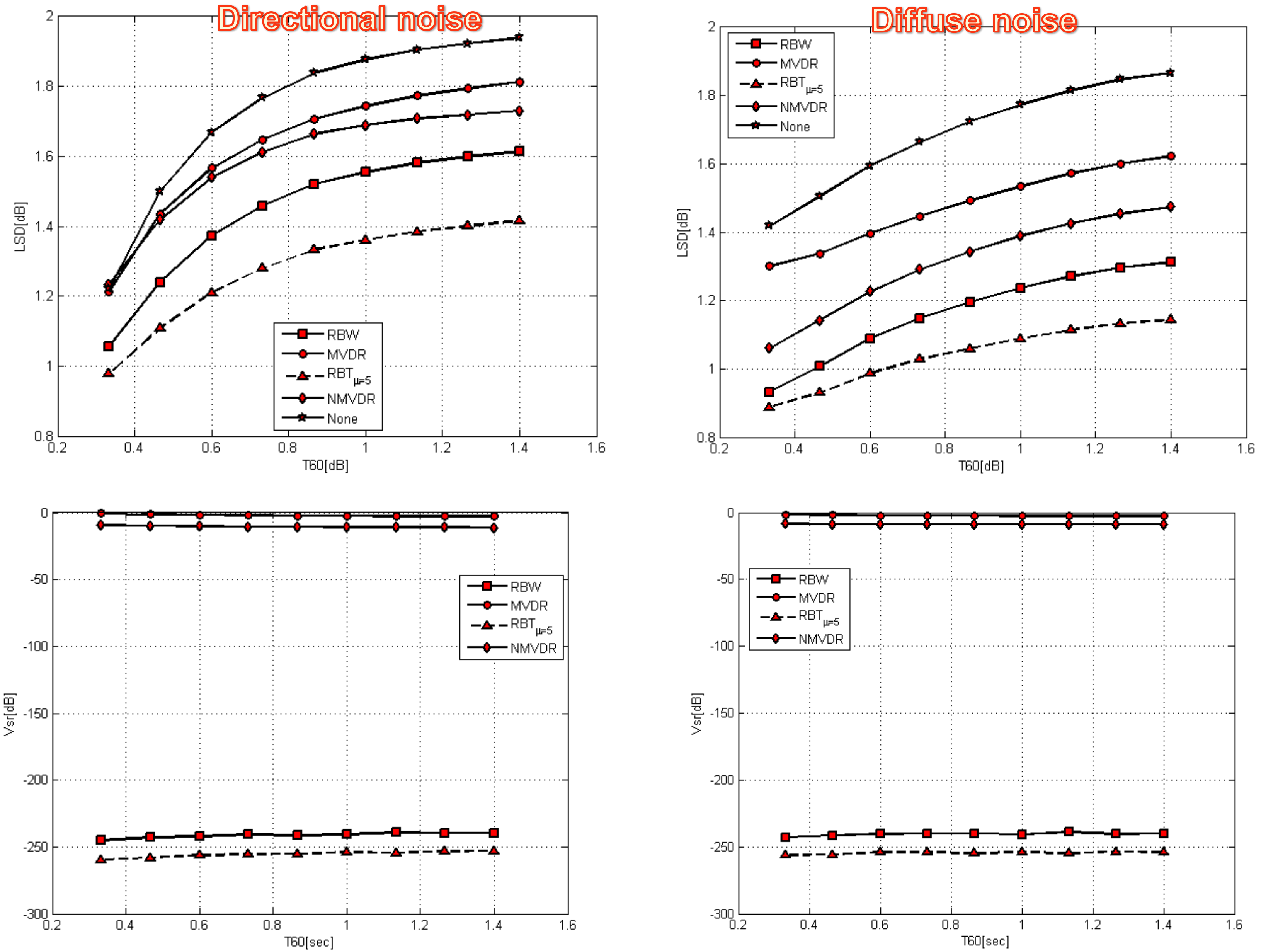
Reverberation Block Trade-off Beamformer

- The RBT Beamformer solves the constraint minimization problem
- $\bar{h}_{\mathrm{RBT},\mu}[l,k] = \underbrace{min}_{\bar{h}} J_d\left[\bar{h}[l,k]\right],$
- $\mathrm{S.T}\; J_{rn}\left[\bar{h}[l,k]\right] = \beta\phi_{V_1}[l,k]$ 1>β>0, $\bar{h}^H[l,k]\bar{r}[k] = 0$
- Using a Lagrange multiplier $\mu > 0$ we get
- $\bar{h}_{\mathrm{RBT},\mu}[l,k] = \phi_{X_{1,c}}[l,k]\Phi_{pp}^{-1}[l,k]\left[I_{NxN} - \frac{\bar{r}[k]\bar{r}^H[k]\Phi_{pp}^{-1}[l,k]}{\bar{r}^H[k]\Phi_{pp}^{-1}[l,k]\bar{r}[k]}\right] i_N$
- $\Phi_{pp}^{-1}[l,k] = \frac{1}{\mu}\left[\Phi_{vv}^{-1}[l,k] - \frac{\phi_{X_{1,c}}[l,k]\Phi_{vv}^{-1}[l,k]\, i_N i_N^T \Phi_{vv}^{-1}[l,k]}{\mu+\phi_{X_{1,c}}[l,k] i_N^T \Phi_{vv}^{-1}[l,k] i_N}\right]$
- When $\mu \rightarrow 0 \rightarrow$ NLCMV, When $\mu = 1 \rightarrow$ RBW
- When $0 < \mu < 1 \rightarrow$ lower speech distortion at the expense of residual noise reduction.
- When $\mu > 1 \rightarrow$ better noise reduction, at the expense of high speech distortion.

Influence of iSCNR T60=0.8[sec]

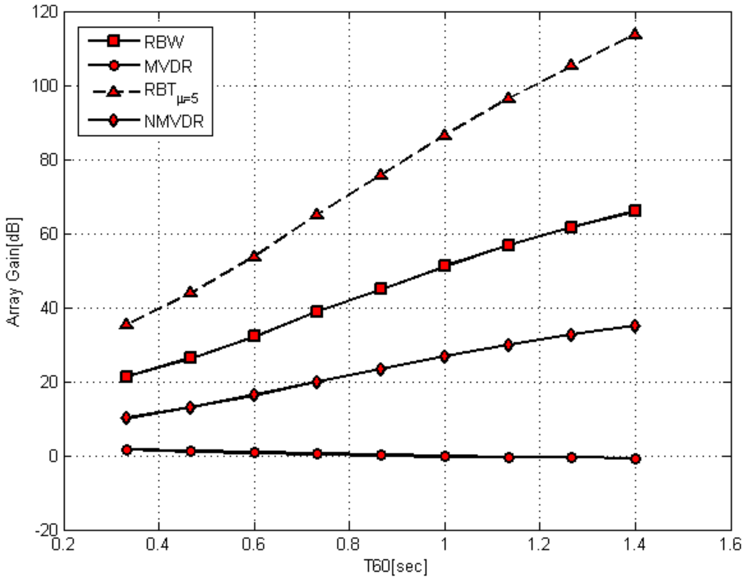


Influence of T60 iSCNR=5[dB]

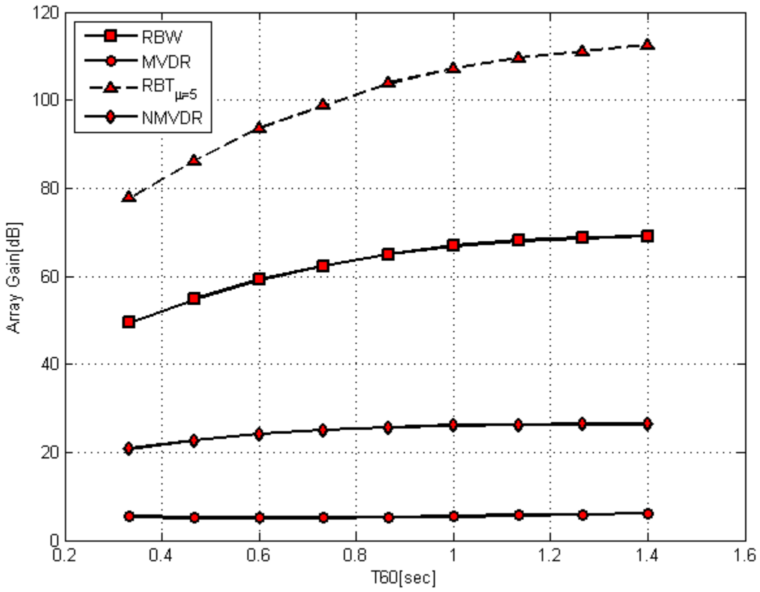


Influence of T60 iSCNR=5[dB]

Directional noise



Diffuse noise



Simulation Results
Different Beamformers

- First approach
- Directional noise field ISCNR 5[dB] T60-0.8[sec]
- Noisy Signal+ rev –
- Wiener GSC MVDR TF-mu=5

- Second approach
- Directional noise field ISCNR 5[dB] T60-0.8[sec]
- Noisy Signal+ rev –
- RBW NMVDR MVDR RBT-mu=5
-

Work Summary

- ***First approach***

➢ Manages to adapt the MVDR/Wiener/Trade-off Beamformers to reverberant environment

➢ Shows promising results in aspects of both denoising and dereverberation, compared to the TF-GSC.

- ***Second approach***

➢ Shows high reverberation blockage capabilities

➢ Outperforms the standard MVDR

➢ The reverberation suppression process is an acting part in the minimization problem

Thank you for listening

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