Polynomial Matrix Eigenvalue Decomposition of Spherical Harmonics for Speech Enhancement

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Introduction

Motivation for Speech Enhancement

Speech enhancement is important for many applications:

- Hearing aids
- Telecommunications
- Automatic speech recognition (ASR) systems
- Voice-controlled home systems

Main causes of speech degradation:

- Background noise
- Reverberation

Challenge: No prior information of target speech or acoustic environment
$\Rightarrow$ Need for blind and unsupervised approaches

Existing Subspace Approaches for Speech Enhancement

- Single-channel subspace speech enhancement [Ephraim1995; Hu2002]
  - Use an EVD to decorrelate spectrally
- Multi-channel subspace speech enhancement [Asano2000]
  - Use an EVD to decorrelate spatially

$\Rightarrow$ Limitation: Only decorrelates instantaneously, inadequate for speech

- PEVD-based speech enhancement [Neo2019a; Neo2020]
  - Use PEVD to impose spatial decorrelation over a range of time shifts
  - Effective for noise reduction and dereverberation
  - Robust for linear and arbitrary array geometries

$\Rightarrow$ Limitation: Complexity $\propto (\#\text{ of mics})^3$

This Talk: Spherical Microphone Array

Background

Multichannel Reverberant Signal Model

The received signal at the q-th sensor with time index n is

$$x_q(n) = \mathbf{h}_q^T \mathbf{s}_0(n) + v_q(n) = \tilde{s}_q(n) + \tilde{v}_q(n)$$

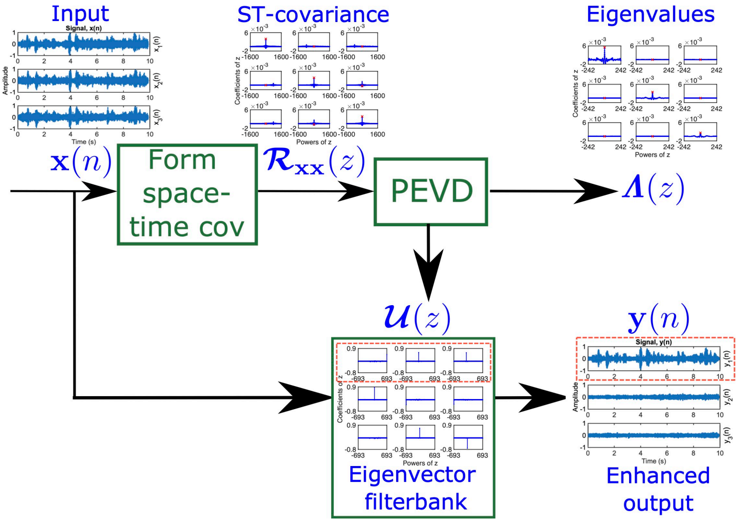
where

- $\tilde{s}_q(n) = (\mathbf{h}_{q,dp}^T + \mathbf{h}_{q,er}^T)\mathbf{s}_0(n)$ is the speech component,
- $\tilde{v}_q(n) = \mathbf{h}_{q,lr}^T \mathbf{s}_0(n) + v_q(n)$ is the noise component.
- $\mathbf{s}_0(n)$ is the anechoic speech signal,
- $v_q(n)$ is the noise signal at the q-th sensor.

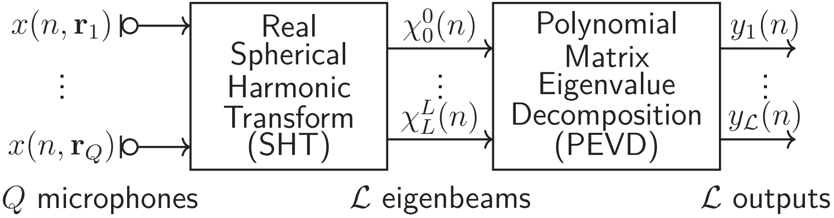
The data vector collected from Q sensors is

$$\mathbf{x}(n) = [x_1(n), x_2(n), \ldots, x_Q(n)]^T.$$

Speech Enhancement Using PEVD [Neo2020]



Sketch: PEVD of Spherical Harmonics (SH)



Spherical Harmonics Decomposition

The ℓ-th order, m-th degree eigenbeam signal, associated with the real SH basis function $R_\ell^m(\mathbf{r}_q)$ and quadrature sampling weight α_q, is

$$\chi_\ell^m(n) \approx \sum_{q=1}^{Q} \alpha_q x(n, \mathbf{r}_q) R_\ell^m(\mathbf{r}_q).$$

Recovery of each microphone signal uses a weighted sum of the SH

$$x(n, \mathbf{r}_q) = \sum_{\ell=1}^{L} \sum_{m=-\ell}^{\ell} \chi_\ell^m(n) R_\ell^m(\mathbf{r}_q)$$

and alias-free spatial reconstruction requires $Q \geq (L+1)^2$ where L is the maximum SH order of the sound field and $\mathcal{L} \triangleq (L+1)^2$ eigenbeams.

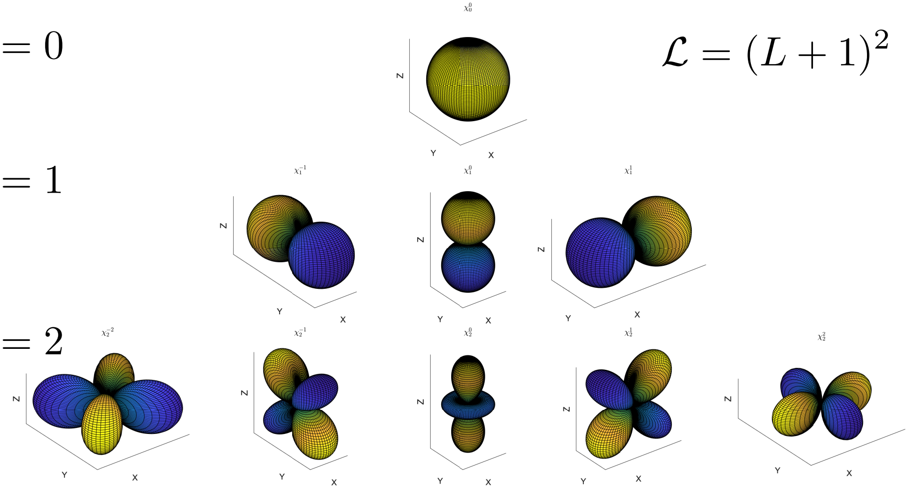
Spherical Harmonics Decomposition

$\ell = 0$

$\ell = 1$

$\ell = 2$

$$\mathcal{L} = (L+1)^2$$



$m=-2$ $\quad m=-1$ $\quad m=0$ $\quad m=1$ $\quad m=2$

Complexity Analysis of a Single Example

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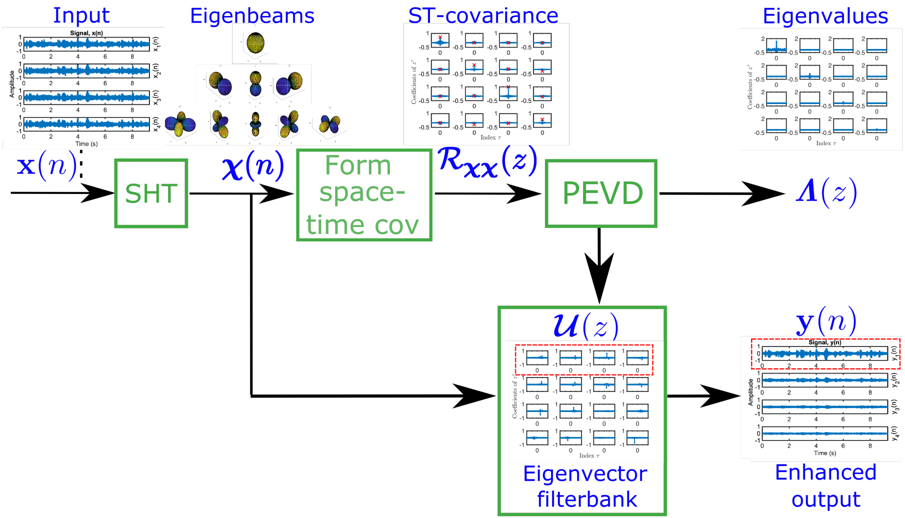
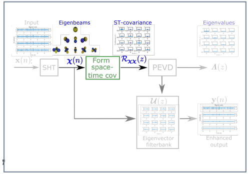
SH Order, L	0	1	2	3	4
# Eigenbeams $\mathcal{L}$	1	4	9	16	25
Approx. Error, $\varepsilon(\%)$	3.82	3.77	3.45	2.74	1.38
Complexity Factor, β	-	0.002	0.022	0.125	0.477

*$\beta = (\frac{\mathcal{L}}{Q})^3$, where $Q = 32$ microphones.

Enhancement Algorithm: PEVD of Eigenbeams



Space-time Covariance Polynomial Matrix



Assuming stationarity, the space-time covariance matrix is

$$\mathbf{R}_{\chi\chi}(\tau) = \mathbb{E}[\boldsymbol{\chi}(n)\boldsymbol{\chi}^H(n-\tau)],$$

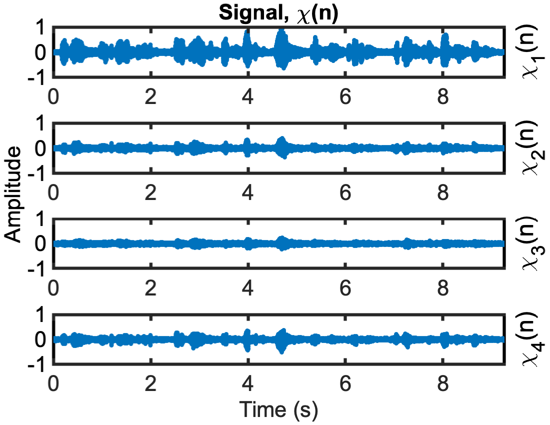
where $(i,j)^{\text{th}}$ element is the correlation function $r_{ij}(\tau) = \mathbb{E}[\chi_i(n)\chi_j^*(n-\tau)]$, τ is the time-shift and $\boldsymbol{\chi} = [\chi_0^0, \chi_1^{-1}, \chi_1^0, \ldots, \chi_L^L]^T$ is arranged in ascending order and degree.

Z-transform of $\mathbf{R}_{\chi\chi}(\tau)$ is a para-Hermitian polynomial matrix

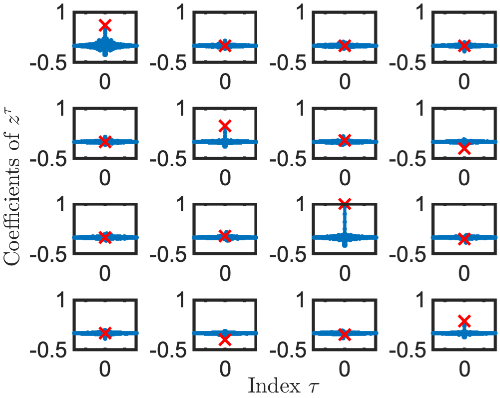
$$\boldsymbol{\mathcal{R}}_{\chi\chi}(z) = \sum_{\tau=-W}^{W} \mathbf{R}_{\chi\chi}(\tau) z^{-\tau},$$

where $\mathbf{R}_{\chi\chi}(\tau) \approx 0$ for $|\tau| > W$, calligraphic $\boldsymbol{\mathcal{R}}$ for polynomial matrices and regular $\mathbf{R}$ for matrices.

Example: Polynomial Matrix from ST-Covariance



Eigenbeam signals $\boldsymbol{\chi}(n)$.



Polynomial matrix, $\boldsymbol{\mathcal{R}}_{\chi\chi}(z)$.

Polynomial Matrix Eigenvalue Decomposition

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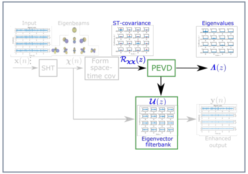


The PEVD of $\boldsymbol{\mathcal{R}}_{\boldsymbol{\chi}\boldsymbol{\chi}}(z)$ is [McWhirter2007]

$$\boldsymbol{\mathcal{R}}_{\boldsymbol{\chi}\boldsymbol{\chi}}(z) \approx \boldsymbol{\mathcal{U}}^{P}(z)\boldsymbol{\Lambda}(z)\boldsymbol{\mathcal{U}}(z),$$

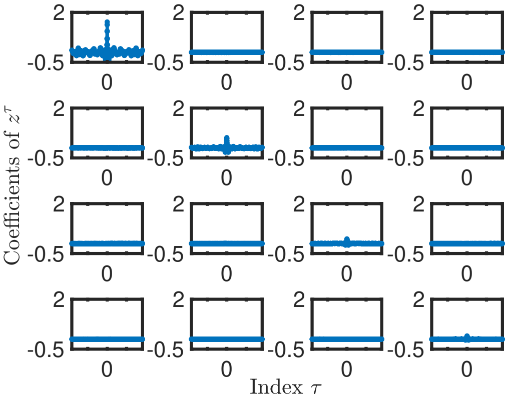
where $\boldsymbol{\Lambda}(z)$,$\boldsymbol{\mathcal{U}}(z)$ contain the eigenvalues and eigenvectors and $\boldsymbol{\mathcal{R}}^{P}_{\boldsymbol{\chi}\boldsymbol{\chi}}(z) = \boldsymbol{\mathcal{R}}^{H}_{\boldsymbol{\chi}\boldsymbol{\chi}}(z^{-1})$.

Since $\tilde{\mathbf{s}}(n)$ and $\tilde{\mathbf{v}}(n)$ are uncorrelated [Naylor2010]

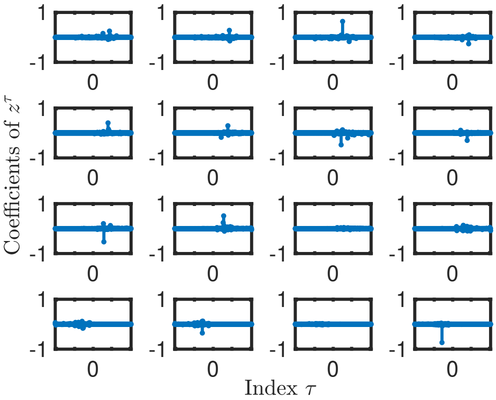
$$\boldsymbol{\mathcal{R}}_{\mathbf{xx}}(z) = \left[\ \boldsymbol{\mathcal{U}}^{P}_{\tilde{s}}(z) \;\middle|\; \boldsymbol{\mathcal{U}}^{P}_{\tilde{v}}(z)\ \right] \left[\begin{array}{c|c} \boldsymbol{\Lambda}_{\tilde{s}}(z) & \mathbf{0} \\ \hline \mathbf{0} & \boldsymbol{\Lambda}_{\tilde{v}}(z) \end{array}\right] \left[\begin{array}{c} \boldsymbol{\mathcal{U}}_{\tilde{s}}(z) \\ \hline \boldsymbol{\mathcal{U}}_{\tilde{v}}(z) \end{array}\right],$$

with orthogonal signal, $\{\cdot\}_{\tilde{s}}$ and noise subspaces, $\{\cdot\}_{\tilde{v}}$.

Example: PEVD Algorithm Outputs



Eigenvalue polynomial matrix, $\boldsymbol{\Lambda}(z)$.

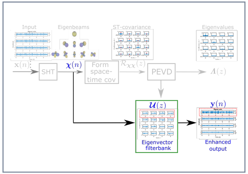


Eigenvector polynomial matrix, $\boldsymbol{\mathcal{U}}(z)$.

PEVD Algorithms

PEVD algorithms include:

- Second-order Sequential Best Rotation (SBR2) [McWhirter2007]
- Sequential Matrix Diagonalization (SMD) [Redif2015]
- Householder-like PEVD [Redif2011]
- Tridiagonal PEVD [Neo2019b]
- Multiple-shift SBR2/SMD [Wang2015; Corr2014]



$\boldsymbol{\mathcal{U}}(z)$ is a filterbank for $\boldsymbol{\chi}(z)$ which produces outputs,

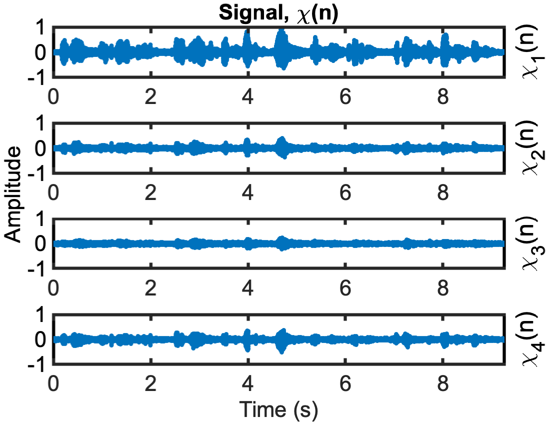
$$\mathbf{y}(z) = \boldsymbol{\mathcal{U}}(z)\boldsymbol{\chi}(z) \implies \boldsymbol{\mathcal{R}}_{\mathbf{yy}}(z) \approx \boldsymbol{\Lambda}(z),$$

that are strongly decorrelated.

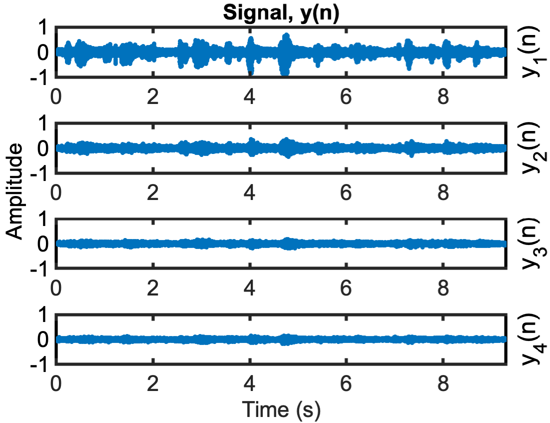
First channel output, $y_1(z)$, is the enhanced speech with ST-covariance

$$\boldsymbol{\mathcal{R}}_{y_1 y_1} = \left[\ \boldsymbol{\mathcal{U}}_{\tilde{s}}^{P}(z) \ \middle|\ \mathbf{0}\ \right] \left[\begin{array}{c|c} \boldsymbol{\Lambda}_{\tilde{s}}(z) & \mathbf{0} \\ \hline \mathbf{0} & \mathbf{0} \end{array}\right] \left[\begin{array}{c} \boldsymbol{\mathcal{U}}_{\tilde{s}}(z) \\ \hline \mathbf{0} \end{array}\right].$$

Example: Filterbank Output

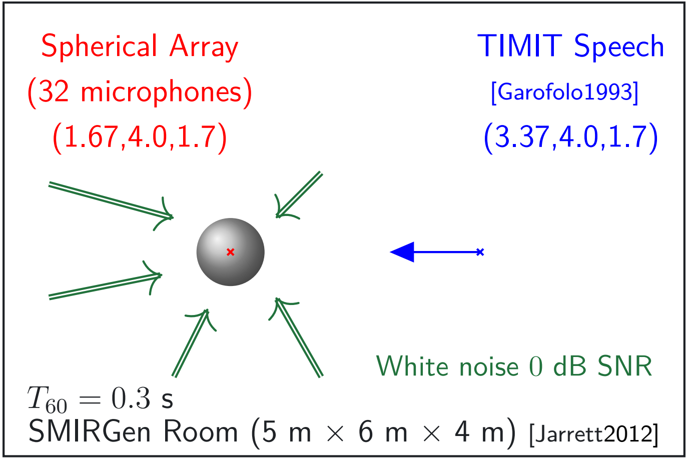


Eigenbeam signals $\boldsymbol{\chi}(n)$.



Enhanced signals, $y(n)$.

Experiment Setup: Reverberant 0 dB White Noise



Comparative Results

Speech Enhancement Evaluation

Comparative algorithms:

1. Eigenbeams χ_0^0, χ_1^1 [Rafaely 2015; Jarrett2017]
2. KLT$\{\chi_0^0\}$ - Uses an EVD on eigenbeam [Ephraim1995]
3. Raw PEVD - 32 microphone signals for PEVD [Neo2020]
4. PEVD L1, L2 - Use SH order 1, 2 eigenbeams $\Rightarrow$ 4, 9 signals for PEVD

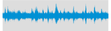
Enhancement measures:

- Frequency-weighted Segmental SNR (FwSegSNR) [Hu2006]
- Short-Time Objective Intelligibility (STOI) [Taal2011]
- Perceptual Evaluation of Speech Quality (PESQ) [ITU-T P.862]
- Bark Spectral Distortion (BSD) [Naylor2010]

Speech Enhancement Performance

Algorithm	ΔFwSegSNR	ΔSTOI	ΔPESQ	ΔBSD
χ_0^0	4.86 dB	0.055	0.42	-1.53 dB
KLT$\{\chi_0^0\}$	5.56 dB	0.054	**0.51**	-1.65 dB
χ_1^1	0.89 dB	0.122	0.44	-0.65 dB
PEVD L1	5.72 dB	0.110	0.47	-1.68 dB
PEVD L2	**5.92 dB**	**0.125**	**0.51**	**-1.71 dB**
RAW PEVD	5.59 dB	0.119	0.49	-1.62 dB

Noisy



χ_0^0

KLT$\{\chi_0^0\}$

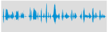
χ_1^1

PEVD L1

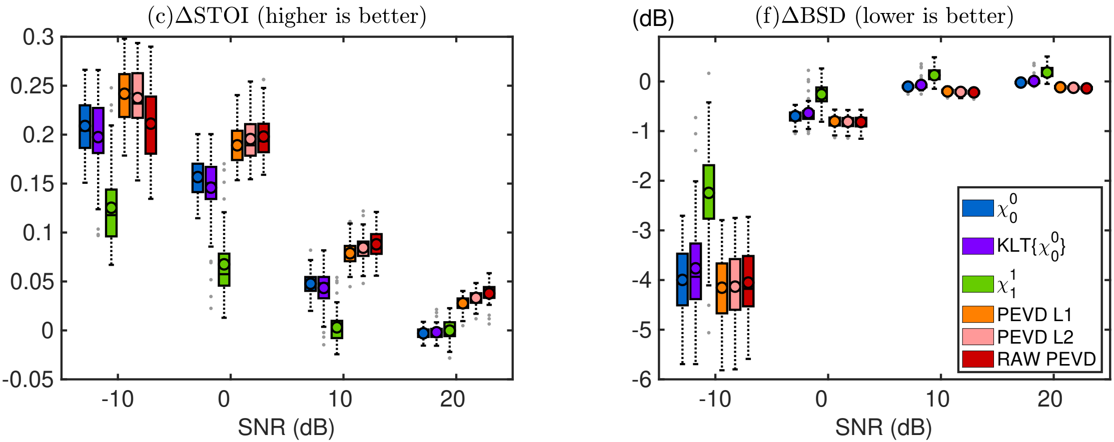
PEVD L2

RAW PEVD

Clean



ACE: Lecture Room 2, Babble Noise [Eaton2016]



Conclusion

Conclusion

- PEVD of eigenbeams remains effective for speech enhancement in noisy, reverberant environments
  - Performs almost identically, and sometimes even better, than Raw PEVD
  - Complexity factor is fraction of Raw PEVD: 0.002 to 0.477 times

- Robust even when eigenbeams are not steered towards the speaker
  - Completely blind and unsupervised

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Thank you

Listening Examples: https://vwn09.github.io/shd-pevd/
Webpage: https://vwn09.github.io