PEVD-based Speech Enhancement in Reverberant Environments

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7 May 2020

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Introduction

Motivation

- 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

- Other methods typically use STFT to process [Cohen2002; Ephraim1984; Gannot 2001; Markovich2009]
  - Use DFT to divide broadband into multiple narrowband signals

$\Rightarrow$ Limitations: Lacks phase coherence across bands
: Ignores correlation between bands

Motivation for PEVD

- Polynomial Matrices and Polynomial Eigenvalue Decomposition (PEVD)
  - Simultaneously captures correlation across space, time and frequency using a 3D tensor
  - Impose spatial decorrelation over a range of time shifts
  - No phase discontinuity
- PEVD-based Speech Enhancement [Neo2019a]
  - Effective for anechoic environments
  - Performance approaches the Oracle Multichannel Wiener Filter (OMWF)
  - No noticeable artifacts

This Talk: Speech Enhancement in Reverberant Environments

Background

Multichannel Signal Model

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

$$x_m(n) = \mathbf{h}_m^T \mathbf{s}_0(n) + v_m(n),$$

where

- $\mathbf{s}_0(n)$ is the anechoic speech signal,
- $\mathbf{h}_m$ is the channel modelled as an order J FIR filter,
- $v_m(n)$ is the noise signal at the m-th sensor.

The data vector collected from M sensors is

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

Space-time Covariance Polynomial Matrix

Assuming stationarity, the space-time covariance matrix is

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

where $(i,j)^{\mathrm{th}}$ element is the correlation function $r_{ij}(\tau) = \mathbb{E}[x_i(n)x_j^*(n-\tau)]$ and τ is the time-shift.

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

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

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

The PEVD of $\boldsymbol{\mathcal{R}}_{\mathbf{xx}}(z)$ is defined as [McWhirter2007]

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

where $\boldsymbol{\Lambda}(z), \boldsymbol{\mathcal{U}}(z)$ are the eigenvalue and eigenvector polynomial matrices and $\boldsymbol{\mathcal{R}}_{\mathbf{xx}}^{P}(z) = \boldsymbol{\mathcal{R}}_{\mathbf{xx}}^{H}(z^{-1})$.

$\boldsymbol{\mathcal{U}}(z)$ is a filterbank for $\mathbf{x}(z) \in \mathbb{C}^{M\times 1\times T}$ which produces outputs,

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

that are strongly decorrelated.

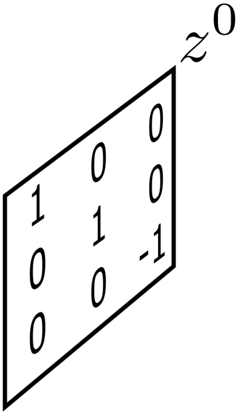
PEVD Algorithms

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]

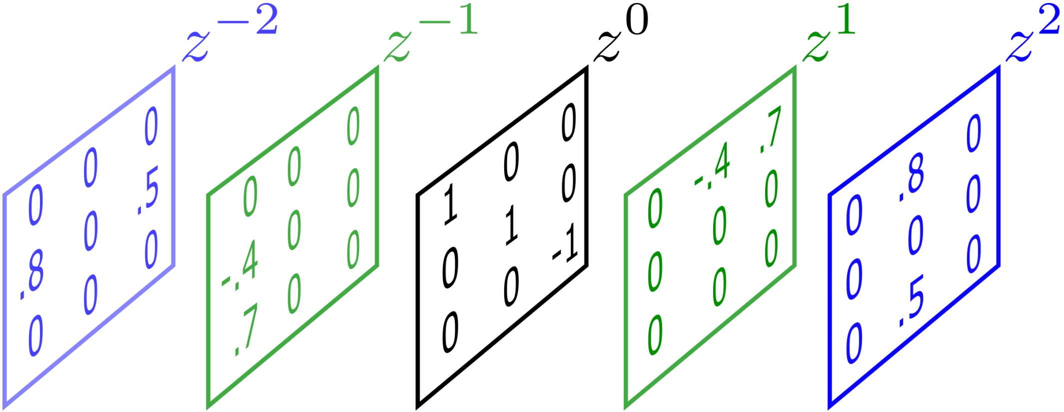
Example of a Polynomial Matrix

Typically compute $\mathbf{R}_{\mathbf{xx}}(0) = \mathbb{E}[\mathbf{x}(n)\mathbf{x}^H(n)]$:



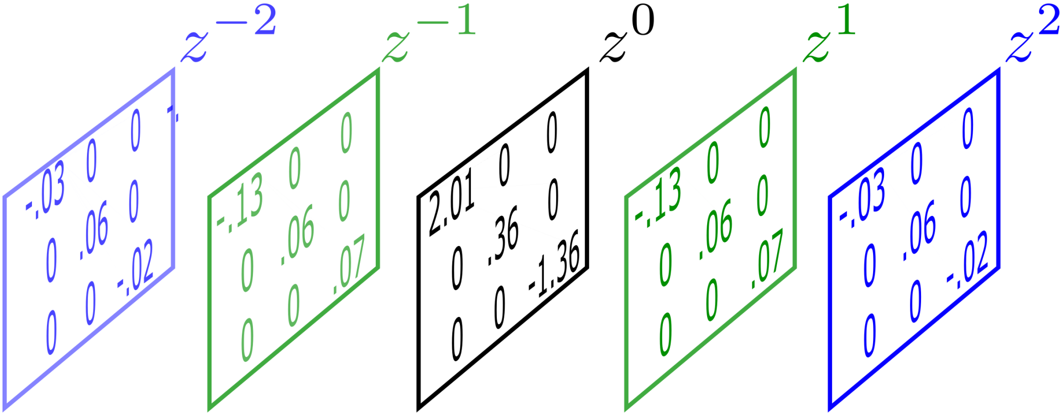
$\mathbf{R}_{\mathbf{xx}}(0)$: instantaneous (spatial) covariance matrix / coefficient of z^0.

Before diagonalization, $\boldsymbol{\mathcal{R}}_{\mathbf{xx}}(z)$:



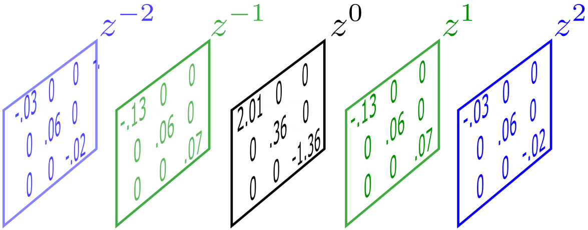
In this example, z^0 plane is diagonal but not at other planes.

After diagonalization using PEVD, $\boldsymbol{\Lambda}(z)$:

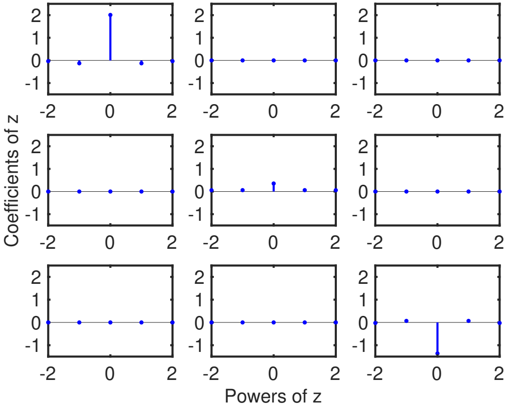


Alternate Representation of Example

Equivalently, expressed as:



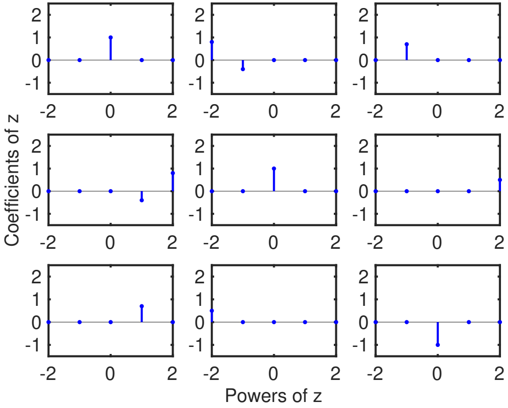
Polynomial with matrix coefficients.



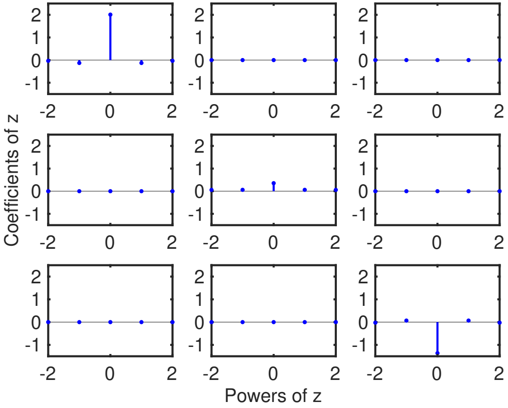
Matrix with polynomial elements.

Alternate Representation of Example

The same example can be represented as:



Original $\boldsymbol{\mathcal{R}}_{\mathbf{xx}}(z)$.

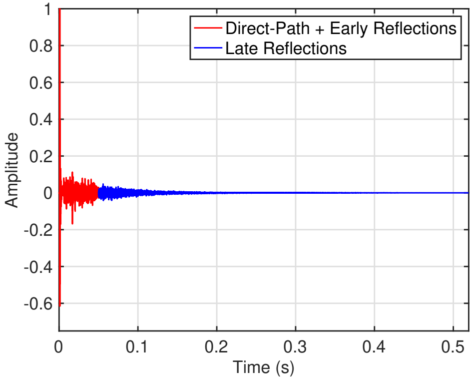


Diagonalized $\boldsymbol{\Lambda}(z)$.

Proposed Methodology

Reverberant Channel Model

The m-th channel: $\mathbf{h}_m = \tilde{\mathbf{h}}_{m,dp} + \tilde{\mathbf{h}}_{m,er} + \tilde{\mathbf{h}}_{m,lr}$



An example of a room impulse response.

Application:Speech Enhancement

Rewriting the signal model using the reverberant channel model gives

$$x_m(n) = \tilde{s}_m(n) + \tilde{v}_m(n)$$

where

- $\tilde{s}_m(n) = (\tilde{\mathbf{h}}^T_{m,dp} + \tilde{\mathbf{h}}^T_{m,er})\mathbf{s}_0(n)$ is the speech component,
- $\tilde{v}_m(n) = \tilde{\mathbf{h}}^T_{m,lr}\mathbf{s}_0(n) + v_m(n)$ is the noise component.

Goal: Obtain some enhanced version of speech using observations, $\mathbf{x}(n)$.

Enhancement targets:

- Segmental SNR (SegSNR)
- Frequency weighted SegSNR (FwSegSNR) [Hu2008]
- STOI [Taal2011]
- PESQ [ITU-T P.862]

Application: Speech Enhancement

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

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

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

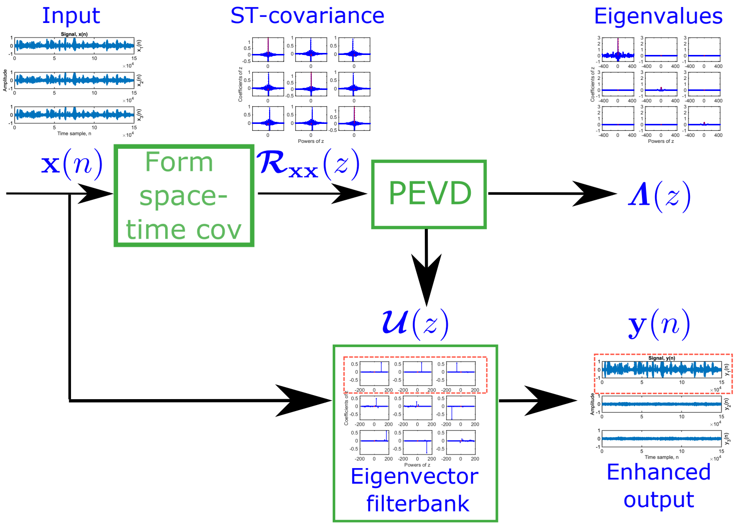
The output

$$\mathbf{y}(z) = \boldsymbol{\mathcal{U}}(z)\mathbf{x}(z),$$

has the first element, $y_1(z) \in \mathbb{R}^{1\times 1\times T}$, as the denoised and enhanced speech signal with the space-time covariance matrix

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

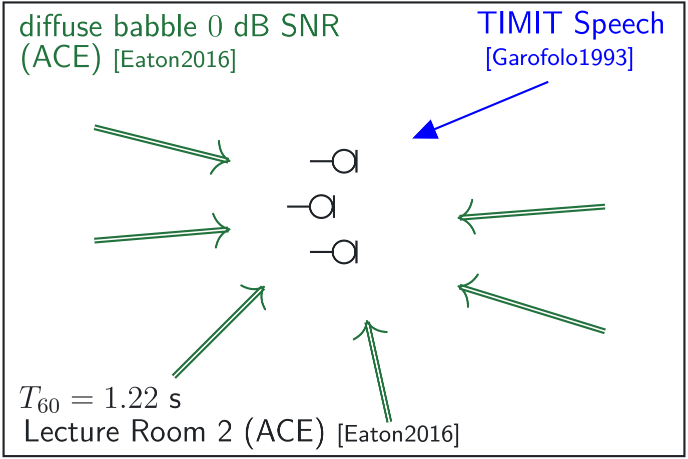
Speech Enhancement Using PEVD



Experimental Results

Experiment Setup

Reverberant Speech in Noise



Evaluation

Comparative algorithms:

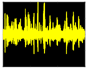
1. Coloured Noise Subspace (COLSUB) [Hu2002]
2. Log-Minimum Mean Square Error (Log-MMSE) [Ephraim1984]
3. Multichannel Subspace (MCSUB) [Huang2008]
4. Multichannel Wiener Filter (MWF) - Relative Transfer Function (RTF) and noise estimator [Kuklasiński2016]
5. Oracle-MWF (OMWF) - Given clean speech [Doclo2002]

Evaluation measures:
ΔSegSNR, ΔFwSegSNR, ΔSTOI, ΔPESQ

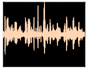
Comparison of Enhancement Algorithms

Algorithm	ΔSegSNR	ΔFwSegSNR	ΔSTOI	ΔPESQ
COLSUB	8.35 dB	7.67 dB	-0.018	-0.20
log-MMSE	3.67 dB	3.05 dB	-0.058	-0.12
MCSUB	-1.52 dB	-1.04 dB	-0.010	-0.03
MWF	1.06 dB	0.78 dB	-0.005	0.02
OMWF	0.57 dB	-0.44 dB	0.084	0.17
PEVD	2.96 dB	2.88 dB	0.078	0.11

Noisy

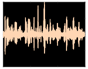


COLSUB

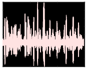


log-MMSE

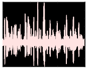
MCSUB



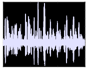
MWF



OMWF



PEVD



Clean

Conclusion

Conclusion

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- Polynomial matrices and PEVD as a tool for processing broadband multichannel signals
- Proposed a PEVD-based speech enhancement algorithm designed for a reverberant signal model
  - Exploits the lack of correlation between the speech and late reflections to provide further noise reduction
  - Incorporates the early reflections to further improve speech intelligibility and quality
  - No noticeable processing artifacts
  - No noise estimation is required

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Thank you

Listening Examples: https://www.commsp.ee.ic.ac.uk/~sap/pevdr
Webpage: https://www.commsp.ee.ic.ac.uk/~sap/vincent-w-neo