Speech Dereverberation of a Polynomial Matrix Eigenvalue Decomposition Subspace Approach

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Outline

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 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

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

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

PEVD Approach for Speech Enhancement

- Polynomial Matrices and Polynomial Eigenvalue Decomposition (PEVD)
  - Simultaneously capture correlations across space, time and frequency
  - Impose spatial decorrelation over a range of time shifts
  - No phase discontinuity

- PEVD-based Speech Enhancement [Neo2019a; Neo2020]
  - Effective for noise reduction
  - Performance approaches the Oracle Multichannel Wiener Filter (OMWF)
  - No noticeable artifacts

This Talk: Speech Dereverberation Performance

Background

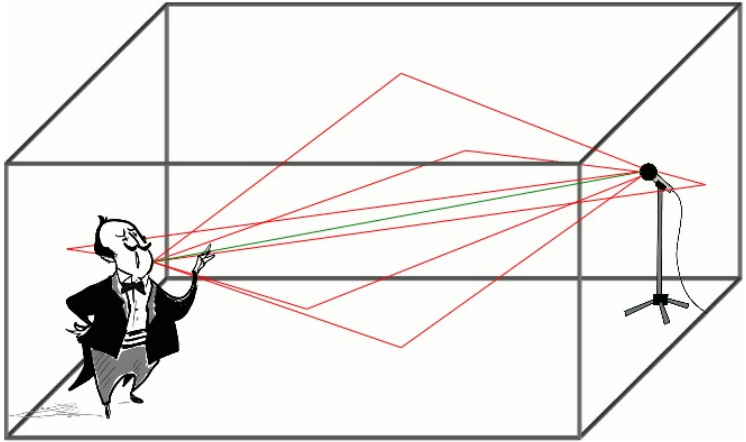
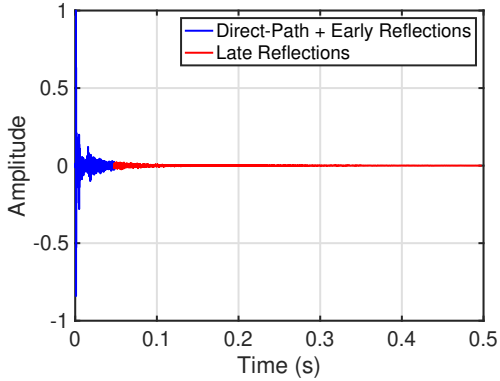


Figure is taken from the DREAMS project on the SAP website.

The m-th channel modelled as a FIR filter: $\mathbf{h}_m = \mathbf{h}_{m,dp} + \mathbf{h}_{m,er} + \mathbf{h}_{m,lr}$



An example of a room impulse response.

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

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

where

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

The data vector collected from M sensors is

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

Speech Enhancement Using PEVD

Speech Enhancement Using PEVD [Neo2020]

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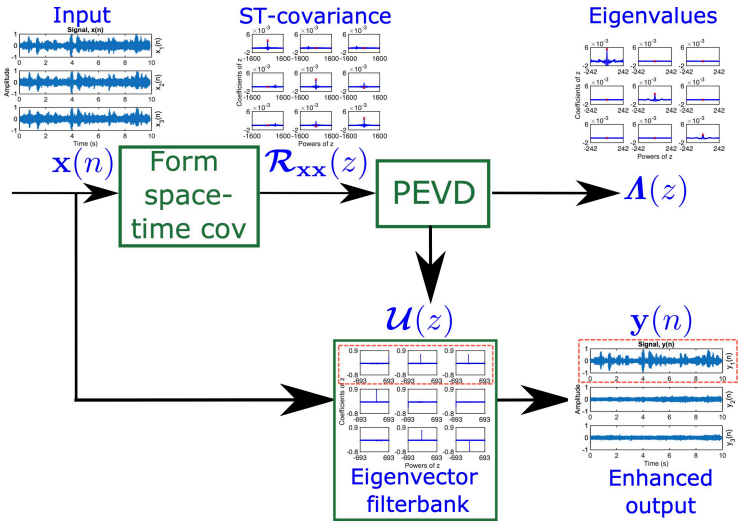
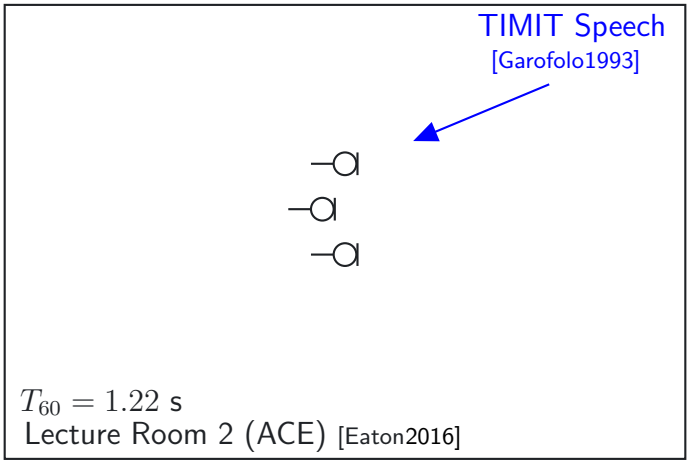
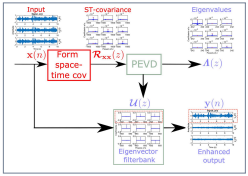


Reverberant Speech (No Noise)





Assuming stationarity, the space-time covariance matrix is

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

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

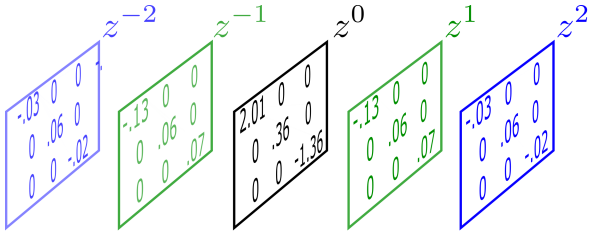
Z-transform of $\mathbf{R}_{\mathbf{xx}}(\tau)$ is a para-Hermitian polynomial matrix

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

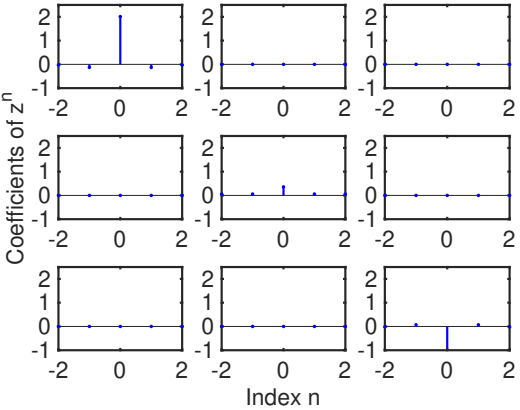
where $\mathbf{R}_{\mathbf{xx}}(\tau) \approx 0$ for $|\tau| > W$, calligraphic $\boldsymbol{\mathcal{R}}$ for polynomial matrices and regular $\mathbf{R}$ for matrices.

Polynomial Matrix Representation

Equivalently, expressed as:



Polynomial with matrix coefficients.



Matrix with polynomial elements.

Example: Polynomial Matrix from ST-Covariance

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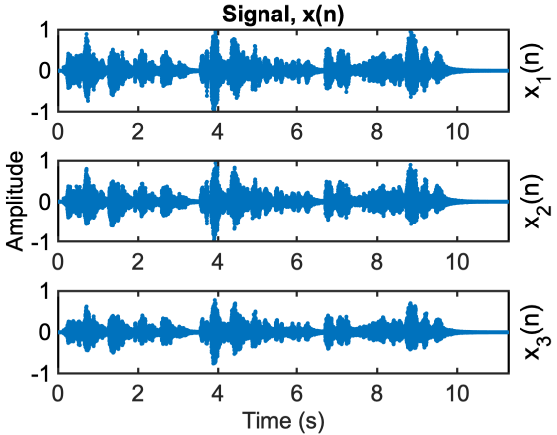
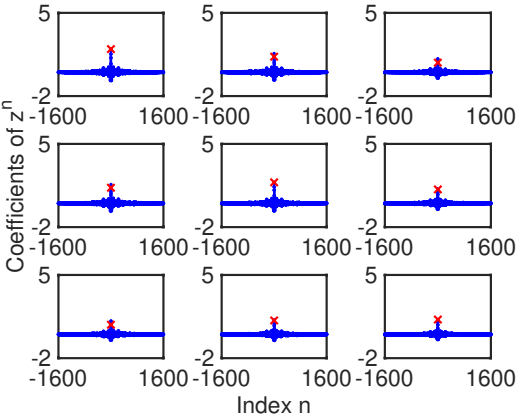


Received signals $\mathbf{x}(n)$.

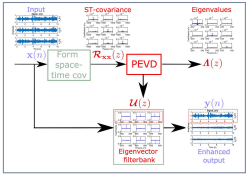


Polynomial matrix, $\boldsymbol{\mathcal{R}}_{\mathbf{xx}}(z)$.

Polynomial Matrix Eigenvalue Decomposition

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

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



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

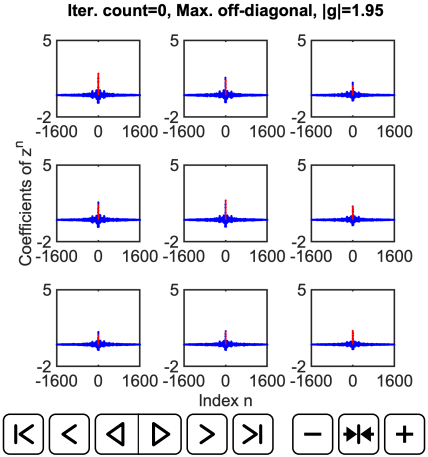
Since $\tilde{\mathbf{s}}(n)$ and $\tilde{\mathbf{v}}(n)$ are uncorrelated [Naylor2010a]

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

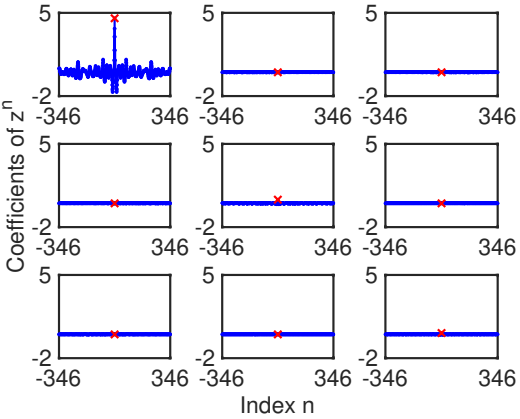
with orthogonal signal, $\{\cdot\}_{\tilde{s}}$ and noise subspaces, $\{\cdot\}_{\tilde{v}}$.

Example: PEVD Algorithm

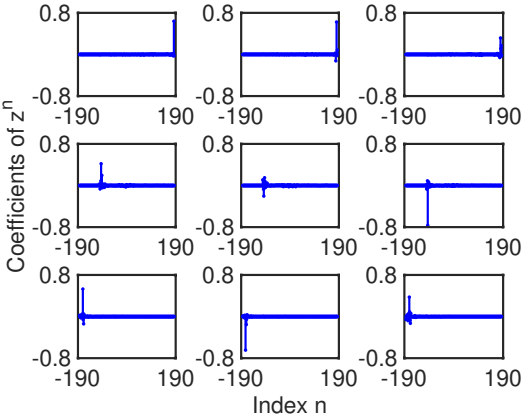
Algorithm converges when $|g| < 1.68 \times 10^{-2}$



Example: PEVD Algorithm Outputs



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

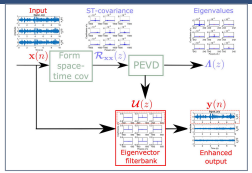


Eigenvector polynomial matrix, $\boldsymbol{\mathcal{U}}(z)$.

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 $\mathbf{x}(z)$ 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.

The output in the first channel, $y_1(z)$, is the enhanced and dereverberated speech signal with space-time covariance matrix

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

Example: PEVD-based Enhancement Outputs

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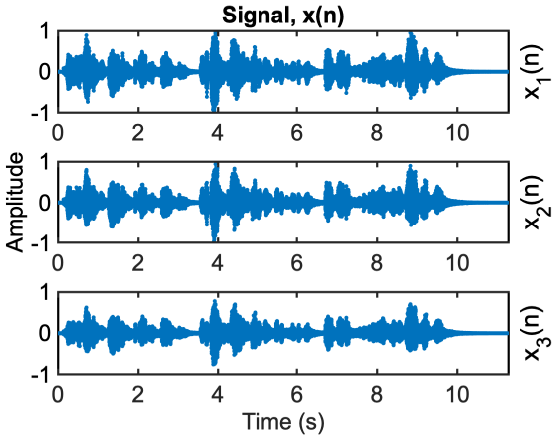
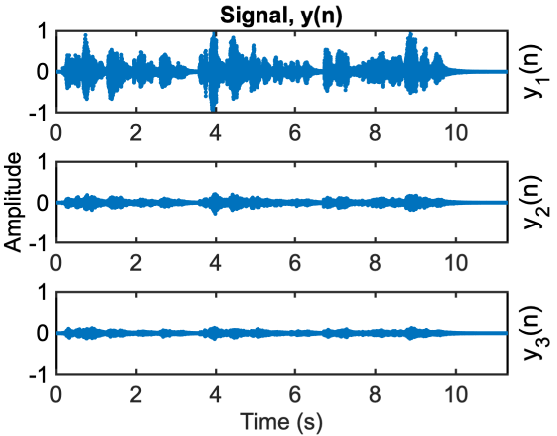


Received signals $\mathbf{x}(n)$.



Enhanced signals, $\mathbf{y}(z)$.

Comparative Results

Speech Dereverberation Evaluation

Comparative algorithms:

1. Generalized weighted prediction error (GWPE) [Yoshioka2012]
2. Multichannel Subspace (MCSUB) - Uses an EVD [Huang2008]
3. Oracle-MWF (OMWF) - Given clean speech [Doclo2002]

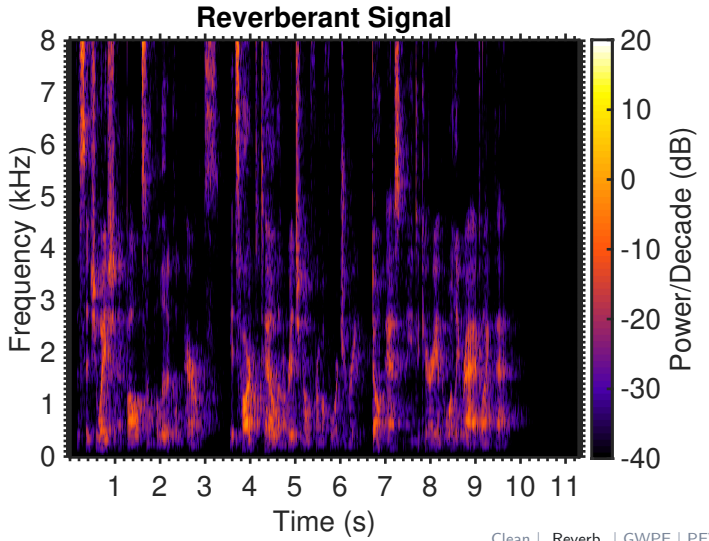
Dereverberation measures:

- Normalized Signal to Reverberant Ratio (NSRR) [Naylor2010b]
- Bark Spectral Distortion (BSD)

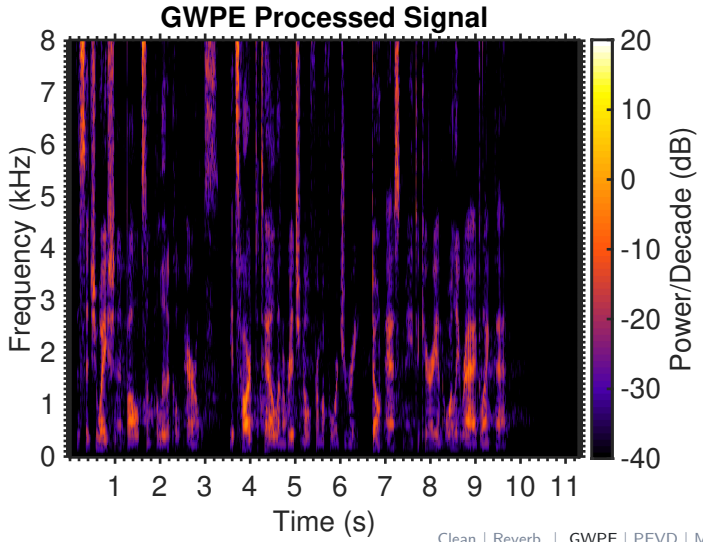
Noise reduction and speech quality measures:

- Frequency-weighted Segmental SNR (FwSegSNR) [Hu2006]
- Perceptual Evaluation of Speech Quality (PESQ) [ITU-T P.862]

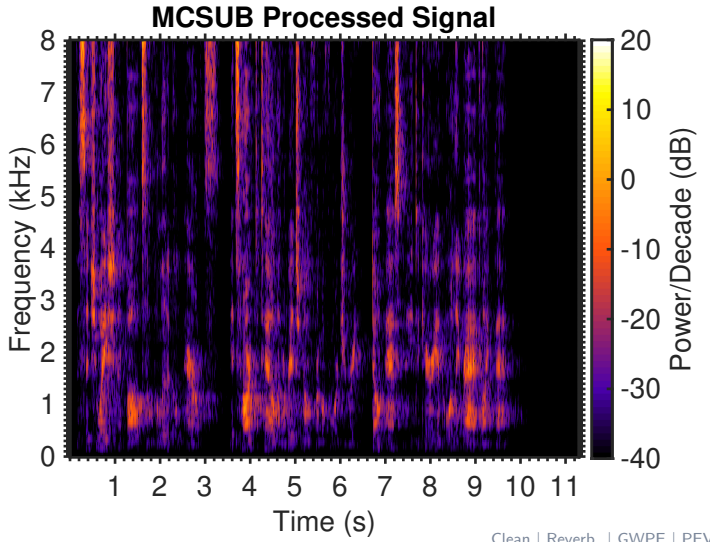
Reverberant Speech Spectrogram (No Noise)



GWPE Processed Spectrogram

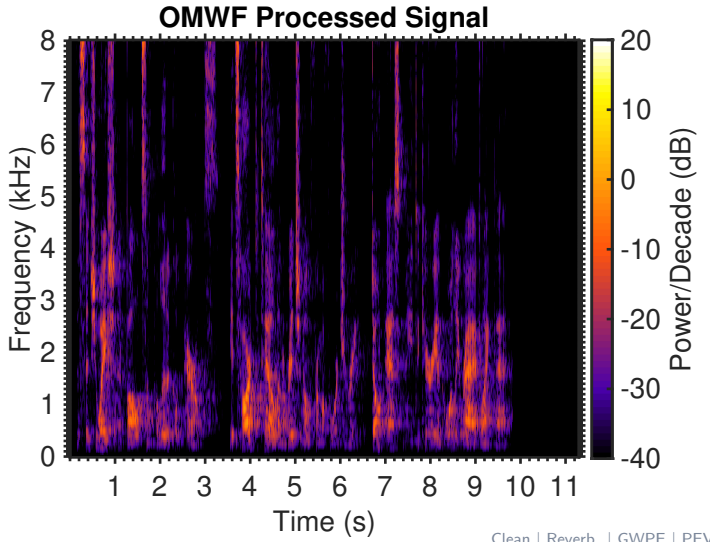


MCSUB Processed Spectrogram

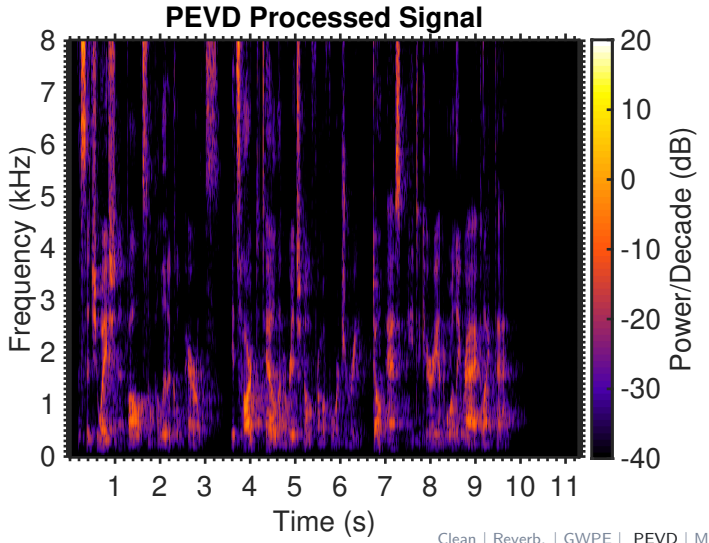


Clean | Reverb. | GWPE | PEVD | MCSUB | OMWF | Table

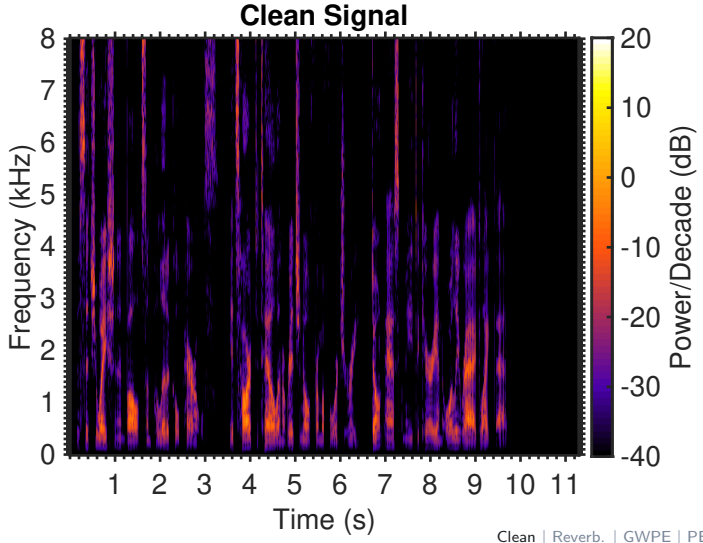
OMWF Processed Spectrogram



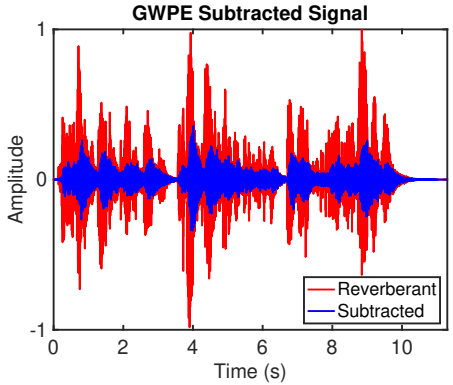
PEVD Processed Spectrogram

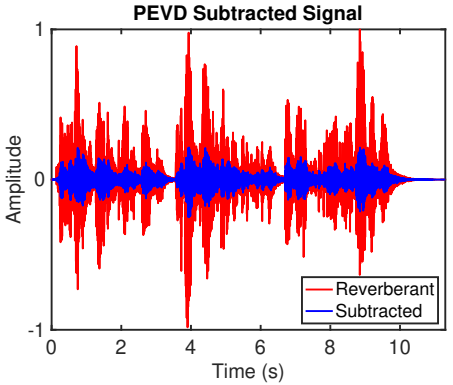


Clean Speech Spectrogram



Comparison of Subtracted Signals

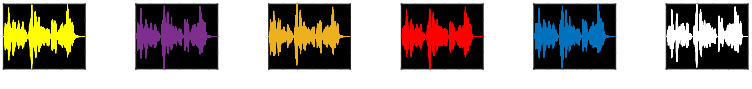


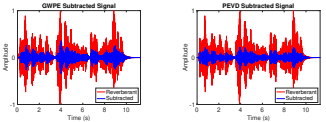


Dereverberation Performance (No Noise)

Algorithm	ΔNSRR	ΔBSD	ΔFwSegSNR	ΔPESQ
GWPE	0.68 dB	**-0.25 dB**	1.46 dB	**0.70**
MCSUB	-3.20 dB	0.28 dB	**1.47 dB**	0.01
OMWF	0.10 dB	0.04 dB	1.46 dB	0.16
PEVD	**1.01 dB**	-0.10 dB	**1.47 dB**	0.11

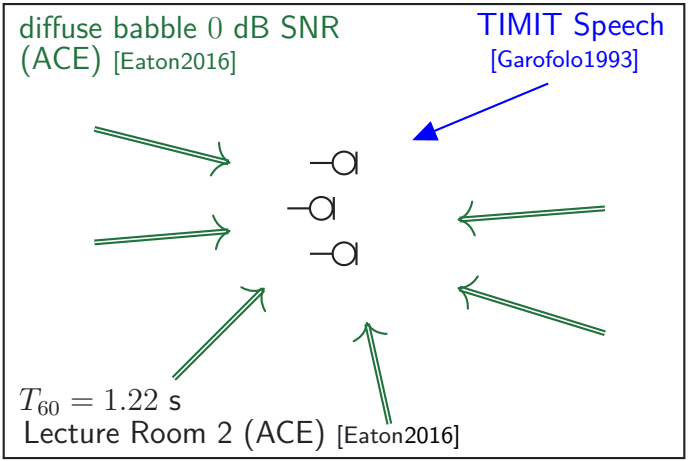
Noisy GWPE MCSUB OMWF PEVD Clean





Clean | Reverb. | GWPE | PEVD | MCSUB | OMWF | Table

Reverberant Speech in Noise



Dereverberation Performance (0 dB Babble Noise)

Algorithm	ΔNSRR	ΔBSD	ΔFwSegSNR	ΔPESQ
GWPE	0.22 dB	-0.12 dB	0.28 dB	0.05
MCSUB	-3.29 dB	0.21 dB	0.64 dB	0.21
OMWF	0.26 dB	-0.25 dB	3.12 dB	**0.29**
PEVD	**5.38 dB**	**-0.52 dB**	**3.56 dB**	0.20

Noisy GWPE MCSUB OMWF PEVD Clean

Conclusion

Conclusion

- Polynomial matrices and PEVD as a tool for processing broadband multichannel signals
- PEVD-based speech enhancement algorithm is effective for dereverberation
  - Performs well even in the presence of noise
  - No noticeable artifacts
  - Completely blind and unsupervised

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Thank you

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