A Polynomial Subspace Projection Approach for the Detection of Weak Voice Activity

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Outline

Introduction

What is Voice Activity Detection (VAD)

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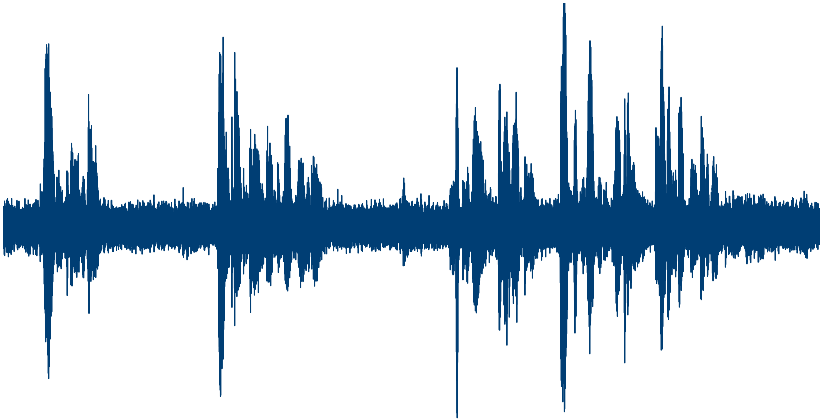

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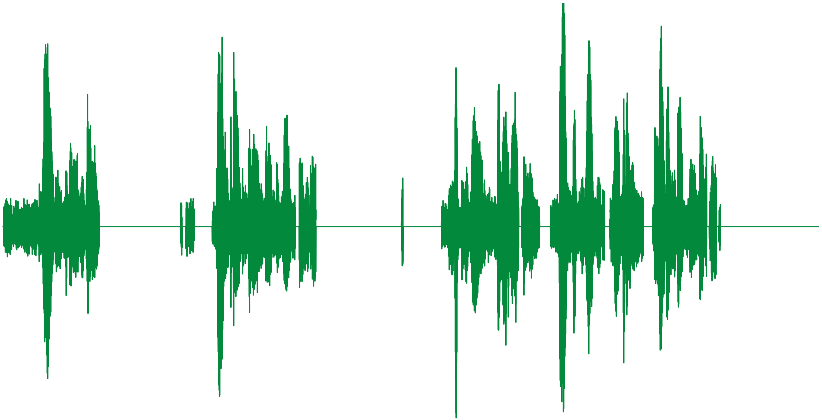

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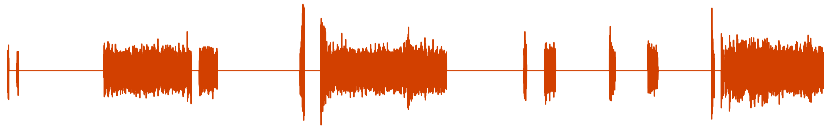

Motivation for VAD

Detection of voice activity is important for many applications:

- Speech enhancement in hearing aids, telecommunications
- Automatic speech recognition (ASR) systems
- Robot audition

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Main challenges:

- Background noise
- Interfering sources
- Reverberation

Existing Approaches to VAD

Statistical-based single channel methods [Sohn1999; ITU-T 2012; Gazor2003]

- Exploit differences in noise and speech distributions

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This Talk: PEVD-based Multichannel Preprocessing for VAD

Background

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

$$x_q(n) = \sum_{p=1}^{p} \mathbf{h}_{p,q}^T(n)\mathbf{s}_p(n)$$

where

- $\mathbf{h}_{p,q}(n)$ is the room impulse response from pth source to qth microphone modelled as a Jth order FIR filter,
- $\mathbf{s}_p(n)$ is the pth localized source signal.

The data vector collected from Q microphones:

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

Assuming stationarity, the space-time covariance matrix is

$$\mathbf{R}(\tau) = \mathbb{E}[\mathbf{x}(n)\mathbf{x}^T(n-\tau)] \in \mathbb{R}^{Q\times Q} \ ,$$

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 $\mathbf{R}(\tau)$ is a para-Hermitian polynomial matrix

$$\mathscr{R}(z) = \sum_{\tau=-W}^{W} \mathbf{R}(\tau) z^{-\tau},$$

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

The PEVD of $\mathcal{R}(z)$ is [Weiss2018a; Weiss2018b]

$$\mathcal{R}(z) = \mathcal{U}(z)\mathbf{\Lambda}(z)\mathcal{U}^P(z)\ , \tag{1}$$

where $\mathbf{\Lambda}(z), \mathcal{U}(z)$ contain the eigenvalues and eigenvectors and $\mathcal{R}^P(z) = \mathcal{R}^H(1/z^*)$.

Subspace decomposition using PEVD:

$$\mathcal{R}(z) = \begin{bmatrix} \mathcal{U}_s(z) & \mathcal{U}_\perp(z) \end{bmatrix} \begin{bmatrix} \mathbf{\Lambda}_s(z) & \mathbf{0} \\ \mathbf{0} & \mathbf{\Lambda}_{\bar{s}}(z) \end{bmatrix} \begin{bmatrix} \mathcal{U}_s^P(z) \\ \mathcal{U}_\perp^P(z) \end{bmatrix}, \tag{2}$$

associated with signal, $\{\cdot\}_s$ and orthogonal complement, $\{\cdot\}_\perp$ subspaces.

Example: Polynomial Matrix from ST-Covariance

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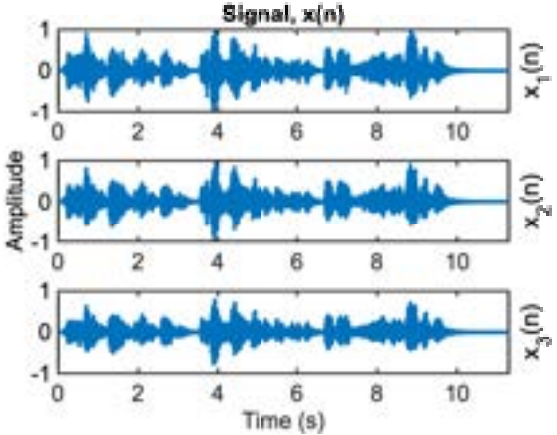
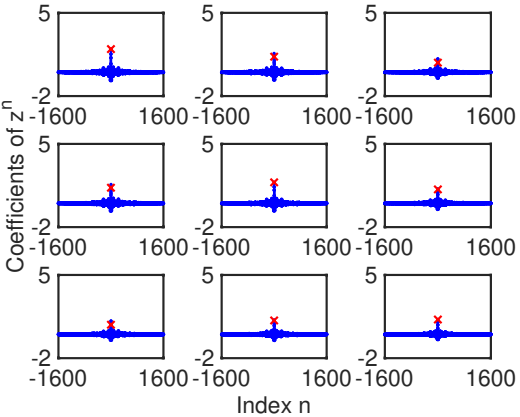


Received signals $\mathbf{x}(n)$.



Space-time polynomial matrix, $\mathcal{R}(z)$.

Example: PEVD Algorithm

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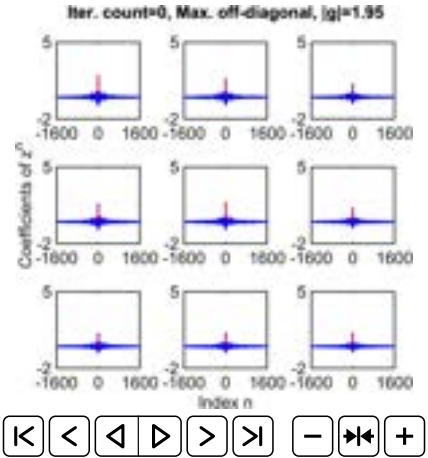
Algorithm converges when $|g| < 1.68 \times 10^{-2}$



Example: PEVD Algorithm Outputs

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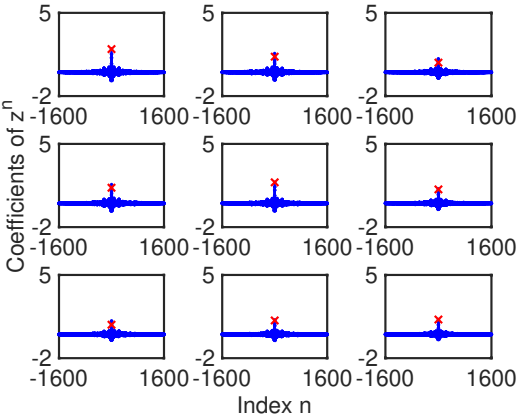
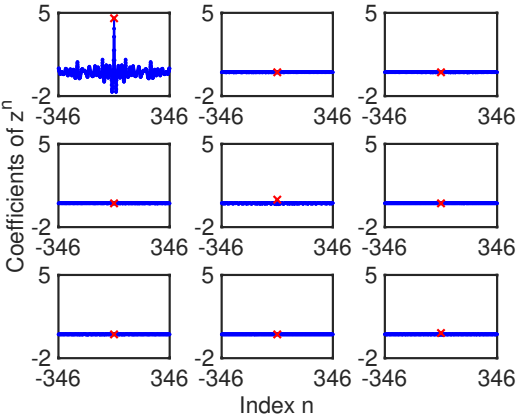


Space-time polynomial matrix, $\mathcal{R}(z)$.



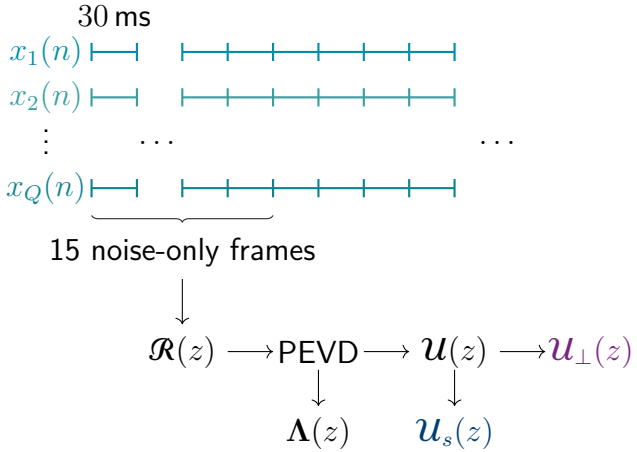
Eigenvalue polynomial matrix, $\mathbf{\Lambda}(z)$.

PEVD Algorithms

Iterative PEVD algorithms approximating (1) include:

- Second-order Sequential Best Rotation (SBR2) [McWhirter2007]
- Sequential Matrix Diagonalization (SMD) [Redif2015]
- Householder PEVD [Neo2019]
- Fixed-order approximate PEVD [Tkacenko 2010]
- Multiple-shift SBR2/SMD [Wang2015; Corr2014b]
- Causality-constrained Multiple-shift SMD [Corr2014a]

PEVD Preprocessor for VAD


30 ms
$x_1(n)$
$x_2(n)$
$x_Q(n)$
15 noise-only frames
$\mathcal{R}(z)$
PEVD
$\mathcal{U}(z)$
$\mathcal{U}_\perp(z)$
$\mathbf{\Lambda}(z)$
$\mathcal{U}_s(z)$

For L estimated signal components, $\mathcal{U}_s(z) \in \mathbb{C}^{Q\times L}$ and $\mathcal{U}_\perp(z) \in \mathbb{C}^{Q\times(Q-L)}$,

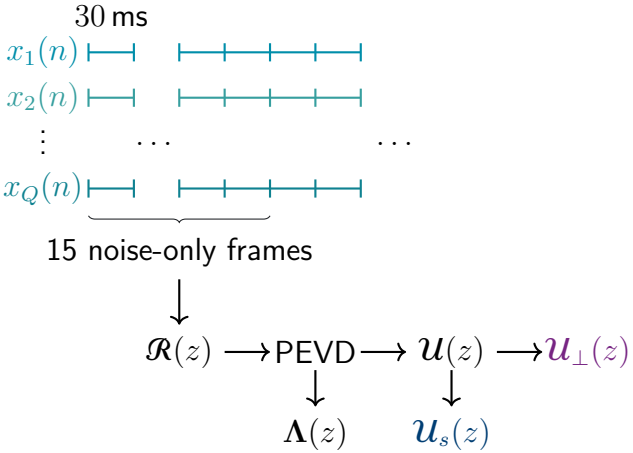
$$\mathcal{U}_s(z)\mathcal{U}_s^P(z) + \mathcal{U}_\perp(z)\mathcal{U}_\perp^P(z) = \mathbf{I}\,.$$

The component associated with $\mathcal{U}_\perp(z) \bullet\!\!-\!\!\circ\, \mathbf{U}(n)$ can be recovered using

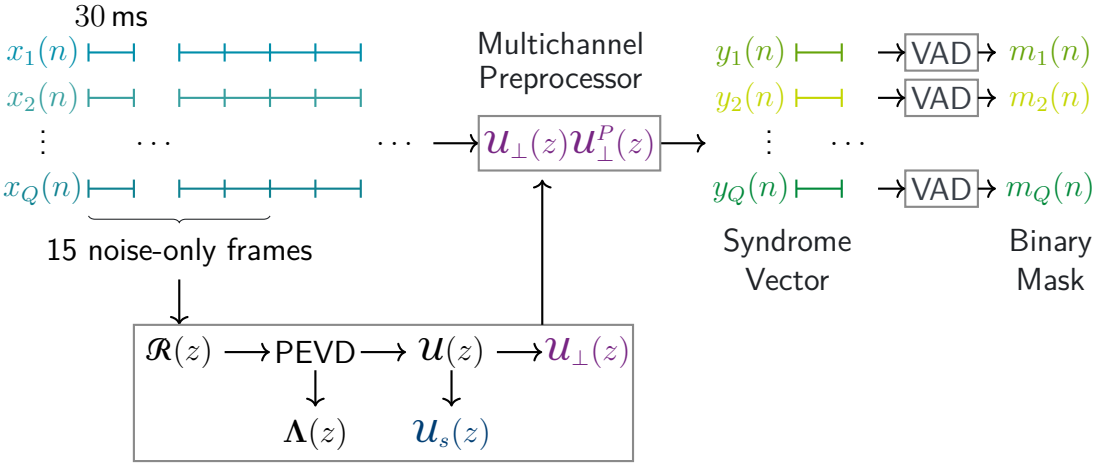
$$\mathbf{y}(n) = \sum_k \sum_m \mathbf{U}_\perp(k)\,\mathbf{U}_\perp^H(k-m)\,\mathbf{x}(n-m)\,.$$

This is equivalent to $\mathbf{x}(n)$ with the $\mathcal{U}_s(z)$ component removed.

Syndrome Signal Generation



Syndrome Signal Generation



Experiment and Results

Setup: Male Speaker in a Measured Room [Kayser2009]

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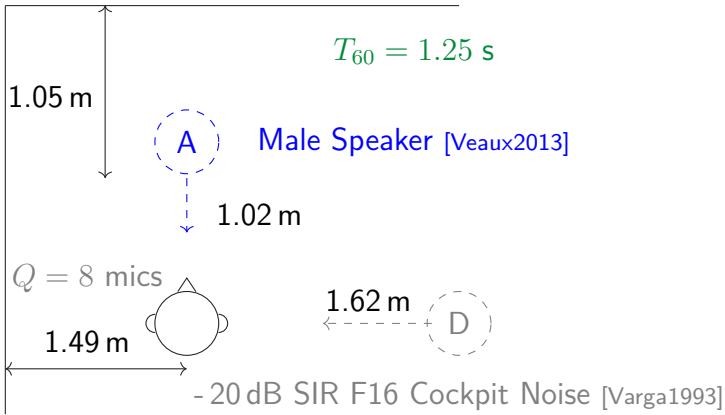

VAD Evaluation

Comparative algorithms:

1. Sohn [Sohn1999]
2. WebRTC [Google 2021] : G0, G3 (Least to most aggressive)
3. Proposed (PEVD+Sohn): R1, R2, R5, R7 (different rank estimates)

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Evaluation measures [Tharwat 2018] :

- Label evaluation metrics
  - Correct labels: True Positive (TP), True Negative (TN)
  - Wrong labels: False Positive (FP), False Negative (FN)
- Overall scores: F1, Balanced Accuracy (BACC)

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$\Longrightarrow$ Focus on first microphone in the results.

VAD Performance for -20 dB SIR F16 Cockpit Noise

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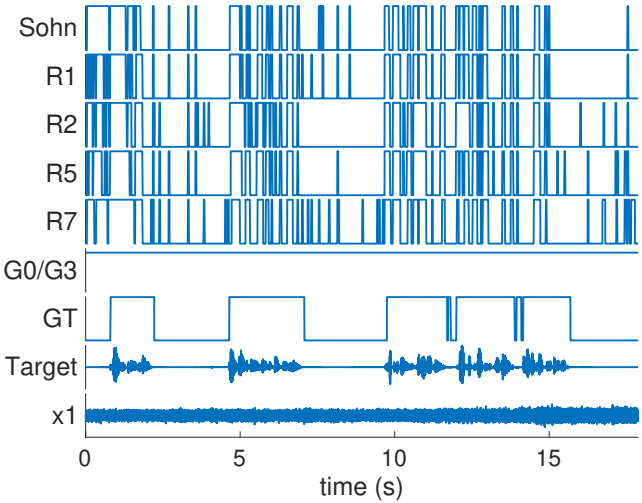

VAD Performance for -20 dB SIR F16 Cockpit Noise

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Method	TP	TN	FP	FN	F1	BACC
Sohn	130	241	38	185	0.538	0.638
R1	136	249	30	179	0.565	0.662
R2	158	244	35	157	0.622	**0.688**
R5	148	247	32	167	0.598	0.678
R7	136	224	55	179	0.538	0.617
G0	315	0	279	0	**0.693**	0.500
G3	315	0	279	0	**0.693**	0.500

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Other results in the paper:

- Since G0, G3 always predict the presence of speech, F1 scores significantly decrease when the speech segment is short.
- Tested on destroyer noise at various SIR from -30 dB to 20 dB.

Conclusion

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- PEVD-based multi-microphone preprocessing for VAD
  - Characterize the ambient acoustics using PEVD to generate multichannel syndrome signals, which are microphone signals without ambient acoustics
  - Apply single channel VAD to each microphone

- Performance of proposed PEVD-based approach
  - Almost always improves F1 and BACC scores over the single channel method even in adverse environments, i.e. -30 dB SIR
  - Consistent performance unaffected by length of speech segments

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Thank you

Listening Examples: https://vwn09.github.io/research/pevd-vad