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

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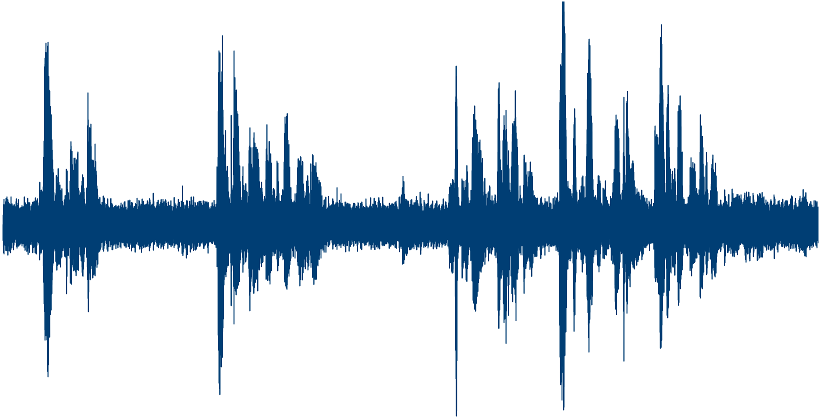
# Outline

# Introduction

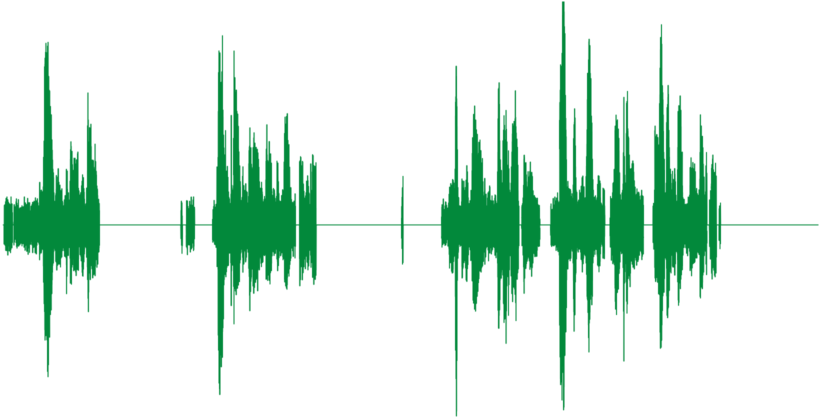
# What is Voice Activity Detection (VAD)



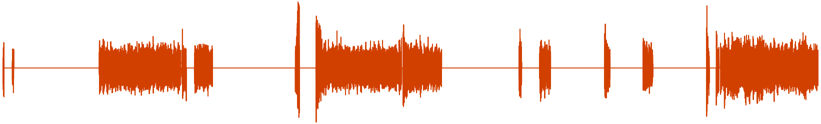


# What is Voice Activity Detection (VAD)





# What is Voice Activity Detection (VAD)



# 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

Main challenges:

- Background noise
- Interfering sources
- Reverberation

# Existing Approaches to VAD

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

- Exploit differences in noise and speech distributions

⇒ Challenging to measure signal statistics in very noisy environments

Machine learning-based methods [Google 2021; Zhang2016; Ivry2019]

- Speech feature extraction for classification

⇒ Feature extraction becomes difficult in adverse acoustic environments

- Weak Transient Signal Detection Using PEVD [Weiss2021]
  - Exploits multichannel signal processing to amplify weak transient signals

This Talk: PEVD-based Multichannel Preprocessing for VAD

# Background

# Multichannel Signal Model



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 $p$th source to $q$th microphone modelled as a $J$th order FIR filter,
- $\mathbf{s}_p(n)$ is the $p$th localized source signal.

The data vector collected from $Q$ microphones:

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

# Space-time Covariance Polynomial Matrix



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 $\tau$ is the time-shift.

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

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

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

# Polynomial Matrix Eigenvalue Decomposition



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

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

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

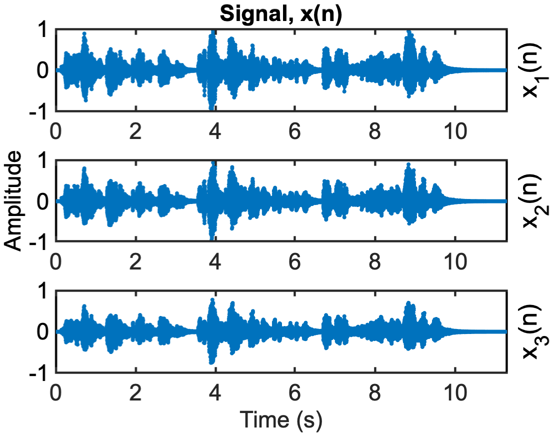
Subspace decomposition using PEVD:

$$\boldsymbol{\mathcal{R}}(z) = \left[\ \boldsymbol{\mathcal{U}}_s(z) \quad \boldsymbol{\mathcal{U}}_\perp(z)\ \right] \left[\begin{array}{cc} \boldsymbol{\Lambda}_s(z) & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Lambda}_{\bar{s}}(z) \end{array}\right] \left[\begin{array}{c} \boldsymbol{\mathcal{U}}_s^P(z) \\ \boldsymbol{\mathcal{U}}_\perp^P(z) \end{array}\right], \tag{2}$$

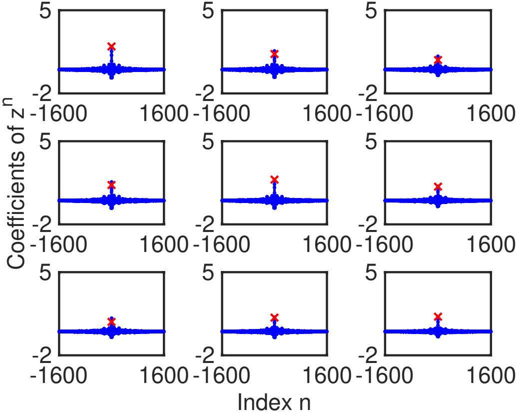
associated with signal, $\{\cdot\}_s$ and orthogonal complement, $\{\cdot\}_\perp$ subspaces.

# Example: Polynomial Matrix from ST-Covariance





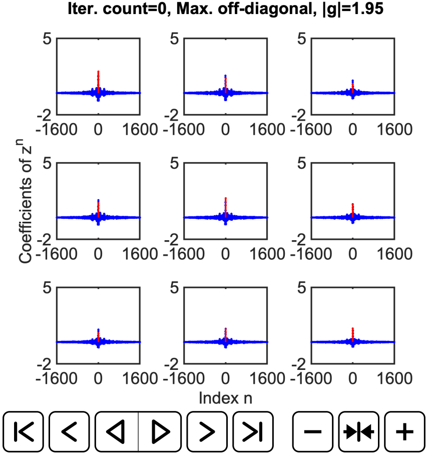

Received signals $\mathbf{x}(n)$.




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

# Example: PEVD Algorithm

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



# Example: PEVD Algorithm Outputs

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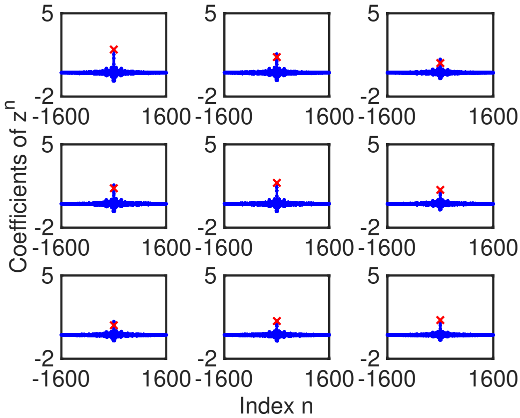
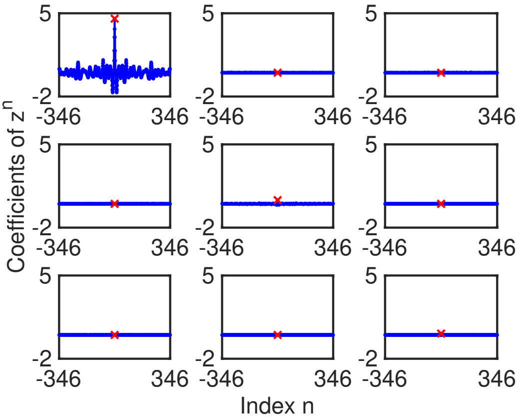



Space-time polynomial matrix, $\mathcal{R}(z)$.




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

# PEVD Algorithms

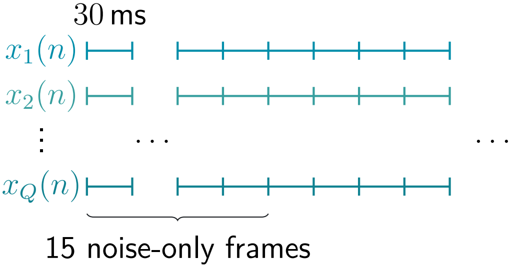


Iterative PEVD algorithms approximating (1) include:

- 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

# Ambient Acoustics Subspace Characterization




$$
\begin{tikzcd}
\mathscr{R}(z) \arrow[r] & \text{PEVD} \arrow[r] \arrow[d] & \mathcal{U}(z) \arrow[r] \arrow[d] & \mathcal{U}_{\perp}(z) \\
& \mathbf{\Lambda}(z) & \mathcal{U}_s(z) &
\end{tikzcd}
$$

# Syndrome Signal Generation



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

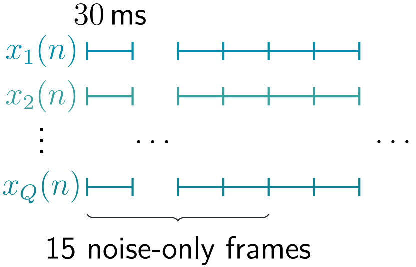
$$\mathcal{U}_s(z)\mathcal{U}_s^P(z) + \mathcal{U}_\perp(z)\mathcal{U}_\perp^P(z) = \mathbf{I}\ .$$

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




$$
\begin{array}{ccccccc}
 & & \downarrow & & & & \\
 & & \boldsymbol{\mathcal{R}}(z) \longrightarrow & \text{PEVD} & \longrightarrow \boldsymbol{\mathcal{U}}(z) & \longrightarrow & \boldsymbol{\mathcal{U}}_{\perp}(z) \\
 & & & \downarrow & \downarrow & & \\
 & & & \boldsymbol{\Lambda}(z) & \boldsymbol{\mathcal{U}}_s(z) & &
\end{array}
$$

# Syndrome Signal Generation

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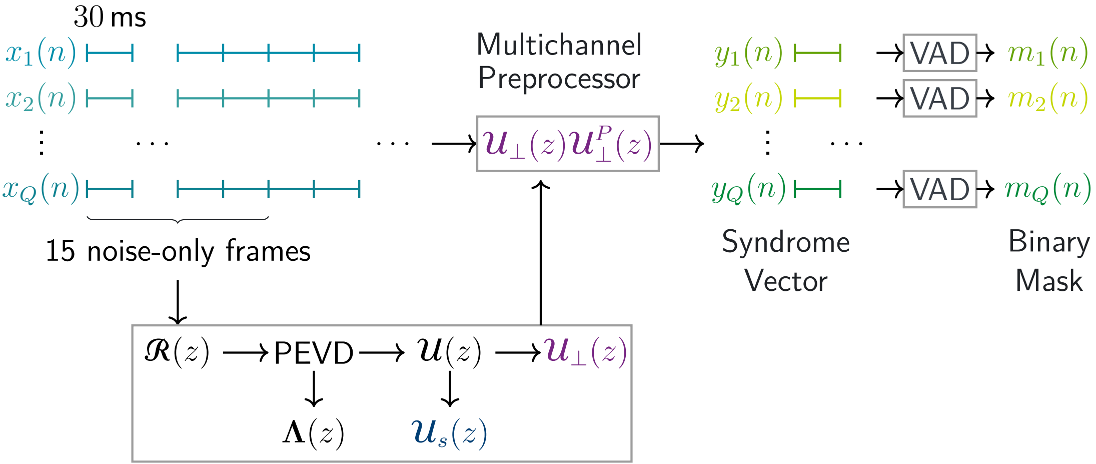

# Experiment and Results

# Setup: Male Speaker in a Measured Room [Kayser2009]

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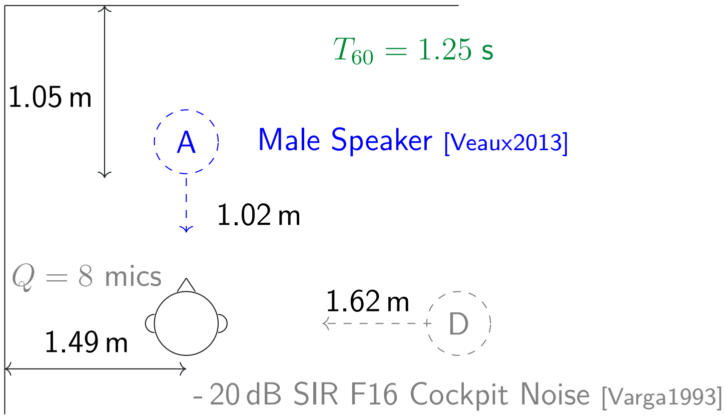

# VAD Evaluation

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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)

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)

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

# VAD Performance for -20 dB SIR F16 Cockpit Noise

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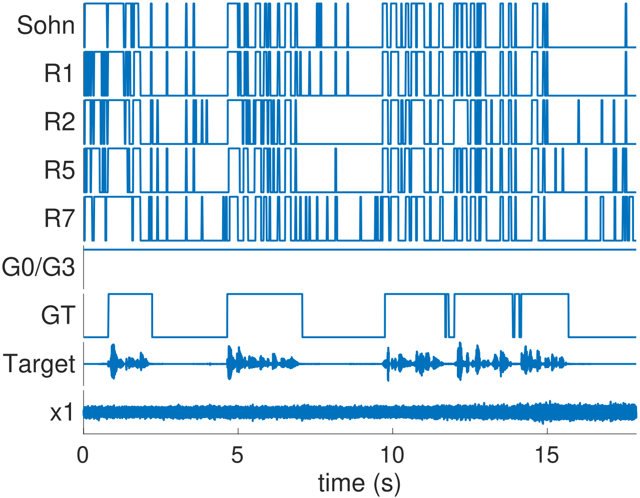

# VAD Performance for -20 dB SIR F16 Cockpit Noise

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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 |

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

# Conclusion



- 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