# Polynomial Eigenvalue Decomposition-Based Target Speaker Voice Activity Detection in the Presence of Competing Talkers

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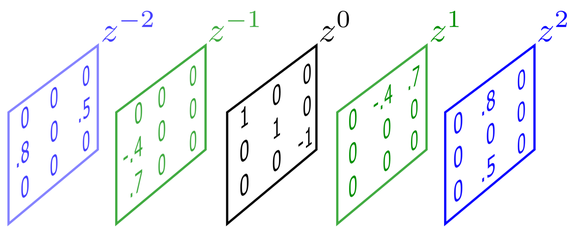
## Summary

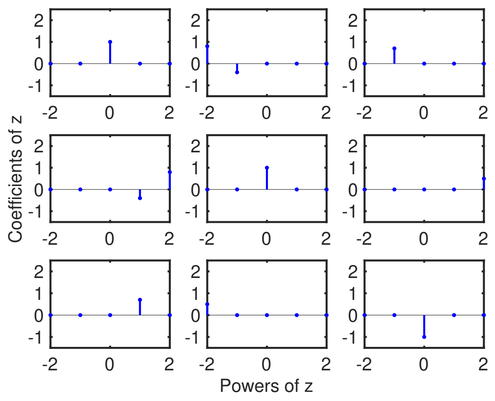
- PEVD-based VAD algorithm, which is inspired by [1], exploits multi-microphone processing to detect target speaker voice activity
- Consistently among the best in F1 and BACC scores even when the target and interfering speaker are of the same gender

## What is a Polynomial Matrix?

Polynomial with matrix coefficients




Matrix with polynomial elements




## How Do Polynomial Matrices Arise?

Multichannel model ($P$ sources, $Q$ microphones):

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

From $Q$ sensors:

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

Assuming stationarity, space-time covariance matrix:

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

Para-Hermitian polynomial matrix:

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

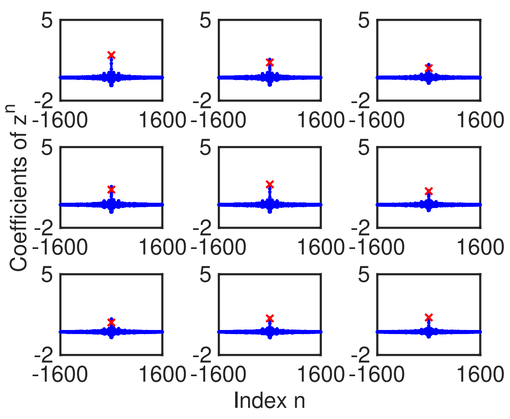
## Polynomial Eigenvalue Decomposition (PEVD)

The PEVD of $\boldsymbol{\mathcal{R}}(z)$ is [2]:

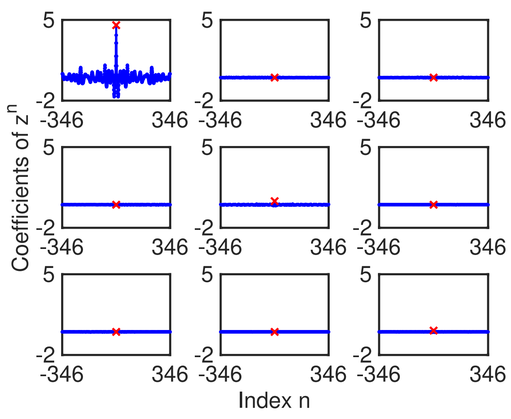
$$\boldsymbol{\mathcal{R}}(z) = \begin{bmatrix} \boldsymbol{\mathcal{U}}_s(z) & \boldsymbol{\mathcal{U}}_\perp(z) \end{bmatrix} \begin{bmatrix} \boldsymbol{\Lambda}_s(z) & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Lambda}_{\bar{s}}(z) \end{bmatrix} \begin{bmatrix} \boldsymbol{\mathcal{U}}_s^P(z) \\ \boldsymbol{\mathcal{U}}_\perp^P(z) \end{bmatrix}, \quad (1)$$

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

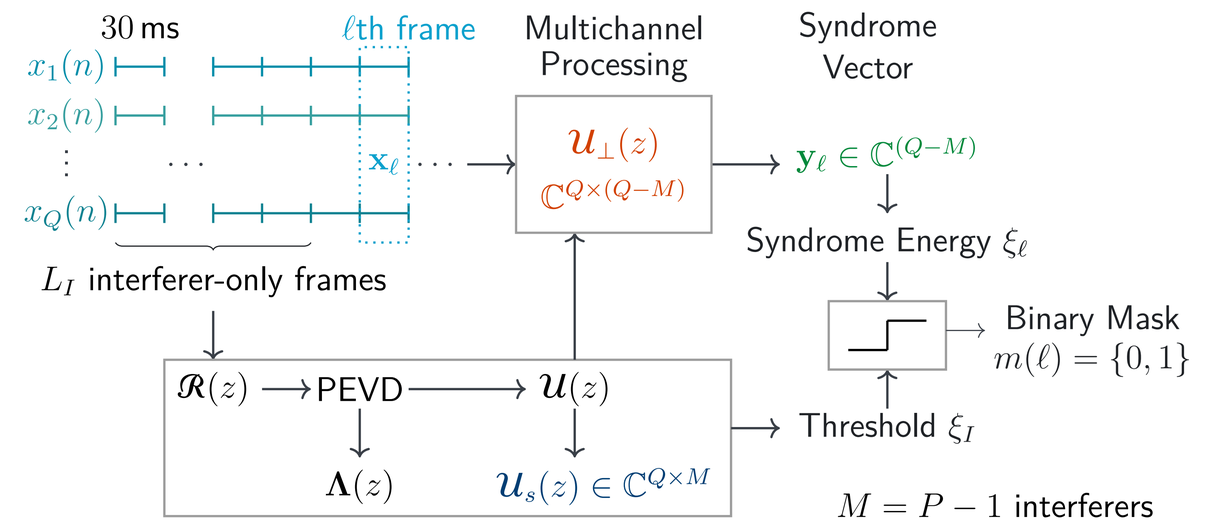
Space time-covariance, $\boldsymbol{\mathcal{R}}(z)$




Eigenvalue, $\boldsymbol{\Lambda}(z)$




## PEVD-based Target Speaker Voice Activity Detection




## Experiment Setup: Reverberant Speech and Interferer

**Comparative Algorithms**

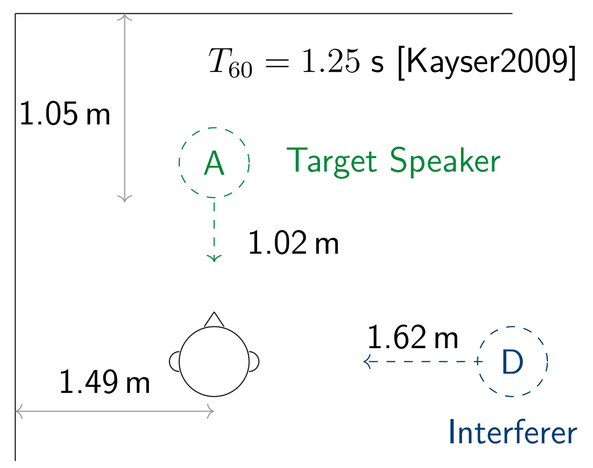
1. Sohn
2. WebRTC: G0 (Least aggressive)
3. WebRTC: G3 (Most aggressive)
4. PEVD (Proposed)

**Evaluation Measures**

- Label evaluation metrics
  - True Positive (TP)
  - True Negative (TN)
  - False Positive (FP)
  - False Negative (FN)
- F1 score
- Balanced Accuracy (BACC)

**Setup**

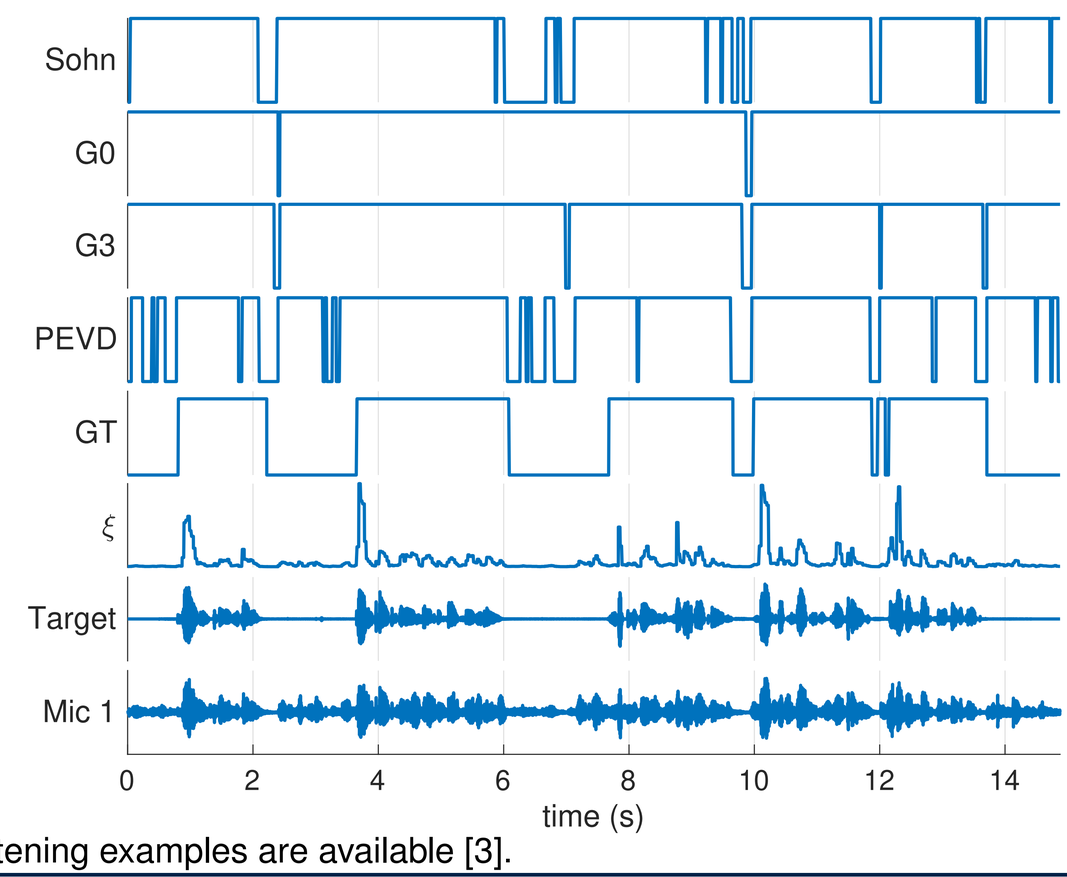
$P = 2$ Sources, $Q = 2$ Microphones




## Simulation Results

VAD performance of female target and male interferer at 5 dB SIR:

| *Metric* | Sohn | G0 | G3 | PEVD |
|---|---|---|---|---|
| TP | 295 | 313 | 310 | 294 |
| TN | 43 | 4 | 10 | 72 |
| FP | 139 | 178 | 172 | 110 |
| FN | 18 | 0 | 3 | 19 |
| F1 | 0.790 | 0.779 | 0.780 | **0.820** |
| BACC | 0.589 | 0.511 | 0.523 | **0.667** |




Listening examples are available [3].

## References

[1] S. Weiss, C. Delaosa, J. Matthews, I. K. Proudler, and B. A. Jackson, "Detection of weak transient signals using a broadband subspace approach," in *Sensor Signal Process. for Defence Conf. (SSPD)*, 2021.

[2] S. Weiss, J. Pestana, and I. K. Proudler, "On the existence and uniqueness of the eigenvalue decomposition of a para-Hermitian matrix," *IEEE Trans. Signal Proc.*, vol. 66, no. 10, pp. 2659–2672, May 2018.

[3] V. W. Neo, *PEVD-based target speaker VAD*, Apr. 2022. [Online]. Available: `https://vwn09.github.io/research/pevd-tsvad-iwaenc`.