

An Iterative Multichannel Subspace-Based Covariance Subtraction Method for Relative Transfer Function Estimation

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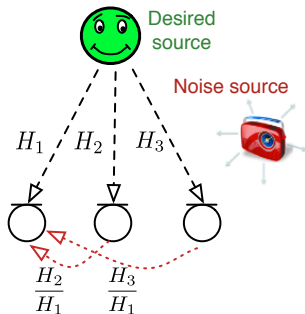
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Introduction and Motivation

Source extraction in noisy environments is ubiquitous in hands-free applications

To estimate the desired source we need to estimate the transfer functions H_m

To extract the desired source as received by the first microphones we only need to estimate H_m/H_1



- RTFs can be estimated from the data when the source is active
- We summarise state-of-the-art estimators and propose an efficient iterative RTF estimator suitable for real-time applications

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1. Signal Model and Source Extraction
2. Existing RTF Estimators
3. Proposed RTF Estimator
4. Performance Evaluation
5. Conclusions

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Signal Model

- Desired speech and noise signals captured by M microphones
- STFT-domain signal at time n , frequency k :

$$\begin{aligned}\mathbf{y}(n, k) &= \mathbf{x}(n, k) + \mathbf{v}(n, k) \\ &= \mathbf{h}(n, k) S(n, k) + \mathbf{v}(n, k) \\ &= \mathbf{g}(n, k) X_1(n, k) + \mathbf{v}(n, k)\end{aligned}$$

- The RTF vector can be expressed in terms of the acoustic transfer functions $H_m(n, k)$:

$$\mathbf{g}(n, k) = \left[1, \frac{H_2(n, k)}{H_1(n, k)}, \dots, \frac{H_M(n, k)}{H_1(n, k)} \right]^T$$

- The RTF vector is time-dependent to model source movements

Signal Model

- The power spectral density (PSD) matrices Φ_y and Φ_v are required for RTF estimation
- The PSD matrix of the received signal:

$$\Phi_y(n, k) = \Phi_x(n, k) + \Phi_v(n, k)$$

- The PSD matrix of the desired signal:

$$\Phi_x(n, k) = \phi_{x_1}(n, k) \mathbf{g}(n, k) \mathbf{g}^H(n, k) \text{ with } \phi_{x_1} = \mathbb{E} \{ |X_1|^2 \}$$

- The PSD matrix of the undesired signal, Φ_v , can be estimated during speech absence, or using speech presence probability-controlled recursive averaging (Souden et al., 2011)

Source Extraction

- Estimate of the desired signal:

$$\begin{aligned}\hat{X}_1(n, k) &= \mathbf{w}^H(n, k) \mathbf{y}(n, k) \\ &= \mathbf{w}^H(n, k) [\mathbf{g}(n, k) X_1(n, k) + \mathbf{v}(n, k)]\end{aligned}$$

- Distortionless response if $\mathbf{w}^H \mathbf{g} = 1$
- Minimum Variance Distortionless Response (MVDR) filter:

$$\begin{aligned}\mathbf{w}(n, k) &= \arg \min_{\mathbf{w}} \mathbf{w}^H \Phi_{\mathbf{v}}(n, k) \mathbf{w} \quad \text{subject to} \quad \mathbf{w}^H \mathbf{g}(n, k) = 1 \\ &= \frac{\Phi_{\mathbf{v}}^{-1}(n, k) \mathbf{g}(n, k)}{\mathbf{g}(n, k)^H \Phi_{\mathbf{v}}^{-1}(n, k) \mathbf{g}(n, k)}\end{aligned}$$

For real-time applications, the RTF vector needs to be efficiently estimated online using the microphone signals $\mathbf{y}(n, k)$

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Existing RTF Estimators

Method 1: Covariance Subtraction

- Recall the definition:

$$\Phi_{\mathbf{x}}(n, k) = \phi_{x_1}(n, k) \mathbf{g}(n, k) \mathbf{g}^H(n, k)$$

- The RTF can be obtained by

$$\mathbf{g}_{\text{CS}}(n, k) = \frac{\Phi_{\mathbf{x}}(n, k) \mathbf{e}_1}{\mathbf{e}_1^T \Phi_{\mathbf{x}}(n, k) \mathbf{e}_1} \quad \text{with} \quad \mathbf{e}_1 = [1, 0, \dots, 0]^T$$

- In practice $\Phi_{\mathbf{x}}$ can be estimated using $\hat{\Phi}_{\mathbf{x}} = \hat{\Phi}_{\mathbf{y}} - \hat{\Phi}_{\mathbf{v}}$

Existing RTF Estimators

Method 2: Covariance Subtraction with EVD

- The RTF vector g is proportional to the principal eigenvector of Φ_x
- An estimate of the RTF vector is given by the principal eigenvector \mathbf{u}_{\max} of $\hat{\Phi}_x = \hat{\Phi}_y - \hat{\Phi}_v$

$$\mathbf{g}_{\text{CS-EVD}}(n, k) = \frac{\mathbf{u}_{\max}(n, k)}{\mathbf{e}_1^T \mathbf{u}_{\max}(n, k)}$$

- The principal eigenvector of $\hat{\Phi}_y - \hat{\Phi}_v$ provides better performance in spatial filtering than the column of $\hat{\Phi}_y - \hat{\Phi}_v$ (Serizel et al., 2014)

R. Serizel *et al.*, "Low-rank approximation based multichannel Wiener filter algorithms for noise reduction with application in cochlear implants", IEEE/ACM Transactions on ASLP, 2014

Existing RTF Estimators

Method 3: Covariance Whitening

- A generalized eigenvalue problem:

$$\underbrace{(\phi_{x_1} \mathbf{g} \mathbf{g}^H + \Phi_v)}_{\Phi_y} \mathbf{u} = \lambda \Phi_v \mathbf{u}$$

- **In theory:** Only one eigenvalue $\lambda \neq 1$
- **In practice:** Use the principal eigenvector \mathbf{u}_{\max} of $\Phi_v^{-1} \Phi_y$

$$\mathbf{g}_{\text{CW}}(n, k) = \frac{\hat{\Phi}_v(n, k) \mathbf{u}_{\max}(n, k)}{\mathbf{e}_1^T \hat{\Phi}_v(n, k) \mathbf{u}_{\max}(n, k)}$$

Existing RTF Estimators

Method 4: Covariance Whitening using PM

- Use power method to estimate the GEVD (Krueger et al., 2011)
- **Iteration matrix:** $\mathbf{A}_{\text{cw}}(n, k) = \hat{\Phi}_v^{-1}(n, k) \hat{\Phi}_y(n, k)$
- **Power iteration:** $\hat{\mathbf{u}}_{\text{max}}(n, k) = \frac{\mathbf{A}_{\text{cw}}(n, k) \hat{\mathbf{u}}_{\text{max}}(n-1, k)}{\|\mathbf{A}_{\text{cw}}(n, k) \hat{\mathbf{u}}_{\text{max}}(n-1, k)\|}$
- Compute the RTF vector:

$$\mathbf{g}_{\text{PM-CW}}(n, k) = \frac{\hat{\Phi}_v(n, k) \hat{\mathbf{u}}_{\text{max}}(n, k)}{\mathbf{e}_1^T \hat{\Phi}_v(n, k) \hat{\mathbf{u}}_{\text{max}}(n, k)}$$

Krueger et al., "Speech enhancement with a GSC-like structure employing eigenvector-based transfer function ratios estimation", IEEE Transactions on ASLP, 2011

Existing RTF Estimators

Summary

- Covariance-Subtraction: g_{CS}
 - ▶ Computationally efficient
- Covariance-Subtraction with EVD: g_{CS-EVD}
 - ▶ More accurate than g_{CS} (Serizel et al., 2014)
 - ▶ Requires EVD
- Covariance-Whitening: g_{CW}
 - ▶ More accurate than g_{CS} (Markovich-Golan et al., 2015)
 - ▶ Requires GEVD
- Covariance-Whitening with PM: g_{PM-CW} (Krueger et al., 2011)

S. Markovich-Golan *et al.*, "Performance analysis of the CS method for relative transfer function estimation and comparison to the CW method", IEEE Transactions on ASLP, 2015

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Proposed RTF Estimator

- Computing $\mathbf{g}_{\text{PM-CW}}$ is less complex than computing \mathbf{g}_{CW}
- It still involves the inversion of $\widehat{\Phi}_v$ to compute \mathbf{A}_{CW} , and multiplication by $\widehat{\Phi}_v$ to obtain $\mathbf{g}_{\text{PM-CW}}$ from the eigenvector \mathbf{u}_{max}
- We propose to estimate $\mathbf{g}_{\text{CS-EVD}}$ using the power method
 - ▶ **Iteration matrix:** $\mathbf{A}_{\text{CS}}(n, k) = \widehat{\Phi}_y(n, k) - \widehat{\Phi}_v(n, k)$
 - ▶ **Power iteration:** $\widehat{\mathbf{u}}_{\text{max}}(n, k) = \frac{\mathbf{A}_{\text{CS}}(n, k)\widehat{\mathbf{u}}_{\text{max}}(n-1, k)}{\|\mathbf{A}_{\text{CS}}(n, k)\widehat{\mathbf{u}}_{\text{max}}(n-1, k)\|}$

$$\mathbf{g}_{\text{PM-CS}}(n, k) = \frac{\widehat{\mathbf{u}}_{\text{max}}(n, k)}{\mathbf{e}_1^T \widehat{\mathbf{u}}_{\text{max}}(n, k)}$$

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Experimental Setup

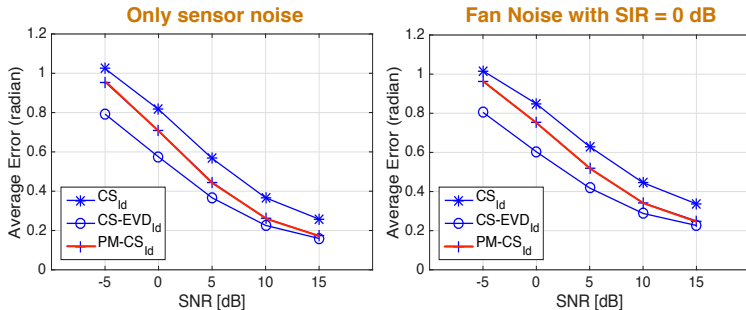
- Simulated room $4.5 \times 4 \times 3 \text{ m}^3$, reverberation time $T_{60} = 0.3 \text{ s}$
- Uniform 5-element linear array, inter-microphone distance 4 cm
- Microphone signals contain desired speech, directional interferer (fan noise), and sensor noise
 - ▶ signal-to-interference ratio (SIR): $\{0, \infty\} \text{ dB}$
 - ▶ signal-to-sensor noise ratios (SNRs): $[-5, 15] \text{ dB}$
- In all experiments, source-array distance was 1-1.2 m
- STFT frame-size is 128 ms, overlap 50%, sampling rate 16 kHz

Noise PSD matrix:

1. Estimated in advance during speech absence (denoted by "ld")
2. Estimated using speech presence probability-based framework

Results: Distance Measure

$$\text{Hermitian Angle: } \Theta(n, k) = \arccos \frac{|\mathbf{g}^H(n, k) \hat{\mathbf{g}}(n, k)|}{\|\mathbf{g}(n, k)\| \|\hat{\mathbf{g}}(n, k)\|}$$

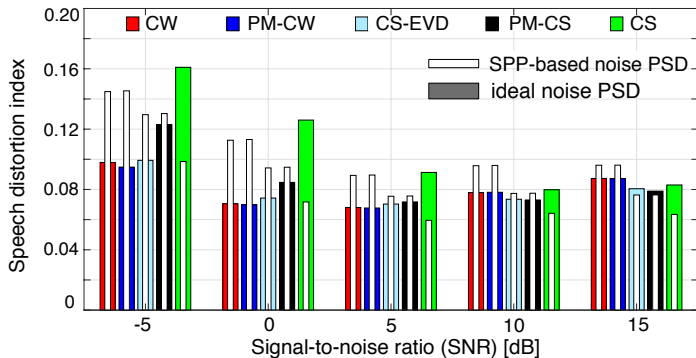


- Averaged $\Theta(n, k)$ over time segment of 15 s for all n and k
- CS-EVD outperforms CS and the error of the proposed PM-CS lies between the two methods

Results: Source Extraction Using MVDR

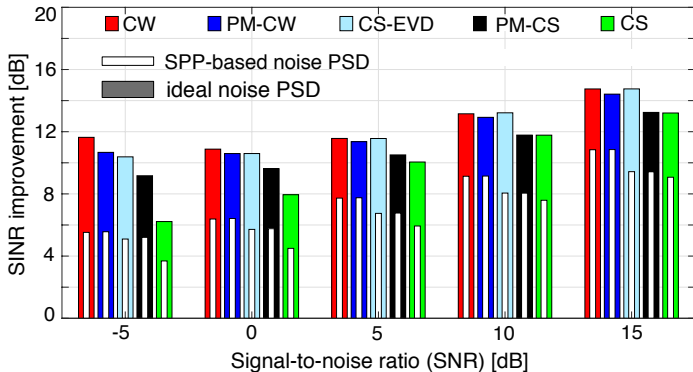
- MVDR filters using different RTF estimates
- Objective quality evaluation:
 - ▶ Speech distortion (SD) index
 - ▶ Signal to interference-plus-noise ratio (SINR) improvement compared to the reference microphone
- The measures are computed for non-overlapping 30 ms frames and are then averaged over all frames (15 seconds)

Speech distortion (fan noise with 0 dB SIR)



- **Ideal noise PSD matrix:** The proposed PM-CS causes similar or larger SD than the CS-EVD, but smaller than the CS
- **Estimated noise PSD matrix:** The distortion of PM-CS and CS-EVD is comparable
- **Estimated noise PSD matrix:** PM-CS causes lower SD than CW and PM-CW

SINR improvement (fan noise with 0 dB SIR)



- CS provides less SINR improvement than the alternatives which is consistent with (Markovich-Golan et al., 2015)
- Estimated noise PSD matrix: The proposed PM-CS has similar SINR improvement than CS-EVD

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Conclusions

- Motivated by the advantage of $\mathbf{g}_{\text{CS-EVD}}$ compared to \mathbf{g}_{CS} , we proposed an iterative estimator to reduce the complexity
- Although the proposed PM-CS estimator has a greater computationally complexity than the CS estimator, it is less complex than the PM-CW estimator
- When the noise statistics are estimated, the performance of the proposed estimator is comparable to the CS-EVD estimator

Thank you for your attention.