

RELATIVE TRANSFER FUNCTION ESTIMATION EXPLOITING SPATIALLY SEPARATED MICROPHONES IN A DIFFUSE NOISE FIELD

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ABSTRACT

Many multi-microphone speech enhancement algorithms require the relative transfer function (RTF) vector of the desired speech source, relating the acoustic transfer functions of all array microphones to a reference microphone. In this paper, we propose a computationally efficient method to estimate the RTF vector in a diffuse noise field, which requires an additional microphone that is spatially separated from the microphone array, such that the spatial coherence between the noise components in the microphone array signals and the additional microphone signal is low. Assuming this spatial coherence to be zero, we show that an unbiased estimate of the RTF vector can be obtained. Based on real-world recordings experimental results show that the proposed RTF estimator outperforms state-of-the-art estimators using only the microphone array signals in terms of estimation accuracy and noise reduction performance.

Index Terms— Relative transfer function, external microphone, acoustic sensor network, speech enhancement, MVDR

1. INTRODUCTION

In many hands-free speech communication systems such as hearing aids, hearables or other assistive listening devices, the captured speech signal is often corrupted by additive background noise, such that speech enhancement methods are required to improve speech quality and speech intelligibility [1]. When more than one microphone is available, it is not only possible to exploit the spectro-temporal properties but also the spatial properties of the sound field to extract the desired speech source at a certain position from the noisy microphone signals. By using spatially distributed microphones, e.g., one or more external microphones in addition to the microphones on the hearing device, the spatial sampling of the sound field can be increased [2–7].

A well-known multi-microphone speech enhancement method is the minimum variance distortionless response (MVDR) beamformer [1, 8]. In a reverberant environment the MVDR beamformer either requires the acoustic transfer functions (ATFs) between the desired speech source and the microphones, which are difficult to accurately estimate in practice, or the relative transfer functions (RTFs) of the desired speech source, which relate the ATFs to a reference microphone [1, 9]. Since RTFs can be exploited in many multi-microphone speech enhancement methods [10–17], accurately estimating the RTFs of one or more sources is an important task. In the literature several methods for estimating the RTFs have been proposed [9–12, 18–21],

where most recent methods are based either on covariance subtraction (CS) or covariance whitening (CW). These methods usually require an estimate of the microphone signal covariance matrix (e.g., estimated during speech-plus-noise periods) and the noise covariance matrix (e.g., estimated during noise-only periods). Although an iterative version of the CS and CW methods has been presented in [12, 21], the computational complexity of the CS-based and CW-based RTF estimation methods is generally high due to the involved matrix operations (possibly involving an eigenvalue decomposition (EVD)), which is especially relevant for an online-implementation.

In this paper, we propose a computationally efficient method to estimate the RTFs of a *local* microphone array (e.g., on a hearing device) by exploiting the availability of an *external* microphone that is spatially separated from the local microphone array. We consider a diffuse noise field and assume that the distance between the external microphone and the local microphone array is large enough such that the spatial coherence (SC) between the noise components in the local microphone signals and the external microphone signal is low. When assuming this SC to be zero, we show that a simple RTF estimator can be derived that only depends on the microphone signal covariance matrix. Based on real-world recordings with (local) head-mounted microphones and an (external) table microphone, we compare the performance of the proposed RTF estimator and different CS-based and CW-based RTF estimators (using only the local microphone signals). Simulation results show that the proposed estimator yields the best performance when used in an online implementation of the binaural MVDR beamformer.

2. SIGNAL MODEL

We consider an acoustic scenario with one desired speech source and diffuse noise (e.g., babble noise) in a reverberant environment. The m -th microphone signal $Y_m(k, l)$ of an M -element *local* microphone array can be written in the short-time Fourier transform (STFT) domain as

$$Y_m(k, l) = X_m(k, l) + N_m(k, l), \quad m \in \{1, \dots, M\}, \quad (1)$$

where $X_m(k, l)$ denotes the speech component, $N_m(k, l)$ denotes the noise component, and k and l denote the frequency and frame indices, respectively. For the sake of brevity, we will omit these indices in the remainder of the paper wherever possible. All microphone signals can be stacked in a vector, i.e.,

$$\mathbf{y} = [Y_1, Y_2, \dots, Y_M]^T \in \mathbb{C}^M, \quad (2)$$

which can be written as

$$\mathbf{y} = \mathbf{x} + \mathbf{n}, \quad (3)$$

where the speech vector \mathbf{x} and the noise vector \mathbf{n} are defined similarly as \mathbf{y} in (2). Without loss of generality, we choose the first microphone

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as the reference microphone. The RTF vector of the desired speech source is then given by

$$\mathbf{h} = \left[1, \frac{A_2}{A_1}, \dots, \frac{A_M}{A_1} \right]^T, \quad (4)$$

where A_m is the ATF between the desired speech source and the m -th microphone. Using (4), the speech vector can be written as

$$\mathbf{x} = X_1 \mathbf{h}. \quad (5)$$

The speech covariance matrix $\mathbf{R}_x \in \mathbb{C}^{M \times M}$ and the noise covariance matrix $\mathbf{R}_n \in \mathbb{C}^{M \times M}$ are given by

$$\mathbf{R}_x = \mathcal{E}\{\mathbf{x}\mathbf{x}^H\} = \Phi_{x_1} \mathbf{h}\mathbf{h}^H, \quad (6)$$

$$\mathbf{R}_n = \mathcal{E}\{\mathbf{n}\mathbf{n}^H\}, \quad (7)$$

where $(\cdot)^H$ denotes complex conjugation, $\mathcal{E}\{\cdot\}$ denotes the expectation operator and Φ_{x_1} is the speech power spectral density (PSD) in the first microphone. Assuming statistical independence between the speech and the noise components, the covariance matrix of the microphone signals $\mathbf{R}_y = \mathcal{E}\{\mathbf{y}\mathbf{y}^H\}$ is equal to

$$\mathbf{R}_y = \mathbf{R}_x + \mathbf{R}_n. \quad (8)$$

When applying a filter-and-sum beamformer $\mathbf{w} \in \mathbb{C}^M$ to the microphone signals, the output signal Z is given by

$$Z = \mathbf{w}^H \mathbf{y}. \quad (9)$$

The MVDR beamformer [1, 9] aims at minimizing the output noise PSD while preserving the speech component in the reference microphone signal and is hence given by

$$\begin{aligned} \mathbf{w} &= \arg \min_{\mathbf{w}} \mathbf{w}^H \mathbf{R}_n \mathbf{w} \quad \text{subject to} \quad \mathbf{w}^H \mathbf{h} = 1, \\ &= \frac{\mathbf{R}_n^{-1} \mathbf{h}}{\mathbf{h}^H \mathbf{R}_n^{-1} \mathbf{h}}. \end{aligned} \quad (10)$$

From (10) it is clear that the MVDR beamformer only requires knowledge about the noise covariance matrix \mathbf{R}_n and the RTF vector of the desired speech source \mathbf{h} .

3. RTF VECTOR ESTIMATION

In this section, we briefly review two commonly used methods to estimate the RTF vector \mathbf{h} , namely the CS method [18, 19, 22] and the CW method [11, 22]. For both methods, we also discuss iterative versions based on the power iteration method [10, 12, 21]. All methods require an estimate of the microphone signal covariance matrix \mathbf{R}_y and the noise covariance matrix \mathbf{R}_n , where $\hat{\mathbf{R}}_y$ is estimated during speech-plus-noise frames and $\hat{\mathbf{R}}_n$ is estimated during noise-only frames, assuming a voice activity detector (VAD) is available. The computational complexity of the CS-based and CW-based methods depends on the required matrix operations, where especially matrix inversion or EVD will result in a large computational complexity.

3.1. Covariance subtraction (CS)

By using the rank-1 model in (6), the RTF vector \mathbf{h} can be calculated as any column of the speech correlation matrix \mathbf{R}_x , normalised by the entry corresponding to the reference microphone, i.e.,

$$\mathbf{h}_{\text{CS}} = \frac{\mathbf{R}_x \mathbf{e}}{\mathbf{e}^T \mathbf{R}_x \mathbf{e}}, \quad (11)$$

where $\mathbf{e} = [1, 0, \dots, 0]^T$ is a selection vector consisting of zeros with one element equal to 1. Usually, the speech covariance matrix \mathbf{R}_x is

estimated as $\hat{\mathbf{R}}_x = \hat{\mathbf{R}}_y - \hat{\mathbf{R}}_n$.

Although the CS method has a relatively low computational complexity, its performance is not always very good since due to estimation errors the estimated speech covariance matrix $\hat{\mathbf{R}}_x$ typically does not have rank-1 [19, 22]. Hence, the RTF vector can also be estimated as the principal eigenvector (corresponding to the largest eigenvalue) of $\hat{\mathbf{R}}_x$ normalising by the entry corresponding to the reference microphone. We denote this estimate as \mathbf{h}_{R1} . It has been shown in [22] that \mathbf{h}_{R1} outperforms \mathbf{h}_{CS} when used in a multichannel Wiener filter (MWF), but obviously has a larger computational complexity due to the EVD.

3.2. Covariance whitening (CW)

By using a square-root decomposition (e.g., Cholesky decomposition) of the noise covariance matrix \mathbf{R}_n , i.e.,

$$\mathbf{R}_n = \mathbf{R}_n^{H/2} \mathbf{R}_n^{1/2}, \quad (12)$$

the pre-whitened microphone signal covariance matrix is given by

$$\mathbf{R}_y^w = \mathbf{R}_n^{-H/2} \mathbf{R}_y \mathbf{R}_n^{-1/2}. \quad (13)$$

The EVD of (13) is equal to

$$\mathbf{R}_y^w = \mathbf{V} \mathbf{\Lambda} \mathbf{V}^H, \quad (14)$$

where $\mathbf{V} \in \mathbb{C}^{M \times M}$ contains the eigenvectors and the diagonal matrix $\mathbf{\Lambda} \in \mathbb{R}^{M \times M}$ contains the eigenvalues. Based on the principal eigenvector \mathbf{v}_{max} , the RTF vector can be estimated as [19]

$$\mathbf{h}_{\text{CW}} = \frac{\mathbf{R}_n^{1/2} \mathbf{v}_{\text{max}}}{\mathbf{e}^T \mathbf{R}_n^{1/2} \mathbf{v}_{\text{max}}}. \quad (15)$$

3.3. Iterative methods

Iterative CS-based and CW-based methods for RTF estimation have been proposed, which aim at reducing the computational complexity of the EVD by using the power iteration method (or von-Mises-Iteration) to calculate the principal eigenvector \mathbf{v}_{max} . Using the power iteration method on the pre-whitened microphone signal covariance matrix \mathbf{R}_y^w [12] or the speech covariance matrix \mathbf{R}_x [21] yields the power method (PM) estimators $\mathbf{h}_{\text{PM-CW}}$ and $\mathbf{h}_{\text{PM-CS}}$, respectively. As mentioned in [12, 21], one iteration per frame is typically sufficient for an online implementation.

4. INCORPORATION OF AN EXTERNAL MICROPHONE

In addition to the local microphone array, we now assume the presence of an *external* microphone that is spatially separated from the local microphones. The *extended* microphone signal vector, containing the microphone signals of the local microphone array and the external microphone signal, is given by

$$\bar{\mathbf{y}} = \begin{bmatrix} \mathbf{y} \\ Y_E \end{bmatrix} \in \mathbb{C}^{M+1}, \quad (16)$$

where Y_E denotes the external microphone signal. The extended speech and noise vectors are defined similarly as $\bar{\mathbf{x}} = [\mathbf{x}, X_E]^T$ and $\bar{\mathbf{n}} = [\mathbf{n}, N_E]^T$, respectively. Similarly to (4), the extended RTF vector is given by

$$\bar{\mathbf{h}} = \begin{bmatrix} \mathbf{h} \\ A_E/A_1 \end{bmatrix} \in \mathbb{C}^{M+1}, \quad (17)$$

where A_E denotes the ATF between the desired speech source and the external microphone. Similarly to (6) and (7), the extended speech co-

variance matrix and the extended noise covariance matrix are equal to

$$\bar{\mathbf{R}}_{\mathbf{x}} = \mathcal{E}\{\bar{\mathbf{x}}\bar{\mathbf{x}}^H\} = \Phi_{\mathbf{x}_1} \bar{\mathbf{h}}\bar{\mathbf{h}}^H \in \mathbb{C}^{(M+1) \times (M+1)}, \quad (18)$$

$$\bar{\mathbf{R}}_{\mathbf{n}} = \mathcal{E}\{\bar{\mathbf{n}}\bar{\mathbf{n}}^H\} \in \mathbb{C}^{(M+1) \times (M+1)}. \quad (19)$$

Similarly to (8), the extended microphone signal correlation matrix is equal to $\bar{\mathbf{R}}_{\mathbf{y}} = \bar{\mathbf{R}}_{\mathbf{x}} + \bar{\mathbf{R}}_{\mathbf{n}}$. We assume that the distance between the external microphone and the local microphones is large enough such that the noise components in the local microphone signals are spatially uncorrelated with the noise component in the external microphone signal, i.e.,

$$\mathcal{E}\{\mathbf{n}N_{\mathbf{E}}^*\} = \mathbf{0}_M, \quad (20)$$

where $\mathbf{0}_M$ is an M -element zero vector. Hence, the extended noise covariance matrix $\bar{\mathbf{R}}_{\mathbf{n}}$ in (19) can be written as

$$\bar{\mathbf{R}}_{\mathbf{n}} = \begin{bmatrix} \bar{\mathbf{R}}_{\mathbf{n}} & \mathbf{0}_M \\ \mathbf{0}_M^T & \Phi_{\mathbf{n}_{\mathbf{E}}} \end{bmatrix}, \quad (21)$$

where $\Phi_{\mathbf{n}_{\mathbf{E}}} = \mathcal{E}\{|N_{\mathbf{E}}|^2\}$ denotes the noise PSD in the external microphone signal. For a diffuse, i.e., spherically isotropic, noise field, the SC between the noise component in the external microphone signal and the noise component in a local microphone signal is equal to (neglecting head shadow effects)

$$\gamma = \text{sinc}(d\omega/c), \quad (22)$$

with d the distance between the external microphone and the local microphone, ω the angular frequency and c the speed of sound. Hence, the assumption in (20) already holds well even for relatively small distances (especially at high frequencies).

Based on the assumption in (20), it can be easily shown that the covariance between the local microphone signals and the external microphone signal is equal to the covariance between the speech components in these microphone signals, i.e.,

$$\mathcal{E}\{\mathbf{y}Y_{\mathbf{E}}^*\} = \mathcal{E}\{(\mathbf{x} + \mathbf{n})(X_{\mathbf{E}}^* + N_{\mathbf{E}}^*)\} = \mathcal{E}\{\mathbf{x}X_{\mathbf{E}}^*\}. \quad (23)$$

Using the CS method described in Section 3.1, the extended RTF vector $\bar{\mathbf{h}}$ in (17) can be estimated as the last column of the extended speech covariance matrix $\bar{\mathbf{R}}_{\mathbf{x}}$, normalized by the first entry (corresponding to the reference microphone), i.e.,

$$\bar{\mathbf{h}} = \frac{\bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}}}{\bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}}} \quad (24)$$

with the $(M+1)$ -dimensional selection vectors $\bar{\mathbf{e}} = [1, 0, \dots, 0]^T$ and $\bar{\mathbf{e}}_{\mathbf{E}} = [0, \dots, 0, 1]^T$. Using (21), it can easily be shown that

$$\bar{\mathbf{R}}_{\mathbf{y}}\bar{\mathbf{e}}_{\mathbf{E}} = \bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}} + \bar{\mathbf{R}}_{\mathbf{n}}\bar{\mathbf{e}}_{\mathbf{E}} = \bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}} + \Phi_{\mathbf{n}_{\mathbf{E}}}\bar{\mathbf{e}}_{\mathbf{E}}, \quad (25)$$

$$\bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{y}}\bar{\mathbf{e}}_{\mathbf{E}} = \bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}} + \bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{n}}\bar{\mathbf{e}}_{\mathbf{E}} = \bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}}, \quad (26)$$

such that, using (24),

$$\frac{\bar{\mathbf{R}}_{\mathbf{y}}\bar{\mathbf{e}}_{\mathbf{E}}}{\bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{y}}\bar{\mathbf{e}}_{\mathbf{E}}} = \frac{\bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}} + \Phi_{\mathbf{n}_{\mathbf{E}}}\bar{\mathbf{e}}_{\mathbf{E}}}{\bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}}} = \bar{\mathbf{h}} + \frac{\Phi_{\mathbf{n}_{\mathbf{E}}}}{\bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{x}}\bar{\mathbf{e}}_{\mathbf{E}}}\bar{\mathbf{e}}_{\mathbf{E}}. \quad (27)$$

Hence, an unbiased estimation for the RTF vector \mathbf{h} can be obtained as the first elements of the vector in (27), i.e.,

$$\mathbf{h}_{\text{SC}} = [\mathbf{I}_M, \mathbf{0}_M] \frac{\bar{\mathbf{R}}_{\mathbf{y}}\bar{\mathbf{e}}_{\mathbf{E}}}{\bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{y}}\bar{\mathbf{e}}_{\mathbf{E}}} \quad (28)$$

where \mathbf{I}_M is the identity matrix of size M and which requires an estimate of the extended microphone covariance matrix $\bar{\mathbf{R}}_{\mathbf{y}}$ and no estimate of any noise covariance matrix. The proposed estimator has

a low computational complexity (similar to the CS estimator using only the local microphone signals), but obviously requires an external microphone signal to be transmitted to the local microphone array (synchronization aspects are outside the scope of this paper). Assuming the availability of a VAD that outputs 1 if speech is present and 0 if speech is absent, the proposed RTF estimation algorithm is summarized in Algorithm 1, where the extended microphone signal covariance matrix is recursively updated during speech-plus-noise frames.

Algorithm 1 Proposed RTF estimation algorithm

Input: $\bar{\mathbf{y}}(l), \bar{\mathbf{R}}_{\mathbf{y}}(l-1), \text{VAD}(l)$

Parameter: smoothing factor α

For each frequency bin:

Estimation of the extended microphone signal covariance matrix:

1: **if** ($\text{VAD}(l) \neq 1$) **then**

2: $\bar{\mathbf{R}}_{\mathbf{y}}(l) = \alpha\bar{\mathbf{R}}_{\mathbf{y}}(l-1) + (1-\alpha)\bar{\mathbf{y}}(l)\bar{\mathbf{y}}^H(l)$

3: **else**

4: $\bar{\mathbf{R}}_{\mathbf{y}}(l) = \bar{\mathbf{R}}_{\mathbf{y}}(l-1)$

5: **end if**

Estimation of the RTF vector:

6: $\mathbf{h}_{\text{SC}}(l) = [\mathbf{I}_M, \mathbf{0}_M] \frac{\bar{\mathbf{R}}_{\mathbf{y}}(l)\bar{\mathbf{e}}_{\mathbf{E}}}{\bar{\mathbf{e}}^T\bar{\mathbf{R}}_{\mathbf{y}}(l)\bar{\mathbf{e}}_{\mathbf{E}}}$

Output: $\mathbf{h}_{\text{SC}}(l)$

5. EXPERIMENTAL RESULTS

In this section we compare the performance of the proposed RTF estimator (using the local and the external microphones) with all RTF estimations discussed in Section 3 (using only the local microphone signals). Section 5.1 describes the experimental setup and the algorithmic parameters. Section 5.2 and 5.3 evaluate the RTF estimation accuracy and the noise reduction performance when using the RTF estimates in an MVDR beamformer.

5.1. Experimental setup

For the simulations we used the database of real-world recordings (sampling frequency $f_s = 16$ kHz) described in [23]. The room dimensions were about $12.7 \times 10 \times 3.6$ m³ with a reverberation time of about 620 ms. The local microphone array consisted of $M = 4$ microphones mounted to the ears of a listener (two microphones per ear). As reference microphone we chose the front microphone mounted to the left ear. The external microphone was located on a table in front of the desired speaker with about 60cm distance to the reference microphone. The desired speaker was an English-speaking female talker who sat to the right of the listener at an angle of about 45°. Both the listener and the desired speaker were seated at a circular table with a diameter of 106 cm. In addition, 56 other talkers which were also seated at tables, generated a realistic babble noise. The noise field hence contained mainly diffuse but also directional components from temporally dominant interfering talkers. Separate recordings of the babble noise and the desired speaker were used to mix them together at different input signal-to-noise ratios (SNRs) $\{-10, -5, 0, 5, 10\}$ dB. The SNR in the external microphone signal was about 13 dB higher than in the reference microphone signal (due to distance and head shadow effect). We calculated all SNRs using the *intelligibility-weighted* SNR [24]. The total signal length was about 23 s.

We used an STFT framework with a frame length $L_f = 512$ samples and a frame-shift of $L_o = L_f/2$ samples and a square-root Hann window. To estimate the covariance matrices $\bar{\mathbf{R}}_{\mathbf{y}}$ and $\bar{\mathbf{R}}_{\mathbf{n}}$ using speech-plus-noise frames and the noise covariance matrix $\bar{\mathbf{R}}_{\mathbf{n}}$ using noise-

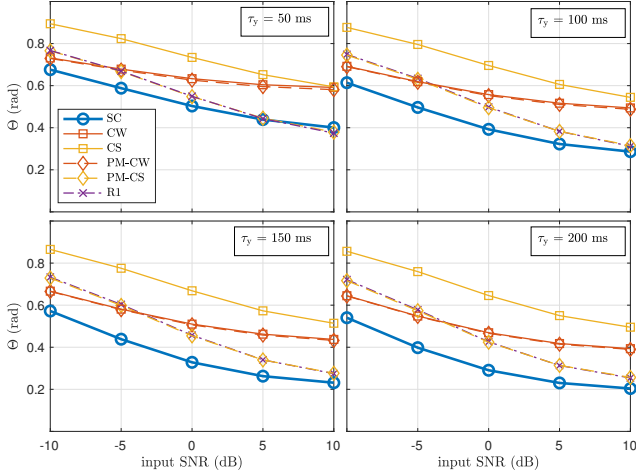


Fig. 1. Hermitian angle Θ between the reference RTF vector \mathbf{h}_{REF} and the estimated RTF vectors (averaged over frequency and time) for different input SNRs and different time constants τ_y .

only frames we used a simple broadband energy-based VAD calculated from the speech component in the reference microphone signal. To recursively estimate these covariance matrices, we used the time constants τ_y and τ_n , respectively. The corresponding smoothing factor (cf. Algorithm 1) is equal to $\alpha = \exp(-\frac{L_t - L_o}{J_s \tau})$. Please note that a smaller time constant corresponds to a smaller smoothing factor and hence to a faster adaptation to possible changes, but may also lead to less accurate estimates of the covariance matrices. Especially in a scenario where the microphones or the desired speaker may change their position, a small time constant is desirable to be able to track changes fast enough. Because the background noise can be assumed to be rather stationary we set the corresponding time constant $\tau_n = 500$ ms. The time constant used to recursively estimate the covariance matrices $\hat{\mathbf{R}}_y$ and $\hat{\mathbf{R}}_n$ was chosen as $\tau_y \in \{50, 100, 150, 200\}$ ms. All covariance matrix estimates were initialised using the corresponding long-term estimate.

5.2. RTF estimation accuracy

As suggested in [21], to evaluate the RTF estimation accuracy we used the Hermitian angle between a reference RTF vector \mathbf{h}_{REF} and the estimated RTF vector $\hat{\mathbf{h}}$, i.e.,

$$\Theta(k, l) = \arccos \frac{|\mathbf{h}_{\text{REF}}^H(k, l) \hat{\mathbf{h}}(k, l)|}{\|\mathbf{h}_{\text{REF}}(k, l)\|_2 \|\hat{\mathbf{h}}(k, l)\|_2}. \quad (29)$$

The reference RTF vector \mathbf{h}_{REF} was calculated as the principal eigenvector of the oracle speech covariance matrix \mathbf{R}_x (estimated using all available speech frames), normalised by its first element (corresponding to the reference microphone). Figure 1 depicts the results (averaged over all frequencies and frames) for different time constants over different input SNRs. As expected, the performance of all estimators improves by increasing the input SNR and the time constant. It can be observed that the proposed SC-based estimator generally outperforms the other estimators for all input SNRs and time constants. The CS method showed worse performance, in line with the literature [19]. Only for a time constant of $\tau_y = 50$ ms and a high input SNR of 10 dB the R1 and PM-CS estimators slightly outperform the proposed estimator. For an exemplary input SNR of 0dB and a time constant of 50 ms Figure 2 depicts the Hermitian angles (averaged over all frequencies) for the first 100 frames. The proposed estimator starts

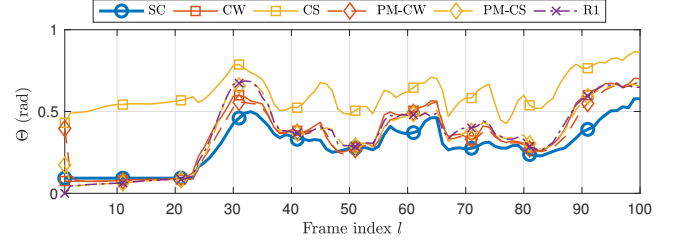


Fig. 2. Hermitian angle Θ between the reference RTF vector \mathbf{h}_{REF} and the estimated RTF vectors (averaged over frequency) for an input SNR of 0 dB and $\tau_y = 50$ ms.

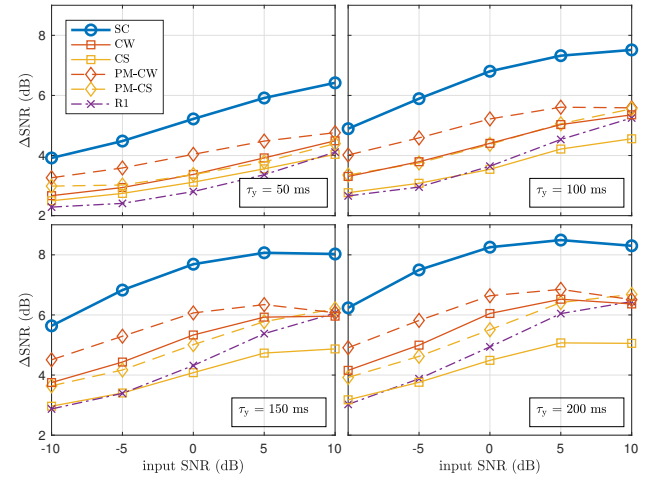


Fig. 3. SNR improvement ΔSNR of an MVDR beamformer steered by using the estimated RTF vectors for different time constants τ_y .

to adapt after about 22 frames because this is the first frame where the speaker is active. All other estimators rely on estimates of both the noisy and the noise covariance matrices and hence adapt during noise-only and speech-plus-noise frames. The R1 and CW estimators both seem to benefit from the long-term initializations in the first frames but perform worse than the proposed estimator afterwards.

5.3. Noise reduction

We evaluated the noise reduction performance when using the estimated RTFs to steer an MVDR beamformer, i.e., using $\hat{\mathbf{h}}(k, l)$ and the time-varying estimate of $\mathbf{R}_n(k, l)$ in (10). Please note, that for all estimators the MVDR beamformer is M -dimensional. Figure 3 depicts the SNR improvement (ΔSNR) calculated by applying the beamformer to the desired speech and noise components separately. As can be seen, the proposed SC estimator clearly outperforms all other estimators for all input SNRs and time constants.

6. CONCLUSION

In this paper, we proposed an RTF estimation method exploiting low spatial coherence between the noise components in local microphone signals and an external microphone signal. We derived a simple and computational efficient RTF estimator that yields an unbiased estimate of the RTF vector corresponding to the local microphone array. Evaluation results in terms of the RTF estimation error and the noise reduction performance using real-world signals in an online implementation showed that the proposed estimator outperforms existing estimators using only the local microphone signals.

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