Similarity-and-Independence-Aware Beamformer: Method for Target Source Extraction using Magnitude Spectrogram as Reference

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Abstract
This study presents a novel method called the similarity-and-independence-aware beamformer (SIBF) for source extraction. The SIBF can extract the target signal using its rough magnitude spectrogram as the reference signal. The advantage of SIBF lies in that it can obtain an accurate target signal, compared to the spectrogram generated by the target-enhancing methods, such as the speech enhancement based on deep neural networks (DNNs). To realize such extraction, we extend the framework of the deflationary independent component analysis, by considering the similarity between the reference and extracted target, as well as the mutual independence among all potential sources. To solve this extraction problem by the maximum-likelihood estimation, we introduce two types of source models that can reflect the similarity. Using the CHiME3 dataset, the experimental results show that the SIBF can extract the target signal more accurate than the reference generated by the DNN.

Index Terms: semi-blind source separation, similarity-and-independence-aware beamformer, deflationary independent component analysis, source model

1. Introduction
The process of extracting the target signal from the mixtures of signals from multiple sources, such as denoising and speech extraction, plays an important role in improving the performance of speech recognition [1]. The associated methods can be generally classified into nonlinear and linear ones. In the last decade, the nonlinear methods have been drastically improved owing to the development of deep neural networks (DNNs). These methods can generate clean speeches from noisy speeches [2][3] and extract the utterance from the overlapped ones [4][5], and they are often referred to as DNN-based speech enhancements (SEs).

On the other hand, linear methods, such as the beamformer (BF), are still advantageous in terms of the following aspects:
1. Avoiding nonlinear distortions, such as musical noises and spectral distortions [6][7].
2. Improving the quality of the extracted sound by increasing the number of microphones [8][9].
3. Estimating proper phases and scales of the extracted sound using designated techniques, such as rescaling in the independent component analysis (ICA) [10][11].

To incorporate both features of linear and nonlinear methods, we aim to develop a new BF that utilizes the signal generated with any target-enhancing method (including the DNN-based SE) as the reference signal. Since the magnitude spectrogram is more available than the time-frequency mask and complex-valued spectrogram, the magnitude spectrogram is used as the reference in this study. Note that such a reference is considered “rough” (or less accurate) in the following regards:
a) It still includes some non-dominant interferences (signals other than the target ones), or it can be distorted due to the side effect of removing these interferences.
b) It does not contain any phase information.

The purpose of proposing the new BF is to generate an extracted target more accurate than the reference. The existing reference-based or DNN-based approaches, however, fail to meet this purpose, as discussed in Section 2. Therefore, a novel method, the similarity-and-independence-aware beamformer (SIBF), is proposed, as described in Section 3.

2. Related works
The basic idea of our proposed method is similar to that of the ICA with references [12][13][14][15]. In particular, the one-unit ICA-R can generate a single signal corresponding to the reference [13]. These approaches, however, do not consider the combination of the real-valued reference and complex-valued signals.

As a framework of semi-blind source separation, the independent deeply learned matrix analysis (IDLMA) is developed [16]. In the IDLMA, the power spectrogram of each source is first estimated by DNNs and then, each source is estimated using the power spectrogram as the reference. However, the IDLMA requires multiple references for all sources, even when only one source is of interest.

Other related works include combining the DNN for time-frequency mask estimation with the existing BFs, such as the minimum variance distortionless response (MVDR) BF [17][18] and generalized eigenvalue (GEV) BF [19][20]. However, these methods do not meet our purpose because they cannot directly treat the magnitude spectrogram.

3. Problem formulation of the similarity-and-independence-aware beamformer
The notations listed in Table 1 are used consistently...
throughout the paper to represent the time-frequency domain signals, with \( f \), \( t \), and \( k \) denoting indices of the frequency bin, frame, and channel, respectively.

The workflow of the proposed SIBF is shown in Figure 1. The inputs are the multichannel observation spectrograms obtained from multiple microphones and the output is an extracted target spectrogram. A rough magnitude spectrogram of the target is used as the reference, which can be estimated using various methods including the DNN-based SE.

3.1. Mixing and separating processes with the reference

Figure 2 shows the modeling procedure of the mixing and separating processes for the SIBF. We assume that the sources \( S_1, \ldots, S_M \) are mutually independent. Without loss of generality, \( S_1 \) is considered as the target in this study. The observations \( X_1, \ldots, X_N \) represent the spectrograms obtained from \( N \) microphones. In the time–frequency domain, \( X_k \) is approximated as the instantaneous mixture of the sources. We generate the uncorrelated observations \( U_1, \ldots, U_N \) to apply the framework of the deflationary ICA. The estimated sources \( Y_1, \ldots, Y_N \) are also mutually independent as a result of the separation.

The uncorrelation process in each frequency bin can be described by (1), using the uncorrelation matrix \( P(f) \):

\[
   u(f, t) = P(f)x(f, t) \quad t. s. t. \quad (u(f, t)u(f, t)^H)_k = I,
\]

where \( \{t\} \) and \( I \) denote the averages over \( t \) and the identity matrix, respectively. Similarly, the separating process can be given by (2), using the separating matrix \( W(f) \) to make \( y(f, t) \) mutually independent.

\[
   y(f, t) = W(f)u(f, t) \quad (2)
\]

Considering the uncorrelation, we can restrict \( W(f) \) to a unitary matrix such that \( W(f)W(f)^H = I \).

To extract only the estimated target, we also use

\[
   y_1(f, t) = w_1(f)u(f, t), \quad (3)
\]

where \( w_1(f) \) is the first row vector in \( W(f) \).

The rest of Figure 2 shows the unique points of our modeling. The reference \( R \) is a rough estimate of the target \( S_1 \). To associate \( Y_1 \) with \( S_1 \), we consider the dependence between \( Y_1 \) and \( R \) as well as the independence among the estimated sources. Conversely, maximizing the independence can make \( Y_1 \) more accurate than the reference, while maximizing the dependence can only make \( Y_1 \) similar to the reference.

Because \( S_1 \) is the only source that is of interest, we employ the deflationary estimation, i.e., the one-by-one separation, to generate \( Y_1 \) only. This means that other estimated sources, \( Y_2, \ldots, Y_N \), are just virtual (potential) ones.

3.2. Maximum-likelihood estimation of the target signal

We solve the target extraction problem shown in Figure 2 by the maximum-likelihood (ML) estimation, which is widely used in blind source separation (BSS) problems [22][23][16].

For the dependence between the estimated target and the reference, we consider the temporally averaged negative log-likelihood of both observations and reference using

\[
   \frac{1}{T}L = -\frac{1}{T} \log p_{RX}(R, X_1, \ldots, X_N), \quad (4)
\]

where \( T \) is the number of frames and \( p_{RX} \) denotes the joint probability density function (PDF) of its arguments. For simplicity, we assume that all elements in the same spectrogram are mutually independent and \( M = N \). Then, (4) turns into (5).

\[
   \frac{1}{T}L = -\sum_{t} \left( \log p_{R}(r(f, t), y_1(f, t)) \right)_t - \sum_{t} \sum_{k=2} \left( \log p_{k}(x_k(f, t)) \right)_t - 2\sum_{t} \log \det(W(f)P(f)), \quad (5)
\]

where \( p_{R} \) denotes the joint PDF between \( r(f, t) \) and \( s_1(f, t) \); and \( p_{k} \) denotes the PDF of \( s_k(f, t) \). We call \( p_{R} \) a source model, which is examined in Section 3.3.

By minimizing (5), we can estimate the most likely sources. Because of the uncorrelation, the determinant of \( W(f)P(f) \) in (5) is constant. Therefore, to estimate \( w_1(f) \), which is the extracting filter for \( y_1(f, t) \), we minimize only the first term in (5) subject to \( w_1(f)W(f)^H = 1 \) as follows:

\[
   w_1(f) = \arg \min_{w_1(f)} \left\{ -\log p_{R}(r(f, t), y_1(f, t))_t \right\} \quad (6)
\]

3.3. Source models

To reflect the dependence into the source model, we examine two types of PDFs: (i) the time-frequency-varying variance (TV) model and (ii) bi-variate spherical (BS) model.

The TV model contains different variances in each frequency bin and frame. The reference \( r(f, t) \) is interpreted as a value related to the variance. Then, the TV Gaussian model, which has been utilized in BSS problems [24][23][16], is also used in this study. To control the influence of the reference, we append \( \beta \) as the reference exponent:
\[
p_{r,t}(r(f, t), y_1(f, t)) \propto \frac{1}{r(f, t)\beta^{\alpha}} \exp\left(-\frac{|y_1(f, t)|^2}{r(f, t)\beta}\right) \tag{7}
\]

On the other hand, the BS model is a two-variable version of the multivariate spherical (MS) distribution. MS models, such as the MS Laplacian model, are utilized in the independent vector analysis to avoid the permutation ambiguity problem \[25\][26][27][28]. To make \(y_1(f, t)\) and \(r(f, t)\) similar to each other, we use the BS Laplacian model:

\[
p_{r,t}(r(f, t), y_1(f, t)) \propto \exp\left(-\sqrt{ar(f, t)^2 + |y_1(f, t)|^2}\right) \tag{8}
\]

where \(\alpha\), which is called the reference weight, controls the influence of the reference. To balance the scales of \(r(f, t)\) and \(y_1(f, t)\), we normalize the reference so that \((r(f, t))^2=1\).

3.4. Rules for estimating the extracting filter

We derive the rules of estimating the filter for each model.

For the TV Gaussian model, we have the closed-form solution written as (9), since assigning (7) to (6) results in the problem of minimizing a weighted covariance matrix.

\[
w_1(f) = EIG((u(f, t)u(f, t)^H)/r(f, t)^2)\tag{9}
\]

where \(EIG(\cdot)\) denotes the eigenvector in the row vector form corresponding to the minimum eigenvalue of the given matrix.

For the BS Laplacian model, we apply iterative updating rules written as (10) and (11), based on the auxiliary function algorithm [29].

\[
b(f, t) \leftarrow \sqrt{ar(f, t)^2 + |w_1(f)u(f, t)|^2} \tag{10}
\]

\[
w_1(f) \leftarrow EIG((u(f, t)u(f, t)^H/b(f, t)))^H \tag{11}
\]

To derive these rules, we use the following inequation, which contains a positive value \(b(f, t)\) called the auxiliary variable:

\[
\sqrt{ar(f, t)^2 + |y_1(f, t)|^2} \leq \frac{\sqrt{ar(f, t)^2 + |y_1(f, t)|^2}}{2b(f, t)} + \frac{b(f, t)}{2} \tag{12}
\]

In the first iteration, we use \(b(f, t) \leftarrow r(f, t)\) instead of (10) because \(w_1(f)\) is unknown. This is equivalent to the rule of the TV Gaussian model (9) with \(\beta = 1\).

3.5. Postprocess

After the filter estimation, we estimate the proper scale and phase of the estimated target by minimizing the following approximate score:

\[
\left\{x_m(f, t) - \sum_k y_k(f)y_k(f, t)\right\}^2_t \tag{13}
\]

where \(x_m(f, t)\) and \(y_k(f)\) denote the observation of the \(m\)th microphone and a rescaling factor for \(y_k(f, t)\), respectively. From the mutual independence of the estimated sources, \(y_k(f, t)\) is simply computed as follows:

\[
y_k(f, t) = \frac{x_m(f, t)y_1(f, t)}{|y_1(f, t)|^2} \tag{14}
\]

We consider \(y_1(f, t)\) as the final estimated target.

### 4. Experiments

To verify the effectiveness of the proposed SIBF, we conducted several experiments using the CHiME3 dataset [30]. This means that we applied the SIBF to the problem of estimating clean speeches in noisy environments. In the dataset, sound data were recorded in four noisy environments using six microphones attached to a tablet device. Clean speeches were also recorded in a recording booth.

4.1. DNN for reference estimation

To prepare the DNN for reference estimation, we modified the configuration that trains a BLSTM-based mask estimator for NN-GEV [19] to output the magnitude spectrogram. The network configuration, as shown in Figure 3, was generally the same as that in [19] except for the following aspects:

- Supervisory data consisted of magnitude spectrograms of clean speeches instead of ideal binary masks.
- The mean squared error (MSE) was used in the training stage as the loss function.
- The training was performed in 20 epochs constantly.

To estimate the reference, the observation spectrogram of Microphone #5 (closest to the speaker position) was used as the input for the DNN.

4.2. Experimental setups

To prepare the input data as a development set with various signal-to-noise ratios (SNRs), we artificially mixed clean speeches recorded in the booth (BH) with background (BG) noises. During the mixing, we applied four multipliers (0.25, 0.5, 1.0, and 2.0) to the noises, and the mixed data are termed as \(\text{“BG”} \times 0.25\)” and so on.

In the preprocess, we converted waveforms into spectrograms using the short-time Fourier transform with 1024 points and 256 shifts. In the postprocess, we employed (14) with \(m = 5\), which was the index of the closest microphone.

4.3. Best parameter sets for each source model

To determine the best parameters for each model, we conducted a series of experiments using the perceptual evaluation of speech quality (PESQ) as the performance score.

First, we examined the TV Gaussian model (7) to find the best reference exponent \(\beta\). For cases \(\beta = 0.5, 1, 2, 4,\) and 8, we found that the case \(\beta = 8\) achieved the best PESQ score while the case \(\beta = 2\) demonstrated the worst, although strictly, only

![Figure 4: PESQ scores of the BS Laplacian model for the reference weight \(\alpha\), reference, and TV Gaussian model \(\beta = 8\). Left: \(BG \times 2\) scenario (Lower SNR); and right: \(BG \times 0.25\) scenario (Higher SNR).](image-url)
the latter case corresponded to the TV Gaussian distribution.

Next, we examined the BS Laplacian model (8) to find the relations between PESQ scores and iteration times (1, 2, 5, and 10) for various reference weights ($\alpha = 10^{-2}$, 1, $10^{2}$, and $10^{4}$). Figure 4 shows a subset of such relations: $BG \times 2$ (left) and $BG \times 0.25$ (right) scenarios. This figure also shows the scores of the reference and the TV Gaussian model ($\beta = 8$ only) with dotted and broken horizontal lines, respectively.

In Table 2, we confirmed the following findings:

1. The NN-SIBF outperformed the references in most cases, except for the $BG \times 2.0$ scenario.
2. The BS Laplacian model outperformed the TV Gaussian model in the NN-SIBF, while both models showed almost identical performance in the Oracle SIBF.
3. For scores in the evaluation set, the NN-SIBF generated with a target-enhancing method, we can extract a more accurate target signal than the reference.

The second is for the relationship between the accuracy of the reference and the performance of the target extraction. We can naturally conclude that a more accurate reference can achieve higher performance for target extraction because the scores of the Oracle SIBF were much higher than those of the NN-SIBF in all experiments. In other words, inaccurate references often result in limited improvement, as shown in the case of $BG \times 2.0$ in Table 2. However, Figure 4 indicates that even with such inaccurate references, the BS Laplacian model can still improve the performance after multiple iterations if the proper reference weight (e.g., $\alpha = 10^{-2}$) was chosen. This figure also suggests that the balance between dependence and independence should vary according to the accuracy of the reference, although this remains an open issue.

The third is how to further improve the performance of the target extraction. From the above discussion, we can have at least two options. One is by improving the accuracy of the reference using state-of-the-art speech enhancement methods to generate a reference. The other is by improving the source models by both refining the proposed models, such as automatic parameter tuning, and examining another type of source model.

6. Conclusions

In this study, we proposed a novel method for target signal extraction, i.e., the SIBF. The proposed method used a rough magnitude spectrogram of the target signal as the reference to more accurately extract the target signal. To realize such extraction, we extended the framework of the deflationary ICA, by considering the similarity between the reference and extracted target signal, as well as the mutual independence among potential sources. To solve the extraction problem by the maximum-likelihood estimation, we developed two types of source models that can reflect the similarity and derived the corresponding rules for the extracting filters.

The advantage of the SIBF lies in its ability to extract a more accurate target signal than the spectrogram generated with target-enhancing methods, such as the DNN-based speech enhancement. We confirmed this through experiments using the CHiME3 dataset.

Finally, the SIBF is based on the theories of the ICA, while it works as a beamformer. Therefore, we hope that the SIBF can further promote future research in both fields of the DNN-based beamformer and ICA-based BSS.

Table 2: PESQ and SDR for each method. NN-SIBF: SIBF using the reference generated with DNN; Oracle SIBF: SIBF using ideal references; “$\times 0.25$,” “$\times 2.0$”: multiplier of noises in mixing speeches and noises; and Eval: CHiME3-simulated evaluation set. The best score for each scenario is bolded (Oracle SIBF is not considered in the comparison).

| Method                        | Source Model | PESQ | SDR [dB] |
|------------------------------|--------------|------|----------|
|                              |              | $\times 0.25$ | $\times 0.5$ | $\times 1.0$ | $\times 2.0$ | Eval ($\times 0.25$) | $\times 0.5$ | $\times 1.0$ | $\times 2.0$ | Eval |
| NN-SIBF (proposed)           | TV Gaussian  | 3.52 | 3.12     | 2.63     | 2.08     | 2.67     | 18.84 | 14.45 | 8.45     | 1.32 | 15.25 |
|                              | BS Laplacian | 3.53 | 3.13     | 2.66     | 2.11     | 2.68     | 19.30 | 14.74 | 8.78     | 1.55 | 15.85 |
| Oracle SIBF                  | TV Gaussian  | 3.58 | 3.21     | 2.80     | 2.39     | 2.75     | 20.62 | 17.03 | 12.25 | 6.54 | 17.99 |
|                              | BS Laplacian | 3.58 | 3.21     | 2.80     | 2.39     | 2.75     | 20.45 | 17.05 | 12.33 | 6.59 | 18.00 |
| Reference generated with the DNN |              | 3.14 | 2.83     | 2.43     | 1.90     | 2.61     | 18.40 | 13.80 | 8.60     | 2.21 | 13.50 |
| Microphone #5                |              | 2.93 | 2.51     | 2.10     | 1.72     | 2.18     | 14.03 | 8.03  | 2.03     | -3.93 | 7.54  |
| CHiME4 SE baseline (BLSTM GEV) [1] |              | 2.46 |          |          |          |          |          |          |          |          |
| Erdogan et.al. (BLSTM MVDR) [17] |              | 2.29 |          |          |          |          |          |          |          |          |

4.4. PESQ and SDR evaluation

Next, we measured the signal-to-distortion ratio (SDR) and the PESQ using the best parameter sets: $\beta = 8$ for the TV Gaussian model and $\alpha = 10^{2}$ for the MS Laplacian model with 10 iterations. To estimate the potential performance of the SIBF, we also attempted to use the magnitude spectrogram of the target signal as the reference. This was termed as the Oracle SIBF, while the use of the reference generated with the DNN was referred to as the NN-SIBF. To compare the SIBF with other methods, we also used the CHiME3-simulated evaluation set.

The results are shown in Table 2, which also includes scores of the reference and observation with Microphone #5. The last two rows demonstrate scores of the CHiME4 SE baseline [1] and BLSTM-based MVDR [17], which were probably trained with the same dataset as in this study. From this table, we confirmed the following findings:

1. The NN-SIBF outperformed the references in most cases, except for the $BG \times 2.0$ scenario.
2. The BS Laplacian model outperformed the TV Gaussian model in the NN-SIBF, while both models showed almost identical performance in the Oracle SIBF.
3. For scores in the evaluation set, the NN-SIBF outperformed the conventional DNN-based methods, despite using the same training dataset.

5. Discussion

In this section, we discuss the following aspects.

The first is for the effectiveness of utilizing both dependence and independence. We can confirm this from the fact that the NN-SIBF was found to outperform the reference in most cases. This suggests that if we have a spectrogram generated with a target-enhancing method, we can extract a more accurate target signal than the reference.
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