EXPLOITING SPATIAL INFORMATION WITH THE INFORMED COMPLEX-VALUED SPATIAL AUTOENCODER FOR TARGET SPEAKER EXTRACTION

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ABSTRACT

In conventional multichannel audio signal enhancement, spatial and spectral filtering are often performed sequentially. In contrast, it has been shown that for neural spatial filtering a joint approach of spectro-spatial filtering is more beneficial. In this contribution, we investigate the spatial filtering performed by such a time-varying spectro-spatial filter. We extend the recently proposed complex-valued spatial autoencoder (COSPA) for the task of target speaker extraction by leveraging its interpretable structure and purposefully informing the network of the target speaker’s position. We show that the resulting informed COSPA (iCOSPA) effectively and flexibly extracts a target speaker from a mixture of speakers. We also find that the proposed architecture is well capable of learning pronounced spatial selectivity patterns and show that the results depend significantly on the training target and the reference signal when computing various evaluation metrics.

Index Terms— speaker extraction, spectro-spatial filtering, training targets, DNN

1. INTRODUCTION

While neural networks represent the state of the art for single-channel audio signal enhancement for some time now, they are only recently moving into the focus for multichannel audio signal enhancement and, hence, spatial filtering. There have been several approaches to guide spatial filters, i.e., beamformers, by estimating intermediate quantities by neural networks [1–5]. Other approaches construct a beamformer by estimating its weights by a neural network [6–11] or replace the beamforming process by a neural network that directly estimates the clean speech signal [12, 13]. The first approach stays with the conventional definitions of beamformers, whereas the second and third approach exploit the nonlinear processing performed by the neural network and are denoted as neural spatial filters.

In this paper, we focus on those neural spectro-spatial filters that estimate the beamformer weights by a neural network. Such neural spectro-spatial filters learn a spatially selective pattern for signal denoising in scenarios where only one speech source is active [6, 14]. In this contribution, we extend one of such neural spectro-spatial filters, the Complex-valued Spatial Autoencoder (COSPA) [6], for the problem of target speaker extraction (TSE) from a mixture of speakers by informing it about the target speaker’s direction of arrival (DoA) via a low-cost extension of the network (cf. Sec. 2.1.1). Furthermore, we explicitly exploit the provided multichannel information by replacing two-dimensional (2D) with three-dimensional (3D) convolutional layers at the beginning of the network (cf. Sec. 2.1.2). We show that these extensions allow to identify the target speaker and enhance its signal in the presence of interfering speakers, rendering the proposed informed COSPA (iCOSPA) a flexible spatial filter. For reverberant scenarios, several options for the target signal used for training the neural filter exist. We examine how the spatial filtering capability is affected by different target signals and also show how the evaluation metrics depend on the choice of reference, i.e., clean signal, used for their computation.

We present the proposed method and discuss the training target signal in Sec. 2. In Sec. 3.1, we detail our experimental setup and present and discuss the corresponding results in Sec. 3.2. Sec. 4 concludes the paper.

2. PROVIDING SPATIAL INFORMATION FOR COSPA

In the following, we briefly introduce the COSPA framework and explain how it is modified to exploit spatial information for TSE (Sec. 2.1). A discussion on the spatial selectivity obtained by appropriate target signals for multichannel processing follows in Sec. 2.2.

2.1. Extension of COSPA

We consider a signal with M microphone channels, captured by an arbitrary microphone array, where the signal at microphone m in time-frequency bin (τ, f) is given by

\[ X_m(\tau, f) = D_m(\tau, f) + \sum_{i=1}^{I} U_{im}(\tau, f) + N_m(\tau, f). \] (1)

where the desired signal is denoted by \( D_m(\tau, f) \), the mixture by \( \sum_{i=1}^{I} U_{im}(\tau, f) \), and the noise by \( N_m(\tau, f) \). The task of TSE is to estimate the desired clean signal from the mixture.

In [6], COSPA was introduced for multichannel denoising. This framework consists of an encoder, which, using a subnetwork denoted by CRUNet, estimates a single-channel mask that is applied to all input channels and subsequently includes feature compression, a compandor which effectuates multichannel processing, i.e., allows to process each channel differently, and a decoder which outputs an individual mask \( M_m \) for each channel. In this paper, we modify COSPA to the problem of TSE by adding DoA information.
2.1.1. Incorporating DoA information

For TSE from multispeaker mixtures, the network needs to be informed about which speaker is the target speaker. This can be achieved by feeding characterizing (instantaneous) information about the target speaker into the network for guidance. This can either be positional, i.e., DoA, information [15, 16], or identity information such as an adaptation utterance spoken by the target speaker [17–20]. The feature extraction involved in using an adaptation utterance for guidance is usually realized by an auxiliary neural network (e.g., [17]), which significantly increases the size of the overall neural network, while features based on DoA information can often be extracted without a neural network (e.g., [15]). In this paper, we want to focus on the spatial filtering aspect of COSPA, for which the DoA information is expected to be more relevant than the speaker identity. Considering these aspects and methods from literature, we find that exploiting the DoA information and adding it to the network using scaled activations [17] works well for COSPA and also keeps the computational overhead small. Therefore, as depicted in Fig. 1, for the proposed iCOSPA we scale the encoder output $V$ by the cosine of the DoA $\theta$ relative to the microphone array axis, pass it through a sigmoid activation function $\sigma$ and append it as a guiding signal $V_{\text{DoA}}$ to the original vector $V$ to obtain the input to the compandor $V' = [V \ V_{\text{DoA}}]^{\top}$. This differs from [17] as the original features are preserved. We add the guiding signal path in front of the compandor as this is the only part of COSPA that can process the different channels differently and where the DoA information can be beneficially used to increase the spatial selectivity. Given the many proven methods for DoA estimation in literature [21, 22], we assume that the utterance-wise DoA of the target speech is available with sufficient precision. The proposed approach doubles the size of the input of the first compandor layer but does not add other trainable parameters.

2.1.2. 3D convolutional layer for multichannel processing

In order to leverage multichannel information in the encoder, we use all channels to compute the single-channel mask in the encoder. We replace the complex-valued 2D convolutions in the CRUNet of COSPA [6], which operate along the time and the frequency axis of the input signal, by complex-valued 3D convolutions, which additionally extract features across all input channels. 3D convolutional layers have been used in biomedical and video signal processing [23, 24], but not in audio signal processing. In the case of multichannel audio signal processing, extracting features across all three dimensions of the input tensor is intuitively beneficial as information about the spatial setup of the acoustic scene is encoded in the phase differences of the signals captured by the different channels, which also calls for complex-valued networks when operating in the time-frequency domain. Due to the relatively small kernel sizes of convolutional layers, replacing the 2D convolutions by 3D convolutions does not increase the size of the network significantly.

2.2. Training targets for spectro-spatial filtering

For joint spectro-spatial filtering with neural networks, several training targets, notably the clean source signal at the first microphone [8], the time-aligned clean source signal [14], and a minimum variance distortionless response-beamformer (MVDR BF)-filtered version of the source signal at the microphones [6] have been used in the literature. Further potentially advantageous target signals can be obtained by processing the clean reverberated signal with other beamformers, e.g., a simple delay-and-sum beamformer (DSB) to align the time of arrival of the microphone channels, or by modifying the source image at the microphone otherwise (e.g., removing the late reverberation). To optimally approximate any of these targets, the network has to reflect different spatial and spectral filters. For the dry source signal as target, dereverberation has to be achieved as part of the spatial filtering, while the beamformer-filtered signals as targets tolerate certain amounts of reverberation. To estimate the source image at the first microphone, the network has to implicitly estimate relative transfer functions. Therefore, the choice of the training target is expected to have a significant impact on the spectro-spatial filtering patterns learned by the network.

In the following, we experimentally investigate the spatial filtering behavior of iCOSPA when guided by the additional DoA information. Furthermore, it is investigated how the training target influences the spatial filtering characteristics of iCOSPA. As target signals we consider: the MVDR BF-filtered reverberant source signal (mvdr), the DSB-filtered reverberant source signal (dsb), the reverberant source signal as captured by the first microphone adding a small delay to avoid a theoretically possible need for noncausal processing (mic1), and the dry source signal (dry), time-aligned with the signal at the first microphone.

3. EXPERIMENTAL VALIDATION

In the experimental evaluation, we compare the proposed informed iCOSPA with the uninformed COSPA for TSE. COSPA can only know which DoA corresponds to the target speaker when trained accordingly. Hence, we train and test COSPA for four exemplary distinct positions of the target speaker separately, while training iCOSPA on a wide range of target DoA simultaneously (cf. Sec. 3.1). We then show in Sec. 3.2.1 that iCOSPA performs very similarly to COSPA, but is much more flexible in deployment as a single trained network can be used for a wide range of different DoAs. Furthermore, in Sec. 3.2.2, we discuss the spatial selectivity patterns learned by iCOSPA based on various training target signals and show the relevance of the characteristics of the reference signal for the computation of the evaluation metrics in reverberant scenarios.

3.1. Setup and evaluation metrics

In our experiments, we consider scenarios with one target and $I = 2$ interfering speakers. For each scenario, the room dimensions (in
the range of \([4 \ldots 8, 4 \ldots 8, 1 \ldots 4]\) m, the reverberation time \((0.2 \ldots 0.5)\) s, and the position of the microphone array are sampled randomly. We use a uniform linear array with \(M = 3\) microphones and an inter-microphone distance of \(4\) cm. In all scenarios, the target speaker is positioned \(0.3 \ldots 1.5\) m from the array. The interferers are placed randomly in the room but at least \(0.3\) m away from the walls and with an angular distance of at least \(10^\circ\) to the target speaker to both sides. The DoAs of all speakers are confined to \(0^\circ \ldots 180^\circ\) between the two endfire positions \((0^\circ)\) and \((180^\circ)\) of the array. Each source signal is convolved with its corresponding room impulse response generated by the image method [25] and the interferers are scaled such that the target-to-interferer power ratio ranges from \(-5\) to \(5\) dB. White noise is added to the mixture signals at a signal-to-noise ratio of \(30\) \ldots \(60\) dB. The speech signals are taken from the TIMIT database [26] and sampled at \(16\) kHz to form sequences of \(7\) s duration. For training, we generate five training datasets. Four training datasets contain \(3000\) sequences each, where the target speaker is positioned at a fixed DoA \(\theta \in [0, 30, 60, 90]^\circ\), respectively. These datasets are used to train COSPA for TSE, where the information about the target speaker’s position has to be fixed in order to be learnable. The fifth dataset contains \(250\) sequences per target DoA covering the range from \(0^\circ\) to \(180^\circ\) in steps of \(5^\circ\) for training iCOSPA. For testing, we create \(250\) sequences per target DoA \(\theta \in [0, 30, 60, 90]^\circ\) with speakers disjoint from the training dataset and otherwise keep the same settings as for training.

In the following, we use the names COSPA and iCOSPA to discuss aspects of general relevance to the networks and use the MVDR BF-filtered source signal as target if not stated otherwise. We append \(-\text{mvdr/dsb/mic1/dry}\) to the name when discussing the networks trained on specific targets. For the mic1-target experiments, the estimated mask for each channel is constrained to a maximum magnitude of \(1/M\) to ensure that the network does not collapse into a single-channel method. We assume the 3D convolutional layer in the \(\text{CNN}\) of iCOSPA to be the default setting and append \(-\text{2D}\) when discussing iCOSPA with the 2D \(\text{CNN}\). We parameterize both COSPA and iCOSPA as in [6], with the exception of the additional convolutional kernels of size \((2, 2, 1, 1)\) along the channel axis in the four modules of iCOSPA’s \(\text{CNN}\). Furthermore, the input of iCOSPA’s commandor, \(V^\text{c}\), is twice the size of that of COSPA, \(V\), due to the appended DoA information \(V_{\text{DoA}}\). All network sizes are given in Table 1. We use signal frames of length \(1024\) with a shift of \(512\) samples. In Sec. 3.2, we show beampatterns for iCOSPA that were generated as described in [6].

For comparison, we provide results from the Embedding and Beamforming Network (EaBNet) introduced in [8] as an alternative neural spectro-spatial filter. We keep the settings of the EaBNet, including the frame length of \(320\) samples and the mic1 training target, as published without using an extra postfilter and train and test the network on the same datasets as COSPA.

The performance of the methods is measured by Perceptual Evaluation of Speech Quality (PESQ) [27], extended Short-Time Objective Intelligibility (ESTOI) [28] and the signal-to-interference ratio (SIR) [29]. We provide the performance metrics as the difference between metrics of the estimated signal and metrics of the mixture signal at the first microphone averaged over the respective test dataset(s). The discussion of which target to use for training, also raises the question which reference, i.e., clean, signal to use to compute the objective evaluation metrics. Here, we present the evaluation metrics based on both the dry source signal (\(\text{dry}\)) and the reverberated source image at the first microphone (\(\text{mic1}\)) as reference to illustrate how the presence or absence of reverberation in the reference signal affects the performance metrics for different target signals. Both signals are time-aligned with the estimate.

### 3.2. Results and Discussion

We split the presentation of the results into two parts: In Sec. 3.2.1, we show the TSE performance of iCOSPA compared to COSPA and the EaBNet. In Sec. 3.2.2, we discuss the influence of the training targets introduced in Sec. 2.2 on the spatial selectivity of iCOSPA.

#### 3.2.1. Performance evaluation

In Table 1, we present \(\Delta\text{PESQ}, \Delta\text{ESTOI}\) and \(\Delta\text{SIR}\) for COSPA, iCOSPA, iCOSPA-2D and the EaBNet for four different target DoAs. As noted in Sec. 3.1, performance metrics are computed based on a dry and a reverberated signal. It can be seen that iCOSPA, even though trained for a wide range of target DoAs, for all metrics performs very similarly as COSPA which was trained for each test-DoA specifically. This confirms that iCOSPA beneficially uses the provided DoA information for finding the correct target speaker. Hence, with only a very slight increase in model size, iCOSPA is able to flexibly extract a target speaker from any direction.

Comparing iCOSPA and iCOSPA-2D, it can be seen that the two networks perform similarly, with iCOSPA outperforming iCOSPA-2D in some cases. The differences in performance are too small to make definite assertions. In our experiments, we noticed that the 3D convolutional layer seems to provide the most benefit in low SNR scenarios with high reverberation times. Further investigation on the contribution of the 3D convolutional layer is left for future work. We also investigated the robustness of iCOSPA to DoA-estimation errors, given that in a real scenario the exact DoA might not be available. Adding uniformly sampled estimation noise from \(-10^\circ\) to \(10^\circ\) to the true DoA in testing does not notably influence the performance of iCOSPA, given that no other speakers are positioned in this region in our experiments.

It can be noted that the metrics computed on the two reference signal versions differ notably, which shows that the choice of the reference signal strongly influences the results. Since the metrics are computed based on the signal at the first microphone, which is closest to a DoA of \(0^\circ\) in our setup, the performance metrics can vary across DoAs for all methods. According to informal listening tests, COSPA and iCOSPA produce very similar results for all DoAs\(^1\).

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\(^1\)Examples are provided at https://github.com/IMSAudio/.

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**Table 1: Performance metrics for TSE for various target DoAs.** Metrics are based on the \(\text{dry/mic1}\) reference signals. Note that the results for iCOSPA-2D are all obtained from the same network, while the results for COSPA and the EaBNet each come from four separately trained networks. The EaBNet is trained on the mic1 target, the other networks on the mvdr target.

| Model   | # Param. \([\text{million}]\) | 0° | 30° | 60° | 90° |
|---------|--------------------------------|----|-----|-----|-----|
| \text{EaBNet} | 2.8 | 0.15/0.45 | 0.21/0.50 | 0.16/0.39 | 0.14/0.37 |
| \text{COSPA} | 2.1 | 0.26/0.24 | 0.25/0.28 | 0.16/0.23 | 0.15/0.29 |
| \text{iCOSPA-2D} | 2.5 | 0.23/0.19 | 0.23/0.25 | 0.15/0.20 | 0.13/0.23 |
| \text{iCOSPA} | 2.6 | 0.24/0.19 | 0.24/0.25 | 0.17/0.23 | 0.14/0.26 |
| \text{EaBNet} | 2.8 | 0.13/0.13 | 0.13/0.13 | 0.10/0.11 | 0.10/0.12 |
| \text{COSPA} | 2.1 | 0.19/0.04 | 0.17/0.04 | 0.11/0.05 | 0.11/0.08 |
| \text{iCOSPA-2D} | 2.5 | 0.18/0.03 | 0.16/0.05 | 0.10/0.04 | 0.09/0.07 |
| \text{iCOSPA} | 2.6 | 0.19/0.03 | 0.17/0.05 | 0.11/0.05 | 0.09/0.07 |

Note: The results for COSPA and the EaBNet each come from four separately trained networks. The EaBNet is trained on the mic1 target, the other networks on the mvdr target.
Furthermore, Table 1 shows significantly different performance for the EaBNet compared to COSPA. While metrics based on the dry reference signal are notably lower, metrics based on the reverberated reference signal are significantly higher than those for COSPA. This is most likely due to the different training targets of the two networks (mic1 for the EaBNet and mvdr for (i)COSPA). We discuss this effect of different training targets on the spatial selectivity and the evaluation metrics for iCOSPA in Sec. 3.2.2.

3.2.2. Influence of training target on spatial filtering

Building on the discussion of training targets for spectro-spatial filtering in Sec. 2.2, Fig. 2 shows exemplary beampatterns for iCOSPA. It can be seen that the beampattern for the network trained on the MVDR BF-filtered signal shows the most pronounced and precise beampattern. The DSB-filtered target also leads to a distinct beampattern, which indicates that the network is able to learn the spatial selectivity patterns imposed on the target signals in the case of the two beamformers. As can be seen in Fig. 2c, using the desired signal at the first microphone as training target also leads to spatial awareness but with less suppression in the non-target directions, while the beampattern of the network trained on the dry source signal shown in Fig. 2d reflects the spatial awareness of the two beamformer-filtered signals with stronger overall suppression. Moreover, Fig. 2d shows that spatial selectivity can also be achieved by iCOSPA without enforcing a specific spatial filtering process by the target signal. The attenuation in Fig. 2d is due to the more aggressive filtering required to suppress the reverberation to attain the dry source target. The less strong suppression for the mvdr-target in Fig. 2c may be attributed to the reverberation contained in the target, which corresponds to signal parts from all directions. In conclusion, the training target not only provides the network with the ideal characteristics of the estimated signal, but also influences the spatial filter represented by iCOSPA. In any case, however, iCOSPA identifies a beampattern pointing to the correct source DoA.

Table 2 summarizes the performance of iCOSPA trained on various target signals. It can be seen that the evaluation metrics vary strongly with the training target and the reference signal. For the metrics based on the dry source signal as reference, the network trained on the first microphone channel performs worst, while the MVDR BF-filtered target and the dry source target compete for the best performance. For the metrics based on the reverberated source signal, the DSB-filtered target and the mic1-target give the best results, possibly because, compared to the other targets, they retain more of the unprocessed reverberation and hence correspond better to the reverberated reference signal.

The listening impression matches the interpretation of the beampatterns and the results presented in Table 2. iCOSPA-mvdr and iCOSPA-dsb generate similar results, while the results from iCOSPA-mic1 preserve more reverberation and with that also more of the interfering signals. The results generated from iCOSPA-dry show the best interferer suppression but also contain some artefacts. This correlates with the strong suppression visible in Fig. 2d. In general, all iCOSPA variants generate very good speech quality for the target speaker and differ mostly in the suppression of the interferers, which is also reflected in the beampatterns in Fig. 2. The decision on the ‘best version’ will still depend on the scenario, as e.g., for sources close to the first microphone dereverberation will not be as desirable as for distant sources in a highly reverberant room, for which training with clean sources may be preferable.

Finally, in experiments with the EaBNet, some dependency of the spatial selectivity of the network on the target signal can also be observed. This supports the findings that choosing the training target for spectro-spatial filtering impacts not only the performance, but also the interpretability of a method. The generalizability of the results discussed above to other neural network architectures will be addressed in further work.

4. CONCLUSION AND OUTLOOK

In this paper, we presented iCOSPA, an informed extension of COSPA for TSE that exploits additional DoA information. Moreover, we adapted the 2D CRUNet in iCOSPA’s encoder to use a 3D convolutional layer. We showed that iCOSPA uses the provided DoA information to form a flexible spatial filter which reliably extracts the target speaker. The main contributions of this paper are the analysis and interpretation of the influence of the training target on the spatial filtering behavior of iCOSPA, and the demonstration of the impact of the reference signal on the evaluation metrics. We found that the iCOSPA architecture allows to learn beamformers directed towards the target speaker even if only a dry source signal is used as training target. When using a target signal that results from spatial filtering, the spatial selectivity of the resulting beamformers is significantly more pronounced.

A more comprehensive evaluation of the 3D convolutional layer for multichannel audio signal processing is planned for future work. This includes analyzing the effect the 3D processing has on mask estimation in iCOSPA’s encoder, and investigating the impact of equalizing the phase differences between microphones before using the 3D convolutional layer.

Table 2: Performance metrics for TSE averaged over test datasets. Metrics are based on the dry/mic1 reference signals. The best value per metric is printed in bold.

| Model       | ∆PESQ | ∆ESTOI | ∆SIR [dB] |
|-------------|-------|--------|-----------|
| iCOSPA-mvdr | 0.20/0.23 | 0.14/0.05 | 10.27/9.25 |
| iCOSPA-dsb  | 0.18/0.31 | 0.11/0.08 | 9.02/10.03 |
| iCOSPA-mic1 | 0.16/0.31 | 0.09/0.08 | 8.55/10.12 |
| iCOSPA-dry  | 0.19/0.09 | 0.12/ -0.01 | 10.82/8.42 |

Fig. 2: Exemplary beampatterns for iCOSPA trained on different target signals. Green line: target speaker; blue lines: interferers.
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