ABSTRACT

Recently we proposed an all-deep-learning minimum variance distortionless response (ADL-MVDR) method where the unstable matrix inverse and principal component analysis (PCA) operations in the MVDR were replaced by recurrent neural networks (RNNs). However, it is not clear whether the success of the ADL-MVDR is owed to the calculated covariance matrices or following the MVDR formula. In this work, we demonstrate the importance of the calculated covariance matrices and propose three types of generalized RNN beamformers (GRNN-BFs) where the beamforming solution is beyond the MVDR and optimal. The GRNN-BFs could predict the frame-wise beamforming weights by leveraging on the temporal modeling capability of RNNs. The proposed GRNN-BF method obtains better performance than the state-of-the-art ADL-MVDR and the traditional mask-based MVDR methods in terms of speech quality (PESQ), speech-to-noise ratio (SNR), and word error rate (WER).

Index Terms— MVDR, Generalized RNN beamformer, ADL-MVDR, GEV, speech separation

1. INTRODUCTION

The MVDR beamformer with NN-predicted masks [1,2,3,4,5] could always achieve less non-linear distortion than the purely neural network (NN) based speech separation approaches [6,7,8,9,10]. However, the residual noise level of mask-based MVDR method is high [5]. Most of the mask-based beamformers are optimized in the chunk-level [1,5]. The calculated beamforming weights are hence chunk-level which is not optimal for each frame. Furthermore, the matrix inverse and PCA processes involved in the traditional beamformers (e.g., MVDR, GEV, etc.) are not stable, especially when they are jointly trained with neural networks. Time-varying beamformers were investigated in [11,12], however they still had the instability problem.

To overcome the above-mentioned issues, recently we proposed an all-deep-learning MVDR (ADL-MVDR) method [13] which was superior to the traditional MVDR beamformer [5]. In the ADL-MVDR [13], the matrix inverse and PCA operations are replaced by two recurrent neural networks (RNNs) with the calculated speech and noise covariance matrices as the input. Significant residual noise reduction capability and better speech recognition accuracy were achieved [13]. Note that Xiao [14] once proposed a learning based beamforming method which was worse than the mask-based MVDR approach due to the lack of explicitly using the speech and noise covariance matrices information.

However, it is not clear whether the advantage of the ADL-MVDR is coming from the calculated covariance matrices or following the MVDR formula. There are three contributions in this work. First, we demonstrate that the calculated speech and noise covariance matrices are the key factors. This finding is important because it paves the road to design more optimal deep learning based beamformers. Second, three types of generalized RNN beamformers (GRNN-BFs) are proposed. Leveraging on the success of RNNs to solve the matrix inverse and eigenvalue decomposition problems [15,16,17,18], any kinds of traditional beamformers (e.g., MVDR [2], GEV [1], Multichannel Wiener filtering [19], etc.) could be solved by the RNNs. However, only RNN-MVDR was investigated [15]. The proposed GRNN-BF achieves the best performance among all methods. Finally, we not only generalize the beamforming formula, but also generalize the RNN-BF model from two branches to one.

The rest of this paper is organized as follows. In section 2 mask based traditional beamformers are described. Section 3 presents the proposed generalized RNN-based beamformers. The experiments and results are provided in Section 4. Section 5 concludes this paper.

2. MASK BASED TRADITIONAL BEAMFORMERS

In the mask based beamforming [11,2,4,5], the masks could be real-valued masks or complex-valued masks [5]. The target speech covariance matrix $\Phi_{SS}$ is calculated as,

$$\Phi_{SS}(f) = \frac{\sum_{t=1}^{T} M_S^2(t,f)Y(t,f)Y^H(t,f)}{\sum_{t=1}^{T} M_S^2(t,f)} \quad (1)$$

Where $Y(t,f)$ is the short-time Fourier transform (STFT) of multi-channel mixture signal at $t$-th time frame and $f$-th frequency bin. $M_S$ denotes the mask of the target speech. $T$ stands for the total number of frames in a chunk. $H$ is the
Hermitian transpose. Then the solution for MVDR is,

$$w_{\text{MVDR}}(f) = \frac{\Phi_{\text{NN}}^{-1}(f)v(f)}{v^H(f)\Phi_{\text{NN}}(f)v(f)}, \quad w_{\text{MVDR}}(f) \in \mathbb{C}^C$$ (2)

where $v(f)$ stands for the steering vector at $f$-th frequency bin. $\hat{v}(f)$ could be calculated by applying PCA on $\Phi_{SS}(f)$, namely $v(f) = \mathcal{P}\{\Phi_{SS}(f)\}$. $w_{\text{MVDR}}(f)$ is a C-channel complex-valued vector at $f$-th frequency bin.

Another beamformer is generalized eigenvalue (GEV) [11]. The solution is derived by maximizing the SNR.

$$w_{\text{GEV}}(f) = \arg \max_w \frac{w^H(f)\Phi_{SS}(f)w(f)}{w^H(f)\Phi_{NN}(f)w(f)}$$ (3)

This optimization problem leads to the generalized eigenvalue decomposition (GEVD) [1]. The optimal solution is the generalized principal component [12, 20].

$$w_{\text{GEV}}(f) = \mathcal{P}\{\Phi_{\text{NN}}^{-1}(f)\Phi_{SS}(f)\}, \quad w_{\text{GEV}}(f) \in \mathbb{C}^C$$ (4)

However, the matrix inverse involved in Eq. (2) and Eq. (4), the PCA needed for solving the steering vector in MVDR, and GEVD required in Eq. (4) are not stable when jointly trained with neural networks in the back-propagation process.

### 3. RNN-BASED BEAMFORMERS

#### 3.1. All deep learning MVDR (ADL-MVDR)

Recently we proposed the ADL-MVDR method [13] to overcome the issues of traditional methods mentioned above. The ADL-MVDR used two RNNs to replace the matrix inverse and PCA in MVDR. As suggested in [13], complex-valued ratio filter (cRF) [21] rather than the complex-valued ratio mask (cRM) [22] was used to calculate the covariance matrices. The cRF used $(2K+1) \times (2K+1)$ neighboring context (i.e., surrounding $(2K+1)$ frames and $(2K+1)$ frequency bins) to stabilize the calculation of covariance matrices at $(t, f)$. Then the estimated target speech is,

$$\hat{S}(t, f) = \sum_{\tau_1=-K}^{\tau_1=K} \sum_{\tau_2=-K}^{\tau_2=K} c_{\text{RF}}(t+\tau_1, f+\tau_2) \cdot Y(t+\tau_1, f+\tau_2)$$ (5)

If $K = 0$, then cRF [21] is exactly the same with cRM [22]. The frame-wise speech covariance matrix is calculated as,

$$\Phi_{SS}(t, f) = \frac{\hat{S}(t, f)\hat{S}^H(t, f)}{\sum_{l=1}^{L} c_{\text{RF}}^H(t, f)\text{cRF}(t, f)}$$ (6)

The temporal sequence of speech and noise covariance matrices are fed into two RNNs to hypothetically learn the steering vector and the matrix inversion, respectively.

$$\hat{v}(t, f) = \text{RNN}(\Phi_{SS}(t, f))$$ (7)

$$\Phi_{\text{NN}}^{-1}(t, f) = \text{RNN}(\Phi_{\text{NN}}(t, f))$$ (8)

The uni-directional RNNs could automatically accumulate and update the covariance matrices from the history frames. Finally, the frame-wise beamforming weights are,

$$w_{\text{ADL-MVDR}}(t, f) = \frac{\Phi_{\text{NN}}^{-1}(t, f)\hat{v}(t, f)}{\hat{v}^H(t, f)\Phi_{\text{NN}}^{-1}(t, f)\hat{v}(t, f)}$$ (9)

#### 3.2. Proposed generalized RNN beamformers

However, it is not clear whether the key factor in ADL-MVDR is the calculated the target speech covariance matrix $\Phi_{SS}(t, f)$ (Eq. 5) and the noise covariance matrix $\Phi_{NN}(t, f)$ as the input to predict the beamforming weights in different forms.

##### 3.2.1. RNN-based GEV beamformer (RNN-GEV)

As defined in Eq. (4), the solution for GEV beamformer is the generalized principal component. However, we propose a generalized RNN-GEV (GRNN-GEV) as shown in Fig. 1. Hinton et al [23] shows that the DNN has the ability to conduct the non-linear generalized PCA. DNN was utilized to calculate the beamforming weights for GRNN-GEV. The uni-directional RNNs could automatically accumulate and update the covariance matrices from the history frames.

$$\Phi_{\text{NN}}^{-1}(t, f) = \text{RNN}(\Phi_{\text{NN}}(t, f))$$ (10)

$$\Phi_{SS}(t, f) = \text{RNN}(\Phi_{SS}(t, f))$$ (11)

$$w_{\text{GRNN-GEV}}(t, f) = \text{DNN}(\Phi_{\text{NN}}^{-1}(t, f)\Phi_{SS}(t, f))$$ (12)

$$\hat{S}(t, f) = (w_{\text{GRNN-GEV}}(t, f))^H Y(t, f)$$ (13)

where $w_{\text{GRNN-GEV}}(t, f) \in \mathbb{C}^C$. $\Phi_{SS}(t, f)$ is the accumulated speech covariance matrix from the history frames by leveraging on the temporal modeling capability of RNNs. Instead of using the actual PCA (as in Eq. (4)), a deep neural network (DNN) was utilized to calculate the beamforming weights for GRNN-GEV. Hinton et al [23] shows that the DNN has the ability to conduct the non-linear generalized PCA.

##### 3.2.2. Generalized RNN beamformer I (GRNN-BF-I)

Similar to GRNN-GEV, we also propose another generalized RNN beamformer (GRNN-BF-I). As shown in Fig. 1, $\Phi_{\text{NN}}^{-1}(t, f)$ and $\Phi_{SS}(t, f)$ are concatenated rather than multiplied as the GRNN-GEV did.

$$w_{\text{GRNN-BF-I}}(t, f) = \text{DNN}([\Phi_{\text{NN}}^{-1}(t, f), \Phi_{SS}(t, f)])$$ (14)

where $w_{\text{GRNN-BF-I}}(t, f) \in \mathbb{C}^C$. We try to predict the beamforming weights directly, without following any traditional beamformers’ formulas (e.g., MVDR or GEV). Note that the physical meaning of $\Phi_{\text{NN}}^{-1}(t, f)$ and $\Phi_{SS}(t, f)$ might be changed in GRNN-BF-I due to the more flexible optimization. All of the covariance matrices and beamforming weights are complex-valued, and we concatenate the real and imaginary parts of any complex-valued matrices or vectors in the whole work.
Fig. 1. Joint training of the proposed generalized RNN-based beamformers (GRNN-BFs) with the dilated conv-1d based complex-valued ratio filters (cRFs). $\alpha = \frac{s^H}{s^H}$ is a scaling factor in the time-domain scale-invariant SNR (Si-SNR) loss [7].

3.2.3. Generalized RNN beamformer II (GRNN-BF-II)

Finally, we also propose GRNN-BF-II. As shown in Fig. 1, the model structure for predicting the beamforming weights from the calculated covariance matrices $\mathbf{F}_{SS}(t, f)$ and $\mathbf{F}_{NN}(t, f)$ are further generalized from two branches to one branch.

$$ w_{GRNN-BF-II}(t, f) = RNN-DNN([\mathbf{F}_{NN}(t, f), \mathbf{F}_{SS}(t, f)]) $$ (15)

where $w_{GRNN-BF-II}(t, f) \in \mathbb{C}$. The input for the RNN-DNN is the concatenated tensor of $\text{Real}(\mathbf{F}_{SS}(t, f)), \text{Imag}(\mathbf{F}_{SS}(t, f)), \text{Real}(\mathbf{F}_{NN}(t, f))$ and $\text{Imag}(\mathbf{F}_{NN}(t, f))$.

4. EXPERIMENTAL SETUP AND RESULTS

Dataset: The methods are evaluated on the mandarin audio-visual corpus [23, 25], which is collected from Tencent Video and YouTube (will be released [26] soon). The dataset has 205500 clean speech segments (about 200 hours) over 1500 speakers. The sampling rate for audio is 16 kHz. 512-point STFT is used to extract audio features along 32ms Hann window with 50% overlap. The multi-talker multi-channel dataset are simulated in the similar way with our previous work [24, 25]. We use a 15-element non-uniform linear array.

Based on the image-source simulation method [27], the simulated dataset contains 190000, 15000 and 500 multi-channel mixtures for training, validation and testing. The room size is ranging from 4m-4m-2.5m to 10m-8m-6m. The reverberation time T60 is sampled in a range of 0.05s to 0.7s. The signal-to-interference ratio (SIR) is ranging from -6 to 6 dB. Also, noise with 18-30 dB SNR is added to all the multi-channel mixtures [24]. A commercial general-purpose mandarin speech recognition Tencent API [28] is used to test the ASR performance.

cRF estimator: we use the complex-valued ratio filter (cRF) [13, 21] rather than the complex-valued ratio mask (cRM) [5, 22] to calculate the covariance matrices (shown in Eq. (5)). The input to the cRF estimator includes the 15-channel mixture audio and the estimated target DOA ($\theta$). From the multi-channel audio, log-power spectra (LPS) and interaural phase difference (IPD) [24] features are extracted. We have the hardware where the 180° wide-angle camera and the 15 linear microphones are aligned [5]. Hence the target DOA ($\theta$) could be roughly estimated from the camera view by locating the target speaker’s face. Then the location guided directional feature (DF) [29], namely $d(\theta)$, is estimated by calculating the cosine similarity between the target steering vector $v$ and IPDs [29, 25]. $d(\theta)$ is a speaker-dependent feature. The LPS, IPDs and $d(\theta)$ are merged and fed into a bunch of dilated 1D-CNNs which is similar to the structure of Conv-TasNet [7]. The details can be found in our previous work [24, 25]. $K$ for cRF is one. The RNNs are 2-layer unidirectional gated recurrent units (GRUs) with 500 hidden nodes. The DNNs have 2-layer 500 hidden units with ReLU activation functions. The model is trained in a chunk-wise mode with 4-second chunk size, using Adam optimizer. Initial learning rate is set to 1e-3. Pytorch 1.1.0 was used. We evaluate the systems with different metrics, including PESQ, Si-SNR (dB), SDR (dB) and word error rate (WER).

4.1. Evaluations of the proposed GRNN-BFs

Three types of generalized RNN beamformers are proposed in this work. The proposed GRNN-GEV still follows the GEV beamformer formula (defined in Eq. (4)) but uses a DNN to replace the generalized PCA. The proposed GRNN-BF-I and GRNN-BF-II directly predict the beamforming weights
from the calculated frame-wise covariance matrices, rather than following any traditional beamforming formulas. The proposed three generalized RNN beamformers have the similar performance. The proposed GRNN-BF-II achieves the best performance in terms of PESQ, Si-SNR, SDR and WER. Compared to the ADL-MVDR [13] where it still follows the classic MVDR formula (defined in Eq. (9)), GRNN-BF-II could obtain better performance with 0.1 higher PESQ and relatively 6.8% WER reduction. It indicates that there is no need to follow any formulas of the traditional beamformers’ solutions in the RNN-based beamforming framework. The calculated target speech and noise covariance matrices play a key role to the success of GRNN-BFs. Compared to the jointly trained cRF-based traditional MVDR [5] or multi-tap MVDR [5] systems, the proposed GRNN-BF-II significantly improves the objective measures, e.g., increasing PESQ from 3.08 to 3.52 on average. GRNN-BF-II also gets lower WER, namely reducing WER from 13.52% to 11.86%. It indicates that the GRNN-BF-II could obtain the optimal beamforming weights for each frame and achieve better noise reduction capability. For the purely NN system without the beamforming module, we only multiply the estimated speech cRF to the 0-th channel of \( Y \) (as in Eq. (5)) to obtain the final enhanced speech. It shows the worst WER 22.07% among all systems due to the non-linear distortion introduced by the purely NN.

4.2. Discussions

Fig. 2 shows the example spectrograms and beam patterns of the MVDR and the proposed GRNN-BF-II. More demos (including real-world recording demos) could be found at [https://yongxuustc.github.io/grnnbf]. The traditional cRF/mask based MVDR method has more residual noise (shown in the dashed rectangle). Its corresponding beam pattern is not sharp enough. However the GRNN-BF-II could significantly reduce most of the residual noise and keep the separated speech nearly distortionless (also demonstrated by the lowest WER 11.86% in Table 1). The sharp beam pattern (selected from one of frames) of the proposed GRNN-BF-II in Fig. 2 also reflects its noise reduction capability.

In summary, we proposed three types of generalized RNN beamformers (GRNN-BFs). The GRNN-BFs are beyond our previous ADL-MVDR work in the beamforming solution and model structure designs. We conclude the finding that the calculated speech and noise covariance matrices are the most important factors. There is no need to follow the formulas of any traditional beamformers. The GRNN-BF could automatically accumulate and update the covariance matrices from the history frames and predict the frame-wise beamforming weights directly. The proposed GRNN-BF-II could achieve the best objective scores and the lowest WER among all systems. In the future work, we will prove the mathematical principles behind the GRNN-BFs, and investigate the GRNN-BF’s capability on the joint separation and dereverberation.

5. CONCLUSIONS AND FUTURE WORK

Table 1. PESQ, Si-SNR [7], SDR and WER results among purely NN, MVDR and proposed GRNN-BF systems.

| systems/metrics | Angle between target speaker & others | # of overlapped speakers | PESQ \([-0.5, 4.5]\) | Si-SNR (dB) | SDR (dB) | WER (%) |
|-----------------|-------------------------------------|--------------------------|-----------------|-----------|---------|--------|
|                 | 0-15° | 15-45° | 45-90° | 90-180° | 1SPK | 2SPK | 3SPK | Avg. | 1SPK | 2SPK | 3SPK | Avg. | Avg. | Avg. | Avg. |
| Reverberant clean | 4.50 | 4.50 | 4.50 | 4.50 | 4.50 | 4.50 | 4.50 | 4.50 | ∞ | ∞ | 8.26 |
| Mixture | 1.88 | 1.88 | 1.98 | 2.03 | 3.55 | 2.02 | 1.77 | 2.16 | 3.39 | 3.50 | 55.14 |
| Purely NN | 2.75 | 2.95 | 3.12 | 3.09 | 3.98 | 2.90 | 2.55 | 2.92 | 12.50 | 13.01 | 22.07 |
| MVDR [5] | 2.55 | 2.77 | 2.96 | 2.89 | 3.82 | 2.90 | 2.55 | 2.92 | 11.31 | 12.58 | 15.91 |
| Multi-tap MVDR [5] | 2.67 | 2.95 | 3.15 | 3.10 | 3.92 | 2.90 | 2.72 | 3.08 | 12.66 | 14.04 | 13.52 |
| ADL-MVDR [13] | 3.04 | 3.30 | 3.48 | 3.48 | 4.17 | 3.41 | 3.07 | 3.42 | 14.80 | 15.45 | 12.73 |
| Prop. GRNN-BF-I | 3.11 | 3.36 | 3.55 | 3.54 | 4.19 | 3.48 | 3.14 | 3.48 | 15.34 | 15.88 | 12.07 |
| Prop. GRNN-BF-II | 3.13 | 3.36 | 3.53 | 3.54 | 4.19 | 3.48 | 3.14 | 3.48 | 15.34 | 15.82 | 12.09 |

Fig. 2. Spectrograms and beam patterns of different systems.
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