

DUAL-PATH TRANSFORMER BASED NEURAL BEAMFORMER FOR TARGET SPEECH EXTRACTION

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ABSTRACT

Neural beamformers, integrating both pre-separation and beamforming modules, have shown impressive efficacy in the target speech extraction task. Nevertheless, the performance of these beamformers is inherently constrained by the predictive accuracy of the pre-separation module. In this paper, we introduce a neural beamformer underpinned by a dual-path transformer. Initially, we harness the cross-attention mechanism in the time domain, extracting pivotal spatial information related to beamforming from the noisy covariance matrix. Subsequently, in the frequency domain, the self-attention mechanism is employed to bolster the model’s capacity to process frequency-specific details. By design, our model circumvents the influence of pre-separation modules, delivering the performance in a more holistic end-to-end fashion. Experimental results reveal that our model not only surpasses contemporary leading neural beamforming algorithms in separation performance, but also achieves this with a notable reduction in parameter count.

Index Terms— Speech separation, microphone array, beamforming, deep learning, attention

1. INTRODUCTION

Neural beamformers have demonstrated exceptional capabilities in the realm of multi-channel target speech extraction [1]. One of the pioneering approaches that meld deep learning with traditional beamforming algorithms is the mask-based neural beamformer [2]. This architecture typically consists of a pre-separation module followed by a beamforming module. Initially, the pre-separation module generates a series of time-frequency masks, such as IBM [3], IRM [4], CRM [5] and CRF [6]. These masks are then used to compute the covariance matrices for either the speech or noise signals as required by the beamforming algorithm. Subsequently, these covariance matrices are fed into classical beamforming algorithms like MVDR [7], GEV [8] and MCWF [9] to derive the beamforming weights. Given that traditional beamforming algorithms are generally deterministic and operate independently of the pre-separation module, any fluctuation in the output accuracy of the pre-separation module can significantly impact the system’s performance. To address this, newer models like ADL-MVDR [10], GRNNBF [11] and SARNN [12] started to integrate neural networks into the beamforming module. This enhances the synergy between the pre-separation and beamforming modules, thereby elevating the overall performance of speech separation algorithms. However, the predictive accuracy of the pre-separation module continues to be a limiting factor in the system’s overall efficacy.

Recently, the integration of neural networks and beamforming algorithms has undergone further development. Researchers have devised models that directly employ neural networks to characterize signals and predict beamforming weights in either the time or frequency domain. For instance, EABNet [13] directly models the time-frequency characteristics of signals captured by microphone arrays, aiming to capture richer information than mere covariance matrices to predict beamforming weights directly. This approach circumvents the need for pre-separation and covariance matrix computations. On a parallel note, Yi Luo et al. introduced FasNet-TAC [14], which executes filtering and summation operations in the time domain. By employing a neural network to model input features, the cohesiveness of the model is enhanced. Nevertheless, it’s important to note that the foundational concept of beamforming revolves around spatial domain signal filtration. The manner in which these models handle spatial signal information remains less transparent. As a result, they exhibit reduced interpretability and robustness when contrasted with neural beamformers rooted in spatial information derived from covariance matrices.

In this paper, we introduce a neural beamformer that leverages a dual-path transformer. Initially, we model both the spatial features of the input and the noisy covariance matrix. We then deploy a cross-attention mechanism [15] at the narrowband level to extract spatial information relevant to beamforming from the noisy covariance matrix, using spatial features as cues. Following this, we employ a self-attention mechanism at the broadband level, enhancing the model’s capability to capture inter-frequency relationships. Ultimately, we derive beamforming weights directly from the spatial information we’ve modeled. Our approach eliminates the need for a pre-separation module, eschews the estimation of intermediate variables, and facilitates a more end-to-end prediction of beamforming weights. Most notably, our model maintains a level of interpretability while significantly reducing the overall parameter count.

The remainder of this paper is organized as follows. Section 2 presents the signal model and the theoretical basis for our proposed model. Section 3 details our proposed neural beamforming algorithm. Section 4 provides an overview of the experimental setup and presents an analysis of the experimental results. Finally, Section 5 concludes the paper.

2. SIGNAL MODELS AND METHODS

Consider the far-field frequency-domain signal model in the real scene, described as

$$Y(t, f) = X(t, f) + S(t, f) + N(t, f) \quad (1)$$

where $Y(t, f) = [Y^{(0)}(t, f), Y^{(1)}(t, f), \dots, Y^{(M-1)}(t, f)]^T$ indicates the frequency-domain signal received by the M-channel mi-

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crophone array. $X(t, f)$, $S(t, f)$ are the reverberated speech signals of the target speaker and the interference speaker respectively, and $N(t, f)$ represents the background noise. When not focusing on the reverberation task, the task goal of multi-channel target speech extraction is to extract the single-channel speech $X'(t, f)$ of the target speaker from the noisy signal $Y(t, f)$ observed by the array.

The purpose of the beamforming algorithm is to obtain the filter weight w for the array observation signal, and extract the desired signal from the array observation signal by performing spatial filtering on the observation signal, that is:

$$X'(t, f) = w^H \otimes Y(t, f) \quad (2)$$

where $(\cdot)^H$ denotes the conjugate transpose operation, \otimes denotes the matrix multiplication operation. A crucial aspect of the beamforming algorithm involves estimating the covariance matrix. Traditional beamforming methods often utilize specific algorithms to ascertain the time period of speech and noise within the signal. However, with the advancements in deep learning technologies, this approach may no longer represent the optimal solution.

Generally, considering the covariance matrix of the noisy signal:

$$\Phi_{YY}(t, f) = Y(t, f) \otimes Y^H(t, f), \Phi_{YY}(t, f) \in \mathbb{C}^{M \times M} \quad (3)$$

when the speech and interference noise signals are independent of each other and the influence of background noise is ignored, we can get:

$$\Phi_{YY}(t, f) \approx \Phi_{XX}(t, f) + \Phi_{NN}(t, f) \quad (4)$$

It is evident that the covariance matrix of the noisy signal encompasses all the information from the covariance matrices of both speech and noise signals. With this understanding, we employ a neural network to model the noisy covariance matrix and input features, thereby predicting the beamforming weights, described as:

$$w(t, f) = Model(Features(t, f), \Phi_{YY}(t, f)) \quad (5)$$

3. OUR PROPOSED NEURAL BEAMFORMER

Fig. 1 illustrates the overall structure of our proposed model. Initially, the model computes the input spatial features as well as the noisy covariance matrix. These are then transformed to a uniform dimensionality via a DNN-RNN architecture. Finally, the beamforming weights are predicted using a dual-path transformer. The specific steps are as follows:

3.1. Feature Extraction

We select the first channel of the microphone array as the reference channel and compute the magnitude spectrum to serve as the input feature.

$$Y_{mag}^{(0)}(t, f) = |Y^{(0)}(t, f)| \quad (6)$$

We then choose P pairs of microphones to calculate the phase difference between each pair, which serves as a spatial feature.

$$\cos IPD_p(t, f) = \cos(\angle Y_p^1(t, f) - \angle Y_p^0(t, f)) \quad (7)$$

while $\angle(\cdot)$ outputs the angle of the input argument. $Y_p^0(t, f)$ and $Y_p^1(t, f)$ represent the spectrum of the signal received by each microphone in the p -th microphone pair, respectively. Ultimately, we compute the angle feature [16] using the Direction of Arrival (DOA) of the target speaker to enhance the spatial perception capability of

the neural beamformer, given that the DOA of the target speaker is known.

$$AF_\theta(t, f) = \sum_{p=1}^P \cos(IPD_p(t, f) - \Delta_{\theta,p}(t, f)) \quad (8)$$

where $\Delta_{\theta,p}(t, f)$ represents the ground truth phase difference given the direction of arrival θ and the p -th microphone pair, and for a speaker at a fixed position, its characteristics remain consistent across all time frames. All these features are stacked along the channel dimension to serve as the model's input features, that is $Features(t, f) \in \mathbb{R}^{P+1+1}$. After computing the complex-valued covariance matrix of the noisy signal through Eq. (3), we concatenate the real and imaginary components along the channel dimension, that is

$$\Phi(t, f) = [\Phi_{YY}^r(t, f), \Phi_{YY}^i(t, f)] \in \mathbb{R}^{M \times M \times 2} \quad (9)$$

3.2. Dimensional modeling

We first process each frequency point independently at the narrow-band level and then transform the input features and noisy covariance matrix to the same dimension through two different Conv1D layers:

$$E_{Feat}(t, f) = Conv1D_1(Features(t, f)) \in \mathbb{R}^D \quad (10)$$

$$E_\Phi(t, f) = Conv1D_2(\Phi(t, f)) \in \mathbb{R}^D \quad (11)$$

where D represents the embedding dimensions. Then they are concatenated along the channel dimension, and then input to the GRU to enhance the modeling and mapping capabilities of the network.

$$E_{mix}(t, f) = [E_{Feat}(t, f), E_\Phi(t, f)] \in \mathbb{R}^{D \times 2} \quad (12)$$

$$E'_{mix}(t, f) = GRU(E_{mix}(t, f)) \in \mathbb{R}^{D \times 2} \quad (13)$$

After splitting the modeled $E'_{mix}(t, f)$, we get $E'_{Feat}(t, f)$ and $E'_\Phi(t, f)$, which represents the spatial information of the input features and the noisy covariance matrix, respectively.

$$[E'_{Feat}(t, f), E'_\Phi(t, f)] = Chunk(E'_{mix}(t, f)), \quad (14)$$

$$E'_{Feat}(t, f), E'_\Phi(t, f) \in \mathbb{R}^D$$

3.3. Dual-path Transformer Based Module

Considering the noisy covariance matrix encapsulates the speech and noise covariance matrices' information, we leverage a cross-attention module in the time domain to extract beamforming-related information. We use the modeled input features, $E'_{Feat}(t, f)$, as the query, and the noisy covariance matrix, $E'_\Phi(t, f)$, as both key and value for performing the operation of the cross-attention mechanism. This approach enables us to focus on beamforming-relevant spatial information.

$$E_w(t, f) = MHCA(E'_{Feat}(t, f), E'_\Phi(t, f), E'_\Phi(t, f)) \quad (15)$$

The prior operations of the model are executed independently at each frequency. To leverage inter-frequency information more effectively, we transform the dimension of the embedding and employ a self-attention module in the frequency domain, and apply it frame by frame at the broadband level.

$$E'_w(t, f) = MHSA(E_w(t, f), E_w(t, f), E_w(t, f)) \quad (16)$$

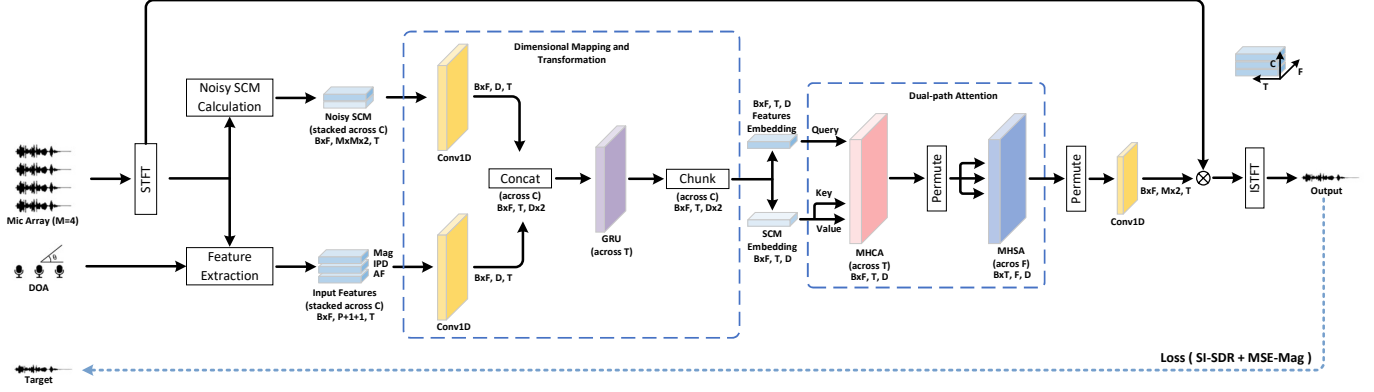


Fig. 1. The overall structure of our proposed model. MHCA is a time-domain multi-head cross-attention module, and MHSA is a frequency-domain multi-head self-attention module. The MHCA and Conv1D layers process each frequency independently at the narrowband level. The MHSA layer models frequency-domain information frame by frame at wideband level. B, C, F, T, D and M represent batch size, channel dimensions, frequency dimensions, time dimensions, embedding dimensions and channels, respectively.

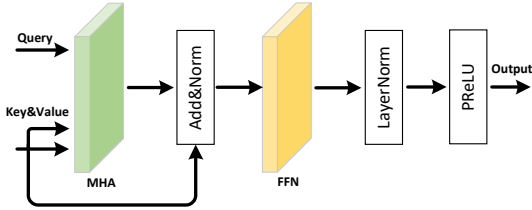


Fig. 2. Structural diagram of the attention module. At the narrowband level, the spatial information is used as Query, and the covariance matrix is used as Key and Value. At the broadband level, Query, Key, and Value are all embedding itself.

Following these steps, the model has extracted beamforming-related information from the noisy covariance matrix. Ultimately, we employ a Conv1D layer to predict the real and imaginary parts of the beamforming weights, thereby enabling the application of beamforming to the array observation signals.

$$w(t, f) = \text{Conv1D}_3(E'_w(t, f)) \quad (17)$$

The time-domain speech signal is restored after the processed frequency spectrum is subjected to ISTFT. Note that only the target speech extraction is considered and dereverberation is not addressed in this paper.

4. DATASET AND EXPERIMENTAL SETUP

4.1. Dataset

The source speech signals for target and interfering speakers are obtained from Aishell [17], with background noise data sourced from DNS2023 [18]. For indoor reverberation scenes, we randomly set room dimensions between [3, 3, 1.5] and [8, 8, 2.5] meters, with a reverberation time (rt60) of 0.1 to 0.6 seconds. The simulation uses the image source method, producing room impulse responses for target and interference signals[19]. The microphone array consists of a four-element linear array with 3 cm spacing. To maintain spatial

independence, we set a minimum 5° angle between the two sources relative to the microphone array. We adjust the Signal-Interference Ratio (SIR) between target and interference signals from [-6, 6] dB, and add background noise from [-5, 20] dB to enhance model robustness. This process yields approximately 133.3 hours of training data (120,000 pieces), 15.6 hours of validation data (14,000 pieces), and 7.8 hours of test data (7,000 pieces), all down-sampled to 16kHz.

4.2. Implementation Details

During the training process, a 512-point STFT is utilized to extract audio features using a 32ms Hann window with a 50% overlap. We select three microphone pairs, specifically (0,1), (0,2), and (0,3), to calculate spatial features. The double-layer GRU network includes 256 hidden layer units, while the cross-attention and self-attention module dimensions are set at 128. The final linear layer predicts complex-valued beamforming weights, hence the output dimension is configured to $8(M \times 2)$. More details of the model are provided here.¹

The network undergoes 60 epochs of training with a batch size of 20. We use the Adam optimizer with an initial learning rate of $2e-3$, decaying exponentially at 0.98 per epoch. A maximum gradient clipping of 10 accelerates network convergence. During training, all data is divided into 4 seconds.

We use the IRM MVDR(oracle)[2], MIMO Conv-TasNet [20] and GRNNBF [11] models as the baseline for experimental comparison. For IRM MVDR, we utilize the oracle IRM to compute the beamforming weights. In line with the settings from the original paper, we use a 3x8 TCN Block to model the input features for the MIMO Conv-TasNet, which predicts the CRM to restore the spectrum of the reference channel. For the GRNNBF, a 4x8 TCN Block is utilized to predict the CRF, which calculates the covariance matrix of the speech and noise respectively. This is then input into the GRU network, which consists of 500 hidden units, to output the beamforming weights. We calculate the Si-SDR [21] of the time-domain signal and the MSE of the magnitude spectrum as the loss function, with both carrying equal weight in the addition.

¹<https://github.com/Aworselife/DPTBF>

Table 1. PESQ, STOI, Si-SDR and WER results of several MISO baselines and the proposed DPTBF system.

Systems	GMACs (per sec.)	Para.(M)	Simulated Data			
			PESQ↑	STOI↑	Si-SDR↑	WER(%)↓
Reverberant Clean	—	—	4.5	1.0	∞	2.25
No processing	—	—	1.148	0.563	-1.76	68.02
IRM MVDR(oracle) [2]	—	—	1.373	0.654	2.78	38.35
MISO Conv-TasNet [20]	0.33	5.4	1.566	0.759	5.96	28.15
GRNNBF [11]	50.17	15.73	2.176	0.845	8.42	13.15
DPTBF (proposed)	13.52	0.96	2.313	0.861	9.34	9.45
DPTBF (less)	3.44	0.24	2.244	0.855	8.96	12.52
-FA	13.24	0.88	2.096	0.83	8.25	14.33
+SC	13.52	0.96	2.242	0.854	8.96	12.44

”FA” means Frequency-domain Attention module and ”SC” means Skip Connection for RNN.

4.3. Experiment Results

Table 1 compares our proposed model, the baseline model, and ablation experiment results. We assess the model’s performance using PESQ[22], STOI[23], Si-SDR metrics and measure WER using the ASR model from a particular source[24]. For the IRM MVDR model, although we use the oracle IRM for MVDR calculation, due to the problem of residual noise in MVDR itself, the performance drops significantly under background noise and strong reverberation conditions. MISO Conv-TasNet predicts target speech mask using TCN, eliminating beamforming operations and reducing computational load. It, however, has numerous parameters due to multi-layer stacked TCN block usage. Based on the stacked TCN block, GRNNBF incorporates an RNN for covariance matrix modelling, which substantially increases the parameter count. In contrast, our proposed DPTBF significantly reduces parameters and computations compared to baseline models, while also improving performance.

We further adapted our model into a lightweight DPTBF by reducing RNN hidden layer units from 256 to 128. Despite a decrease in performance with fewer parameters, the experimental results are still promising. Ablation experiments on DPTBF demonstrate that using a frequency-domain self-attention module enhances the model’s ability to model frequency-domain information, improving system separation performance. However, adding skip connections to the GRU layer modelling spatial information and noisy covariance matrix information did not enhance performance, possibly due to the network’s shallow depth and minimal information loss.

4.4. Spectrogram Analysis

We selected a challenging audio sample from test set with a low signal-to-noise ratio and a small angle between the two speakers, to compare various models’ performance under difficult conditions. Both the baseline and DPTBF models processed this data, with results displayed in Fig. 3. Due to the distortionless constraint in MVDR, although we use the oracle IRM for calculation, IRM MVDR still has more residual noise. MISO Conv-TasNet uses TCN for direct mask prediction, demonstrating strong noise suppression but significant spectral distortion. GRNNBF also struggles with noticeable residual noise and spectral distortion. Compared to these baseline models, our proposed DPTBF model excels in reducing interfering noise, mitigating background noise, and improving spectral distortion.

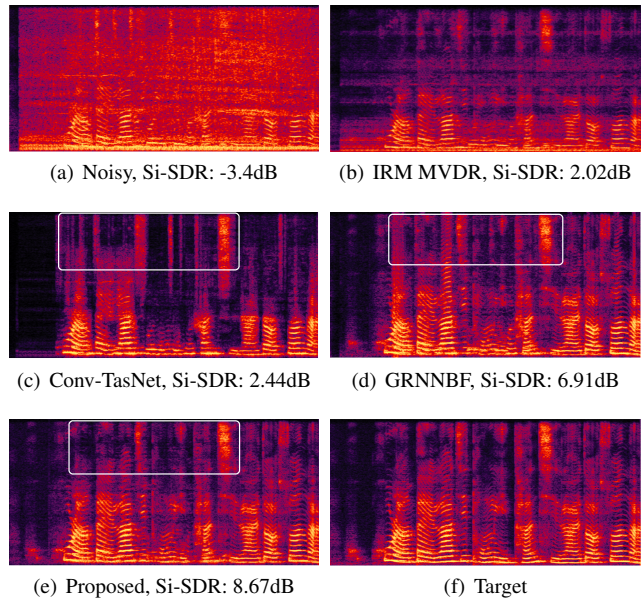


Fig. 3. Spectrum of a piece of data in the test set after model processing. SIR=-2.2dB, SNR=-4.8dB. The angle between the speaker is 9°.

5. CONCLUSIONS

In summary, we introduce a neural beamformer based on a dual-path transformer. By leveraging both cross-attention and self-attention mechanisms, our model bypasses intermediate variable estimation and circumvents pre-separation module constraints. Experimental results highlight the model’s outstanding performance in target speech extraction tasks, further confirming the effectiveness of the attention mechanism in extracting spatial information relevant to beamforming from the covariance matrix. Looking forward, we aim to adapt this model for MIMO applications without compromising its separation capabilities.

6. REFERENCES

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