BINAURAL SPEECH ENHANCEMENT USING DEEP COMPLEX CONVOLUTIONAL TRANSFORMER NETWORKS

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ABSTRACT

Studies have shown that in noisy acoustic environments, providing binaural signals to the user of an assistive listening device may improve speech intelligibility and spatial awareness. This paper presents a binaural speech enhancement method using a complex convolutional neural network with an encoder-decoder architecture and a complex multi-head attention transformer. The model is trained to estimate individual complex ratio masks in the time-frequency domain for the left and right-ear channels of binaural hearing devices. The model is trained using a novel loss function that incorporates the preservation of spatial information along with speech intelligibility improvement and noise reduction. Simulation results for acoustic scenarios with a single target speaker and isotropic noise of various types show that the proposed method improves the estimated binaural speech intelligibility and preserves the binaural cues better in comparison with several baseline algorithms.

Index Terms— Binaural speech enhancement, complex convolutional neural networks, hearing assistive devices, interaural cues, noise reduction.

1. INTRODUCTION

Binaural speech enhancement has been established in recent years as the state-of-the-art approach for enhancement in hearing aids and augmented/virtual reality devices [1, 2]. Binaural signals contain the spatial characteristics of sounds, which carry the necessary information for accurate sound source localization [3]. Moreover, binaural unmasking effects have been found to increase speech intelligibility therefore accentuating the importance of preservation of interaural cues for binaural signals along with noise reduction [4]. Interaural Level Differences (ILD), and Interaural Time Differences (ITD) or Interaural Phase Differences (IPD) are the primary cues helpful in localizing and boosting the perceived loudness of sounds, and improving speech intelligibility [5]. Binaural speech enhancement using multichannel Wiener filters [6, 7], beamforming [1], and mask-based enhancement methods [8, 9] has been previously proposed. In [10], a time domain Convolutional Encoder-Decoder (CED) model for binaural speech separation was proposed and achieved state-of-the-art performance. In contrast to binaural methods, monaural speech enhancement approaches operating on each binaural channel independently enhance the signals but at the cost of damaging vital binaural cues. Monaural speech enhancement methods using deep learning techniques have shown significant results in both the time domain [11, 12] and the Time-Frequency (TF) domain [13, 14].

In the TF domain, spectrograms are used as the input to the network [8, 14, 15]. Most of the TF domain methods rely only on magnitude-based enhancement, and the noisy TF phase is used in the reconstruction of the enhanced speech signal [8, 16]. One of the ways to address the issue of optimal phase estimation for signal reconstruction is to jointly estimate the TF phase and magnitude, which can be achieved by using complex-valued spectrograms. Monaural speech enhancement methods using complex-valued networks have shown promising results and have outperformed real-valued networks [15, 16]. The Convolutional Recurrrent Network (CRN) introduced in [13] employed a Convolutional Encoder-Decoder (CED) architecture with Long short-term memory (LSTM) blocks placed in between the encoder and decoder. Moreover, Attention-based Transformer Neural Networks (TNN) have shown state-of-the-art performance on Natural Language Processing (NLP) problems compared to other Deep Neural Network (DNN) models [17]. Speech enhancement using attention models has been demonstrated in [16] with promising results.

In [15], a deep complex CRN was trained to optimize the Scale Invariant SNR (SI-SNR) for monaural speech signals. However, using a similar approach for binaural signals could be damaging to the interaural cues. More specifically, for the case of binaural signals, phase information is vital for preserving the IPD values and the enhanced signals should retain level differences as the original signal to have the same ILD. Even if the model achieves significant noise reduction and improves speech intelligibility, altering the level and phase information would modify the spatial information of the target and therefore compromise the localization and spatial awareness of the listener [4, 5].

In this paper, we propose a method that uses a complex-valued Convolutional Encoder-Decoder (CED) based transformer network which enables phase-aware training [15, 18] for binaural speech and introduces terms in the loss function to simultaneously improve speech intelligibility and preserve the interaural cues of the speech signal.

2. MODEL ARCHITECTURE

The proposed Binaural Complex Convolutional Transformer Network (BCCTN) model uses a Convolutional Encoder-Decoder (CED) structure with a transformer block between the encoder and decoder and is trained to estimate an individual Complex Ratio Mask (CRM) for each channel. The block diagram of the architecture is shown in Fig. 1a. A CED architecture for monaural speech enhancement has been previously introduced in [11, 13, 15]. The proposed Multiple Input Multiple Output (MIMO) architecture uses a similar structure that has in this work newly modified to work with binaural signals by using individual encoder and decoder blocks for each channel. The Short Time Fourier Transform (STFT) blocks transform the signals into the TF domain. The encoder block is made of 6 complex convolutional

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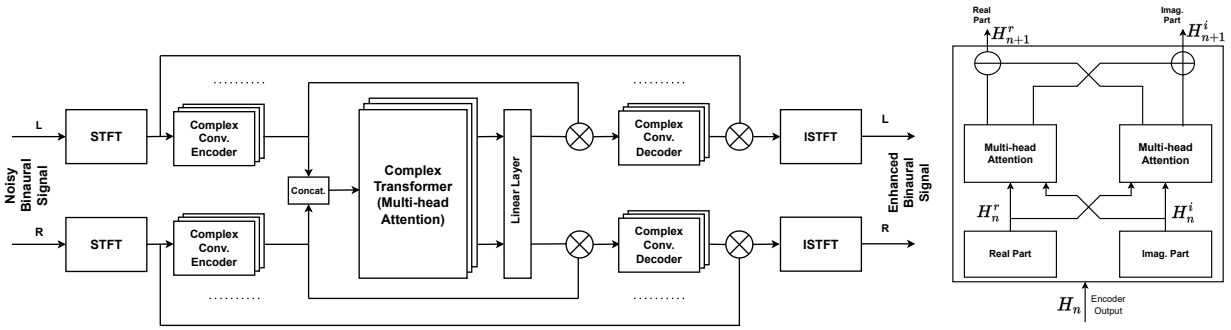

(a) (b)

Fig. 1: Architecture of (a) the proposed model and (b) the complex transformer block which implements (1) and (2).

layers with Parametric Rectified Linear Unit (PReLU) activation and employs batch normalization. The convolutional encoder blocks help in identifying the local patterns in the input spectrogram [11, 15]. Individual encoder blocks are used for the left and right-ear channels as the network needs to estimate two individual CRMs. The encoded information from both channels is concatenated and supplied as the input to the transformer. The transformer block consists of multi-head attention layers based on the architecture proposed in [17]. The structure of the complex transformer is shown in Fig. 1b. The real and imaginary output of the transformer H_{n+1} for the $(n+1)^{th}$ hidden state are given by

$$H^r_{n+1} = (H^r_n \circledast H^r_n) - (H^i_n \circledast H^i_n), \tag{1}$$

$$H^i_{n+1} = (H^r_n \circledast H^i_n) + (H^i_n \circledast H^r_n), \tag{2}$$

where H^r_n and H^i_n are the real and imaginary parts of the encoder output H_n. The multi-head attention operation is denoted by $\circledast$. The transformer block focuses on identifying relationships within the encoded information from both channels [16, 17]. The convolutional decoder consists of 6 transposed complex convolutional blocks which are symmetric in design to the convolutional layers of the encoder to reconstruct the signal to its original size using the processed feature information from the transformer. Skip connections are placed between each encoder and decoder layer based on the CRN architecture [13] which concatenates the output of each encoder block to the decoder layer. This improves the information flow and facilitates network optimization [13]. The left and right channel decoders output individual CRMs that are applied to the noisy binaural signal for enhancement. The Inverse STFT (ISTFT) blocks in Fig. 1a transform the enhanced TF domain signal back into the time domain. Implementation code is available online [1].

3. SIGNAL MODEL AND LOSS FUNCTION

For the left channel, the noisy time-domain input signal y_L is given by

$$y_L(t) = s_L(t) + v_L(t), \tag{3}$$

where s_L is the anechoic clean speech signal, v_L is the noise and t is the discrete-time index. The STFT is used to transform the signals into the TF domain and the respective TF representations are $Y_L(k,\ell)$, $S_L(k,\ell)$ and $V_L(k,\ell)$ with k and ℓ being the frequency and time frame indices respectively. During training, the network learns to estimate a CRM, $M_L(k,\ell)$ which is applied to the noisy signal Y_L to obtain the enhanced speech signal $\hat{S}_L$ for the left ear. The right channel is described similarly with a R subscript. For clarity, the L and R indices are omitted for the remainder of this paper. The enhanced speech is obtained for each channel by applying the estimated complex mask $(M_r + jM_i)$ to the complex-valued noisy signal $(Y_r + jY_i)$ in the TF domain (omitting k and ℓ indices),

$$\hat{S}_r + j\hat{S}_i = (M_r + jM_i) \cdot (Y_r + jY_i), \tag{4}$$

where r and i indicate the real and imaginary parts. The computed CRM [19] is given by

$$M_r + jM_i = \frac{\hat{S}_r + j\hat{S}_i}{Y_r + jY_i} = \frac{Y_r\hat{S}_r + Y_i\hat{S}_i}{Y_r^2 + Y_i^2} + j\frac{Y_r\hat{S}_i - Y_i\hat{S}_r}{Y_r^2 + Y_i^2}. \tag{5}$$

3.1. Loss Function

The proposed loss function for model training contains four terms and optimizes the network for noise reduction, intelligibility improvement, and interaural cue preservation. The proposed loss function $\mathcal{L}$ is given by

$$\mathcal{L} = \alpha\mathcal{L}_{SNR} + \beta\mathcal{L}_{STOI} + \gamma\mathcal{L}_{ILD} + \kappa\mathcal{L}_{IPD}, \tag{6}$$

where $\mathcal{L}_{SNR}$ is the Signal-to-Noise Ratio (SNR) loss, $\mathcal{L}_{STOI}$ is the Short-Time Objective Intelligibility (STOI) [20] loss, and $\mathcal{L}_{ILD}$ and $\mathcal{L}_{IPD}$ are the proposed ILD and IPD error losses which are functions of both $\hat{S}_L$ and $\hat{S}_R$. The parameters α, β, γ, and κ are the weights applied to each term.

The SNR of the enhanced signal, $\hat{\mathbf{s}}$, is defined as

$$\text{SNR}(\mathbf{s},\hat{\mathbf{s}}) = 10\log_{10}\left(\frac{\|\mathbf{s}\|^2}{\|\mathbf{e}_{noise}\|^2}\right), \tag{7}$$

where $\mathbf{e}_{noise} = \hat{\mathbf{s}} - \mathbf{s}$ with $\mathbf{s}$ and $\hat{\mathbf{s}}$ being the clean and enhanced signal vectors respectively and $\|.\|$ is the L2 norm. We define $\mathcal{L}_{SNR}$ to be the mean of the left and right-ear channel values and append a negative sign to maximize the SNR value, such that $\mathcal{L}_{SNR} = -(\text{SNR}_L + \text{SNR}_R)/2$.

While $\mathcal{L}_{SNR}$ optimizes the network for noise reduction, $\mathcal{L}_{STOI}$ is designed for intelligibility improvement. Similar to $\mathcal{L}_{SNR}$ we optimize the network to maximize intelligibility and $\mathcal{L}_{STOI}$ [20] is computed for the left and right channels individually and averaged so that $\mathcal{L}_{STOI} = -(\text{STOI}_L + \text{STOI}_R)/2$ [21].

As the network is trained to compute two individual CRMs for binaural speech, it has to be forced to preserve the interaural cues of the target speech while enhancing the noisy signal. To optimize the network for cue preservation, ILD and IPD errors of the target speech are computed for the enhanced speech signal. The ILD and IPD for the clean speech signal are given by

$$ILD_S(k,\ell) = 20\log_{10}\left(\frac{|S_L(k,\ell)|}{|S_R(k,\ell)|}\right), \tag{8}$$

$$IPD_S(k,\ell) = \arctan\left(\frac{S_L(k,\ell)}{S_R(k,\ell)}\right). \tag{9}$$

[1] https://github.com/VikasTokala/BCCTN

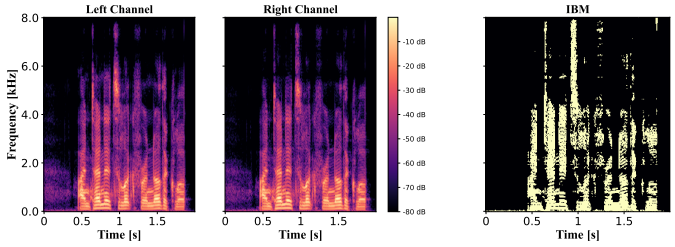

Fig. 2: Spectrograms of the left and right-ear clean speech signals and the corresponding IBM computed for interaural cue error masking.

The ILD and IPD for the enhanced speech are calculated similarly to (8) and (9). The $\mathcal{L}_{ILD}$ and $\mathcal{L}_{IPD}$ terms are given by,

$$\mathcal{L}_{ILD} = \frac{1}{N}\sum_{k,\ell}\mathcal{M}(k,\ell)(|ILD_S(k,\ell) - ILD_{\hat{S}}(k,\ell)|), \quad (10)$$

$$\mathcal{L}_{IPD} = \frac{1}{N}\sum_{k,\ell}\mathcal{M}(k,\ell)|IPD_S(k,\ell) - IPD_{\hat{S}}(k,\ell)| \quad (11)$$

where $N = \sum_{k,\ell}\mathcal{M}(k,\ell)$ is the total number of speech-active frequency and time bins determined from the mask. To compute the ILD and IPD errors only in the speech-active regions, an Ideal Binary Mask (IBM) [22] $\mathcal{M}$ is computed by choosing the TF bins which have energy above a threshold. The energy $E(k,\ell)$ of the clean signal is given by

$$E(k,\ell) = 10\log_{10}|S(k,\ell)|^2. \quad (12)$$

The IBM $\mathcal{M}(k,\ell)$ that defines the speech active TF tiles is then defined as,

$$\mathcal{M}(k,\ell) = \begin{cases} 1 & E(k,\ell) > \max_{\ell}(E(k,\ell)) - \mathcal{T} \\ 0 & \text{otherwise.} \end{cases} \quad (13)$$

$\max_l(E(k,\ell))$ is the maximum energy computed for each frequency k. Individual IBMs, $\mathcal{M}_L$ and $\mathcal{M}_R$ are computed for the left and right-ear channels. The final mask $\mathcal{M}$ is obtained by choosing the bins that have energy above the threshold, $\max_\ell(E(k,\ell)) - \mathcal{T}$, in both channels and is given by

$$\mathcal{M}(k,\ell) = \mathcal{M}_L(k,\ell) \odot \mathcal{M}_R(k,\ell), \quad (14)$$

where $\odot$ denotes the Hadamard product. For training and evaluation, $\mathcal{T} = 20$ dB was used [22]. As an example, Figure 2 shows the spectrograms of the clean speech signal and the corresponding target speech-based binary mask. Using the target speech-based mask guides the optimization of the network to focus on the preservation of the interaural cues of the target speech. The ILD and IPD errors are computed in the TF domain and the SNR and STOI losses are computed in the time domain by synthesizing the waveform using the ISTFT.

4. EXPERIMENTS

4.1. Datasets

To generate binaural speech data, monaural clean speech signals were taken from the CSTR VCTK corpus [24] and were spatialized using the measured Head Related Impulse Response (HRIRs) from [25]. The speech corpus [24] has around 13 hours of speech data uttered by 110 English speakers with various accents that were used to generate 2-second speech utterances and spatialized to have the left and right-ear channels. The dataset was made of 20000 speech utterances which were split into training, validation, and testing sets. Unseen speech data from the TIMIT corpus [26] were also used for testing. Noise signals from the NOISEX-92 database [27] were used to generate diffuse isotropic noise. Isotropic noise was generated using uncorrelated noise sources uniformly spaced every 5° in the azimuthal plane [9] using HRIRs from [25]. Binaural signals were generated with the target speech placed at a random azimuth in the frontal plane (-90° to $+90^\circ$), using the HRIRs from [25] recorded using a Head and Torso Simulator (HATS). For training, isotropic noise was added to the VCTK corpus [24] so that $(SNR_L + SNR_R)/2$ lies between -7 dB and 16 dB. The noise types used for training are White Gaussian Noise (WGN), Speech Shaped Noise (SSN), factory noise, and office noise and, for evaluation, an additional car engine noise was included. The datasets were generated in the anechoic condition for training. The evaluation set consists of speech signals from the VCTK corpus [24] (i.e, "matched" condition) and the TIMIT [26] (i.e, "unmatched condition") with random target azimuth and isotropic noise added at a random SNR between -6 dB and 15 dB. The speaker was placed at 0° elevation and at a distance of either 80 cm or 300 cm chosen randomly for each signal. Reverberant speech signals for evaluation were generated using Binaural Room Impulse Responses (BRIR)s from [25] and were placed in isotropic noise fields for the anechoic signals. Rooms with T_{60} varying from 0.3 to 1.2 s were used.

4.2. Training setup and baselines

For the STFT computation, an FFT length of 512, a window length of 25 ms, and a hop length of 6.25 ms were used. A sampling rate of 16 kHz was used for all signals. The following methods were used for the evaluation and comparison to the proposed binaural enhancement model.

BCCTN: This is our proposed method. The number of channels used in the MIMO model's convolutional layers for the encoder and decoder blocks layers are $\{16,32,64,128,256,256\}$, with a stride of 2 in the frequency and 1 in the time dimension with a kernel size of (5,1) and all the convolutions in these layers are causal. The Multihead attention block has an embedded dimension of 512 for real and imaginary blocks shown in Fig. 1b, a hidden size of 128, and 32 heads. The model was implemented with Pytorch which provides native complex data support for most of the functions. The linear layer placed after the transformer block has an input and output feature size of 1024. The Pytorch model was trained using the Adam optimizer, an initial learning rate of 0.001, and a multi-step learning rate scheduler to modify the learning rate with the validation loss. The model has around 10 million parameters and was trained for 100 epochs with an additional early stopping condition of no improvement in the validation loss for three consecutive epochs. The loss functions weights $\alpha,\beta,\gamma,\kappa$, in (6), were set to $\{1,10,1,10\}$ respectively. These weights were chosen to equalize the difference in the scale of the respective units of the individual loss function terms where SNR and ILD are computed in dB, IPD is computed in radians and STOI is a bounded score between 0 and 1. The model was trained with the proposed loss function described in (6) and, for comparison, the model was also trained to maximize the SNR from (7).

Binaural STOI-Optimal Masking (BSOBM): A binaural speech enhancement method using STOI-optimal masks proposed in [8]. Here a feed-forward DNN was trained to estimate a STOI-optimal continuous-valued mask to enhance binaural signals using dynamically programmed High-resolution Stochastic WSTOI-optimal Binary Mask (HSWOBM) as the training target [8]. To preserve the ILDs, a better-ear mask was computed by choosing the maximum of the two masks. The mask is used to supply Speech Presence Probability (SPP) to an Optimally-modified Log Spectral Amplitude (OM-LSA) enhancer. The model was trained and evaluated on the same dataset as the proposed model.

Binaural TasNet (BiTasNet): A time-domain MIMO CED-based network for binaural speech separation which was introduced in [10]. The best-performing version of the model, the parallel encoder with mask and sum, was modified and retrained for single-speaker binaural speech enhancement. The network was trained to maximize SNR [10].

Input SNR	-6 dB				-3 dB				0 dB				3 dB			
Method	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$
Noisy signal	0.61	0	-	-	0.69	0	-	-	0.78	0	-	-	0.8	0	-	-
BSOBM [8]	0.63	4.3	0.94	11	0.7	6.8	1.27	10	0.76	6.5	1.05	11	0.78	6.9	1.08	13
BiTasNet [10]	0.69	**14.5**	0.86	12	0.76	**13.1**	0.79	9	0.82	**12.8**	0.74	10	0.86	**11.6**	0.67	9
BCCTN-SNR (7)	0.63	13.2	0.74	11	0.71	11.9	0.95	11	0.77	12.1	0.6	10	0.83	11	0.86	11
BCCTN-Proposed Loss (6)	**0.73**	14.3	**0.61**	**8**	**0.79**	12.7	**0.62**	**7**	**0.85**	12.7	**0.4**	**5**	**0.87**	11.5	**0.36**	**4**
Input SNR	**6 dB**				**9 dB**				**12 dB**				**15 dB**			
Method	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$
Noisy signal	0.88	0	-	-	0.92	0	-	-	0.95	0	-		0.95	-	-	-
BSOBM [8]	0.82	5.6	1.14	13	0.84	3.6	1.03	12	0.84	1.3	1.6	12	0.82	-1.1	1.54	8
BiTasNet [10]	0.89	**9.9**	0.63	7	0.92	**8.6**	0.55	6	0.93	**7.2**	0.35	8	0.93	**5.6**	0.46	7
BCCTN-SNR (7)	0.87	9.2	0.82	11	0.9	7.6	0.66	8	0.93	6.3	0.8	9	0.92	4.8	0.87	8
BCCTN-Proposed Loss (6)	**0.91**	9.7	**0.34**	**3**	**0.94**	8.4	**0.2**	**2**	**0.96**	7	**0.19**	**2**	**0.96**	5.4	**0.19**	**2**

Table 1: Results for anechoic speech signals with isotropic noise averaged over all frames, frequency bins and utterances. Δ SegSNR [23] and $\mathcal{L}_{ILD}$ (10) are in dB, $\mathcal{L}_{IPD}$ (11) are in degrees.

Input SNR	-6 dB				-3 dB				0 dB				3 dB			
Method	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$
Noisy signal	0.59	0	-	-	0.68	0	-	-	0.76	0	-	-	0.79	0	-	-
BSOBM [8]	0.62	2.9	1.27	17	0.69	4.8	1.45	18	0.76	3.9	1.25	13	0.77	3.8	1.22	12
BiTasNet [10]	0.58	10.1	1.1	14	0.66	**9.2**	0.97	12	0.74	**8.8**	0.92	11	0.78	**7.7**	0.87	10
BCCTN-SNR (7)	0.43	9.6	1.43	16	0.52	8.9	1.18	13	0.57	8.2	0.91	12	0.62	6.8	0.9	11
BCCTN-Proposed Loss (6)	**0.66**	**10.3**	**1.12**	**12**	**0.74**	9	**0.72**	**10**	**0.8**	8.4	**0.62**	**8**	**0.83**	7.1	**0.45**	**5**
Input SNR	**6 dB**				**9 dB**				**12 dB**				**15 dB**			
Method	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$	**MBSTOI**	**ΔSegSNR**	$\mathcal{L}_{ILD}$	$\mathcal{L}_{IPD}$
Noisy signal	0.87	0	-	-	0.92	0	-	-	0.95	0	-	-	0.95	0	-	-
BSOBM [8]	0.81	2.6	1.19	12	0.84	0.2	1.7	16	0.85	-2.2	1.9	12	0.83	-4.8	2.1	13
BiTasNet [10]	0.85	**6.9**	0.81	8	0.9	**5.8**	0.59	7	0.93	**4.8**	0.53	8	0.92	**3.7**	0.59	7
BCCTN-SNR (7)	0.73	5.5	1.26	12	0.81	4.2	0.88	11	0.9	2.8	0.73	10	0.88	1.5	0.91	9
BCCTN-Proposed Loss (6)	**0.89**	6.1	**0.38**	**5**	**0.93**	5	**0.29**	**3**	**0.96**	4.6	**0.21**	**3**	**0.96**	3.3	**0.2**	**2**

Table 2: Results for reverberant speech signals with isotropic noise and are averaged over all frames, frequency bins and utterances. Δ SegSNR [23] and $\mathcal{L}_{ILD}$ (10) are in dB, $\mathcal{L}_{IPD}$ (11) are in degrees.

The encoder and decoders in the model had a size of 128, a feature dimension of 128, kernel size of 3 and 12 layers. All other parameters were adapted from the original article and the model has a size of 9.7 million parameters. The model was trained and evaluated on the same dataset used for the proposed method.

5. RESULTS AND DISCUSSION

The model was evaluated using 750 speech utterances from both datasets for each noisy input SNR. In total, the model was evaluated on 6000 noisy speech utterances. Improvement in the frequency weighted Segmental SNR (SegSNR) [23] was used to show the noise reduction performance of the methods. The Modified Binaural STOI (MBSTOI) [28] score was computed to measure the objective binaural speech intelligibility of the enhanced signals. The error in ILD and IPD after processing were computed using equations (8) and (9) respectively to evaluate the preservation of interaural cues. Tables 1 and 2 show the results tabulated for multiple SNRs for anechoic and reverberant speech signals respectively. For noise reduction measured by the improvement (Δ) in frequency weighted SegSNR [23], BiTasNet has the best performance with SegSNR for almost all SNRs. However, the proposed method shows comparable performance to BiTasNet on the noise reduction task for both SNR-optimization and the proposed loss function. The proposed loss function had better noise reduction performance compared to the model with the SNR loss function. A possible explanation is that the addition of intelligibility and masked interaural cue terms in the loss function enables the network to better identify the active speech regions which results in better noise reduction performance. A maximum of 14 dB of SegSNR can be observed when the signal is very noisy at -6 dB SNR. Even though the BiTasNet has better noise reduction performance, it exhibits a lower MBSTOI binaural intelligibility score. Informal listening tests revealed that the BiTasNet produced more artefacts. Audio examples of all the methods can be found online [2]. The model provides an average of 0.15 to 0.25 improvement in MBSTOI scores over the noisy speech when the SNR is below 6 dB. As the input signal's SNR improves, the noisy signals inherently have a higher MBSTOI, and the proposed model provides a lower improvement. In cases with high input SNR, the BSOBM, BiTasNet and BCCTN-SNR methods degrade the MBSTOI score due to processing but the proposed method and loss function do not reduce the score or deteriorate the signal at high SNRs. The proposed model and loss function have the lowest ILD and IPD error for all SNRs. The proposed model with SNR loss function performs similarly to the proposed loss function in noise reduction but does not focus on retaining the interaural differences and the additional terms in the loss function help the network in the preservation of interaural cues better. From Table 2, similar performance trends for reverberant signals can be observed from all the methods. A maximum of 10 dB of SegSNR can be observed when the signal is very noisy and up to a maximum of 0.15 improvement in MBSTOI score. The ILD and IPD errors are slightly higher than the anechoic condition which could be due to the effects of reverberation [10].

6. CONCLUSION

In this paper, we have presented a MIMO complex-valued convolutional transformer network for binaural speech enhancement. A novel loss function that optimizes the network for noise reduction, speech intelligibility enhancement, and interaural cue preservation is proposed. Experimental results show that the proposed method was able to significantly reduce noise and has the ability to preserve ILD and IPD information in the enhanced output. Furthermore, the proposed method outperforms the baselines in terms of estimated binaural speech intelligibility. Future works include adapting the model to include a remote microphone and a distributed microphone network for binaural speech enhancement.

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