Speech Dereverberation with Frequency Domain Autoregressive Modeling

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Abstract—Speech applications in far-field real world settings often deal with signals that are corrupted by reverberation. The task of dereverberation constitutes an important step to improve the audible quality and to reduce the error rates in applications like automatic speech recognition (ASR). We propose a unified framework of speech dereverberation for improving the speech quality and the ASR performance using the approach of envelopecarrier decomposition provided by an autoregressive (AR) model. The AR model is applied in the frequency domain of the subband speech signals to separate the envelope and carrier parts. A novel neural architecture based on dual path long short term memory (DPLSTM) model is proposed, which jointly enhances the sub-band envelope and carrier components. The dereverberated envelope-carrier signals are modulated and the sub-band signals are synthesized to reconstruct the audio signal back. The DPLSTM model for dereverberation of envelope and carrier components also allows the joint learning of the network weights for the down stream ASR task. In the ASR tasks on the REVERB challenge dataset as well as on the VOiCES dataset, we illustrate that the joint learning of speech dereverberation network and the E2E ASR model yields significant performance improvements over the baseline ASR system trained on log-mel spectrogram as well as other benchmarks for dereverberation (average relative improvements of 10-24% over the baseline system). The speech quality improvements, evaluated using subjective listening tests, further highlight the improved quality of the reconstructed audio.

Index Terms—Frequency domain auto-regressive modeling, Dereverberation, end-to-end ASR, Joint modeling.

I. INTRODUCTION

THE wide spread adoption of voice technologies like meeting assistants, smart speakers, in-car entertainment systems, and virtual assistants imply that the audio signal at the input of these system is impacted by reverberation and noise artifacts [1]. The performance of the downstream applications like, automatic speech recognition, speaker/language recognition, emotion recognition or voice activity detection, is shown to degrade significantly in reverberant conditions [2]– [6]. The performance deterioration is primarily attributed to the smearing of the temporal envelopes caused by reverberation [7]. The temporal smearing is caused by the emplacement of the direct path signal on reflected signals, resulting in a weighted summation of delayed components [8]. One of the approaches to deal with the adverse far-field conditions is to develop a front-end which performs signal enhancement. Several techniques for dereverberation like signal processing based (for example, weighted prediction error (WPE) [9]), mask estimation based (for example, timefrequency mask estimation [10]) and multi-channel beamforming based (for example, time-delay estimation [11], generalized eigen-value [12], [13]) have been explored to improve the signal quality. On the other hand, another effective approach for system development in reverberant conditions is that of multi-condition training [14]. However, even with these preprocessing and multi-condition training methods, the beamformed signal contains significant amount of temporal smoothing which adversely impacts the ASR performance [15].

In the traditional setting, the first step in the analysis of a signal is the short-term Fourier transform (STFT). The key assumptions about the convolution model of reverberation artifacts, is applicable for a long-analysis window in the time domain, or using convolutional transfer function with cross-band filters in the STFT domain [16], [17]. In our case, we use the former approach of long analysis window and explore dereverberation in the sub-band envelope domain. As the reverberation is a long-term convolution effect, we highlight that room impulse response (typically with a T60 > 400ms) can be absorbed as a multiplication in the frequency domain, as well as a convolution in the sub-band envelope domain.

In this paper, we investigate the effect of reverberation on the long-term sub-band signals of speech using an envelopecarrier decomposition. The extraction of the sub-band envelope is achieved using the autoregressive (AR) modeling approach in the spectral domain, termed as frequency domain linear prediction (FDLP). Our previous work showed that a feature level enhancement with the FDLP envelope improves speech recognition performance [18], [19]. However, the prior works did not allow the reconstruction of the audio signal for quality improvement. Further, the enhancement of the carrier signal was not addressed in the previous work due to the challenges in the handling the impulsive nature of the carrier signal.

In this paper, we propose a novel approach to the joint dereverberation of the envelope and carrier signals using a neural modeling framework. While using the sub-band signals directly, the sample level de-convolution with a suitable loss function can be a difficult design choice to learn using neural models. Hence, we propose using an envelope-carrier decomposition of the sub-band signals. Our rationale for the envelope-carrier decomposition based setup is the fact the envelope information is alone used in the ASR experiments.

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Thus, the ASR loss has to impact only the envelope dereverberation branch. However, the carrier and the envelope components are part of the signal reconstruction branch.

We develop a dual path long short term memory (DPLSTM) architecture for the dereverberation of the temporal envelope and carrier signals. In our case, the goal of the neural model is to perform a dereverberation of the envelope and the carrier components of the sub-band signal. These signals have a time profile, with varying dynamic range and properties. Further, merging all the sub-band signals in the decomposition also brings in a frequency profile. Thus, the design choice of the neural model, for enhancing the sub-band envelope-carrier signals, has to learn the sequence level patterns in both the time and frequency domains. The DPLSTM [20] is a suitable choice, as the model is able to integrate information effectively in both the time and frequency domains.

Following the dereverberation step, the sub-band modulation and synthesis step generates the reconstructed audio signal. The neural enhancement and sub-band synthesis can also be implemented as a part of the larger neural pipeline for downstream tasks like ASR, thereby enabling the joint learning of the ASR and dereverberation model parameters. We refer to the proposed approach as Dual path dereverberation using Frequency domain Auto-Regressive modeling (DFAR) and the joint end-to-end model as E2E-DFAR.

Various ASR experiments are performed on the REVERB challenge dataset [21] as well as the VOiCES dataset [22], [23]. The key contributions from this work, over the prior work [18], can be summarized as follows,

- Proposing an analysis for dereverberation with a sub-band decomposition and envelope-carrier demodulation.
- Proposing a dual-path long short time memory model named, DPLSTM for the dereverberation of sub-band envelope and carrier signals. This approach is termed as DFAR.
- Developing a joint learning scheme, where the ASR model and the DFAR model are optimized in a single end-to-end framework. This model is referred to as the E2E-DFAR.
- Evaluating the proposed approaches on speech quality improvement tasks as well as on ASR tasks on two benchmark datasets REVERB challenge dataset and the VOiCES dataset.

II. RELATED PRIOR WORK

A. Enhancement and dereverberation

For speech enhancement, Xu et. al. [24] devised a mapping from noisy speech to clean speech using a supervised neural network. In a similar manner, ideal ratio mask based neural mappings [25] have been explored for speech separation tasks. On the dereverberation front, Zhao et. al. proposed an LSTM model for late reflection prediction in the spectrogram domain [26]. Han et. al [27] developed a spectral mapping approach using the log-magnitude inputs and Williamson et. al [10] proposed a mask-based approach for dereverberation on the complex short-term Fourier transform. In a different line of work, speech enhancement in the time domain was pursued by Pandey et. al [28].

The application of speech dereverberation as a preprocessing step for downstream applications like ASR have been explored in several works (for example, [29]–[31]). The recent years have seen the use of recurrent neural network architectures for dereverberation. For example, Maas et. al [32], utilized a recurrent neural network (RNN) to establish mapping between noise-corrupted input features and their corresponding clean targets. Also, the use of a context-aware recurrent neural network-based convolutional encoder-decoder architecture was investigated by Santos et. al. [33].

B. Robust multi-channel ASR

In the design of robust ASR, Generalized sidelobe canceller (GSC) [34], [35] is a common approach. It was introduced by Li et. al in [36], where the authors proposed a neural network-based generalized side-lobe canceller. To combine spectral and spatial information from multiple channels using attention layers, an end-to-end multi-channel transformer was investigated in [37]. In another attention modelling approach, the streaming ASR model based on monotonic chunk-wise attention was proposed by Kim et. al in [38]. Ganapathy et. al. [4] proposed a 3-D CNN model for far-field ASR.

C. Joint modeling of enhancement and ASR

The attempt proposed by Wang et. al. [39] incorporates a DNN based speech separation model coupled with a DNN based acoustic model. The work reported by Wu et. al. [40] explored a unification of separately trained speech enhancement neural model and the acoustic model, where the joint model is fine-tuned to improve the ASR performance. Here, the DNN based dereverberation front end leverages the knowledge about reverberation time. While traditional GSC is optimized for signal level criteria, the neural network-based GSC, proposed by Li et. al [36], was optimized for ASR cost function.

III. PROPOSED DFAR APPROACH

A. Quadrature Mirror Filter (QMF)

For the sub-band decomposition, we had the following design considerations

- The decomposition approach should allow the long-term artifacts of reverberation to be captured in the sub-band domain as a convolution,
- The analysis method should allow a perfect reconstruction back to the audio using the synthesis part, and
- The sub-band components should be critically sampled for efficient computation of the dereverberated components in a deep neural model.

The quadrature mirror filter (QMF) met all the above requirements and hence, this work has used the QMF analysis and synthesis for speech dereverberation task.

A quadrature mirror filter (QMF) is a filter whose magnitude response is a mirror reflection at quadrature frequency $(\frac{\pi}{2})$ of another filter [41]. In signal processing, the QMF filterpairs are used for the design of perfect reconstruction filter



Fig. 1. Illustration of a 4-channel uniform QMF decomposition using a 2-stage binary QMF tree. In our work, we use 64-channel decomposition, using a 6-way binary tree.

banks. Let $H_0(e^{j\Omega})$ and $H_1(e^{j\Omega})$ denote low-pass and highpass filter's frequency domain function, where Ω is the digital frequency. In addition to the quadrature property ($H_1(e^{j\Omega}) = H_0(e^{j(\Omega-\pi)})$), the filters used in QMF filter-banks also satisfy the complimentary property,

$$|H_0(e^{j\Omega})|^2 + |H_1(e^{j\Omega})|^2 = 1.$$
 (1)

The design of sub-band decomposition scheme with QMF involves a series of filtering and down-sampling operations for the analysis [42]. The synthesis is achieved by up-sampling and filtering operations. A tree-like structure can be formed using a recursive decomposition operation. The down-sampling process enables a critical rate of processing, where the sum of the number of samples in each sub-band equals the number of the samples in the full-band signal.

In this work, we use an uniform 64-band Quadrature Mirror Filter bank (QMF) for decomposing the input signal into 64 uniformly spaced frequency bands. Inspired by the audio decomposition scheme outlined in Motlicek et. al. [43], we use a 6-level binary tree structure. The schematic of the sub-band decomposition is shown in Fig. 1. For the implementation in a neural pipeline, the down-sampling operation is equivalent to a stride, while the up-sampling operation is that of un-pooling.

B. Autoregressive modeling of temporal envelopes

The application of linear prediction model in the frequency domain, an approach called frequency domain linear prediction (FDLP), enables the modeling of the temporal envelopes of a signal with an autoregressive (AR) model [8], [44]. The sub-band signal is transformed to the spectral domain using a discrete cosine transform (DCT) [8], where a linear prediction model is applied.

Let the sub-band signal be denoted as $x_q[n]$, where q = 1, ..., Q denotes the sub-band index. The analytic signal, in signal processing theory, is a complex valued function, whose real value is the original signal while the imaginary value is the Hilbert transform of the signal. It finds application in single side-band amplitude modulation and quadrature filtering. Let the analytic version of sub-band signal, $x_q[n]$ be denoted as, $x_q^a[n]$. The corresponding analytic signal in the frequency domain, $X_q^a[k]$ can be shown to be the one-sided discrete Fourier transform (DFT) [8] of the even symmetric version of $x_q[n]$.

We apply linear prediction (LP) on the frequency domain signal, $X_a^a[k]$. The corresponding LP coefficients are denoted

by $\{b_p\}_{p=0}^m$, where *m* is the order of the LP. The temporal envelope estimate of $x_q^a[n]$, is given by,

$$e_q[n] = \frac{\alpha}{|\sum_{p=0}^m b_p e^{-2\pi i p n}|^2}$$
(2)

where α denotes the LP gain. The envelope represents the autoregressive model of the Hilbert envelope. In this paper, we use the Burg method [45] for estimating the AR envelope.

The corresponding carrier (remaining residual signal), $c_q[n]$ is found as,

$$c_q[n] = \frac{x_q[n]}{\sqrt{e_q[n]}} \tag{3}$$

The division operation in the expression above is well defined as the envelope given in Eq. (2) is always positive. Further, the modeling of the temporal envelopes using the AR model ensures that the peaks of the sub-band signal in the timedomain are well represented [46], [47].

C. Effect of reverberation on envelope and carrier signals

The effect of reverberation on the time-domain speech signal can be expressed in the form of a convolution operation,

$$y[n] = x[n] * r[n], \tag{4}$$

where x[n] denotes the clean speech signal, r[n] is the impulse response of the room and y[n], is the reverberant speech signal. The room response function can be further split into two parts, $r[n] = r_e[n] + r_l[n]$, where $r_e[n]$ and $r_l[n]$ are the early and late reflection components, respectively.

Let $x_q[n]$, $r_q[n]$ and $y_q[n]$ denote the sub-band versions of the clean speech, room-response function and the reverberant speech signal respectively. Assuming an ideal band-pass filtering, it can be shown that the analytic signal, $x_q^a[n]$, is given by [8], [48],

$$y_q^a[n] = \frac{1}{2} [x_q^a[n] * r_q^a[n]],$$
(5)

For band-pass filters with narrow band-width, the envelopes of the reverberant speech can be approximated as [18],

$$e_{yq}[n] \simeq \frac{1}{2} e_{xq}[n] * e_{rq}[n],$$
 (6)

where $e_{yq}[n]$, $e_{xq}[n]$, $e_{rq}[n]$ denote the sub-band envelopes of reverberant speech, clean speech and room response respectively. Prior efforts in envelope normalization focus on suppressing the linear effects of reverberation by setting the



Fig. 2. Block schematic of speech dereverberation model, the feature extraction module and the E2E ASR model. The red arrows denote the envelopes, e[n], and the green arrows represent the carrier, c[n]. The entire model can be constructed as an end-to-end neural framework.

gain of the reconstructed envelopes to unity [49]. However, in this work, we develop neural models that can remove the non-linear effects of reverberation. The reverberant sub-band envelope can also be viewed an additive model [18], [50].

$$e_{yq}[n] = e_{yqe}[n] + e_{yql}[n], \tag{7}$$

where, $e_{yqe}[n]$ is the early reflection component (which includes the direct path and the early reflections), while $e_{yql}[n]$ is the late reflection part of the sub-band envelope $e_{yq}[n]$.

The key assumptions about the reverberation model of Eq. (4-6), is a long-analysis window in the time domain. As the reverberation is a long-term convolution effect, we highlight that the room impulse response (typically with a T60 > 400ms) can be absorbed as a multiplication in the frequency domain, as well as a convolution in the sub-band envelope domain, only in the case of a long analysis window. The widely used short-time Fourier transform (STFT) does not capture the room impulse response function directly, and hence does not allow a convolutive modeling of the artifacts. Further, the phase effects in STFT domain are somewhat cumbersome to model. The above mentioned issues of STFT are also verified experimentally in Sec. V.

Envelope enhancement: A neural model can be used to learn late reflection component $e_{xql}[n]$ from the sub-band temporal envelope $e_{xq}[n]$. The predicted late reflection component can be subtracted from the sub-band envelope to suppress the artifacts of reverberation.

We pose the problem in the log domain to reduce the dynamic range of the envelope magnitude. The neural model is trained with reverberant sub-band envelopes $(log \ (e_{xq}[n]))$ as input. The model outputs the gain (in the log domain, i.e., $log \ \frac{e_{sq}[n]}{e_{sq}[n]}$). This gain is added in the log-domain to generate dereverberated signal envelope $(log \ (\hat{e}_{sq}[n]))$.

Envelope-carrier dereverberation model: In a similar manner, the non-linear mapping between the reverberant carrier, $c_{xq}[n]$ and clean carrier, $c_{xq}[n]$, can be learned using a neural network. A neural model is trained with reverberant sub-band carrier ($c_{xq}[n]$) as input and model outputs the residual (an estimate of the late reflection component, $c_{xql}[n]$), which when added with the reverberant carrier generates the estimate of source signal carrier ($\hat{c}_{sq}[n]$). Instead of independent operations of dereverberation of the envelope and the carrier, we propose to learn the mapping between clean and

reverberant versions of both the envelope and the carrier in a joint model. The input to the neural model is the sub-band reverberant envelope spliced with the corresponding carrier signal. The network is trained to output the late reflection components of both the envelope and carrier. With this approach, the model also learns the non-linear relationships between the envelope and carrier signals for the dereverberation task. From the model output, the estimate of the clean sub-band signal $\hat{s}_q[n]$ is generated. In our implementation, the audio signal is divided into non overlapping segments of 1 sec. length and passed through the envelope-carrier dereverberation model. The model is outlined in Fig. 2.

D. DFAR model architecture using DPLSTM

We propose the dual path long short term model (DPLSTM) for the dereverberation of the envelope-carrier components of the sub-band signal. Our proposed model is inspired by dual path RNN proposed by Luo et. al [20]. The block schematic of the DPLSTM model architecture is shown in Fig. 3. For 1 sec. of audio sampled at 16 kHz, the envelope (E^y) and carrier (C^y) components of the critically sampled sub-band signals (64 channel QMF decomposition) are of length 250. The envelope/carrier signals of all the sub-bands, for the reverberant signal (Y), is of size 64×250 . The combined envelope-carrier input is therefore of size 128×250 , which forms the input to the DPLSTM model. The DPLSTM model outputs are also of the same size of the input, and the model is trained using the mean squared error (MSE) loss.

The proposed DPLSTM has two paths, one LSTM path models the recurrence along the time dimension, while the other models the recurrence along the frequency dimension. We use two separate 3-layer LSTM architectures for these paths. The output dimensions are kept the same as the input dimension for each of these paths. The frequency recurrence LSTM output is transposed and these are concatenated in the frequency dimension. This combined output is fed to a multi layer bi-directional LSTM, which performs recurrence over time. The final output is split into sub-band specific envelope and carrier components. The modulation of the envelope with the respective carrier components generates the sub-band signals, which are passed through the QMF synthesis to generate the full-band dereverberated signal.

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Fig. 3. The dual path LSTM model architecture for envelope-carrier dereverberation. The top LSTM path models the recurrence along the time dimension while the one on the bottom models the recurrence along the frequency dimension.

E. Joint learning of dereverberation model for ASR

The joint learning of the envelope-carrier dereverberation module with the E2E ASR architecture is achieved by combining the two separate models to train a single joint neural model. This is shown in Fig. 2. We initialize the modules with weights obtained from the independent training of each component. Specifically, the envelope-carrier dereverberation model is trained using MSE loss, which is followed by a sub-band synthesis (right side half of Fig. 1). The QMF synthesis is implemented using a 1-D CNN layer to generate the dereverberated speech signal. Further, the E2E ASR architecture is separately trained on the log-mel filter bank features, obtained from the dereverberated speech. The melfilter bank feature generation can also implemented using a neural framework. Thus, the final model, composed of neural components from the envelope-carrier dereverberation, subband synthesis, feature extraction and ASR, can now be jointly optimized using the E2E ASR loss function. This model is refered to as E2E-DFAR model¹. The trainable components are the DPLSTM model and the ASR model parameters, while the sub-band synthesis and feature extraction parameters are not learnable.

IV. EXPERIMENTAL SETUP

A. Datasets

1) REVERB Challenge ASR: The audio samples in RE-VERB challenge dataset [51] are 8 channel recordings with both real and simulated reverberant conditions. The real samples are utterances from MC-WSJ-AV corpus [52], spoken by human speakers in a noisy reverberant room. The simulated samples of the dataset are generated by convolving six different room impulse responses with the clean WSJCAMO recordings followed by the addition of noise at the signalto-noise ratio (SNR) of 20 dB. The training data consists of 7861 (\sim 17.5 hours) utterances which are obtained by convolving WSJCAMO train data with 24 measured RIRs. The reverberation time of the measured impulse responses range from 0.2 to 0.8 sec. The training, development and evaluation data sets consist of 92, 15 and 38 speakers respectively. The development data consists of 1663 (3.3 hours) utterances and the evaluation data consists of 2548 (5.4 hours) utterances.

2) VOiCES Dataset: The VOiCES training set is a subset (80 hours) of the LibriSpeech dataset. This set has utterances from 427 speakers recorded in clean environments with close-talking microphones. The development and evaluation sets are far-field microphone recordings from diverse room dimensions, environments and noise conditions containing 19 and 20 hours of speech, respectively. The three sets namely training, development and evaluation, do not have any overlap in terms of the speakers. The robustness of the developed models is challenged by the mismatch that exists between the training and development/evaluation sets. We artificially added reverberation and noise on the 80 hours training set, which served as the training set for all the E2E ASR experiments on the VOiCES dataset. The development set contains 20 hours of distant recordings from the 200 speakers. The evaluation data of 19 hours consists of recordings 100 speakers. The training set has 22741 utterances, development set has 4318 utterances and evaluation set has 4600 utterances.

B. E2E ASR baseline system

For all the ASR experiments, we use the weighted prediction error based pre-processing [9] and unsupervised generalized eigenvalue (GEV) beamforming [13]. The baseline features are 36-dimensional log-mel filter bank features with frequency range from 200 Hz to 6500 Hz. The ESPnet toolkit [57] is used to perform all the end-to-end ASR experiments, with a Pytorch backend [58]. The model architecture uses 12 conformer encoder layers with 2048 units in the projection layer. The 6layer transformer architecture with 2048 units in the projection layer serves as the decoder. Both connectionist temporal cost (CTC) loss and attention based cross entropy (CE) loss are used in the training, with CTC-weight set at 0.3 [59]. A single layer of 1000 LSTM cell recurrent neural network is used for language modeling (RNN-LM). For training the model, we use stochastic gradient descent (SGD) optimizer with a batch size of 32. For language model training, data is augmented from Wall Street Journal (WSJ) corpus.

¹The implementation of the work can be found in https://github.com/ anurenjan/DFAR

TABLE I

WER (%) ON THE REVERB DATASET FOR ENVELOPE/CARRIER, ENVELOPE-CARRIER DEREVERBERATION (DFAR) AND THE JOINT E2E-DFAR MODEL. THE RELATIVE IMPROVEMENTS (%) PERTAIN TO THE COMPARISON OF THE VARIOUS CONFIGURATIONS W.R.T. THE BF-FBANK BASELINE SYSTEM.

Model	Dev			Eval		
Config.	Real	Sim.	Avg. [Rel. Imp.]	Real	Sim	Avg. [Rel. Imp.]
BF-FBANK (baseline)	12.8	8.7	10.8 []	11.9	7.9	9.9 []
DCCRN [53] + BF-FBANK Fullsubnet + BF-FBANK [54] Deep non-linear filter [55] + BF-FBANK Reverb. time shortening [56]+ BF-FBANK	17.4 11.8 12.4 11.5	10.4 7.9 8.1 7.6	13.9 [-28.7] 9.9 [+8.3] 10.3 [+4.6] 9.6 [+11.1]	15.3 10.5 10.5 10.1	8.8 7.4 7.2 7.6	12.1 [-22.2] 9.0 [+9.1] 8.9 [+10.1] 8.9 [+10.1]
STFT Deverb. + BF-FBANK Sub-band sig. Dereverb. + BF-FBANK	12.0 13.3	7.8 9.8	9.9 [+8.3] 11.6 [-7.4]	10.8 12.8	7.3 8.6	9.1 [+8.1] 10.7 [-8.1]
FDLP Env. Derevb. + BF-FBANK FDLP Carr. Dereverb. + BF-FBANK DFAR + BF-FBANK	12.7 11.2 10.6	8.5 8.3 7.6	10.6 [+1.9] 9.8 [+9.3] 9.1 [+15.7]	10.1 10.8 9.1	7.8 7.6 6.9	9.0 [+9.1] 9.2 [+7.1] 8.0 [+19.2]
E2E-DFAR	9.4	6.4	7.9 [+26.9]	7.3	5.7	6.5 [+34.3]

C. Performance metrics

- 1) ASR performance metrics:
- WER/CER (Word/Character Error Rate): The word/character error rate is given by the ratio of number of word/character insertions, deletions and substitutions in the system output to the total number of words/characters in the reference.
- 2) Speech quality metrics:
- **SRMR**: Speech to reverberation modulation ratio (SRMR) is a non intrusive measure. Here, a representation is obtained using an auditory-inspired filter bank analysis of critical band temporal envelopes of the signal. The modulation spectral information is used to get an adaptive measure termed as speech to reverberation modulation energy ratio [60], [61]. A higher value indicates an improved quality of the given speech signal.
- **MOS** (Mean Opinion Score): To evaluate the performance of dereverberation algorithms, subjective quality and intelligibility measurement methods are needed. The most widely used subjective method is the ITU-T standard [62], where a panel of listeners are asked to rate the quality/intelligibility of the audio.

V. EXPERIMENTS AND RESULTS

The baseline features are the beamformed log-mel filterbank energy features (denoted as BF-FBANK).

A. REVERB Challenge ASR

The word error rates (WER) for the dereverberation experiments are shown in Table I. Note that, all the experiments use the same input features (log-mel filter bank features) along with the same E2E ASR architecture (conformer encoder and transformer decoder). The only difference between the various rows, reported in Table I, is the dereverberation pre-processing applied on the raw audio waveform. All the dereverberation experiments use the DPLSTM architecture described in Sec. III.

TABLE II Comparison of the results with other works reported on the REVERB challenge dataset.

System	Eval-sim.	Eval-real	Avg.
Subramanian et. al. [63]	6.6	10.6	8.6
Heymann et. al. [64]	-	10.8	-
Fujita et. al. [65]	4.9	9.8	7.4
Purushothaman et. al. [18]	7.1	12.1	9.6
Zhang et. al. [66]	-	10.0	-
This work	5.7	7.3	6.5

TABLE III WER (%) IN REVERB DATASET FOR DIFFERENT ARCHITECTURES FOR THE DEREVERBERATION MODEL.

Model	Dev			Eval			
Config.	Real	Sim	Avg	Real	Sim	Avg	
Baseline	12.8	8.7	10.8	11.9	7.9	9.9	
CLSTM	14.5	9.7	12.1	12.4	9.1	10.8	
4-layer LSTM	12.5	8.0	10.3	10.1	7.1	8.9	
DPLSTM	10.6	7.6	9.1	9.1	6.9	8.0	

1) Various dereverberation configurations: In Table I, the first row is the baseline result with the beamformed audio (unsupervised GEV beamforming [13] and weighted prediction error (WPE) processing [9].

The next set of rows compare several prior works.

- Fullsubnet A full-band and sub-band fusion model for speech enhancement [54].
- DCCRN Deep complex convolution recurrent neural network model for speech enhancement [53].
- Deep non-linear filter for multi-channel audio [55]
- Reverberation time shortening [56]

The prior works are trained on the same data settings as used in the DFAR framework. All the prior works, except DCCRN (which is not designed for ASR), improve the baseline system in range of 8-11% in terms of relative WER. However, the proposed DFAR/E2E-DFAR approach is observed to provide

TABLE IV WER (%) IN REVERB DATASET FOR HYPER PARAMETER λ , IN $MSE \ loss = \lambda \times env. \ loss + (1 - \lambda) \times carr. \ loss.$

Parameter	Dev			Eval			
λ	Real	Simu	Avg	Real	Simu	Avg	
0	12	8.2	10.1	10.4	7.5	9.0	
0.2	11.9	8.6	10.3	10.7	7.7	9.2	
0.4	11.6	8.2	9.9	10.1	7.2	8.7	
0.5	11.3	7.2	9.3	9.7	6.5	8.1	
0.6	10.6	7.6	9.1	9.1	6.9	8.0	
0.8	13.1	8.7	10.9	10.9	7.9	9.4	
1	13.5	8.0	10.8	10.4	6.9	8.7	

the best WER, with relative improvement in WER of 19/34% on the evaluation data.

In Table I, we have also performed two ASR experiments - i) using STFT inputs (log magnitude), and ii) using the sub-band signal directly without the envelope-carrier decomposition. Both these experiments, use the DPLSTM dereverberation model proposed in this work. As seen in Table I, the dereverberation on the STFT magnitude component improves the ASR systems significantly over the baseline, while the dereverberation on the sub-band signal directly is not effective. However, the STFT approach is also seen to be inferior to the DFAR approach where the envelope-carrier dereverberation is performed.

The fourth set of rows corresponds to the WER results with envelope/carrier based dereverberation alone. The relative improvements of 2 - 9% are seen here compared to the baseline BF-FBANK. Separately, with dereverberation based on the carrier signal alone, a similar improvement is achieved. Further, the dereverberation of the temporal envelope and carrier components in a combined fashion using the DPLSTM model improves the ASR results over the separate dereverberation of envelope/carrier components. Here, average relative improvements of 16% and 19% are seen in the development set and evaluation set respectively, over the BF-FBANK baseline system for the DFAR approach.

The final row in Table I reports the results using the joint learning of the dereverberation network and the E2E ASR model. The E2E-DFAR is initialized using the dereverberation model and the E2E model trained separately. The proposed E2E-DFAR model yields average relative improvements of 27% and 34% on the development set and evaluation set respectively over the baseline system. The joint training is also shown to improve over the set up of having separate networks for dereverberation and E2E ASR. While the DFAR model is trained only on simulated reverberation conditions, the WER improvement in real condition is seen to be more pronounced than those observed in the simulated data. This indicates that the model can generalize well to unseen reverberation conditions in the real-world.

2) Comparison with prior works: The comparison of the results from prior works reported on the REVERB challenge dataset is given in Table II. The Table includes results from end-to-end ASR systems [63], [65], [66] as well as the joint enhancement and ASR modeling work reported in [64]. We

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 TABLE V

 Performance (WER %) on the VOICES dataset.

Model Config.	Dev	Eval
FBANK (baseline)	40.3	50.8
+ Env. derevb.	38.4	48.6
+ Envcarr. derevb. (DFAR)	37.1	45.4
+ E2E-DFAR	36.4	44.7

also compare with our prior work reported in [18]. Specifically, many of the prior works compared in Table II are based on STFT based enhancement. The work reported in Subramanian et. al. [63], used a neural beamforming approach in the STFT domain, while the efforts described in Heymann et. al. [64], used a long-short term memory network for mask estimation in power spectral domain (PSD). The dynamic convolution method proposed in Fujita et. al. [65] used deconvolution of log-mel spectrogram features. Similar to the proposed work, all these efforts have also used the E2E ASR model training. As seen in Table II, the proposed work improves over these prior works considered here, further highlighting the benefits of the dereverberation in the sub-band time domain using longterm envelope-carrier based DPLSTM models.

3) Dereverberation model architecture: The ASR experiments on the REVERB challenge dataset, pertaining to the choice of different model architectures used in the dereverberation model, are listed in Table III. We have experimented with convolutional LSTM (CLSTM) [50] and time-domain LSTM (4-layer LSTM) architecture [67] in addition to the DPLSTM approach. As seen here, the Dual-path recurrence based DPLSTM gives the best word error rate in comparison with the other LSTM neural architectures considered. This may be attributed to the joint time-frequency recurrence performed to the other approaches which perform only time domain recurrence.

4) Dereverberation loss function: The MSE loss function used in the DPLSTM model training consists of a combination of loss values from the envelope and the carrier components. We experimented with the hyper parameter, λ , which controls the proportion of envelope based loss and carrier based loss in the total loss (*Total loss* = $\lambda \times env$. *loss* + $(1 - \lambda) \times carr$. *loss*). The ASR results for the various choices of the hyper parameter λ are shown in Table IV. Empirically, the value of $\lambda = 0.6$ gives the best WER on the REVERB challenge dataset. Further, the choice of $\lambda = 1$ or $\lambda = 0$, corresponding to envelope/carrier only dereverberation, are inferior to other choices of λ , indicating that the joint dereverberation of the envelope and carrier components is beneficial.

B. VOiCES ASR

The ASR setup used in the VOiCES dataset followed the ESPnet recipe with the conformer encoder and a transformer decoder. The rest of the model parameters and hyperparameters are kept similar to the ones in the REVERB challenge dataset. The WER results on the VOiCES dataset are given in Table V. The dereverberation of the envelope alone provides an absolute improvement of 1.9% and 2.2% on the development and evaluation data respectively, compared

Signal			SRMR		
	Dev. (Real)	Dev. (Sim.)	Eval. (Real)	Eval. (Sim.)	REVB. (Train)
Unsupervised GEV beamforming [13]	5.18	4.1	4.58	4.67	4.23
+ WPE [9]	5.35	4.2	4.61	4.75	4.48
+ DCCRN [53]	5.43	4.37	4.63	4.94	4.67
+ Fullsubnet [54]	5.36	4.32	4.64	4.97	4.63
+ Deep Non-Linear Filters [55]	5.51	4.22	4.64	5.02	4.61
+ Reverberation Time Shortening Target [56]	5.49	4.57	4.62	5.2	4.58
+ STFT Mag. + DPLSTM	5.44	4.33	4.64	4.94	4.6
+ Sub-band signal + DPLSTM	5.45	4.28	4.61	4.87	4.63
+ env. derevb. (this work)	4.62	3.83	4.12	4.25	4.11
+ crr. derevb. (this work)	5.52	4.46	4.69	5.27	4.77
+ env. & crr. derevb. [DFAR] (this work)	5.52	4.47	4.69	5.27	4.77

 TABLE VI

 SRMR values on the REVERB dataset for various signal enhancement strategies.

 TABLE VII

 MOS values in REVERB dataset for envelope and carrier based enhancements.

	ET Real - near	ET Real - far	ET Simu - near	ET Simu - far
Baseline - GEV [13] + WPE [9]	3.78	3.65	3.74	4.12
+ envcarr. derevb. [DFAR] (this work)	3.98	3.67	4.01	4.40

to the FBANK baseline system. The dereverberation based on envelope-carrier modeling further improves the results. An absolute improvement of 3.3%/5.4% on the development/evaluation data is achieved, compared to the FBANK baseline. Further, the joint training on envelope-carrier dereverberation network with the ASR model improves the WER results. We observe relative improvements of 10% and 12% on the development and evaluation data respectively.

C. Speech quality evaluation

A comparison of the SRMR values for different dereverberation approaches is reported in Table VI. Here, we compare the baseline unsupervised GEV beamforming [13] and weighted prediction error (WPE) [9] with various strategies for beamforming. The deep complex convolutional recurrent network (DCCRN) based speech enhancement [53] is also implemented on the REVERB dataset, and these results are reported in Table VI. While the envelope based dereverberation did not improve the SRMR values, the carrier based dereverberation is shown to improve the SRMR results. Further, the DFAR model also achieves similar improvements in SRMR for all the conditions over the baseline approach (GEV+WPE) and the DCCRN approach.

We conducted a subjective evaluation to further assess the performance of the dereverberation method. The subjects were asked to rate the quality of the audio on a scale of 1 to 5, 1 being poor and 5 being excellent. The subjects listened to the audio in a relatively quiet room with a high quality Sennheiser headset. We perform the A-B listening test, where the two versions of the same audio file were played, the first one with GEV + WPE dereverberation and the second one with the proposed dereverberation approach. We chose 20 audio samples, from four different conditions (real and simulated data and from near and far rooms) for this evaluation and recruited 20 subjects.

The subjective results are shown in Table VII. As seen, the proposed speech dereverberation scheme shows improvement in subjective MOS scores for all the conditions considered. The subjective results validate the signal quality improvements observed in the SRMR values (Table VI).

VI. CONCLUSION

In this paper, we propose a speech dereverberation model using frequency domain linear prediction based sub-band envelope-carrier decomposition. The sub-band envelope and carrier components are processed through a dereverberation network. A novel neural architecture, based on dual path recurrence, is proposed for dereverberation. Using the joint learning of the neural speech dereverberation module and the E2E ASR model, we perform several speech recognition experiments on the REVERB challenge dataset as well as on the VOiCES dataset. These results show that the proposed approach improves over the state of art E2E ASR systems based on mel filterbank features.

The dereverberation approach proposed in this paper also reconstructs the audio signal, which makes it useful for audio quality improvement applications as well as other speech processing systems in addition to the ASR system. We have further evaluated the reconstruction quality subjectively and objectively on the REVERB challenge dataset. The quality measurements show that the proposed speech dereverberation method improves speech quality over the baseline framework of weighted prediction error. The ablation studies on various architecture choices provides justification for the choice of the DPLSTM network architecture. Given that the proposed model allows the reconstruction of the audio signal, it can be used in conjunction with self-supervised neural approaches for representation learning of speech as well. This will form part of our future investigation.

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