LATE REVERBERATION SUPPRESSION USING U-NETS

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ABSTRACT

In real-world settings, speech signals are almost always affected by reverberation produced by the working environment; these corrupted signals need to be dereverberated prior to performing, e.g., speech recognition, speech-to-text conversion, compression, or general audio enhancement. In this paper, we propose a supervised dereverberation technique using U-nets with skip connections, which are fully-convolutional encoder-decoder networks with layers arranged in the form of an “U” and connections that “skip” some layers. Building on this architecture, we address speech dereverberation through the lens of Late Reverberation Suppression (LS). Via experiments on synthetetic and real-world data with different noise levels and reverberation settings, we show that our proposed method termed “LS U-net” improves quality, intelligibility and other performance metrics compared to the original U-net method and it is on par with the state-of-the-art GAN-based approaches.

Index Terms— dereverberation, speech processing, convolutional networks, deep autoencoders, U-net.

1. INTRODUCTION

Speech reverberation is an acoustic phenomenon whereby reflections of the acoustic signal (over surfaces and objects) are combined with the original signal at the receiver’s end. The resulting reverberated signal is thus a corrupted one, where the intelligibility and quality of the speech is degraded [1]. Perceived reverberation levels depend on a number of factors, including the geometry of the room, the materials used in it, and the distance between the speaker and the receiver [2].

Reverberation can be modelled as a convolution between a source signal and the room impulse response. Based on this modelling assumption one can design dereverberation techniques to recover the source (original) signal from observations of the received (convolved) signal. A popular unsupervised approach is the Weighted Prediction Error (WPE) method. WPE estimates the original signal by applying a linear filter to the received signal, where the filter, learnt via maximum likelihood, assumes a Gaussian prior on the source signal (possibly heteroscedastic [4]). There are several extensions of WPE, in particular, the frequency domain normalized delayed linear prediction (FD-NDLP) method [5] is an efficient implementation of WPE which uses the short-time Fourier transform (STFT) and is known to outperform its temporal-domain counterpart.

Deep learning has also been recently used in speech dereverberation. For instance, multilayer perceptrons (MLP) and long short-term memory (LSTM) networks have been developed to learn mappings from a window of reverberated frames (or “context” windows) to a source frame, thus learning to dereverberate by inverse transformations [6][8]. Additionally, Zhao et al. [9] proposed an LSTM-based late-reverberation-suppression strategy which learns the difference between the source and reverberated signals, therefore, dereverberation is performed by subtracting the late reverberation estimation from the observed reverberated signal.

Architectures using deep autoencoders have too been considered for audio generation [10] and in particular for dereverberation [11], while generative adversarial networks (GAN) have been shown to improve training for some dereverberation methods [12,13]. Building on these tools, Ori Ernst et al. [14] used an encoder-decoder fully convolutional neural network called U-net (due to its layers arranged in the shape of an “U” [15]) for speech dereverberation. Their strategy was to learn the mapping between the (log) power spectrum between the reverberated and source signals as if they were images. In the same work, Ori Ernst et al. used a U-net as generator in a GAN.

In this work, we propose a novel U-net architecture for speech dereverberation. The unique feature of the proposed method is that it implements the U-net in a Late Reverberation Suppression (LS) setting, while in previous works i) LS has been addressed using LSTMs [8], and ii) U-nets have been used for direct reverberation [14] (and not for LS). Our proposed method exhibits significantly better results than traditional U-net in terms of popular intelligibility, quality and reverberation objective measures (e.g., speech-to-reverberation modulation energy ratio, SRMR), and achieves dereverberation indicators that are similar to recent extensions of the U-net architecture trained using GANs.

2. PROBLEM FORMULATION

Let \( x(\cdot) \) be the source signal and \( g(\cdot) \) the reverberated signal given by the convolution between the source and a room impulse response (RIR) \( h(\cdot) \). Let us also consider the reverberation time \( T_{60} \), given by the time it takes for a signal to decay 60 dB relative to the level of direct sound (initial impulse) [2]. The reverberation time \( T_{60} \), uniquely determined by \( h \), is relevant since it is a measure “how reverberant” a signal is when is convolved with \( h(\cdot) \). For instance, a reverberation time \( T_{60} = 0.2s \) represents a low level of reverberation, while \( T_{60} = 0.6s \) produces a noticeable reverberation level.

By considering a source of additive noise \( \eta(\cdot) \), the model relating the above defined objects is given by

\[
y(t) = (x * h)(t) + \eta(t),
\]  

(1)

where “\(*\)” denotes convolution operator. Dereverberation is thus defined as a blind deconvolution, that is, the task of recovering \( x(t) \) using observations of \( y(t) \) in eq. (1) when the \( h(t) \) is unknown. Notice that by splitting the room impulse response \( h(t) \) in early reflections
Fig. 1: Proposed U-net architecture for speech dereverberation. Skip connections are represented by horizontal continuous black arrows and the dashed connection is the distinguishing feature of our method that enables it use for late reverberation suppression.

The intuition supporting the proposed architecture follows the idea that estimating the late reflections $y_{late}(t)$ is simpler than estimating the full reverberated signal $y(t)$, since it is known that the true signal does appear as a component in the reverberated signal—see eq. (2). Therefore, by giving the U-net a less challenging task (by placing the input-output skipped connection shown at the top of Figure 1) our hypothesis is that the proposed U-net architecture will have improved performance in reconstructing the source signal against over the baseline U-net in [15]. This is because the baseline U-net aims to learn the reverberant-dereverberant mapping without any prior knowledge of the dereverberation process, in particular it does not considers that the source appears as an early reflection. The proposed model is trained in the same fashion as the baseline U-net using the MSE loss function.

For purposes of experimental validation, we will consider a recently proposed dereverberation method [14] based on a Generative Adversarial Network (GAN) using a U-net as generator, this architecture is known to improve the quality of dereverberated spectrograms generated over the original U-net method in [15]. In this method, the discriminator network classifies between the generator output spectrogram and the clean spectrogram or “target”. Learning using this strategy uses the following loss function:

$$L(G, D) = L_{GAN}(G, D) + \lambda L_{MSE}(G),$$

where $L_{MSE}(G)$ is the mean square error between the generator output and the target log power spectrum, $\lambda$ is an hyper-parameter controlling the MSE weight in the loss function and $L_{GAN}(G, D)$ has the traditional form of GAN loss.

In addition to U-net-based architectures above, we consider other known methodologies to dereverberation, mainly based on MLP and LSTMs. Summarising, all the architectures to be implemented in our experiments are

- **LS U-net**: Proposed Late Reverberation Suppression U-net
- **U-net**: The original U-net method, a symmetric U-net structure for dereverberation [15] trained on an MSE loss
- **U-net GAN**: a GAN architecture using a symmetric U-net as generator [14]
- **Context-MLP**: An MLP with Context Window [6][7]
- **Context-LSTM**: An LSTM with Context Window [8]
- **LS-LSTM**: A late reverberation suppression LSTM [9]
- **FD-NDLP**: The frequency domain normalized delayed linear prediction [5] (which is unsupervised)

All the above architectures were implemented exclusively for our experiments with the exception of FD-NDLP, for which we relied on officially released code. Training was performed using Adam [16] and a batch size of 16. U-net GAN, in particular, was trained using $\lambda = 1e-2$, chosen experimentally in order to keep MSE and $L_{GAN}$ in the same magnitude order. Furthermore, the input log power spectrum for U-net GAN was not normalized, but we set a minimum value of -80 dB and a maximum of 30 dB; this was because our preliminary results exhibited poor performance using normalization to confine the input in the [-1, 1] range or confining the output in the same range using tanh().

4. EXPERIMENTS

4.1. Datasets and pre-processing

Our experiments considered synthetic and real-world data. The former were taken from the LibriSpeech [17] database, whose utterances (audio examples in dataset) are sampled at 16 kHz. Our procedure to generate the synthetic reverberated speech was by convolving the LibriSpeech audio signals with RIR from the Omni [18] and MARDY [19] databases. The real-world data considered in our experiments came from the BUT Speech@FIT Reverber Database [20], which are retransmitted signals also taken from LibriSpeech, and are thus naturally reverberated.

Spectrograms, in all cases, were computed using FFT with a window length of 2048 samples and hop length of 512 samples; a Mel filterbank was used to reduce the bin size. Experimentally, we chose between 128 and 256 bins, in both cases it was possible to recover the temporal signal appropriately but when using a smaller number of bins (e.g., 64 bins) the signal was recovered with difficulty. Lastly, we used 128 bins and set the number of frames for each spectrogram to 340 (which was the mean value of frames over all training spectrograms) using Lanczos interpolation available on OpenCV.
4.1.1. Simulated data

RIRs from databases Omni [18] and MARDY [19] were used to generate reverberant speech audios. Omni is composed of 3 rooms, 2 of which were used for training and the remaining one for testing. MARDY (1 room) was used for testing only.

The reverberant training data was produced using random RIR utterances and random SNRs chosen from the range [15, 35] dB for each example. This strategy allowed for a training set with a wide variety of noise and reverberation time. Reverberation time varied in an approximate range of 0.3s and 0.7s for the considered databases. The reverberant test data was generated using Omni RIRs dataset for SNR = 15dB and SNR = 35dB (the same 500 utterances for each SNR). Another 500 utterances were produced using the MARDY RIRs dataset for near and far microphones, where noise was fixed at SNR = 35dB.

These synthetic signals were produced using the RIR generator based on the original method proposed by [21], in order to introduce $T_{60}$ variability. This way, the simulated data were generated for $T_{60}$ varying between 0.2 and 1.0s (9 values spaced in 0.1s) and using 50 utterances for each $T_{60}$ value.

4.1.2. Re-transmitted real-world data

We used the BUT Speech@FIT Reverb Database [20], which contains LibriSpeech re-transmitted for near and far microphones. We used 500 utterances for near and far microphones. Our quantitative evaluation was based on the following metrics:

- **PESQ**: Perceptual Evaluation of Speech Quality [22]
- **CD**: Cepstral Distance
- **LLR**: Log-Likelihood Ratio
- **fwSNRseg**: Frequency Weighted Segmental SNR [23] [24] [25]
- **SRMR**: Speech to Reverberation Modulation Energy Ratio [26]

The first four metrics are intrusive metrics, which compare the input signal with a clean signal (in terms of reverberation and noise) and then provide “similarity” scores. The SRMR metric, on the contrary, is a representation obtained by means and auditory-inspired filterbank (based on the functioning of the cochlea) analysis of critical band temporal envelopes of the speech signal [26]. Using this last non-intrusive measure is relevant regarding the realistic evaluation of the methods considered, since in real-world applications clean signals that can be used as benchmarks may not be available.

4.2. Results for synthetic data: varying noise

Table 1 shows the results of simulated data for SNR = 15dB and SNR = 35dB. The three variants of the U-net architecture exhibit the best dereverberation performance for all metrics and for both noise levels. Performances are consistent across SNR values, which shows advantages (in terms of noise) of the approaches based on U-net. The proposed LS U-net exhibits the best performance under most metrics while U-net GAN shows excels under the SRMR score, however, LS U-net still shows a clear advantage over the all other benchmarks, including the baseline U-net, for the SRMR score.

4.3. Results for synthetic data: varying $T_{60}$

Table 2 shows the results of simulated data for near and far microphones. Recall that the reverberation time $T_{60}$ (defined in Section

\[\text{Available on https://pypi.org/project/rir-generator/}\]
Table 1: Results of simulated data for SNR = 15dB y SNR = 35dB using Omni RIRs dataset. (↑): higher is better, (↓): lower is better.

| SNR (dB) | PESQ (↑) | CD (↓) | LLR (↓) | fwSNRseg (↑) | SRMR (↑) |
|----------|----------|--------|---------|--------------|----------|
| Reverberant | 1.98 | 2.11 | 7.30 | 5.39 | 1.36 | 0.81 | 6.38 | 7.69 | 3.08 | 3.17 |
| Context-MLP | 1.66 | 2.18 | 6.84 | 4.16 | 1.38 | 0.59 | 5.04 | 7.74 | 2.06 | 3.94 |
| Context-LSTM | 1.68 | 2.31 | 6.73 | 3.91 | 1.36 | 0.52 | 5.20 | 8.42 | 1.93 | 4.06 |
| LS-LSTM | 1.86 | 2.25 | 6.17 | 4.04 | 1.18 | 0.52 | 5.98 | 8.34 | 2.71 | 4.75 |
| FD-NDLPL | 2.09 | 2.43 | 7.45 | 4.30 | 1.39 | 0.54 | 6.96 | 9.66 | 4.25 | 4.47 |
| U-net | 2.59 | 2.66 | 4.44 | 3.26 | 0.61 | 0.36 | 9.35 | 10.00 | 5.93 | 5.61 |
| LS U-net | 2.65 | 2.72 | 4.38 | 3.23 | 0.59 | 0.34 | 9.56 | 10.20 | 6.30 | 5.98 |
| U-net GAN | 2.62 | 2.69 | 4.37 | 3.34 | 0.60 | 0.36 | 9.15 | 9.82 | 7.18 | 6.73 |

Table 2: Results of simulated data using MARDY RIRs dataset. Reverberation times are 291 and 447 ms for near and far microphones respectively. (↑): higher is better, (↓): lower is better.

| Mic. distance | PESQ (↑) | CD (↓) | LLR (↓) | fwSNRseg (↑) | SRMR (↑) |
|---------------|----------|--------|---------|--------------|----------|
| Near | Far | Near | Far | Near | Far | Near | Far | Near | Far |
| Reverberant | 2.57 | 2.15 | 5.25 | 5.71 | 0.85 | 0.97 | 8.68 | 6.58 | 5.21 | 4.49 |
| Context-MLP | 2.09 | 1.87 | 5.48 | 5.62 | 1.02 | 1.07 | 6.72 | 5.82 | 3.13 | 2.81 |
| Context-LSTM | 2.14 | 1.90 | 5.49 | 5.64 | 0.99 | 1.05 | 7.21 | 6.12 | 3.05 | 2.60 |
| LS-LSTM | 2.38 | 2.07 | 4.97 | 5.29 | 0.81 | 0.92 | 8.06 | 6.64 | 4.53 | 4.12 |
| FD-NDLPL | 2.71 | 2.24 | 5.44 | 5.83 | 0.90 | 1.00 | 8.57 | 6.60 | 6.03 | 5.34 |
| U-net | 2.65 | 2.28 | 4.12 | 4.57 | 0.54 | 0.65 | 9.23 | 7.52 | 5.47 | 4.88 |
| LS U-net | 2.74 | 2.36 | 4.09 | 4.59 | 0.52 | 0.64 | 9.32 | 7.63 | 5.73 | 5.36 |
| U-net GAN | 2.72 | 2.36 | 4.11 | 4.56 | 0.53 | 0.64 | 9.24 | 7.63 | 6.60 | 6.19 |

4.4. Qualitative evaluation for synthetic data

Figure 3 shows SRMR results of simulated data using RIR generator as a function of $T_{60}$. The RIR generator was used assuming a room of dimensions $5[m] \times 4[m] \times 6[m]$ (width, length and depth). As expected, the SRMR score decreases for increasing $T_{60}$ for all methods, with the reverberant (unprocessed, shown in blue) signal having the sharpest decay and the proposed LS U-net (orange) closely following the state-of-the-art U-net GAN (black). None of the model considered improved over the mean score of the reverberant utterances at $T_{60} = 0.2s$; this was expected since a reverberation time of 0.2s represents a very subtle reverberation level. Reverberation times in [0.5, 1.0] seconds allow us to observe the dereverberation effectiveness of LS U-net and U-net GAN, since SRMR score is appreciably higher compared to reverberant utterances and the rest of models. U-net GAN (black) and the proposed architecture LS U-net (orange) show robust behavior in terms of reverberation time and also in terms of noise as previously shown in Table 1.

4.5. Results for real-world data

Table 3 shows the SRMR for the real-world data. U-net GAN exhibited the best results for near microphones and Late Reverberation Suppression LSTM (LS-LSTM) (7) for far microphones. Though the proposed architecture LS U-net did not exhibit the best performance for real data, it improved over the baseline U-net and FD-NDLPL performance for near and far microphones nonetheless. Critically, if we ranked the seven methods considered in Table 3 based on their SRMR score, the proposed LS U-net would be third for both near and far microphones. This makes the proposed alternative for late reverberation suppression applied to U-net effective in real data.

5. CONCLUSIONS

We have proposed a U-net architecture for late reverberation suppression, termed LS U-net, and have experimentally validated it on synthetic and real-world data of different noise levels and reverberation times and microphone distances. Our results show that LS-Uenet outperforms a wide range of deep-learning dereverberation methods under multiple performance indicators. In particular, LS U-net improves over the original U-net architecture and stands as a competitive alternative to the state-of-the-art GAN-trained version of U-net. In the light of this results, future work will focus on developing a GAN-trained version of the proposed LS U-net method.

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